When Information Markets Export Noise: Spillovers from Prediction Markets to Traditional Assets

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Abstract

Prediction markets are widely promoted as efficient mechanisms for aggregating dispersed information and generating signals for the broader economy. We document cross-market learning between Polymarket and traditional financial markets during the 2024 U.S. presidential election. Changes in Polymarket-implied victory probabilities predict next-day returns of "Trump trades" across asset classes, followed by partial reversals, indicating that cross-market learning transmits both information and noise. Using blockchain-based transaction data, we classify Polymarket traders as informed or uninformed and show that price impact from uninformed trading explains a substantial share of the lead–lag predictability and the subsequent reversal. To establish causality, we instrument Polymarket trading volume with Ethereum gas fees—an exogenous component of market entry costs. We further document an "information hangover" effect: informed trading increases traditional-market reliance on Polymarket signals, amplifying subsequent noise spillovers. In summary, information and noise in prediction-market prices spill over into far larger and deeper traditional asset markets.

Keywords: Prediction markets, learning, spillover, information aggregation, noise trading, political uncertainty, Polymarket, DeFi, and blockchain.
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1 Introduction

Prediction market probabilities are increasingly treated as a gold standard for real-time assessments of event outcomes, routinely embedded in financial market participants' decision-making process: asset managers track them in their risk models, sell-side researchers and strategists cite them in their analysis, and firms use them as scenario weights. This information pipeline creates cross-market learning: prediction-market price variations influence asset prices in traditional financial markets.

It is challenging to empirically identify learning: variations in economic fundamentals may drive asset prices in both markets—that is, as news may arrive sequentially to one market after another, one cannot take any lead-lag relationship as evidence for cross-market learning rather than sequential information arrival. Our approach focuses instead on noise spillover. We establish that noise in the prediction-market prices affects prices of traditional asset. As noise is orthogonal to fundamental news, this approach achieves a cleaner identification of cross-market learning.

To identify noise in prediction markets, we take advantage of data availability and semi-experimental settings provided by the blockchain infrastructure of Polymarket, one of the major prediction markets and the largest one based on blockchain infrastructure. By examining the wallet-level footprint of trading activities, we classify traders into informed and uninformed based on their trading performances. The price impact of uninformed traders' transactions on Polymarket is the noise.[1] Beyond identifying uninformed trades, our causal inference utilizes an instrumental variable based on exogenous variation of the market entry cost that is in turn related to the gas fees of Ethereum, the layer-1 blockchain underlying the Polymarket settlement layer (Polygon).

Our paper provides convincing evidence on cross-market learning and reveal that alongside information, prediction markets export noise—that is, investors in the traditional financial markets cannot perfectly filter out noise in prediction-market prices. As a result, non-fundamental price pressure can propagate from the newly developed prediction markets to traditional financial markets, such as stocks, currencies, and commodities, that are magnitudes larger in trading volume and

[1] Unlike traditional financial markets where firms, households, and the government raise financing, prediction markets do not serve a financing role, so the price impact is solely from the asset demand rather than securities supply.

market capitalization. In the following, we summarize our methodology and findings.

Our empirical setting is the 2024 U.S. presidential election. We work with several data sources. We obtain daily and intraday changes in Polymarket probabilities of Donald Trump winning the election and compute the returns of a portfolio of "Trump trades" in the traditional asset classes, such as stocks, bonds, currencies, and commodities. Financial media and sell-side research consistently flagged certain assets as sensitive to Trump's election outcome and his policy priorities. In addition, we directly work with on-chain data on individual wallets' Polymarket trading activities to identify uninformed traders. Our analysis takes four steps: documenting the lead-lag relationship from Polymarket to traditional assets (i.e., the Trump trades), establishing the noise transmission by identifying uninformed Polymarket traders and their price impact, establishing causality through an instrumental variable approach, and developing a theoretical framework for additional empirical tests of the economic mechanisms.

We first document a robust lead-lag relationship from variations in prediction-market probabilities to traditional-asset returns and thereby provide suggestive evidence of cross-market learning. We construct a portfolio of highly liquid, "Trump-trade" assets identified through systematic review of media coverage and sell-side research reports and find that changes in Polymarket's Trump-winning probability predict next-day returns of Trump trades: a one-percentage-point increase in Polymarket probability is associated with approximately 3.7 basis points (9.8% annualized) higher returns of Trump trades next day. A trading strategy based on this signal earns a 1.9 annualized Sharpe ratio and a total return of 18.55% from Jan. 2024 through the election date. Interestingly, this lead-lag effect concentrates in the first 2 days and largely reverses after 5 days, suggesting what is being transmitted across markets is partly noise. In addition, we find that these patterns are stronger among assets more sensitive to the U.S. presidential election outcome.

Second, to distinguish information from noise, we exploit the unique transparency of Polymarket's blockchain ledger. It offers an immutable, trader (wallet)-level audit trail—a granular dataset typically unavailable in traditional financial markets—allowing us to classify traders based on their performances. We classify a trader as informed if their trades on average generates profits,

or equivalently, the Polymarket price moves in the direction of their trades on average. The rest of traders are classified as uninformed (noise) traders. We then decompose the daily change of Polymarket price into a component driven by informed trading and a component driven by uninformed trading. We find that the former leads Trump trades and its effect does not reverse while the latter predicts Trump trade returns on the following day but a full reversal happens on the second day.

Beyond decomposing Polymarket price changes into components driven by informed and uninformed trading, we also examine directly how informed and uninformed trading volumes on Polymarket affect subsequent Trump-trade returns. We find a similar lead–lag pattern: the impact of informed trading persists, whereas the effect of uninformed trading fully reverses after one day. Taken together, these empirical results provide consistent evidence of both information transmission and noise spillovers from Polymarket to the broader financial system.

Third, we expand our findings on information and noise transmission and, in particular, establish causality using an instrumental-variables (IV) strategy. Participation in Polymarket requires traders to move funds onto the Polygon network through an on-ramp process that typically incurs Ethereum gas fees.[2] These fees compensate Ethereum network validators and fluctuate with aggregate demand for block space across the entire Ethereum ecosystem, of which Polymarket represents only a small share. This institutional feature provides a measure of participation costs that is plausibly exogenous to Trump trade returns, except via its effect on Polymarket trading.

Using Ethereum gas fees to instrument for total Polymarket trading volume, we find that the instrumented volume—just like the uninformed traders' trading volume—predicts positive Trump-trade returns on the following day, followed by a reversal on the second day. This pattern provides causal evidence that prediction-market activity driven by exogenous participation costs transmits noise, rather than information, to traditional financial markets.

Our IV approach serves two purposes. First, it establishes a causal link between trading activity on Polymarket and subsequent price movements across assets in the broader financial system. Second, it demonstrates consistency between two complementary approaches to identifying

[2]Specifically, a Polymarket user pays Ethereum gas fees when transferring U.S. dollars in the form of USDC stablecoins from the Ethereum network (Layer 1) to Polygon (Layer 2) to fund a Polymarket account.

noise trading on Polymarket. Because our trader classification based on average trading performance is necessarily imperfect—informed traders may occasionally place noise trades, while traders classified as uninformed may sporadically trade on private information—an alternative source of identification is valuable. In the IV approach, trading volume instrumented by transaction costs is most likely to reflect uninformed trading, as traders possessing valuable private information face a short-lived informational advantage and are therefore eager to trade promptly, rendering them relatively insensitive to fluctuations in transaction costs. The close alignment between results based on instrumented total trading volume and those based on trader classification thus provides mutual validation of the two approaches and reinforces the robustness of our findings.

In addition, although our primary focus is on establishing cross-market learning through noise transmission, we provide compelling evidence of information transmission from Polymarket to the broader financial system, reflected in the heterogeneous effects across periods with differing intensities of information arrival. Specifically, we find that in the days preceding major polling releases, the impact of informed Polymarket trading on subsequent Trump-trade returns is stronger and, consistent with our baseline results, does not reverse. In contrast, during these same periods of imminent information arrival, the effect of uninformed Polymarket trading is attenuated. This pattern suggests that participants in traditional financial markets are more likely to distinguish between informed and uninformed prediction-market trading when new information is about to be revealed, while paying less attention to this distinction at other times, allowing noise to transmitted.

In the last and forth step, we formalize the mechanism of cross-market learning by adopting the framework in Goldstein et al. (2025). In the model, rational investors in a traditional asset market observe a prediction-market price that mixes information about the asset's fundamentals and noise. As the investors cannot perfectly filter out noise, they place positive weight on the prediction-market price no matter whether it is driven by informed trades or uninformed trades in the prediction market. Therefore, the prediction-market price transmitting noise alongside information. The model provides an intuitive account of our empirical findings and provide additional implications that lead to a more nuanced characterization of the noise transmission mechanism.

According to our model, noise transmission from the prediction market to traditional assets is stronger when traditional-asset investors face greater uncertainty over the event (i.e., the U.S. presidential election result). Intuitively, when their belief is less precise—proxied by the dispersion of election polling results—investors rely more on external signals, such as prediction market prices, allowing noise to be transmitted alongside with information. This is exactly what we find.

Interestingly, noise transmission is stronger precisely when prediction-market prices more accurately reflect the underlying event outcome. Existing studies document that prediction-market prices often reveal valuable information (e.g., Ng et al., 2025; Diercks et al., 2026). However, it is this very informativeness that creates a channel for noise transmission: when signals are perceived as more precise, investors place greater weight on them, and when price variation is instead driven by noise, that greater weight amplifies the transmission of noise to traditional markets. We test this hypothesis using two proxies for the quality of prediction-market signals. The first is market depth—deeper markets are less susceptible to transitory price pressure from noise trades, making prices more likely to reflect fundamental information. The second proxy is recent trading volume by informed traders. Consistent with the hypothesis, both measures, when interacted with Polymarket price variation, exhibit a statistically significant impact on subsequent Trump-trade returns.

Related Literature. First, we contribute to the literature on prediction markets. While a large body of work documents their remarkable forecasting accuracy and informational efficiency (e.g., Wolfers and Zitzewitz, 2004; Arrow et al., 2008; Berg et al., 2008; Ng et al., 2025; Chernov et al., 2025), another stream highlights potential inefficiencies arising from behavioral biases, participant selection, or thin liquidity (Page and Siemroth, 2017; Ottaviani and Sørensen, 2012). We bridge these views by showing that even if a market is informationally efficient on average, its prices can export non-fundamental noise to external observers. Our work relates to the theoretical literature on the distortion of information aggregation in markets (Grossman and Stiglitz, 1980; Bond and Goldstein, 2015). We show that when sophisticated agents treat prediction market prices as an input under cross-market learning, they can rationally propagate noise.

Second, our theoretical framework builds on the literature on noise trading and limits to arbitrage Goldstein et al. (2025). While this literature traditionally focuses on noise originating within a single market, we provide trader-level evidence of noise transmission across markets. Our findings complement the price discovery literature (Hasbrouck, 1995) by documenting a lead-lag relationship where the leading signal contains a measurable noise component. This cross-market transmission of non-fundamental shocks echoes work on cross-country information spillovers (King and Wadhwani, 1990) but provides a distinct mechanism based on signal extraction rather than wealth effects or correlated information and highlights the connection between the newly developed prediction markets and the much deeper traditional financial markets.

Third, we contribute to the literature on political uncertainty and asset prices (e.g., Pástor and Veronesi, 2012, 2013). In particular, we show that during heightened political uncertainty (proxied by the dispersion of election polling results), noise transmission from prediction markets to traditional financial markets becomes more potent. Therefore, instead of examining the impact of policy uncertainty on asset prices, we provide evidence on how it affects cross-market lead-lag relationships driven by noise propagation.

Fourth, our work offers a methodological contribution to the empirical literature on decentralized finance (DeFi) and financial technology. We use exogenous variation in blockchain transaction costs (gas fees) as an instrument for trading activity, in the spirit of identification strategies that exploit institutional frictions in financial technology (Bartlett et al., 2022; Makarov et al., 2022). This approach allows us to causally identify the effect of uninformed trading in Polymarket on prices of traditional financial assets. To our knowledge, this is the first paper to provide causal, trader-level evidence that noise originating in a prediction market spills over into other markets.

Finally, in the broader literature on distorted information transmission, the focus has been on how information intermediaries, including traditional media and prediction markets, can affect the real economy through information propagation (e.g., DellaVigna and Kaplan, 2007; Snowberg et al., 2007). Instead, we analyze how distorted information transmission generates connections between two types of financial markets of drastically different magnitudes.

The remainder proceeds as follows. Section 2 reviews Polymarket's institutional details and our sample and defines Trump trades. Section 3 establishes the lead-lag relationship from Polymarket to Trump trades, and evaluates economic significance via a trading strategy. Section 4 develops the trader-level classification, ties uninformed trading to the lead-lag relationship with an IV design for causal inference, and provides evidence on information transmission upon imminent resolution of uncertainty. Section 5.1 lays out a theoretical framework that rationalizes our findings and generates additional predictions tested in Section 5.2. Section 6 concludes.

2 Polymarket and Trump Trade in 2024

In this section, we provide institutional background on Polymarket and describe our sample. We also document key patterns of market activities that inform our subsequent empirical analysis.

2.1 An overview of the prediction market

In a prediction market, payoffs are tied to the outcomes of future events. The winner-takes-all contract for a binary outcome is most common.[3] A salient example is the contract on the 2024 U.S. presidential election, which is the focus of our analysis. For the 2024 U.S. presidential election, users trade "Yes" and "No" shares for each candidate's victory. Our analysis focuses on the shares for Donald J. Trump. The price reflects the market-implied probability of an outcome. For each contract ("share"), the share price fluctuates between \$0 and \$1. Upon event resolution, shares for the realized outcome pay \$1; other contracts expire worthless.

The prediction market that we analyze in Polymarket. During 2024, Polymarket became the dominant venue for predicting the outcome of U.S. presidential election, attracting widespread media attention and interests from traditional financial institutions.[4] Unlike traditional centralized exchanges, it runs on the Polygon network—a Layer-2 scaling solution of Ethereum, a blockchain-

[3]There are also index contracts, in which the payout varies along a continuum of outcomes. Another type is spread betting, where, for example, the bet is either that one team wins by at least a certain number of points or not.

[4]Examples of financial media coverage appear in Internet Appendix Figures A.3 and A.4.

based decentralized ledger. This architecture makes all trading activities publicly verifiable and immutable and eliminates concerns about data manipulation or traders' selective disclosure of transactions.[5] Our analysis utilizes trade-level data and information on order books.

The market is set up as a central limit order book (CLOB) with price-time priority, mirroring traditional exchanges.[6] Large market orders can "walk the book" by penetrating multiple price levels, generating price impact. This mechanism is central to our analysis: large trades may create detectable price movements that subsequently reverse as liquidity providers refill the limit orders.

2.2 Polymarket price

Our Polymarket dataset spans January 5, 2024 through November 4, 2024 (the day before the presidential election), integrating on-chain and off-chain data sources. On-chain data, sourced directly from Polygon, provides complete transaction details: timestamps, wallet addresses, volumes, gas fees, and prices. This granular structure enables reconstruction of wallet-level trading histories—an almost impossible task with traditional market data—facilitating our classification of market participants into informed versus uninformed ones. Off-chain data from Polymarket's APIs supplements trade records with contract specifications and real-time, high-frequency price feeds.

Trump's winning probability from Polymarket price exhibits substantial temporal variation throughout 2024. Figure 1 displays the complete time series at the daily frequency, ranging from approximately 44% in early 2024 to peaks exceeding 60% approaching the election. Key inflection points correspond to major political developments: the Biden-Trump debate in late June, attempted assassination of Donald Trump, Joe Biden's withdrawal, and subsequent polling releases.

Panel A of Table 1 presents summary statistics for key Polymarket variables. Trump's mean winning probability is 53% with a standard deviation of 5.9%. Daily probability changes exhibit mean-reversion with positive skewness and excess kurtosis, indicating occasional large movements superimposed on typical gradual adjustments. Trading volume varies, clustering around major

[5] Screenshots of the platform interface appear in Internet Appendix Figures A.1 and A.2.
[6] This represents a shift from earlier decentralized automated market makers (AMMs) in December 2022.

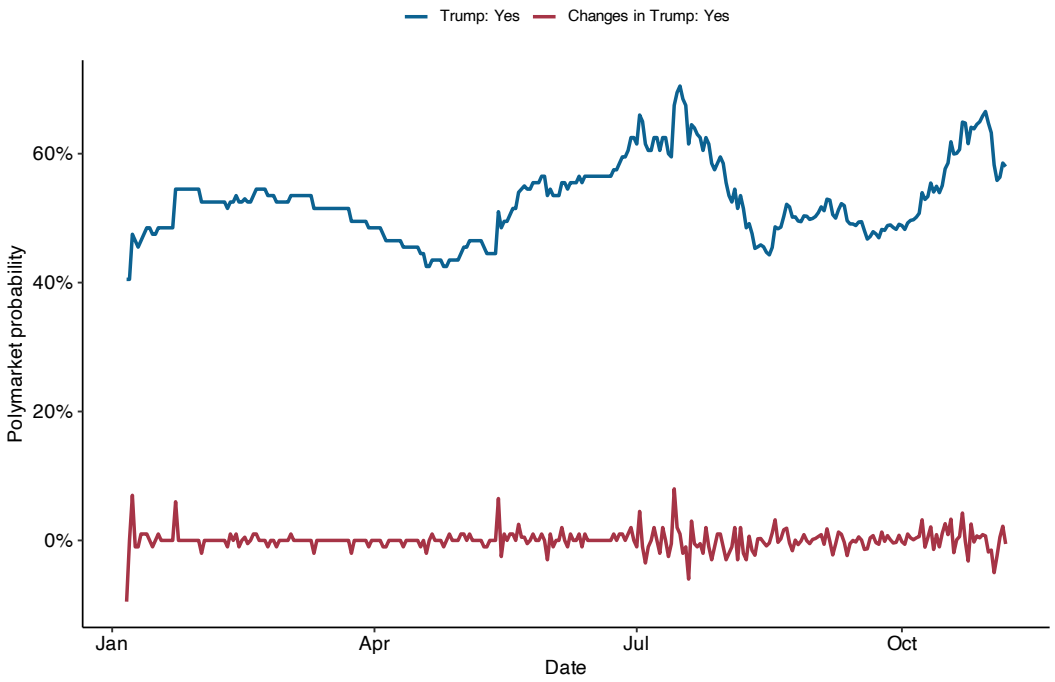


Figure 1 Polymarket Trump Winning Probability Over Time

Trump probability exhibits clustered jumps around identifiable political events. The probability is derived from the price of the "Yes" token, which pays $1 if Trump wins and $0 otherwise. The sample period spans from January 5, 2024, through the election date.

events. This substantial variation over time provides sufficient statistical power to identify cross-market spillover from Polymarket to traditional financial markets, which is the focus of our paper.

2.3 Identifying the Trump trades

We identify the traditional financial assets whose prices can be sensitive to the 2024 election outcome, i.e., the "Trump trades", and we document return patterns consistent with their sensitivity to the ongoing developments of U.S. presidential election over the year 2024.

"Trump trades" are financial assets that market participants expect to respond systematically to Trump's electoral prospects. These include assets expected to benefit from Trump's policies as well as those expected to be harmed. We adopt a narrative-based strategy to identify such assets, systematically reviewing financial media coverage to catalog assets consistently characterized as Trump-sensitive. This approach captures real-time market participant perceptions rather than

Table 1 Summary Statistics: Polymarket Trump Winning Probability and the Trump Trades

This table presents summary statistics for the Polymarket Trump winning probability and Trump trade assets. Panel A reports the daily end-of-day probability (0–100%) that Trump wins the 2024 presidential election according to Polymarket ($\mathcal{P}(Trump)$), along with its daily change ($\Delta\mathcal{P}(Trump)$). Panel B lists the assets identified as "Trump trades" through systematic review of financial media and analyst reports during the 2024 election cycle, categorized by asset class. Panel C reports summary statistics for daily log returns of these assets. Returns are signed to reflect directional exposure to Trump's electoral prospects: positive (long) for assets expected to benefit from Trump's win, negative (short) otherwise (see Table A.1 in the Internet Appendix for a complete list of trading directions). The sample period spans January 5, 2024 through November 4, 2024. All statistics are in percentage terms.

Panel A: Polymarket Trump Winning Probability

	nobs	mean	sd	p5	p25	median	p75	p95
$\mathcal{P}(Trump)$	307	52.665	5.876	44.500	48.500	52.500	55.500	64.070
$\Delta\mathcal{P}(Trump)$	306	0.026	1.549	-2.188	-0.400	0.000	0.538	2.000

Panel B: Trump Trade Tickers by Category

Stock ETF	SPY, QQQ, IWM, MAGS, DIA, XLF, KRE, XLI, XLE, XAR
Bond	SHY, IEI, IEF, TLH, TLT, GOVT, TIP
Banks	GS, MS, JPM, C, BAC, WFC
Currency & Commodity	UUP, EURUSD, GBPUSD, USDJPY, USDCNH, USDMXN
	BTC, ETH
	XAU

Panel C: Trump Trade Daily Returns

	# of tickers	nobs	mean	sd	p5	p25	median	p75	p95
All	32	7,402	0.088	1.345	-1.737	-0.379	0.047	0.565	1.934
By category:									
Stock ETF	10	2,240	0.108	1.195	-1.769	-0.516	0.128	0.748	1.811
Bank	6	1,320	0.173	1.643	-2.120	-0.660	0.149	1.017	2.414
Bond	7	1,604	0.003	0.522	-2.153	-0.259	-0.020	0.220	2.478
Currency & Commodity	9	2,238	0.078	1.663	-0.787	-0.323	0.035	0.428	0.897

imposing ex-post classifications based on realized asset performances.

We review financial media coverage from Bloomberg, Wall Street Journal, and the Financial Times throughout the 2024 election cycle. We focus on articles, analyst reports, and market commentary that explicitly link assets to Trump's electoral prospects or policy priorities. This ensures our classification reflects contemporaneous market perceptions. Internet Appendix Figure A.5 illustrates Bloomberg's real-time tracking of "Trump trades" as a distinct investment theme.

The economic rationale for these trades stems from anticipated policy differences across

several key dimensions between the presidential candidates. Trump's campaign platform is broadly associated with lower corporate taxes, deregulation of the financial sector, and pro-fossil fuel policies. His approach to international trade, centering around tariff policies, creates distinct exposures for certain sectors and foreign currencies. His broader fiscal policy stance on government spending and taxation, along with his public statements on cryptocurrency regulation, are expected to influence related assets ranging from cryptocurrencies to Treasury securities. Finally, a general market perception of Trump as pro-business and pro-growth underpins the expectation of broad benefits for equities and other risk assets (e.g., commodities).

Panel B of Table 1 presents our catalog of Trump trades, organized by asset category. The portfolio includes stock ETFs, bonds, bank stocks, currencies and commodities. We specify the expected directional relationship for each asset: "long" positions benefit from Trump victory, "short" positions benefit from Trump defeat. Complete directional specifications appear in Internet Appendix Table A.1. Bank stocks comprise a leading category due to expected deregulation benefits. Traditional energy represents another major category benefiting from pro-fossil fuel policies. Renewable energy assets face potential headwinds. Currency exposures reflect trade policy and fiscal expectations, with dollar strength anticipated under Trump's tariff policies. Category-average cumulative returns appear in Internet Appendix Figure A.6.

We obtain daily pricing data for all Trump trades from two sources: Center for Research in Security Prices (CRSP) for U.S. Stocks and ETFs price and LSEG (formerly Refinitiv) Workspace for currency, commodity, and crypto assets. Returns for stocks are adjusted for dividends and corporate actions, such as stock splits, M&A, seasoned equity offering, etc. For currencies, commodities, and cryptocurrencies, we calculate the log return as the log differences of adjusted closing prices.[7] Finally, all returns are signed to reflect their expected directional sensitivity to Trump's electoral prospects (long for positive sensitivity, short for negative sensitivity), with complete directional specifications provided in Internet Appendix Table A.1.

Panel C of Table 1 presents summary statistics of Trump trade daily returns by asset category.

[7] All prices of commodities are spot prices (not futures prices).

The mean daily return across all Trump trades is 0.09% (9 bps) with a standard deviation of 1.3%. The standard deviation is high relative to the typical equity market, reflecting substantial volatility in these assets during an election year. Among all the categories, bank stocks exhibit highest average returns with high volatility, consistent with their regulatory sensitivity.

3 Cross-Market Return Predictability

We document the lead-lag relationship between prediction market prices and traditional asset returns. Our findings suggest that participants in the traditional financial markets rely on signals from the prediction markets. This section first validates the unique information content in Polymarket prices and then establishes the systematic cross-market lead-lag relationship and its partial reversal.

3.1 Polymarket leading traditional assets

While market participants have multiple sources of information, they may still find variation of Polymarket prices distinctively informative about Trump's presidential prospect. For example, in the Appendix II, we show that Polymarket price contains information that is distinct from what's embedded in prices of traditional-market assets that are directly tied to then presidential candidate Donald J. Trump and his family (e.g., the stock of Trump Media, DJT). Below we test whether information spills over from the prediction market to traditional assets.

Next, we examine whether prediction-market price variations systematically lead traditional assets' movements through predictive regressions across multiple horizons:

$$r^{TT}_{i,t+1\to t+h} = \alpha_h + \beta_h \cdot \Delta\mathcal{P}_t(\text{Trump}) + \gamma_h \cdot \text{Controls}_t + \varepsilon_{i,t+1\to t+h} \tag{1}$$

We define cumulative log returns as $r^{TT}_{i,t+1\to t+h} = \sum_{j=1}^{h} r_{i,t+j}$ for Trump trade asset i. For each asset, signed returns $r^{TT}_{i,t} = d_i r_{i,t}$ encode trading direction ($d_i \in \{+1, -1\}$) based on Trump policy exposure. Here $\Delta\mathcal{P}_t(\text{Trump})$ denotes daily changes in Trump's winning probability, and Controls_t includes potential confounding factors such as DJT returns. The key coefficient β_h captures horizon-

dependent predictive power for $h = 1, 2, 5$ trading days. We align signals to the timing of U.S. markets by computing end-of-day changes, ensuring signals are available before next trading day.

We sign the returns so that positive coefficients ($\beta_h > 0$) consistently indicate higher Trump winning probability predicts returns in expected directions. Our primary specification pools all Trump trades to capture the average transmission effects. This pooling result is robust to different assets' time-varying sensitivities to Trump's policies and policy priorities that evolved throughout the election season. We also conduct analysis category-by-category to explore the heterogeneity.

Panel A of Table 2 presents our results from pooled regressions spanning Jan. 2024 through the election date. Polymarket price changes systematically predict Trump trade returns in the next two days with the coefficient on $\Delta\mathcal{P}_t(\text{Trump})$ is positive and statistically significant for $h = 1, 2$. The magnitude is economically meaningful: a one percentage point increase in Trump's Polymarket probability predicts a 3.7 basis point increase in next-day Trump trade returns and 4.4bps on a cumulative basis over the next two days (see the second row of Panel A). The effect reverses at longer horizons—reaching -0.8 basis points after five days and becoming statistically insignificant. This subsequent reversal indicates that the initial response partly reflects transitory noise.

Panels B and C of Table 2 confirms robustness across alternative sample periods beginning Apr. 1, 2024 or Biden's withdrawal. Polymarket's predictive power strengthens as the sample period shortens towards the election date. One-day coefficients increase from 3.7 bps in the full sample to 6.8 bps after April 1 and over 10 bps after Biden's withdrawal, with t-statistics exceeding 4.0. This amplification suggests market participants place greater weight on prediction market signals as political uncertainty intensifies and the election data approaches. The one-day R^2 rises to 0.5% and 1.0% in Column (1) in later samples, indicating Polymarket changes explain meaningful variation in the returns of traditional assets over the next day. Critically, the pattern of initial predictability followed by partial reversal holds across all samples, reinforcing our interpretation that prediction market prices contain both information and noise.

Tables A.3 in the appendix presents results of placebo tests. We run predictive regressions using two sets of assets that have relatively small exposure to Trump's policies, such as taxation,

Table 2 Trump Winning Probability on Polymarket Predicts Asset Returns at Multiple Horizons

This table presents results from predictive regressions of Trump trade returns on lagged changes in Trump's winning probability on Polymarket. The dependent variable is the h-day ahead signed return for Trump trades, where returns are signed to align with expected directional relationships. $\Delta\mathcal{P}_t(\text{Trump})$ is the daily change in Trump's Polymarket probability (in percentage points). Standard errors are clustered by asset. Panel A, B and C use the full sample, the sample beginning April 1, 2024 and the sample after Biden withdrawal, respectively. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

	$r^{TT}_{i,t+1}$			$r^{TT}_{i,t\to t+2}$			$r^{TT}_{i,t\to t+5}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Full Sample									
Constant	0.001***	0.001***	0.001***	0.002***	0.002***	0.002***	0.004***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
$\Delta\mathcal{P}_t(Trump)$	0.037***		0.029***	0.044***		0.036***	-0.008		-0.005
	(0.009)		(0.009)	(0.012)		(0.011)	(0.011)		(0.017)
$r_{DJT,t}$		0.004***	0.004***		0.009***	0.010***		0.011***	0.012***
		(0.001)	(0.001)		(0.002)	(0.002)		(0.002)	(0.002)
R^2	0.002	0.001	0.002	0.001	0.003	0.004	0.000	0.001	0.001
Observations	6,985	6,998	6,739	6,972	6,956	6,726	6,933	6,834	6,687
Panel B: Since 4/1/2024									
Constant	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.003***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
$\Delta\mathcal{P}_t(Trump)$	0.068***		0.051***	0.073***		0.038***	0.016		-0.002
	(0.014)		(0.013)	(0.018)		(0.011)	(0.016)		(0.017)
$r_{DJT,t}$		0.010***	0.009***		0.018***	0.020***		0.015***	0.016***
		(0.003)	(0.003)		(0.004)	(0.005)		(0.004)	(0.005)
R^2	0.005	0.004	0.007	0.003	0.007	0.010	0.000	0.002	0.002
Observations	5,085	5,051	4,920	5,077	5,014	4,912	5,053	4,907	4,888
Panel C: Post Biden Withdrawal									
Constant	0.001***	0.001***	0.001***	0.001***	0.002***	0.002***	0.005***	0.005***	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
$\Delta\mathcal{P}_t(Trump)$	0.104***		0.109***	0.154***		0.127***	-0.017		-0.003
	(0.023)		(0.023)	(0.023)		(0.022)	(0.022)		(0.022)
$r_{DJT,t}$		0.007**	0.001		0.017***	0.016***		-0.001	0.001
		(0.003)	(0.003)		(0.004)	(0.005)		(0.006)	(0.006)
R^2	0.010	0.002	0.012	0.011	0.005	0.016	0.000	0.000	0.000
Observations	2,535	2,593	2,462	2,533	2,562	2,460	2,527	2,473	2,454

financial deregulation, trade, energy, etc. The first set of assets is a portfolio of ETFs—XLU (Utilities), XLP (Consumer Staples), VNQ (REITs), MUB (Municipal Bonds), and USMV (iShares Minimum Volatility Factor). The second set of assets is an equal-weighted portfolio of all the top 5,000 U.S. stocks by market capitalization as of December 31, 2023. We find no significant lead-

lag relationship between Polymarket probability changes and returns of these placebo assets at any horizon. These findings support our classification of Trump trades.

Results by asset category are reported in the Internet Appendix in Tables A.4, A.5, and A.6. Large banks' stocks exhibit the strongest effect, with coefficients around three times the pooled estimate, consistent with their heightened regulatory sensitivity. Stock ETFs and currencies & commodities show significant lead-lag relationships in later samples. Bonds exhibit weaker effects. These cross-sectional differences align with plausible policy exposures and thus support our interpretation that participants in traditional financial markets learn from the prediction market.

3.2 Economic significance: trading strategies

We assess economic significance of the lead-lag relationship between Polymarket price variations and Trump trades through a simple trading strategy. We take three steps to extract the predictive information in the Polymarket price. First, we apply a five-day exponential moving average to daily changes in the Trump winning probability, $\Delta\mathcal{P}_t(\text{Trump})$, smoothing out the very short-term fluctuations likely due to noises due to market structure issues. Second, we convert the smoothed signals to rolling percentile ranks over the preceding 60 trading days. Third, the percentile ranks can be easily transformed in a linear fashion into positions in $[-1, 1]$, where +1 indicates maximum bullishness and -1 maximum bearishness relative to recent history.

Position construction follows:

$$\text{Position}_{i,t} = \text{Transformed Signal}_{t-1} \times \text{Direction}_i \tag{2}$$

where Signal_{t-1} is the transformed signal in $[-1, 1]$ lagged by one day and Direction_i equals +1 for assets that benefit from Trump's win and -1 for others. The lag ensures implementability. Daily returns of this strategy are the equal-weighted averages across assets:

$$\text{StrategyReturn}_t = \frac{1}{N}\sum_{i=1}^{N} \text{Position}_{i,t} \times r_{i,t}^{TT} \tag{3}$$

Figure 2 plots our processed signal based on Trump's winning probability on Polymarket. The

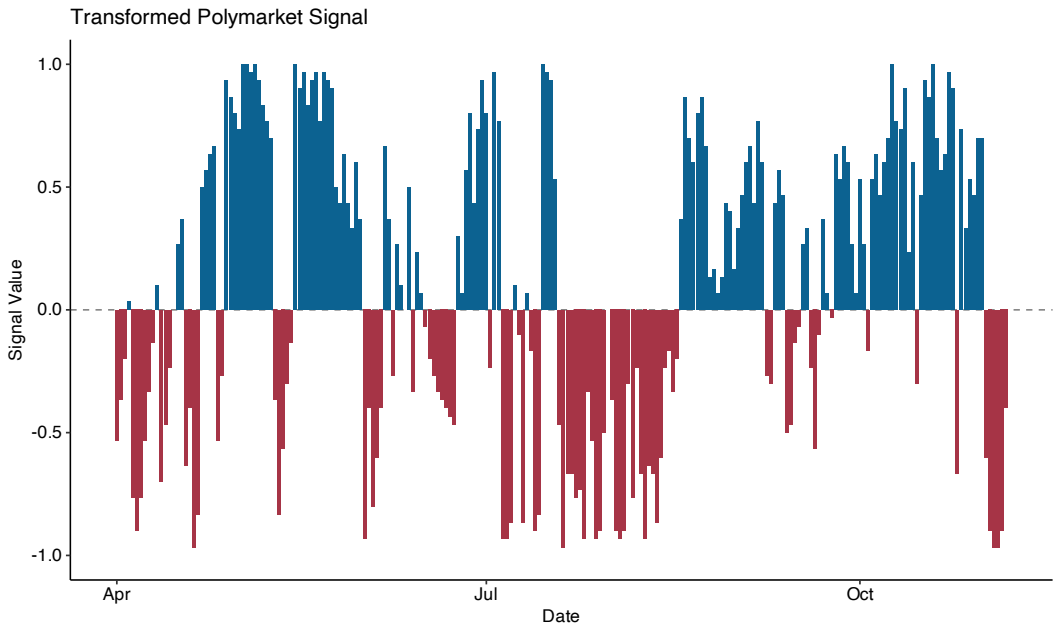


Figure 2 Transformed Polymarket Trading Signal

This figure plots our transformed Polymarket signal used in the trading strategy. The signal is constructed by applying a 5-day exponential moving average to daily changes in Trump's winning probability, converting to 60-day rolling percentile ranks, and linearly transforming to the range [-1, 1]. Higher values indicate increased Trump winning probability relative to recent history. Key event dates: late-June debate and late-July withdrawal.

signal fluctuates meaningfully around major political developments and demonstrates persistence, suggesting gradual information evolution. The following properties typically favor systematic trading as done through our strategy: mean reversion over extended horizons, persistence over shorter periods, and reasonable turnover avoiding excessive costs while remaining event-responsive.

The strategy achieves 21.35% annualized returns with 11.20% volatility, yielding a 1.91 Sharpe ratio. The 4.78% maximum drawdown is also modest. This performance is strong for a single-factor strategy, though it is in-sample and without accounting for transaction costs. Table A.7 in the Internet Appendix presents the full set of performance statistics. Figure 3 plots cumulative returns. The strategy generates consistent positive returns throughout the sample, accelerating during heightened political uncertainty. As Trump's presidential prospect fluctuated significantly, our strategy is able to avoid major ups and downs, indicating that the positions have been properly adjusted, often flipping from short to long, for each Trump trade based on Polymarket prices.

Figure A.7 in the Internet Appendix decomposes performance by asset categories. The trading

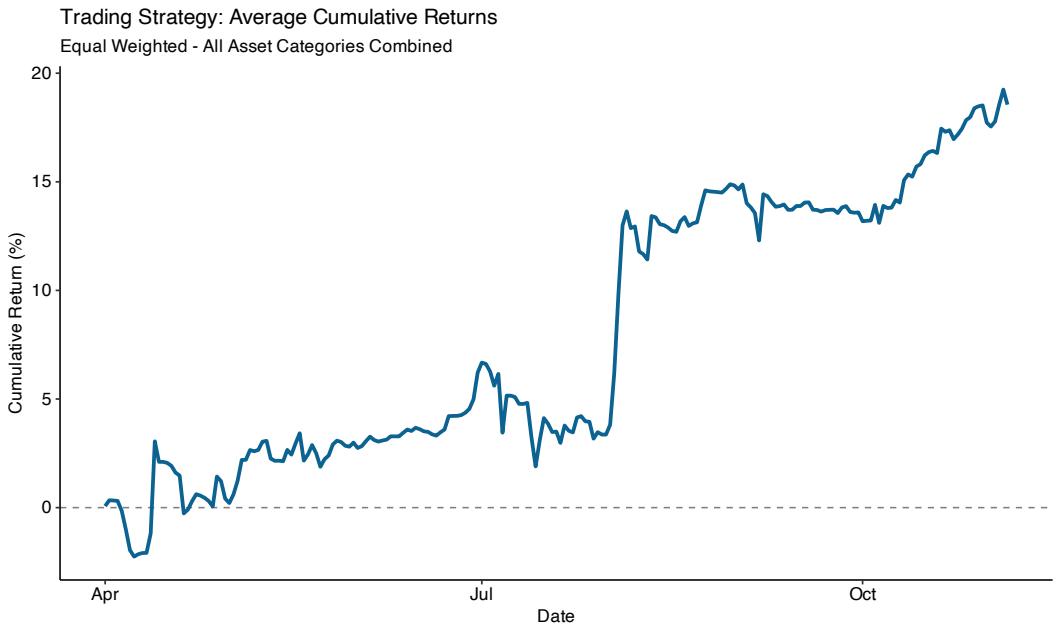


Figure 3 Cumulative Returns of Polymarket Trading Strategy

This figure shows the cumulative returns of the Polymarket-based trading strategy over the sample period. The strategy takes positions in Trump trades based on transformed Polymarket signals, with returns calculated as equal-weighted averages across all positions. Key event dates: late-June debate and late-July withdrawal.

strategy's position in the financial sector contributes most substantially to its performance, consistent with our regression findings of strongest predictive relationships for these assets. Currency and commodity positions also contribute positively, aligning with significant regression coefficients.

4 Prediction-Market Information and Noise Spillover

The lead-lag relationship indicates that participants in traditional markets learn from Polymarket price variations, and the subsequent reversal suggests at least part of the learning transmits noise. This section exploits features of Polymarket's blockchain infrastructure to identify the sources of information and noise at the trader level. Specifically, we classify traders into informed ones and the rest (noise traders) and analyze the impact of their trading activities.

After classifying traders, we establish the transmission of noise from Polymarket to traditional assets. Establishing noise transmission is important for two reasons. First, because noise is orthogonal to fundamentals, its transmission convincingly shows that cross-market learning takes

place. In contrast, when establishing cross-market learning through lead-lag relationships driven by fundamental news, one faces the challenge that the lead-lag arises from participants in the two markets being sequentially informed about the same fundamental news rather than cross-market learning. Second, the fact that noise in the prediction market—a newly developed market with a much smaller volume—can affect prices in the broader financial markets that are magnitudes larger in market value and volume is an intriguing fact by itself.

4.1 Identifying informed traders

Polymarket transaction data. We obtain transaction data through Polymarket's subgraph API. Each record includes a timestamp of the transaction, wallet addresses of the maker (who places the limit order) and taker (who places the market order), trade size, and the trade direction (buy or sell) determined by the taker's action. To focus on economically meaningful trades and ensure a manageable sample, we focus on orders of at least 1,000 contracts. As a reminder, the payout of each contract is $1 when its event materializes. Our final sample comprises 114,646 transactions from 21,189 unique wallets between January 5 and November 4, 2024, the day of 2024 U.S. presidential election. We cross-validate the largest trades against records on Polymarket's official website to verify the accuracy of the on-chain data from the API access.

Table 3 presents summary statistics of the trades. The trade data exhibits a skewed distribution: the mean of buy trade size (9,707 contracts) is nearly three times the median (3,373 contracts), indicating that a small number of very large trades account for a disproportionately large share of volume. To confirm that trading activity is not solely concentrated in the final days before the election—a common pattern in sports betting—we examine trading patterns over different sub-periods. Panels B and C of Table 3 present summary statistics for trades executed before election day (November 4, 2024) and before November 2024, respectively. Although volume increased closer to the election, the statistics for these earlier periods are quantitatively similar to those for the full sample in Panel A. This indicates that substantial trading activity occurs throughout the sample period, rather than solely in days leading to the event resolution.

Table 3 Summary Statistics of Polymarket Trades

This table presents summary statistics for Polymarket trades on the 2024 U.S. presidential election contract, for trades of at least 1,000 contracts. Trade size is measured in number of contracts, where each contract has a maximum payout of $1. Panel A covers the full sample period from January 5 to November 4, 2024. Panel B covers the period up to the first polling station opening on election day. Panel C excludes all trades in November to avoid potential information leakage from the election outcome (January 5 to November 4, 2024).

	nobs	mean	sd	min	p25	median	p75	max
Full Sample:								
buy	43,845	9,707.116	32,819.35	1,003.771	2,172.670	3,372.681	6,889.764	2,019,489.25
sell	70,801	-4,954.988	19,945.78	-1,684,033.210	-4,000.000	-2,000.000	-1,503.760	-1,000.01
Before First Poll Opening on the Election Day:								
buy	40,689	9,045.188	27,782.17	1,390.278	2,167.331	3,317.230	6,708.478	1,190,092.98
sell	65,481	-4,480.484	17,169.57	-1,684,033.210	-3,715.610	-1,981.000	-1,500.000	-1,000.01
Excluding November:								
buy	31,595	9,169.716	27,806.88	1,390.278	2,155.206	3,602.850	7,013.041	1,190,092.98
sell	56,276	-4,236.555	16,109.14	-1,684,033.210	-3,642.980	-1,870.010	-1,439.872	-1,000.01

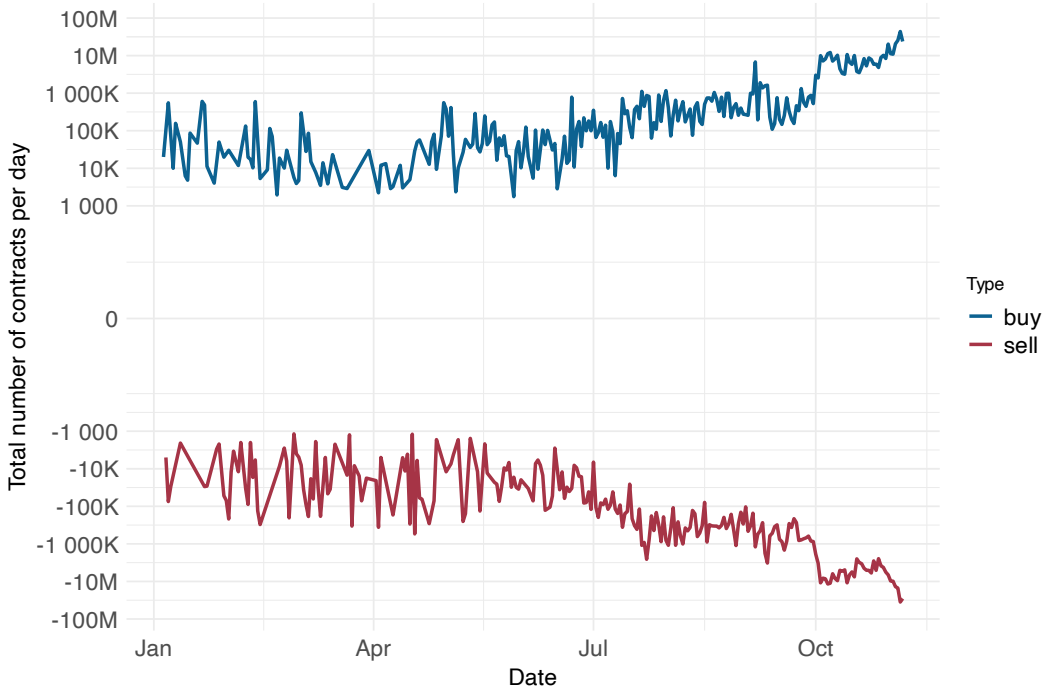


Figure 4 Daily Signed Volume on Polymarket

This figure shows the total number of contracts traded per day on Polymarket's 2024 U.S. presidential election contracts. Volume is measured in thousands of contracts. The sample period spans January 5, 2024, through November 4, 2024.

Figure 4 plots aggregate daily volume for buys and sells. The volumes exhibit substantial variation over time, with pronounced clustering around major events and sustained growth ap-

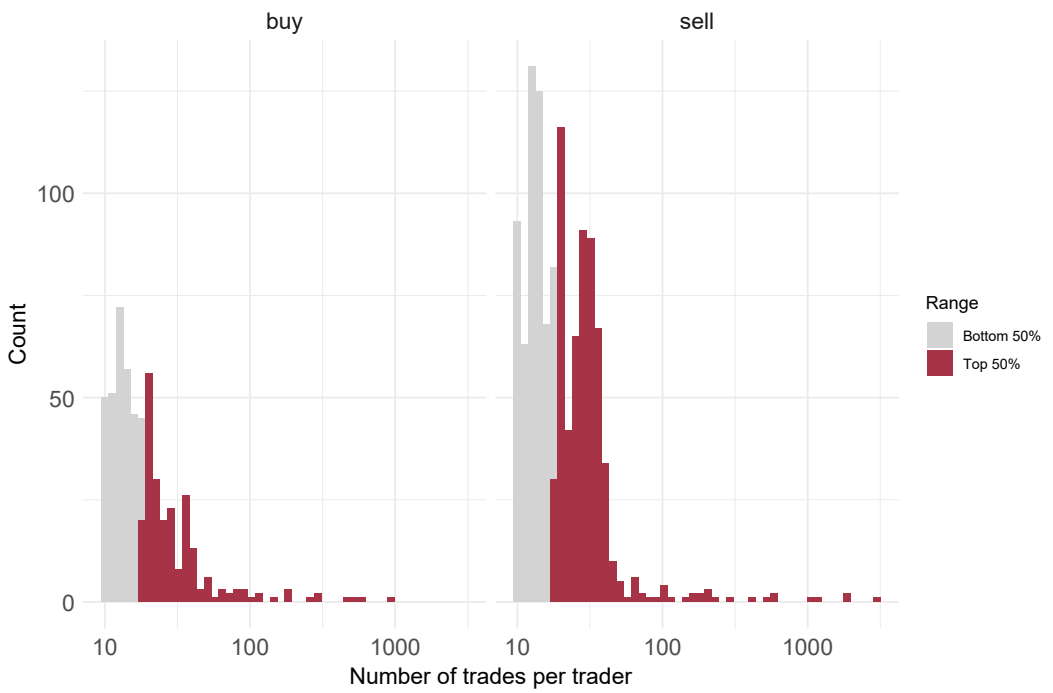


Figure 5 Distribution of Traders by Total Volume

This figure shows a histogram of the total number of contracts traded by each trader (for trades ≥ 1,000 contracts) over the sample period. The x-axis uses a log10 scale. The sample includes traders who made at least one trade of 1,000 contracts or more during January 5, 2024, through October 31, 2024.

proaching the election. Figure 5 displays the highly skewed distribution of traders by their total transaction volume, with relatively few large participants accounting for disproportionately shares. Note that we avoid double counting: when tallying transactions, we only count market orders.

Trader classification. We identify informed traders (wallets) through their trading performances that are evaluated based on the post-trade price patterns.[8] The economic intuition is straightforward: after an informed trader places a trade, the market price should move her trading direction, as information is incorporated, and thereby allow the trader to profit.

For each wallet, we evaluate trading performance following every trade in our sample. A key challenge is that the trader's exit time is unobserved. A trader may close the entire position at once, in which case we would observe an offsetting order in the opposite direction after some

[8]Throughout the paper, we use wallet and trader interchangeably. However, we do acknowledge that in reality a trader can own multiple wallets.

time. Alternatively, the trader may unwind the position gradually, making it impossible to identify a precise exit time. To address this issue, we divide the 48 hours following each trade into eight 6-hour intervals and compute the Polymarket price change over the eight trading horizons, yielding eight returns per trade. We then impose our first criterion for a trader to be informed: across the eight horizons and across all trades, the trader's average return must be non-negative.[9]

Our second criterion for identifying informed traders ensures a robust assessment of traders' performance: trader's total order volume (including market and limit orders) on Polymarket during our sample period exceeds the 50th percentile.[10] High transaction volume arises either from frequent trading, which provides a sufficiently large sample for reliable performance evaluation, or from occasional large trades, which is consistent with the possession of superior private information.[11]

Finally, for a trade to be informed, there must be information to be informed about—that is, information must be revealed to the market after the trade is placed. Put differently, profitability alone does not imply that a trade is based on private information; a trade may instead be profitable because the trader exploits temporary price dislocations arising from market structure frictions. Accordingly, we impose the last criterion: across all trades placed by a trader, the Polymarket price moves in the direction of the trade by at least 2% after 48 hours. This threshold ensures that market-moving information is revealed in the post-trade window.[12]

When assessing whether a trader meets the criteria, we consider the trader's buy and sell orders separately, as a trader may be asymmetrically informed about favorable versus unfavorable news regarding Trump's campaign. Overall, 20.5% of traders satisfy all three criteria either in their buy or sell trades and are therefore classified as informed. The rest are labeled as uninformed.[13]

[9]Note that for every wallet, we evaluate the post-transaction performances of both market orders and limit orders because informed traders utilize both (e.g., Collin-Dufresne and Fos, 2015, 2016).

[10]Our results are robust to thresholds ranging from 25th to 90th percentiles.

[11]Theories suggest that agents with valuable private information trade aggressively to maximize profits before their signal is incorporated into prices, particularly when information acquisition is costly (e.g., Kyle, 1985).

[12]Our focus is on cross-market learning—specifically, whether participants in traditional financial markets extract signals from Polymarket trading activity—so the final criterion also ensures that Polymarket price moves sufficiently to attract attention from investors in the traditional financial markets.

[13]Figure A.8 in the Internet Appendix displays the daily uninformed trading volume over time, based on market orders for its potential price impact. The daily total volume of uninformed trades averages 1,337,483 contracts for buys and -1,204,547 contracts for sells. The volume fluctuated over time and increased towards the election day.

Table 4 Cross-Market Spillover from Decomposed Polymarket Price Change

This table presents regressions of Trump trade returns on lagged components of daily Polymarket price changes attributed to informed versus uninformed trading. The dependent variables are the signed log return of the Trump trades over horizons $t+1$, $t+2$ and $t \to t+2$. These returns are signed to reflect their expected sensitivity to Trump's electoral prospects. The independent variables, $\Delta\mathcal{P}_t^{Informed}$ and $\Delta\mathcal{P}_t^{Uninformed}$, represent the daily price changes on Polymarket driven by informed and uninformed trades, respectively. To construct these variables, we first attribute price changes within each 10-minute interval. If a price change in an interval is accompanied only by one type of trade (informed or uninformed) in the same direction, it is fully attributed to that type. If both trade types occur and move the price in the same direction, the price change is attributed proportionally based on their respective volumes. These 10-minute components are then summed to the daily level. The sample period is January 5, 2024, to November 4, 2024. Standard errors are clustered by asset ticker.

	$r^{TT}_{i,t+1}$ (1)	$r^{TT}_{i,t+2}$ (2)	$r^{TT}_{i,t\to t+2}$ (3)
Constant	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
$\Delta\mathcal{P}_t^{Informed}(Trump)$	0.089***	0.028**	0.117***
	(0.019)	(0.012)	(0.029)
$\Delta\mathcal{P}_t^{Uninformed}(Trump)$	0.046***	-0.030***	0.016
	(0.010)	(0.006)	(0.010)
R^2	0.007	0.003	0.007
Observations	6,885	6,885	6,872

4.2 Information and noise spillover from Polymarket trading

Having identified the informed traders, we classify the remaining traders (wallets) as uninformed and examine their distinct roles in the cross-market lead–lag relationship.[14]

Transactions by Polymarket traders generate price impact, and the resulting movements in Polymarket prices are interpreted by participants in traditional financial markets as signals, giving rise to the lead–lag relationship. Price impact is generated by market orders "walking the book"—market orders consuming available liquidity (hitting limit orders) layer-by-layer—so, accordingly, in the analysis below we focus on "taker" trades, i.e., market orders that initiate transactions against the limit order book, placed by identified informed and uninformed traders.

[14]Table A.8 of the Internet Appendix summarizes the performance metrics for informed and uninformed traders. Uninformed traders lose money on average across the eight trading horizons (-2.3% for buys and -2.9% for sells), indicating that prices tend to move against their trade direction within 48 hours. In contrast, informed traders yield positive average profitability (2.8% for buys and 2.5% for sells).

Decomposing Polymarket price change. We start by decomposing daily Polymarket price changes into components driven by informed versus uninformed trades. Specifically, we segment each trading day into 10-minute intervals starting from midnight New York time. Within each interval, we aggregate all market orders from informed and uninformed traders separately. We then attribute the price change during a single interval to informed or uninformed trades as follows. If a price change occurs in the same direction as only one type of trade (informed or uninformed), we attribute the entire price change to that type. If the price change in the direction that is aligned with both types of trades, we allocate the price change proportionally based on their respective volumes. Across these 10-minute intervals, we aggregate the price changes attributed to informed and uninformed trades, denoted as $\Delta\mathcal{P}_t^{Informed}$ and $\Delta\mathcal{P}_t^{Uninformed}$, respectively.

We run the predictive regressions of pooled Trump-trade returns on these decomposed price changes:

$$r_{i,h}^{TT} = \alpha_h + \beta_h^i \cdot \Delta\mathcal{P}_t^{Informed} + \beta_h^u \cdot \Delta\mathcal{P}_t^{Uninformed} + \varepsilon_{i,h}, \tag{4}$$

where the dependent variable, $r_{i,h}^{TT}$, is the signed log return of Trump trade i over the next day ($h = t + 1$), in the second day ($h = t + 2$), and over the next two days on a cumulative basis ($t = t \longrightarrow t + 2$). Note that the sum of the two right-side variables is slightly different from the daily change of Polymarket price in our baseline analysis presented in Table 2, due to occasions when neither net informed or uninformed volumes are in the same direction with the price movement.

Table 4 presents the results. Both price changes attributed to informed and uninformed trades positively and significantly predict Trump-trade returns on the next day, with the magnitude of the informed-trade effect being twice as large as that of uninformed trades. This indicates that price movements originating from both types of trades in Polymarket affect traditional assets, with the stronger effect from informed traders' transactions. On the second day, however, the effect of informed trades persists, while that of uninformed trades reverses sharply. Consequently, the cumulative effect over two days for informed trades remains statistically significant and large in magnitude; in contrast, that of uninformed trades is statistically indistinguishable from zero.

The direct impact of Polymarket trading activities. Beyond decomposing the Polymarket price changes, we also test whether informed and uninformed trading activities directly drive the cross-market lead-lag relationship. Our hypothesis is that the the effect of noise trading would reverse while that of informed trading persists. To be consistent with the price decomposition exercise, we consider trades that align with the direction of the price movement within the subsequent 10-minute interval. These trades are likely to be associated with Polymarket price impact, and the resultant price change is regarded as a signal by Trump-trade investors. We aggregate these trades to the daily level to obtain the net trading volumes (buys minus sells) for informed and uninformed traders, respectively, denoted as $InformedTrade_t$ and $UninformedTrade_t$, respectively.[15]

We run the following predictive regressions of pooled Trump trade returns on the volumes of informed and uninformed daily market orders:

$$r^{TT}_{i,h} = \alpha_h + \beta^i_h \cdot InformedTrade_t + \beta^u_h \cdot UninformedTrade_t + \varepsilon_{i,h} \tag{5}$$

where the dependent variable, $r^{TT}_{i,h}$, is the signed log return of Trump trade i over the next day ($h = t + 1$), in the second day ($h = t + 2$), and cumulatively over the next two days ($t = t \longrightarrow t + 2$), and $InformedTrade_t$ and $UninformedTrade_t$ denote the daily net volumes (buys minus sells) for informed and uninformed traders, respectively, measured in millions of contracts.

Table 5 presents results, which corroborate the findings from the price decomposition analysis. We find that informed trading positively predicts Trump trade returns on the next day (day $t + 1$), and this effect persists without significant reversal on day $t + 2$. Economically, a one-standard-deviation increase in net informed trading volume (0.46 million contracts) is associated with an approximately 6 basis point increase in next-day returns. In contrast, uninformed trading exhibits a distinct pattern of noise transmission: it predicts a positive return on day $t + 1$ (about 1.5 bps), followed by a rather significant negative return on day $t + 2$.

Taken together, evidence from both price decomposition (Table 4) and trading activity (Table 5) paints a consistent picture: cross-market learning exists and transmits both information and noise. Informed trades on Polymarket contribute to permanent price discovery in traditional

[15] Our results in this subsection remain robust if we do not include this filter.

Table 5 Cross-Market Spillover Effects of Polymarket Trading: Informed vs. Uninformed

This table presents OLS regressions of Trump trade returns on lagged informed and uninformed trading volume from Polymarket. The dependent variables are the signed log returns of the Trump trade on day $t+1$, day $t+2$, and cumulatively over days t to $t+2$, following trading on day t. Informed and uninformed trading volumes are the daily net volumes (buys minus sells, in millions of contracts). Trump trade returns are signed to reflect their expected sensitivity to Trump's electoral prospects. The sample period is January 5, 2024, to November 4, 2024. Standard errors are clustered by asset ticker.

	$r^{TT}_{i,t+1}$ (1)	$r^{TT}_{i,t+2}$ (2)	$r^{TT}_{i,t\to t+2}$ (3)
$UninformedTrade_t$	0.037***	-0.024**	0.014
	(0.009)	(0.010)	(0.013)
$InformedTrade_t$	0.130***	-0.042	0.088**
	(0.027)	(0.035)	(0.033)
R^2	0.042	0.043	0.056
Observations	6,083	6,083	6,083
DOW FE	✓	✓	✓
DOM FE	✓	✓	✓

financial markets, whereas uninformed trades generate temporary spillovers that are subsequently corrected. Our findings on noise spillovers provide particularly compelling evidence of cross-market learning. A central empirical challenge in establishing such evidence is that a lead–lag relationship may reflect the sequential arrival of the same information in two markets rather than learning across markets. This concern, however, does not apply to noise-driven spillovers, which by construction cannot be attributed to the gradual diffusion of fundamental information. The Polymarket setting—and in particular the availability of granular transaction records at the trader (wallet) level—allows us to identify noise trading and directly trace its spillover across markets.

4.3 An alternative approach and the causal effects of noise spillover

One potential concern with the approach in the previous subsection is that we infer informed and noise trades from trader classifications, whereas in practice informed traders may occasionally place noise trades, and conversely, noise traders may sporadically obtain and trade on private information. To address this concern, we adopt an alternative identification strategy based on exogenous variation

in transaction costs. Transaction costs are more likely to affect uninformed trading than informed trading because traders with private information face a time-sensitive advantage that decays as information diffuses across the population. As a result, informed traders have stronger incentives to trade promptly and are therefore less sensitive to fluctuations in transaction costs.

We implement a two-stage least squares (2SLS) analysis using variation in Polymarket transaction costs as an instrument for total trading volume, and examine the effect of the instrumented volume—predominantly reflecting uninformed trading—on subsequent returns of Trump-related assets. We find that the lead–lag relationship is present at the one-day horizon but reverses on the following day, yielding a statistically insignificant cumulative effect over a two-day window. This pattern is consistent with transaction-cost-induced Polymarket volume being largely uninformed: while such noise initially spills over into traditional financial markets, a reversal ensues.

This exercise serves two purposes. First, the instrumental-variables (2SLS) approach identifies the causal effect of Polymarket trading activity on Trump trade returns. The transaction-cost shock is plausibly exogenous to Trump trade returns and is unlikely to affect them through channels other than Polymarket trading, thereby satisfying the exclusion restriction. Second, our findings validate the approach in the previous subsection based on trader classification. In particular, we show that variation in Polymarket trading volume induced by transaction-cost shocks operates primarily through uninformed investors. This result demonstrates the alignment between identifying noise trades via trader classifications and via cost-sensitive trading—that is, using transaction-cost variation to instrument for total volume. Next, we provide details on our methodology and results.

The transaction-cost shock we exploit arises from variation in Ethereum gas fees. Unlike traditional exchanges, where transaction costs are set by exchange operators and brokers and are relatively stable, Polymarket operates on Polygon—a Layer-2 platform built on the Ethereum blockchain—where participation costs fluctuate exogenously with network-wide demand for Ethereum block space. A key institutional feature is the on-ramp (bridging) process. To trade on Polymarket, users must transfer funds from Ethereum's Layer-1 ledger to Polygon's Layer-2 ledger, incurring gas fees that vary with congestion across the broader Ethereum ecosystem. These fees reflect aggregate

demand for block space and are largely unrelated to conditions specific to Polymarket. Because Polymarket's on-ramp activity constitutes only a small fraction of total Ethereum usage, fluctuations in gas fees can be treated as exogenous to Polymarket-specific trading fundamentals.

Ethereum gas fees therefore constitute a component of Polymarket's entry cost. When deciding whether to participate, a trader compares this entry cost with the gains from betting on the event. Informed traders, by virtue of superior information, anticipate higher payoffs and are thus more willing to incur the entry cost. Consequently, in a population of traders heterogeneous in informational advantage, the entry cost induces a participation threshold that determines how informed the marginal entrant is. A decline in Ethereum gas fees lowers this threshold, enabling the entry of more marginal—and hence less informed—traders. As a result, the composition of total trading volume shifts with gas fees, with lower fees increasing the relative share of uninformed trading. Capponi et al. (2024) provide related evidence from blockchain markets, showing that informed traders are more willing to pay higher transaction fees on decentralized exchanges.

When constructing instrumental variables for Polymarket trading volume, we exploit Ethereum gas fees at different time lags. This approach satisfies the relevance condition: as discussed above, participation costs influence traders' entry decisions. It also satisfies the exclusion restriction, as Ethereum gas fees are driven by network-wide demand for block space rather than by factors related to the performance of Trump-related assets in traditional financial markets.

We compute the dollar value of gas fees as the product of the gas price in Gwei—the unit for gas fees which is one billionth of an Ether or ETH, the native cryptocurrency of Ethereum—and the USD price of ETH:

$$GasFee_t = \text{Gas Price}_t^{\text{Gwei}} \times \text{ETH Price}_t^{\text{USD}}. \tag{6}$$

Figure 6 displays the temporal evolution of Ethereum gas fees. The substantial volatility provides the identifying variation required for our IV analysis.

The first stage of our IV estimation incorporates multiple lags of gas fees to account for the fact that traders may smooth out transaction costs over time in response to temporarily elevated

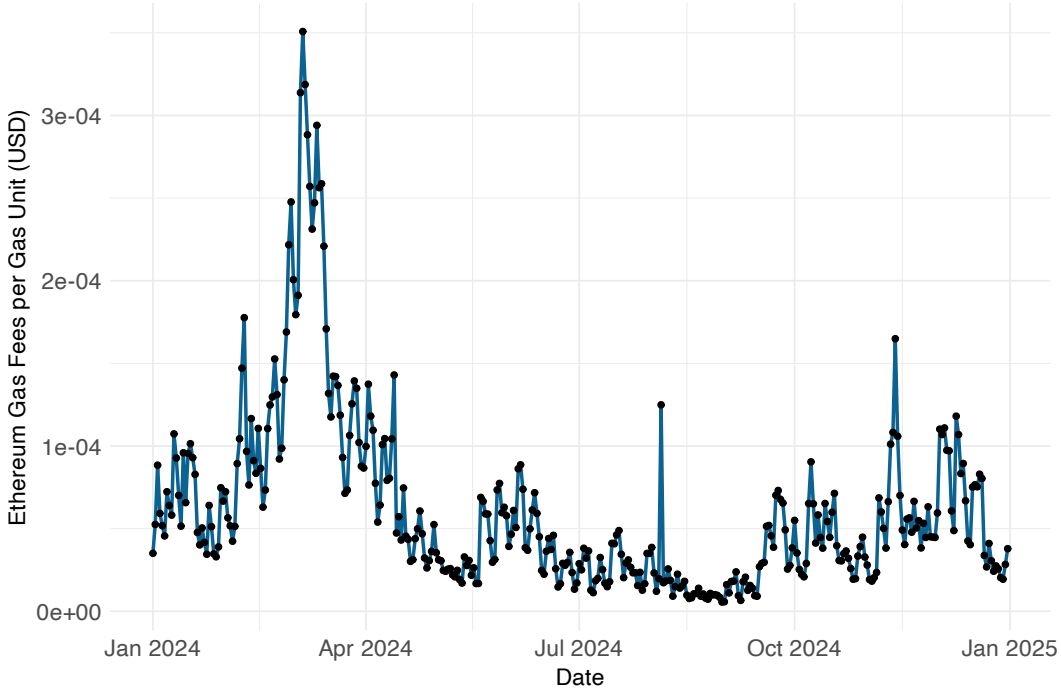


Figure 6 Ethereum Gas Fees Over Time This figure shows daily average Ethereum gas fees measured in USD over the sample period. Gas fees are calculated as the product of gas price in Gwei and the USD price of Ethereum.

costs, so what matters are the overall gas fees over several days. The specification is given by

$$\begin{aligned} \textit{Total Polymarket Volume}_t = \alpha + \sum_{j=0}^{3} \beta_j \cdot GasFee_{t-j} \\ + \sum_k \gamma_k \cdot \text{DOW}_{k,t} + \sum_l \delta_l \cdot \text{DOM}_{l,t} + u_t, \end{aligned} \tag{7}$$

where $\text{DOW}_{k,t}$ and $\text{DOM}_{l,t}$ represent day-of-week and day-of-month fixed effects, respectively, controlling for potential seasonality. Note that since our Trump Trades portfolio includes Bitcoin and Ethereum, a spike in gas fees might correlate with broader crypto market sentiment that directly affects these assets, independent of any Polymarket spillover. To ensure the exclusion restriction holds, we exclude cryptocurrencies (Bitcoin and Ether) from the Trump trade portfolio.

The first-stage regressions estimate the effects of contemporaneous and lagged Ethereum gas fees on Polymarket trading volume, controlling for day-of-week and day-of-month fixed effects. The results, reported in Panel A of Table 6, indicate that gas fees are strong instruments for both trading activities. The F-statistics comfortably exceed conventional thresholds, and the high R^2 values

Table 6 Cross-Market Transmission of Noise: IV Estimates

This table presents instrumental variable (IV) regressions of Trump trade returns on trading volume from Polymarket. The dependent variables are the signed log returns of the Trump trade on day $t + 1$, day $t + 2$, and cumulatively over days t to $t + 2$, following trading on day t. Panel A reports the first-stage regression of total trading volume on lagged Ethereum gas fees. Panel B decomposes the instrument's effect by trader type: we regress informed and uninformed volume (classified via on-chain wallet tagging) on the fitted values from Panel A; implied weights represent each type's share of the total first-stage coefficient. Panel C reports the second-stage estimates. Both stages include day-of-week and day-of-month fixed effects. To satisfy the exclusion restriction, cryptocurrencies (Bitcoin and Ether) are excluded from the Trump trade portfolio. Trump trade returns are signed to reflect their expected sensitivity to Trump's electoral prospects. The sample period is January 5, 2024, to November 4, 2024. Standard errors are clustered by asset ticker.

Panel A: First Stage			
	$TotalTrade_t$		
	(1)		
$GasFee_{t-1}$	-5,877.603***		
	(123.090)		
$GasFee_{t-2}$	4,346.861***		
	(42.648)		
$GasFee_{t-3}$	411.996***		
	(124.011)		
R^2	0.204		
F-test	62.970		
Observations	5,813		
Panel B: Complier Composition			
	$InformedTrade_t$	$UninformedTrade_t$	
	(1)	(2)	
$\hat{Z}_{Gas,t}$	0.076***	0.794***	
	(0.010)	(0.012)	
R^2	0.125	0.243	
Observations	5,813	5,813	
Panel C: Second Stage			
	$r^{TT}_{i,t+1}$	$r^{TT}_{i,t+2}$	$r^{TT}_{i,t\to t+2}$
	(1)	(2)	(3)
Constant	0.746***	-0.647***	0.099
	(0.054)	(0.083)	(0.122)
$TotalTrade_t$	0.224**	-0.521***	-0.297
	(0.083)	(0.159)	(0.199)
Pseudo R^2	0.002	-0.061	0.002
Observations	5,813	5,813	5,813
F-test (1st stage)	62.970	62.970	62.970
Wald (1st stage)	3,660.5	3,660.5	3,660.5

mitigate concerns about weak instruments. Moreover, the coefficients on gas fees and their lags differ in magnitude and sign, consistent with traders smoothing transaction costs intertemporally.

Before turning to the second-stage results, we relate the first-stage findings to our trader-classification exercise. Specifically, we regress transaction volumes by informed and uninformed traders (i.e., $InformedTrade_t$ and $UninformedTrade_t$ in the previous subsection), respectively, on the fitted value from the first—stage regression, denoted by $\hat{Z}_{\text{Gas},t}$—that is, the linear combination of lagged gas fees weighted by the first-stage coefficients. The results, reported in Panel B of Table 6, show that uninformed traders' transaction volume responds much more strongly to variation in gas fees than does informed traders' volume. As emphasized by Angrist et al. (2025), when an instrument affects an endogenous variable through multiple channels, this type of decomposition in Panel B of Table 6 helps reveal the channel through which the variation operates. Our findings indicate that gas-fee-induced variation in total Polymarket volume (i.e., the sum of $InformedTrade_t$ and $UninformedTrade_t$) operates primarily through uninformed trading. Accordingly, whether noise trading is identified via trader classification or via transaction-cost-sensitive trading, the results are fully aligned. Therefore, our two approaches therefore corroborate one another.

Finally, Panel C of Table 6 reports the second-stage results. In the second stage, we regress Trump-trade returns on instrumented Polymarket trading volume. We examine returns over the first day, the second day, and the cumulative two-day window following Polymarket trading. Because variation in trading volume induced by gas fees primarily reflects uninformed trading, the resulting predictability captures noise transmission rather than information spillovers. Consistent with this interpretation, instrumented Polymarket trading volume predicts positive and statistically significant next-day returns (column 1), followed by a reversal on Day 2 (column 2). As a result, the cumulative effect over the two-day horizon is statistically insignificant (column 3).

Overall, the results in this subsection establish a causal link between noise trading in prediction markets and prices in traditional financial markets. A one–standard-deviation increase in Polymarket volume instrumented by Ethereum gas fees leads to a 14–basis–point increase in next-day Trump-trade returns—an economically meaningful effect—that subsequently reverses. This finding provides causal evidence that noise originating in a small, new market can generate substantial, albeit temporary, price dislocations in systemically important financial markets.

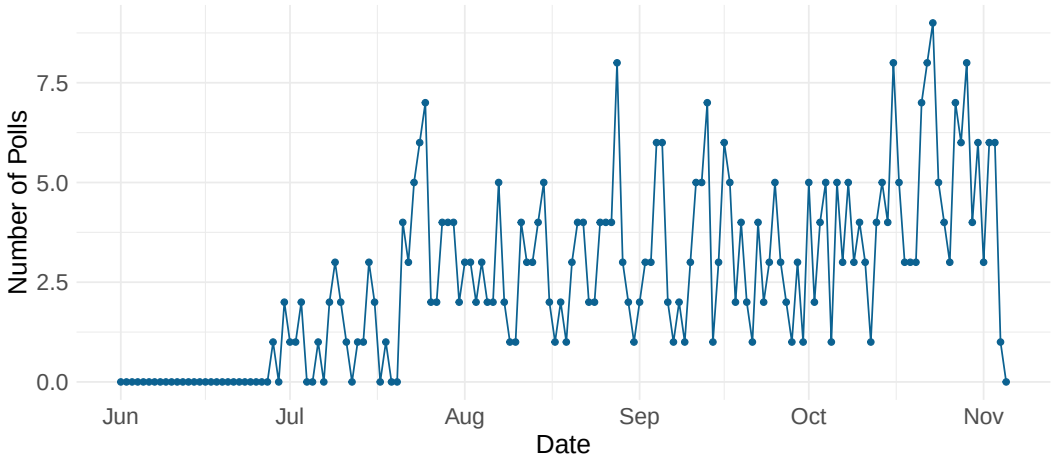


Figure 7 Number of National Polls Over Time

This figure shows the number of national polls over time, focusing on the period from June 1, 2024, onwards.

Our identification strategy exploits a unique feature of Polymarket infrastructure—exogenous variation in participation costs driven by network-wide demand for Ethereum block space—that is unavailable on centralized prediction platforms such as Kalshi. More broadly, our approach offers a methodological blueprint for leveraging on-chain frictions to establish causal relationships.

4.4 Additional evidence on information transmission

While the previous subsection focuses on noise transmission from Polymarket to Trump trades, in the final part of this section, we provide additional evidence on information transmission by exploiting the seasonality in information revelation. During a U.S. presidential election cycle, polling information is released in waves. Each release represents a partial and temporary resolution of uncertainty regarding candidates' relative electoral prospects. Consequently, periods preceding clusters of major poll releases are precisely those in which informed traders are most likely to possess a temporary informational advantage. During such periods, informed trading on Polymarket should exert a stronger influence on future Trump-trade returns by moving Polymarket prices and generating informative signals that are incorporated by participants in traditional financial markets.

To operationalize this idea, we construct a variable, $NPoll$, defined as the number of "A-rated" national polls scheduled for release on the following day. We obtain polling data compiled by

Table 7 Cross-Market Transmission of Information: Poll Interaction

This table presents regressions of Trump trade returns on lagged informed and uninformed trading volume from Polymarket, interacted with the count of upcoming national polls on the following day. The dependent variables are the signed log returns of the Trump trade on day $t+1$, day $t+2$, and cumulatively over days t to $t+2$, following trading on day t. We use the count of national polls on the following day, $NPoll$, as a proxy for the imminence of information revelation. Trump trade returns are signed to reflect their expected sensitivity to Trump's electoral prospects. The sample period is January 5, 2024, to November 4, 2024. Standard errors are clustered by asset ticker.

	$r^{TT}_{i,t+1}$		$r^{TT}_{i,t+2}$		$r^{TT}_{i,t\to t+2}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$InformedTrade_t$	0.130***	0.036	-0.042	-0.093	0.088**	-0.057
	(0.027)	(0.053)	(0.035)	(0.057)	(0.033)	(0.066)
$UninformedTrade_t$	0.037***	0.123***	-0.024**	-0.019	0.014	0.104**
	(0.009)	(0.030)	(0.010)	(0.030)	(0.013)	(0.050)
$NPoll$		-0.014		0.008		-0.006
		(0.014)		(0.009)		(0.021)
$NPoll \times InformedTrade_t$		0.026*		0.011		0.036***
		(0.015)		(0.011)		(0.013)
$NPoll \times UninformedTrade_t$		-0.020**		-0.002		-0.022
		(0.008)		(0.007)		(0.014)
R^2	0.042	0.044	0.043	0.044	0.056	0.057
Observations	6,083	6,083	6,083	6,083	6,083	6,083
DOM FE	✓	✓	✓	✓	✓	✓
DOW FE	✓	✓	✓	✓	✓	✓

Nate Silver covering the period from June 28, 2024, through Election Day, and assign zero values to days with no national poll releases as well as to earlier dates before June 28 when polling data is not available from Nate Silver. Figure 7 plots the time series of national poll releases, illustrating pronounced clustering as the election approaches.

Table 7 reproduces the baseline results from Table 5 for comparison. In Columns (2), (4), and (6), we augment the regression specification by including $NPoll$ and its interactions with informed and uninformed Polymarket trading volumes on the right side.

The interaction terms in Column (2) of Table 7 indicate that when information revelation is imminent—proxied by the number of national polls released the following day—the lead–lag relationship between Polymarket trading and next-day Trump-trade returns strengthens for informed

trading and weakens for uninformed trading. This pattern suggests that participants in traditional financial markets place greater weight on the trading activity of informed Polymarket traders while discounting uninformed activity when near-term information arrival is anticipated.

In contrast, the interaction terms are not statistically significant for second-day returns (Column (4) of Table 7). On a cumulative basis, however, the two-day return window exhibits a significant effect of the interaction between $NPoll$—our proxy for upcoming information intensity—and informed trading volume (Column (6) of Table 7). Taken together, these results suggest that traditional-market participants are able to distinguish between informed and uninformed Polymarket traders primarily in periods immediately preceding major information releases. Outside such windows, traditional-market participants may not pay as much attention to this distinction.

5 A Simple Theoretical Framework and Additional Predictions

Our empirical analysis establishes a link from uninformed trading in a prediction market to price movements in traditional financial markets. In this section, we develop a simple model that formalizes the mechanisms underlying cross-market learning and noise transmission highlighted in the data and provides a conceptual framework to guide our subsequent empirical analysis.

5.1 A simple model of noise spillover

Our model builds upon the classic framework reviewed in Goldstein et al. (2025). We consider an economy with two dates, $t = 1$ and 2. The risk-free asset offers a normalized return of 1 at $t = 2$ and is perfectly elastic supply at $t = 1$. In the prediction market, there are risk-averse arbitrageurs and noise traders. At $t = 1$, they bet on v, an risky event outcome that will be realized at $t = 2$ and follows a normal distribution, $\mathcal{N}(0, \tau_v^{-1})$, where we follow the standard notation denoting variance as the inverse of precision, τ_v. Each of a unit mass of arbitrageurs receives a signal, $s = v + \varepsilon$, where ε is an idiosyncratic disturbance with a normal distribution $\mathcal{N}(0, \tau_\varepsilon^{-1})$. The unit mass of arbitrageurs maximize utility over consumption at $t = 2$, $-e^{-\gamma c_2}$, and optimally choose their investment in the

risky bet and risk-free asset. The noise traders' position in the risky bet, denoted by x, is modeled as a normal random variable with distribution $\mathcal{N}(0, \tau_x^{-1})$.

The equilibrium price in the prediction market at $t = 1$, q, is given by

$$q = \beta_v v + \beta_x x, \tag{8}$$

where β_v and β_x are constant coefficients that are in turn functions of the aforementioned primitive parameters, derived in Goldstein et al. (2025). Note that how β_v and β_x relate to the parameters hinges on whether we solve the rational expectations equilibrium or cursed equilibrium in Eyster et al. (2019) but the fact that q is a linear combination of the event outcome, v, and noise, x, does not change. A larger value of β_x indicates that the prediction-market price contains more noise.

In the traditional financial market, competitive risk-neutral investors trade a risky asset at $t = 1$ whose payoff at $t = 2$ is given by $\beta_a v$, where $\beta_a > 0$ is the asset's sensitivity to the event outcome. The investors' prior over v is the distribution $\mathcal{N}(0, \tau_i^{-1})$, and they rely on the prediction-market price, q, as a signal. The investors' learning follows the standard Bayesian rule, so the equilibrium asset price, denoted by p, is given by the posterior expectation of $\beta_a v$, i.e.,

$$p = \beta_a \left(\frac{\beta_v}{\beta_v^2 + \beta_x^2 \tau_i / \tau_x} \right) q \tag{9}$$

where $\frac{\beta_v}{\beta_v^2 + \beta_x^2 \tau_i / \tau_x}$ is the covariance between v and q scaled by the variance of q under the investors' prior. Thus, we obtain a causal chain that underpins our empirical findings:

$$\Delta x \rightarrow \Delta q \rightarrow \Delta p \, .$$

That is, variation in the prediction-market noise trade, Δx, generates price impact, Δq, which, through cross-market learning, generates variation in the price of the traditional asset.

When modeling the prediction market, we assume the informed arbitrageurs are risk-averse, which is the reason why noise trade has price impact—that is, $\gamma > 0$ represents limited market depth. In fact, if $\gamma = 0$, we have $\beta_x = 0$ in both the rational expectation equilibrium and the cursed equilibrium (Goldstein et al., 2025). In contrast, investors in the traditional asset market are risk-neutral, which corresponds to a deep market, so asset price simply reflects their posterior

after cross-market learning. The difference in market depth between the prediction market and traditional asset market is realistic. An average 1.2 million contrasts (with maximum payout of $1.2 million) were traded in 2024 on the U.S. election outcome, while the traditional financial markets of stocks, currencies, and commodities have trading volumes in the magnitude of trillions of dollars.

Finally, we emphasize that for an asset with a high β_a (for example, the bank stocks in our sample), cross-market learning is stronger, and so is the noise spillover. This is consistent with our findings. This simple model thus far provides a theoretical underpinning of the empirical results in the previous sections. Next, we explore additional empirical implications of the model.

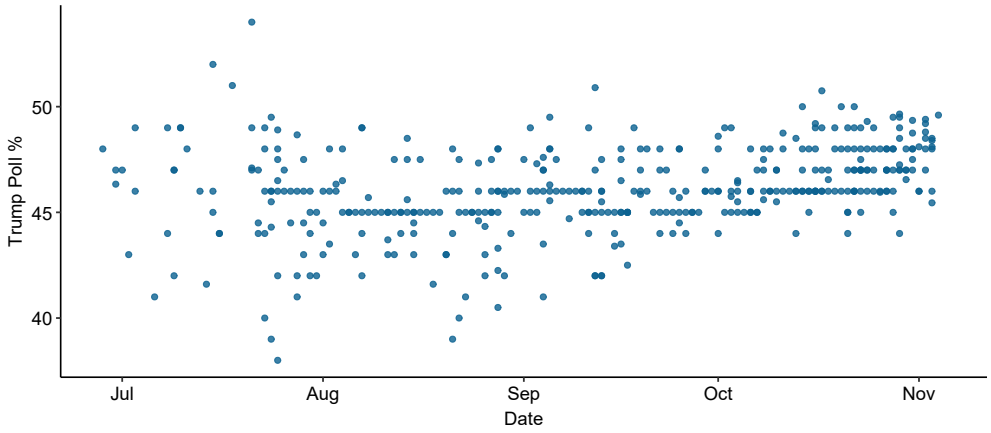
5.2 Additional empirical predictions and tests

Beyond its primary predictions, our model in Section 5.1 generates a set of more nuanced, testable implications about the conditions that should amplify or dampen cross-market learning and noise spillover. By examining the strength of noise spillover under different conditions, we provide stronger evidence for the economic mechanism. We test two predictions below.

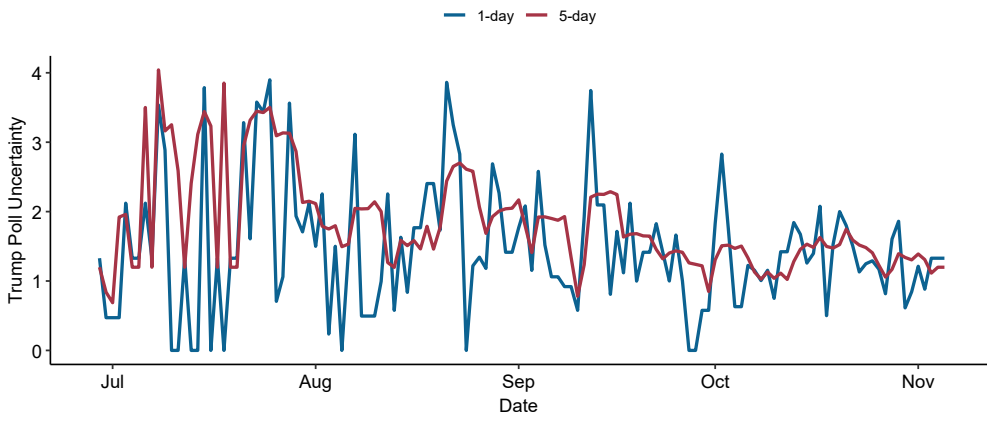
Prediction 1 (Traditional-Asset Investors' Belief Uncertainty) *The noise spillover from the prediction market to the price of the traditional asset is stronger when the traditional-asset investors face greater uncertainty in their prior (i.e., when τ_i is lower).*

When investors in the traditional financial market are less certain about the event outcome, they rationally place more weight (a higher $\frac{\tau_q}{\tau_i+\tau_q}$) on the prediction-market price, q, as a signal, increasing their exposure to the noise embedded in q. To test this prediction, we proxy for traditional-asset investors' prior uncertainty using the dispersion of national polls, where higher dispersion indicates greater uncertainty, leading investors to rely more heavily on Polymarket signals.

As in the previous section, we obtain national polling data aggregated by Nate Silver spanning June 28, 2024, through the election date. For each date t, we compute PollUnc_t as the standard deviation of Trump winning probabilities across polls published on that day, and $\text{PollUnc}_{t-5,t}$ as the standard deviation across polls published between dates $t-5$ and t. Figure 8 shows the considerable



(A) Polling Data



(B) Polling Uncertainty

Figure 8 Election Polling Data and Uncertainty Measures Panel A shows the evolution of Trump winning probability from various national polls aggregated by Nate Silver. Panel B shows the standard deviation of poll results (uncertainty measure) over time. Sample period: June 28, 2024, through the election date.

variation in our uncertainty measure. We test the prediction by interacting this uncertainty measure with daily change in the Polymarket price. Table 8 reports a positive and significant interaction term, confirming that on days with higher uncertainty, variations in the Polymarket price lead the Trump trade returns more strongly, consistent with our model's prediction.[16]

Next, we consider the role of β_x, the impact of noise trade on the prediction-market price. One the one hand, a lower β_x implies the impact of noise is smaller, but on the other hand, precisely because the prediction-market price, q, becomes more informative, the traditional-asset investors place a higher posterior weight on q, allowing the noise component of q to be transmitted more

[16]The results in Column 1 is based on the sample starting on June 28, 2024 (a different sample period from Table 2).

Table 8 Noise Spillover Effects and Polling Uncertainty

This table tests Prediction 1 by examining whether Polymarket predictability is stronger during periods of higher election uncertainty. The dependent variable is next-day Trump trade returns. $\Delta\mathcal{P}_t(\text{Trump})$ is the daily change in Trump's Polymarket probability. PollUnc measures the standard deviation of polling results. Standard errors are clustered by asset. Sample period: June 28, 2024, through the election date.

	$r^{TT}_{i,t+1}$		
	(1)	(2)	(3)
Constant	0.001***	0.000	0.002***
	(0.000)	(0.000)	(0.001)
$\Delta\mathcal{P}_t(Trump)$	0.072***	0.016	-0.048
	(0.016)	(0.018)	(0.050)
$PollUnc_t$		0.001***	
		(0.000)	
$\Delta\mathcal{P}_t(Trump) \times PollUnc_t$		0.042***	
		(0.013)	
$PollUnc_{t-5,t}$			-0.001*
			(0.000)
$\Delta\mathcal{P}_t(Trump) \times PollUnc_{t-5,t}$			0.068**
			(0.027)
R^2	0.007	0.012	0.010
Observations	2,973	2,973	2,973

effectively. Indeed, the impact of β_x on the derivative of the price of traditional asset, p, with respective to x is ambiguous in its sign: $\frac{d^2p}{dxd\beta_x} = \beta_a\beta_v\frac{\beta_v^2-(\tau_i/\tau_x)\beta_x^2}{(\beta_v^2+\beta_x^2\tau_i/\tau_x)^2}$. Therefore, the impact of β_x on noise spillover is an empirical question. We summarize our result below and test the sign of $\frac{d^2p}{dxd\beta_x}$.

Prediction 2 (Prediction-Market Signal Quality) *When the prediction market price's loading on noise trade, β_x, is lower, whether the noise spillover from the prediction market to the price of the traditional asset is stronger depends on the sign of $\beta_v^2 - (\tau_i/\tau_x)\beta_x^2$.*

To test this model prediction, we consider two proxies for β_x, the impact of noise trade on the prediction-market price. The first one is market depth: in a deeper market—which corresponds to a lower γ and greater capacity of informed arbitrageurs in the model—uninformed trades are less likely to have large price impact. We test this by splitting our sample into an early period of low market liquidity (lower τ_q, January-May 2024) and a later period of high liquidity (higher

Table 9 Noise Spillover Effects Across Periods of Different Prediction Market Depth

This table tests Prediction 2 by comparing spillover effects in early (H1: Jan–May 2024) versus later (H2: June–November 2024) sample periods. H2 is an indicator variable that equals one for the later period with higher Polymarket liquidity and signal quality. The dependent variables are Trump trade returns for the next day, next two days and next five days. Standard errors are clustered by asset.

	$r^{TT}_{i,t+1}$		
	(1)	(2)	(3)
Constant	0.001***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)
$\Delta\mathcal{P}_t(Trump)$	-0.015		-0.011
	(0.010)		(0.011)
H2	0.000	0.001***	0.000
	(0.000)	(0.000)	(0.000)
$\Delta\mathcal{P}_t(Trump) \times$ H2	0.086***		0.064**
	(0.020)		(0.027)
$r_{DJT,t}$		0.001	0.002
		(0.001)	(0.001)
$r_{DJT,t} \times$ H2		0.008***	0.005*
		(0.003)	(0.003)
R^2	0.004	0.001	0.004
Observations	6,985	24,654	6,739

τ_q, June-November 2024). Table 9 shows that in the more liquid later part of our sample, the prediction-market price leads the Trump-trade returns more strongly.

The second proxy for β_x is more directly about the informed arbitrageurs' capacity. Consider a decrease in γ, which, as shown in Goldstein et al. (2025), leads to a decrease in β_x under in both the rational expectation equilibrium and the cursed equilibrium of Eyster et al. (2019). Therefore, we interact the recent informed trading intensity, which is measured as the absolute value of recent informed trades, with changes in the prediction-market price. Specifically, we construct a measure of recent informed trading intensity, $|\overline{InformedTrade}|_{t-1}$, as the five-day moving average of absolute informed trading volume ending on day $t-1$.

The results in Table 10 show a positive and significant interaction coefficient. Intuitively, the traditional-asset investors increase their reliance on the prediction-market price as a signal based on its perceived credibility of its quality, which is higher when the prediction-market has more informed

Table 10 Information Hangover: Noise Spillover Effects Following Recent Informed Trading

This table tests Prediction 2 by examining whether recent informed trading activity amplifies the predictive power of Polymarket price changes. The dependent variable is the next-day Trump trade return. We interact the daily change in Trump's Polymarket probability, $\Delta\mathcal{P}_t(\text{Trump})$, with a measures of recent informed trading intensity: $|\overline{InformedTrade}|_{t-1}$, the five-day moving average of absolute informed trading volume ending on day $t-1$. Standard errors are clustered by asset.

	$r^{TT}_{i,t+1}$	
	(1)	(2)
Constant	0.001***	0.001***
	(0.000)	(0.000)
$\Delta\mathcal{P}_t(Trump)$	0.037***	0.008
	(0.009)	(0.008)
$\lvert\overline{InformedTrade}\rvert_{t-1}$		0.122***
		(0.037)
$\Delta\mathcal{P}_t(Trump) \times \lvert\overline{InformedTrade}\rvert_{t-1}$		9.095***
		(2.050)
R^2	0.002	0.005
Observations	6,985	6,985

trades. However, precisely because the prediction-market becomes more informative, when it is the noise that moves the prediction-market price, the transmission of such noise is more potent. We call this channel—past informativeness strengthens current noise spillover—"information hangover".

Taken together, these additional tests provide a more nuanced understanding of the economic mechanism underlying the cross-market learning and noise spillover. The evidence shows that the magnitude of noise transmission is not constant; rather, it varies predictably with the economic environment. This heterogeneity strengthens the case that the cross-market noise spillover we document is a systematic feature of rational learning under uncertainty, not an anomaly.

6 Conclusion

This paper studies how trading activity in prediction markets affects prices in traditional financial markets. Using detailed transaction-level data from Polymarket during the 2024 U.S. presidential election, we document a robust lead–lag relationship between prediction-market activity and returns

on Trump-sensitive assets. We show that this relationship reflects both information transmission and noise spillovers, and that the two have sharply different economic implications.

Informed trading on Polymarket contributes to price discovery in traditional markets, while uninformed trading generates temporary price pressure that subsequently reverses. Exploiting exogenous variation in Ethereum gas fees, we establish a causal link from uninformed prediction-market trading to short-lived price dislocations in traditional assets. These findings demonstrate that even relatively small, new markets can influence systemically important financial markets through cross-market learning.

Our results have broader implications. They suggest that prediction markets are not merely passive aggregators of beliefs but active participants in the information ecosystem by influencing participants' beliefs in traditional financial markets. They also highlight a novel channel through which noise can propagate across markets, raising questions about the welfare effects of prediction markets and the interpretation of their signals by investors and policymakers.

A simple model of cross-market information spillover rationalizes these findings and predicts that transmission is strongest under specific, empirically verifiable conditions. We confirm that noise spillovers are amplified by greater uncertainty in the prediction outcome and greater perceived quality of prediction market signal.

Our paper also illustrates the power of blockchain-based data and empirical settings for economic research. By combining trade-level data with exogenous variation in market frictions, researchers can address long-standing identification challenges in asset pricing and market microstructure. As decentralized financial markets continue to grow, understanding their interaction with traditional markets will be increasingly important.

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Internet Appendix

When Information Markets Export Noise: Spillovers from Prediction Markets to Traditional Assets

I. Additional Institutional Background

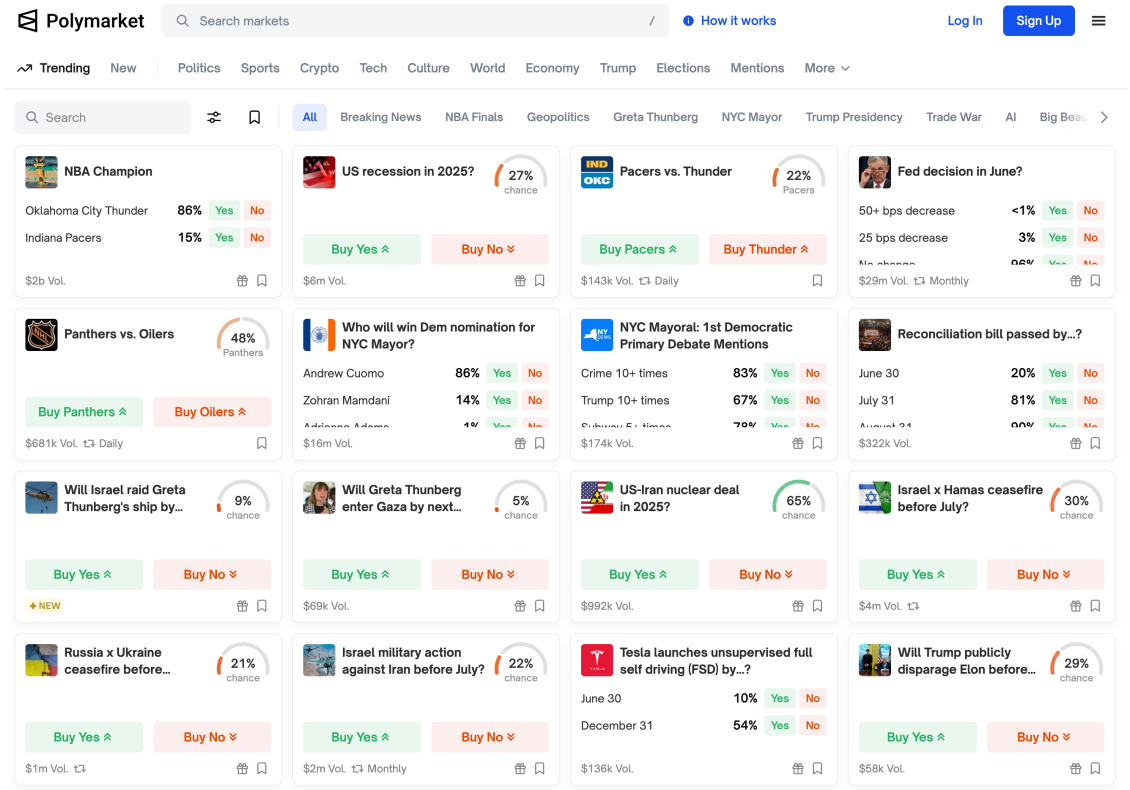


Figure A.1 Polymarket Homepage

This supplementary figure provides visual documentation of the Polymarket platform interface during our sample period, illustrating the user experience and the diverse range of prediction markets available beyond our focus on the 2024 presidential election.

Polymarket user interface. Figure A.1 provides supplementary visual documentation of the Polymarket platform interface, showing the homepage that illustrates the variety of prediction markets available to users during our sample period.

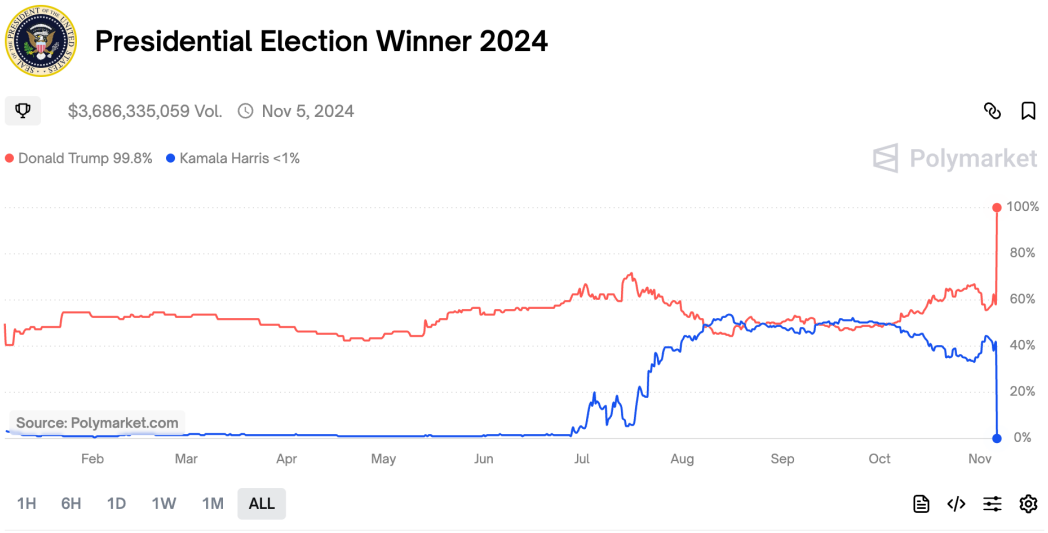


Figure A.2 Polymarket 2024 U.S. Presidential Election Contract

This supplementary figure provides detailed visual documentation of the specific 2024 U.S. presidential election contract that forms the core of our empirical analysis, showing the interface elements that display probability, volume, and contract specifications.

2024 U.S. election market. Figure A.2 displays the price (i.e., market-implied probability) of each candidate's winning in 2024 U.S. presidential election, the event contract used in our analysis.



MARKETS & FINANCE

A Mystery $30 Million Wave of Pro-Trump Bets Has Moved a Popular Prediction Market

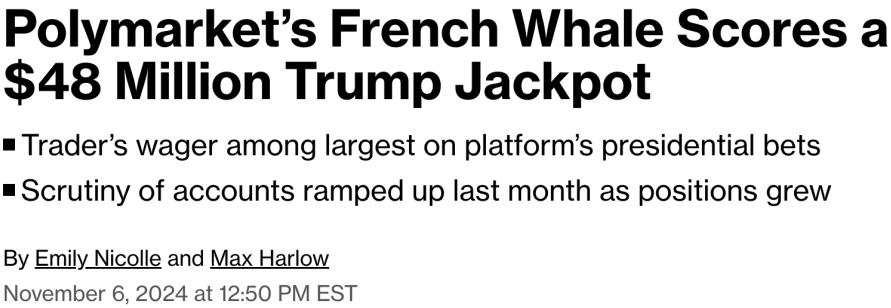
Four Polymarket accounts have systematically placed frequent wagers on a Trump election victory

By Alexander Osipovich Follow

Updated Oct. 18, 2024 4:24 pm ET

Figure A.3 Wall Street Journal Coverage of Whale Trader

This figure shows Wall Street Journal coverage of the large Polymarket trader known as "Fredi9999," who became prominent due to extremely large trades that significantly moved market prices.



Polymarket's French Whale Scores a $48 Million Trump Jackpot

- Trader's wager among largest on platform's presidential bets
- Scrutiny of accounts ramped up last month as positions grew

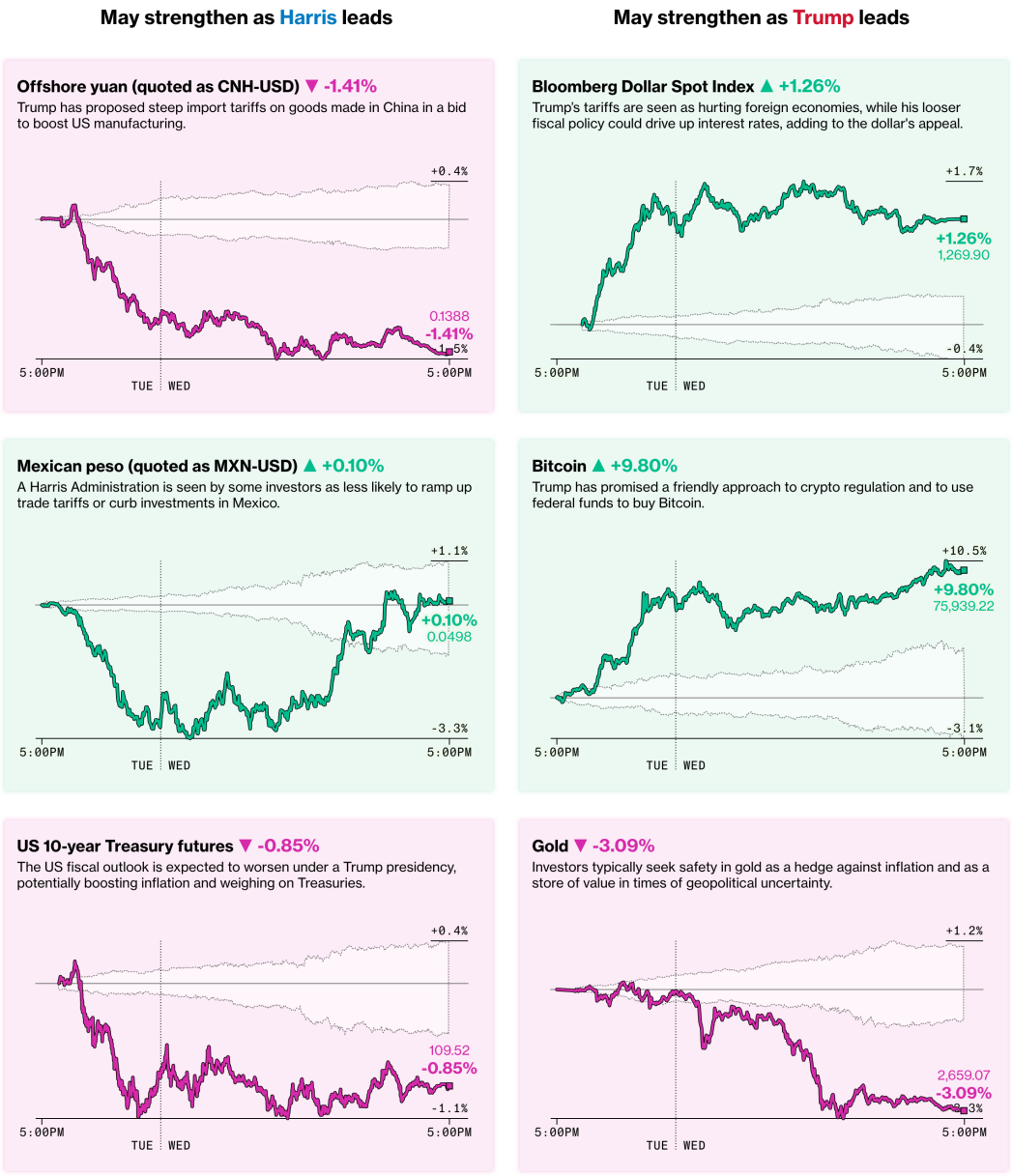
By Emily Nicolle and Max Harlow

November 6, 2024 at 12:50 PM EST

Figure A.4 Bloomberg Coverage of Whale Trader

This figure shows Bloomberg's coverage of the same large trader, illustrating the widespread media attention attracted by individual participants with substantial trading volume on prediction markets.

Media coverage on Polymarket whales. Figures A.3 and A.4 document extensive media coverage of the trader known as "Fredi9999," illustrating how individual large traders can attract significant attention and potentially influence broader market perceptions.



Note: For chart symmetry purposes, Offshore Yuan is quoted as CNH-USD and Mexican Peso is quoted as MXN-USD.

Figure A.5 Bloomberg Coverage of Trump Trades

This supplementary figure documents real-world financial media recognition of Trump trades as a distinct investment theme, providing empirical support for our narrative-based asset identification methodology through Bloomberg's real-time coverage of election-sensitive asset movements.

Media coverage of Trump trades. Figure A.5 provides an example of financial media coverage linking asset price movements to Trump's electoral prospects, supporting our narrative approach to identifying Trump trades.

Table A.1 Trump Trade Directional Specifications

This supplementary table documents the complete directional specifications for all assets in our Trump trades universe, providing transparency and replicability for our analysis. Up arrows indicate assets expected to benefit from Trump winning, while down arrows indicate assets expected to benefit from Trump losing. We list the rationale for each directional expectation based on policy implications and historical performance, based on the narrative from financial media and analyst reports available at the time of analysis.

Type	Name	Ticker	Direction	Policy Channel
Equity ETFs	SPDR S&P 500 ETF	SPY	↑	Pro-growth policies, deregulation
	Invesco QQQ Trust	QQQ	↑	Pro-growth policies, deregulation
	iShares Russell 2000 ETF	IWM	↑	Domestic focus, tax cuts
	Roundhill Magnificent Seven ETF	MAGS	↑	Pro-business sentiment
	SPDR Dow Jones Industrial Average ETF	DIA	↑	Pro-growth policies
	SPDR Financial Select Sector ETF	XLF	↑	Financial deregulation
	SPDR S&P Regional Banking ETF	KRE	↑	Financial deregulation
	SPDR Industrial Select Sector ETF	XLI	↑	Infrastructure, tariffs
	SPDR Energy Select Sector ETF	XLE	↑	Pro-fossil fuel policies
	SPDR S&P Aerospace & Defense ETF	XAR	↑	Increased defense spending
Bond ETFs	iShares 1-3 Year Treasury Bond ETF	SHY	↓	Fiscal expansion, inflation risk
	iShares 3-7 Year Treasury Bond ETF	IEI	↓	Fiscal expansion, inflation risk
	iShares 7-10 Year Treasury Bond ETF	IEF	↓	Fiscal expansion, inflation risk
	iShares 10-20 Year Treasury Bond ETF	TLH	↓	Fiscal expansion, inflation risk
	iShares 20+ Year Treasury Bond ETF	TLT	↓	Fiscal expansion, inflation risk
	iShares U.S. Treasury Bond ETF	GOVT	↓	Fiscal expansion, inflation risk
	iShares TIPS Bond ETF	TIP	↓	Fiscal expansion, inflation risk
Bank Stocks	Goldman Sachs Group	GS	↑	Financial deregulation
	Morgan Stanley	MS	↑	Financial deregulation
	JPMorgan Chase & Co.	JPM	↑	Financial deregulation
	Citigroup Inc.	C	↑	Financial deregulation
	Bank of America Corp.	BAC	↑	Financial deregulation
	Wells Fargo & Company	WFC	↑	Financial deregulation
Currency & Commodity	Invesco DB US Dollar Index Bullish	UUP	↑	Tariffs, "strong dollar" policy
	Euro	EURUSD	↓	Tariffs, trade disputes
	British Pound	GBPUSD	↓	Tariffs, trade disputes
	Japanese Yen	USDJPY	↑	Tariffs, trade disputes
	Chinese Yuan (Offshore)	USDCNH	↑	Tariffs, trade war risk
	Mexican Peso	USDMXN	↑	Tariffs, immigration policy
	Gold	XAU=	↑	Geopolitical risk, inflation hedge
	Bitcoin	BTC=	↑	Pro-crypto stance, deregulation
	Ethereum	ETH=	↑	Pro-crypto stance, deregulation

Trump trade directions. Table A.1 provides supplementary documentation of the expected directional relationships between Trump's electoral prospects and each asset in our Trump trades universe, supporting the main analysis with complete asset-level specifications.

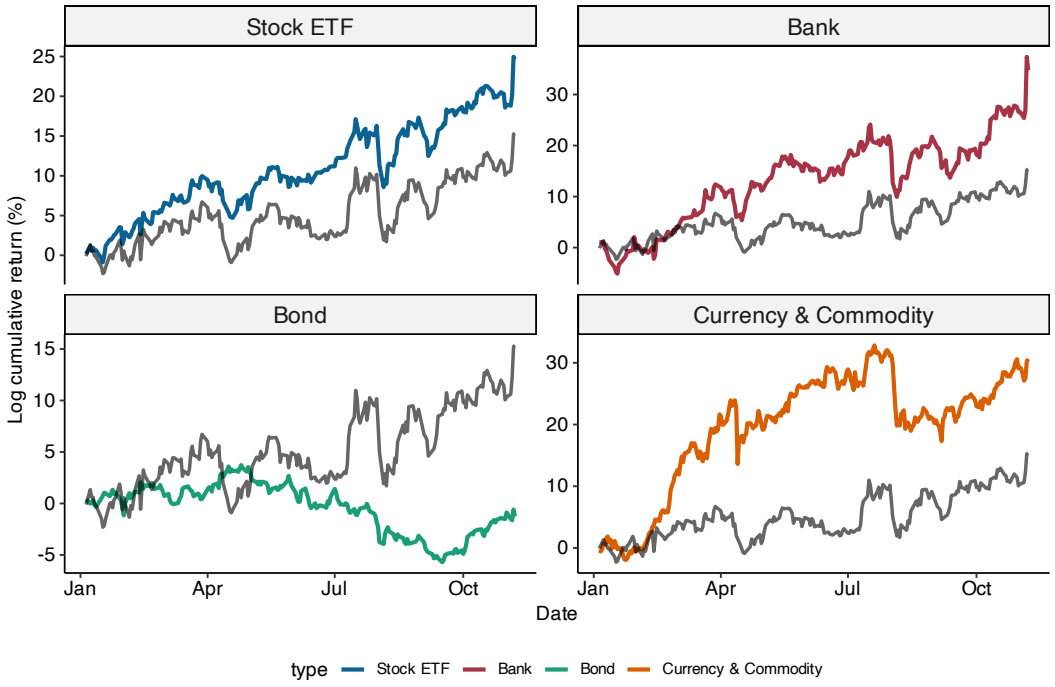


Figure A.6 Trump Trades: Category-Average Cumulative Returns

This figure shows cumulative returns averaged within each major Trump trade category over the sample period. This provides a cleaner visualization of the systematic co-movement patterns across different asset classes compared to individual asset returns.

Trump trade cumulative returns. Figure A.6 shows category-average cumulative returns, providing a cleaner visualization of the systematic patterns across asset categories.

II. Polymarket Prices vs. Alternative Trump Proxy

We start by demonstrating that Polymarket contains information beyond that embedded in prices of assets in traditional markets by comparing it with Trump Media & Technology Group (DJT)—the most direct equity exposure to Trump's political prospects. DJT, a SPAC that took Trump Media public in 2022, was widely viewed as a barometer of Trump's electoral chances. If Polymarket merely reflected traditional market information, DJT returns should fully span Polymarket prices.

Table A.2 Polymarket vs. DJT Stock as Trump Proxy

This table compares the predictive power of Polymarket probability changes versus DJT stock returns for other Trump trades. Both variables are standardized to facilitate comparison. The sample period spans January 5, 2024, through the election date.

	$\Delta\mathcal{P}_t(Trump)$		
	Since 1/1/2024	Since 4/1/2024	Since 7/21/2024
	(1)	(2)	(3)
Constant	0.001	0.001	0.001
	(0.001)	(0.001)	(0.002)
$r_{DJT,t}$	0.017**	0.034***	0.063***
	(0.008)	(0.013)	(0.019)
R^2	0.013	0.036	0.115
Observations	211	154	77

Table A.2 presents regressions of daily Polymarket probability changes on contemporaneous DJT returns across three sample periods: (1) January 5 through election date, (2) April 1 through election date (substantial Polymarket activity), and (3) July 21 through election date (post-Biden withdrawal, heightened uncertainty). We find significant positive correlations throughout, confirming both variables capture common information about Trump's prospects. However, modest R^2 values ranging from 1.3% to 11.5% indicate DJT explains only a small fraction of Polymarket's variation. This suggests Polymarket contains unique information not spanned by the most direct equity proxy, indicating prediction markets process information differently than traditional markets.

Table A.3 Trump Winning Probability on Polymarket and Placebo Asset Returns at Multiple Horizons

This table presents results from predictive regressions of placebo asset returns on lagged changes in Trump's winning probability on Polymarket. The dependent variable is the h-day ahead return for placebo assets. $\Delta\mathcal{P}_t(\text{Trump})$ is the daily change in Trump's Polymarket probability (in percentage points). This table presents results from predictive regressions of placebo asset returns on lagged changes in Trump's winning probability on Polymarket. The dependent variable is the h-day ahead return for placebo assets. $\Delta\mathcal{P}_t(\text{Trump})$ is the daily change in Trump's Polymarket probability (in percentage points). Placebo 1 (Columns 1–4) is a portfolio of five low-policy-sensitivity ETFs—XLU (Utilities), XLP (Consumer Staples), VNQ (REITs), MUB (Municipal Bonds), and USMV (Minimum Volatility)—selected for their minimal exposure to Trump's policy platform (taxes, regulation, trade, energy). Placebo 2 (Columns 5–8) is the equal-weighted average return of the top 5,000 U.S. stocks by market capitalization as of December 31, 2023, across NYSE, AMEX, and NASDAQ. Standard errors are clustered by asset for columns 1–4 and Newey-West with optimal lags for columns 5–8. ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

	Placebo 1: ETFs				Placebo 2: Average U.S. Stock			
	$r^{TT}_{i,t+1}$	$r^{TT}_{i,t+1\to t+3}$	$r^{TT}_{i,t+1\to t+5}$	$r^{TT}_{i,t+1\to t+10}$	$r^{TT}_{i,t+1}$	$r^{TT}_{i,t+1\to t+3}$	$r^{TT}_{i,t+1\to t+5}$	$r^{TT}_{i,t+1\to t+10}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.001**	0.002**	0.003**	0.007**	0.001	0.002	0.004	0.007*
	(0.000)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.004)
$\Delta\mathcal{P}_t(Trump)$	-0.003	-0.006	-0.041***	-0.144**	0.030	-0.021	-0.066	0.000
	(0.015)	(0.007)	(0.009)	(0.051)	(0.055)	(0.080)	(0.097)	(0.148)
R^2	0.000	0.000	0.001	0.010	0.002	0.000	0.002	0.000
Observations	1,055	1,055	1,055	1,055	211	211	211	211

III. Additional Tables and Figures

Placebo test of the predictive relationship. Tables A.3 presents results from placebo predictive regressions using two sets of assets with minimal exposure to Trump's policy platform. Placebo 1 is a portfolio of five low-policy-sensitivity ETFs—XLU (Utilities), XLP (Consumer Staples), VNQ (REITs), MUB (Municipal Bonds), and USMV (Minimum Volatility)—selected for their minimal exposure to Trump's policy platform (taxes, regulation, trade, energy). Placebo 2 is the equal-weighted average return of the top 5,000 U.S. stocks by market capitalization as of December 31, 2023, across NYSE, AMEX, and NASDAQ. We purposely drop microcaps and small caps to avoid any potential confounding microstructure effects (e.g., illiquidity). We find no significant predictive relationship between Polymarket probability changes and returns of these placebo assets at any horizon, supporting our classification of Trump trades.

Additional cross-market lead-Lag results. Tables A.4, A.5 and A.6 present category-specific predictability results across alternative sample periods.

Table A.4 Predictability Results by Asset Category

This table presents predictive regression results separately for each major Trump trade category. The dependent variable is the one-day-ahead signed return for assets in each category. All other specifications are identical to the pooled regressions. Sample period: January 5, 2024, through election date.

	$r^{TT}_{i,t+1}$	$r^{TT}_{i,t+1\to t+3}$	$r^{TT}_{i,t+1\to t+5}$	$r^{TT}_{i,t+1\to t+10}$	$r^{TT}_{i,t+1}$	$r^{TT}_{i,t+1\to t+3}$	$r^{TT}_{i,t+1\to t+5}$	$r^{TT}_{i,t+1\to t+10}$
Category	Stock ETF				Bank			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.001***	0.004***	0.006***	0.011***	0.002***	0.005***	0.009***	0.017***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
$\Delta\mathcal{P}_t(Trump)$	0.028	0.019	-0.034	0.000	0.116***	0.020	-0.014	0.098
	(0.016)	(0.019)	(0.031)	(0.036)	(0.008)	(0.025)	(0.028)	(0.053)
R^2	0.001	0.000	0.000	0.000	0.010	0.000	0.000	0.001
Observations	2,110	2,096	2,082	2,007	1,266	1,266	1,266	1,236
Category	Currency & Commodity				Bond			
Constant	0.001**	0.002**	0.003**	0.006**	0.000	0.000*	0.000	-0.001**
	(0.000)	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
$\Delta\mathcal{P}_t(Trump)$	0.020	0.071	0.010	-0.051	0.006*	-0.001	0.005	0.091***
	(0.011)	(0.040)	(0.014)	(0.058)	(0.003)	(0.001)	(0.003)	(0.021)
R^2	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.008
Observations	2,132	2,120	2,108	2,042	1,477	1,477	1,477	1,452

Table A.5 Predictability Results by Asset Category: Sample Since April 1, 2024

This table presents predictive regression results separately for each major Trump trade category using a sample period beginning April 1, 2024. The dependent variable is the one-day-ahead signed return for assets in each category. All other specifications are identical to the pooled regressions.

	$r^{TT}_{i,t+1}$	$r^{TT}_{i,t+1\to t+3}$	$r^{TT}_{i,t+1\to t+5}$	$r^{TT}_{i,t+1\to t+10}$	$r^{TT}_{i,t+1}$	$r^{TT}_{i,t+1\to t+3}$	$r^{TT}_{i,t+1\to t+5}$	$r^{TT}_{i,t+1\to t+10}$
Category	Stock ETF				Bank			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.001***	0.003***	0.006***	0.010***	0.001***	0.005***	0.008***	0.015***
	(0.000)	(0.001)	(0.001)	(0.002)	(0.000)	(0.001)	(0.001)	(0.003)
$\Delta\mathcal{P}_t(Trump)$	0.058**	0.023	-0.037	0.026	0.188***	0.057*	0.010	0.220**
	(0.020)	(0.022)	(0.036)	(0.045)	(0.011)	(0.024)	(0.038)	(0.065)
R^2	0.005	0.000	0.000	0.000	0.025	0.001	0.000	0.004
Observations	1,540	1,532	1,524	1,459	924	924	924	894
Category	Currency & Commodity				Bond			
Constant	0.000	0.001	0.002	0.002	0.000***	-0.001***	-0.001***	-0.002***
	(0.000)	(0.001)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
$\Delta\mathcal{P}_t(Trump)$	0.052*	0.084*	0.065**	-0.027	0.004**	0.009***	0.023***	0.132***
	(0.027)	(0.039)	(0.023)	(0.057)	(0.002)	(0.002)	(0.005)	(0.029)
R^2	0.002	0.002	0.001	0.000	0.000	0.000	0.001	0.017
Observations	1,543	1,535	1,527	1,466	1,078	1,078	1,078	1,053

Table A.6 Predictability Results by Asset Category: Sample Since Biden Withdrawal

This table presents predictive regression results separately for each major Trump trade category using a sample period beginning July 21, 2024, after Biden withdrew from the presidential race. The dependent variable is the one-day-ahead signed return for assets in each category. All other specifications are identical to the pooled regressions.

Category	$r^{TT}_{i,t+1}$	$r^{TT}_{i,t+1\to t+3}$	$r^{TT}_{i,t+1\to t+5}$	$r^{TT}_{i,t+1\to t+10}$	$r^{TT}_{i,t+1}$	$r^{TT}_{i,t+1\to t+3}$	$r^{TT}_{i,t+1\to t+5}$	$r^{TT}_{i,t+1\to t+10}$
	Stock ETF				Bank			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.001***	0.004***	0.007***	0.012***	0.002***	0.006***	0.010***	0.018***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.002)	(0.003)
$\Delta\mathcal{P}_t(Trump)$	0.108***	0.006	-0.138***	-0.173**	0.303***	0.065	-0.068	-0.014
	(0.028)	(0.018)	(0.034)	(0.064)	(0.017)	(0.038)	(0.060)	(0.068)
R^2	0.013	0.000	0.004	0.004	0.046	0.001	0.000	0.000
Observations	770	768	766	716	462	462	462	432
Category	Currency & Commodity				Bond			
Constant	0.000	0.001	0.002	0.003	0.000***	-0.001***	-0.001***	0.000
	(0.000)	(0.001)	(0.002)	(0.004)	(0.000)	(0.000)	(0.000)	(0.001)
$\Delta\mathcal{P}_t(Trump)$	0.004	0.140**	0.070***	-0.089	0.071***	0.045***	0.069***	0.161***
	(0.034)	(0.056)	(0.013)	(0.122)	(0.018)	(0.011)	(0.015)	(0.032)
R^2	0.000	0.004	0.001	0.001	0.043	0.006	0.008	0.023
Observations	764	762	760	714	539	539	539	514

Table A.7 Trading Strategy Performance Summary

This table presents performance statistics for the Polymarket-based trading strategy. Daily Mean and Daily Vol refer to the daily mean return and daily volatility, respectively. Sharpe Ratio is calculated as the ratio of mean excess return to volatility, annualized. Max DD represents the maximum drawdown. Statistics are in-sample and exclude trading costs. Sample period: January 5, 2024, through the election date.

Start Date	2024-04-01
End Date	2024-11-05
Trading Days	219
Mean Daily Return (ann.%)	21.35
Daily Volatility (ann.%)	11.20
Sharpe Ratio	1.91
Total Return (%)	18.55
Max Drawdown (%)	4.78

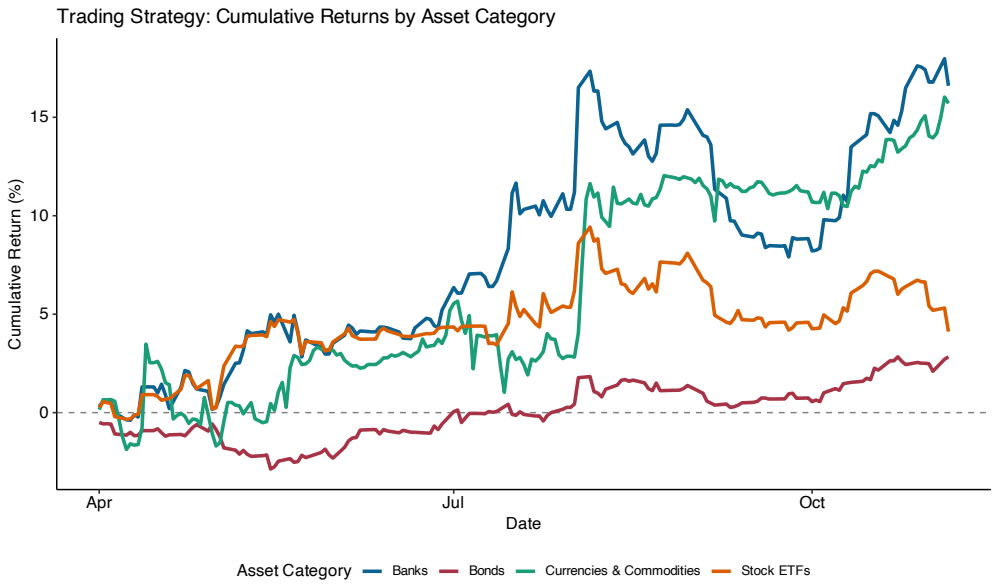


Figure A.7 Strategy Performance by Asset Category

This figure shows cumulative returns of the Polymarket trading strategy by asset category. Each line represents the strategy applied only to one type of assets. The sample period spans Jan. 1, 2024, through the election date.

Trading strategy based on Polymarket signals. Table A.7 reports the full set of statistics of our Trump-trade portfolio dynamically adjusted based on Polymarket price variations. Figure A.7 breaks down the performance into different asset categories and plots the cumulative return.

Table A.8 Summary Statistics of Informed vs. Uninformed Traders

This table compares characteristics of traders classified as informed versus uninformed based on post-trade price patterns. Classification is based on whether a trade is on average profitable within 48 hours, applied separately for buy and sell trades. Statistics include trades ≥ 10,000 contracts (both market and limit orders) during Jan. 1, 2024, through Oct. 31, 2024.

	n	mean	sd	p5	p25	median	p75	p95
Uninformed Traders: Buys								
Average profitability	15,508	-0.004	0.033	-0.065	-0.022	-0.001	0.015	0.052
Average post-trader price movement	15,508	-0.006	0.044	-0.084	-0.030	0.002	0.017	0.061
Total trade size	15,508	20,013	253,011	60	943	2,608	6,500	38,338
Informed Traders: Buys								
Average profitability	3,993	0.037	0.018	0.013	0.022	0.034	0.046	0.068
Average post-trader price movement	3,993	0.045	0.021	0.021	0.028	0.041	0.055	0.089
Total trade size	3,993	54,540	659,563	4,155	5,928	9,812	21,106	122,898
Uninformed Traders: Sells								
Average profitability	22,152	-0.012	0.033	-0.060	-0.031	-0.013	0.004	0.050
Average post-trader price movement	22,152	-0.014	0.041	-0.072	-0.037	-0.016	0.002	0.069
Total trade size	22,152	20,715	300,213	69	1,051	2,637	7,800	42,384
Informed Traders: Sells								
Average profitability	1,907	0.041	0.022	0.012	0.022	0.037	0.054	0.084
Average post-trader price movement	1,907	0.058	0.028	0.022	0.034	0.054	0.077	0.111
Total trade size	1,907	36,245	265,889	3,454	4,687	7,545	15,172	81,544

Trader activity distributions. Table A.8 provides the summary statistics of uninformed and informed traders' performances, emphasizing within the subsequent 24 hours whether reversal occurs. Figure A.8 plots the daily time series of uninformed buys and sells. Figures A.9 and A.10 provide additional information on trading activities and its distribution among Polymarket participants.

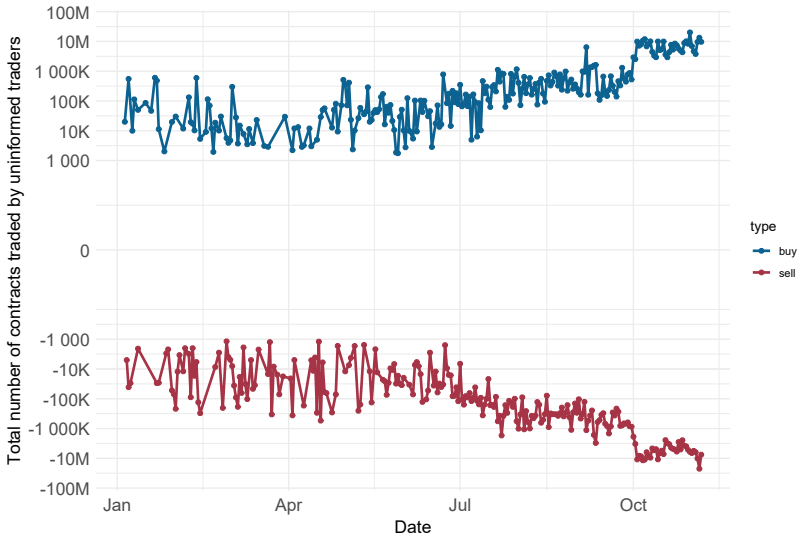


Figure A.8 Daily Signed Volume of Uninformed Trades

This figure shows the daily volume of uninformed traders' transactions (contracts ≥ 1,000) from Jan. to Oct., 2024.

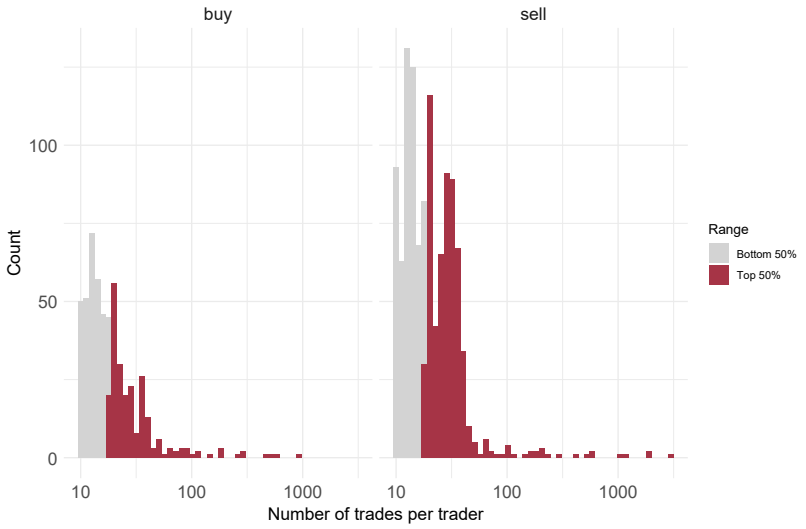


Figure A.9 Distribution of Number of Trades per Trader

This figure shows a histogram of the number of trades per trader (for trades ≥ 1,000 contracts) over the sample period using a log10 scale. The distribution reveals the highly concentrated nature of trading activity on Polymarket.

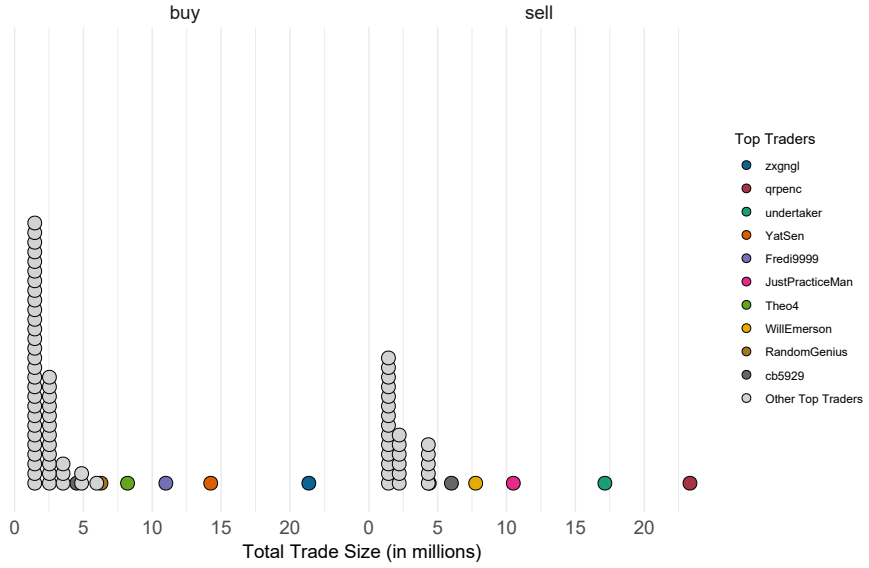


Figure A.10 Trading Volume Distribution Among Largest Traders

This figure shows a dotplot of total trading volume for traders who traded at least 1 million contracts during the sample period. The plot illustrates the extreme concentration of trading volume among the largest market participants.