Learning from Prediction Markets: The Transmission of Information and Noise to Traditional Assets

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July 28, 2026

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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 information spillover from Polymarket to traditional financial markets during the 2024 U.S. presidential election. Changes in Polymarket-implied probabilities predict next-day returns of "Trump trades" across asset classes, followed by partial reversals, indicating that both information and noise are transmitted. Using the blockchain-based transaction data, we classify Polymarket traders as informed or uninformed at the wallet level and show that the price impact of uninformed trading contributes to the next-day predictability, but, unlike the price impact of informed trading, does not persist and fades over the following days. As the transmitted noise cannot reflect the sequential arrival of fundamental information, it identifies an active cross-market learning channel through which both information and noise propagate. We further document an "information hangover" effect: recent informed trading amplifies the traditional market's subsequent reliance on Polymarket signals, which in turn facilitates noise spillovers.

Keywords: Prediction markets, learning, spillover, information aggregation, noise trading, political uncertainty, Polymarket, DeFi, and blockchain.
JEL Code: G12, G14, G41

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1 Introduction

Markets are thought to be a very useful tool for the production and aggregation of information (Hayek, 1945). This idea is the basic premise behind the creation of prediction markets, which are designed to provide information in advance about the expected outcomes of key events (Wolfers and Zitzewitz, 2004). While prediction markets have been around for a long time, they have seen tremendous growth in activity and attention recently after the rise of platforms like Kalshi and Polymarket, which are attempting to be user friendly and compliant with regulation. Recent papers (Ng et al., 2025; Gomez Cram et al., 2025; Diercks et al., 2026) suggest that prediction markets indeed efficiently aggregate information about upcoming events.

With this rise of activity and interest, basic questions about the broader effects of prediction markets and how they should be regulated are resurfacing and capturing renewed attention among regulators, media, and the general public. Given that production and aggregation of information are at the heart of prediction markets, central questions about the broader effects of these markets naturally revolve around information transmission. Specifically, for these markets to have an effect, people should attempt to learn from prediction market prices and use the information when taking actions with consequences that go beyond the boundaries of prediction markets. Whether this happens or not is an empirical question and we attempt to address it in this paper.

We build on data from Polymarket, whose blockchain infrastructure provides a unique empirical setting with which we can shed light on whether an active channel of learning and information transmission is present. As mentioned above, Polymarket is one of the major prediction markets, and it is also the largest one that is based on a blockchain infrastructure. Our analysis focuses on the 2024 U.S. presidential election: a major event with vast economic implications that triggered a surge in prediction market activity. For the period leading up to the election, we obtain data on daily and intraday changes in Polymarket prices, which translate to probabilities of Donald Trump winning the election, and Polymarket participants' transaction records on the blockchain ledger.

Our goal is to examine whether the updates in Polymarket probabilities spill over to the traditional financial markets in a way that indicates that traders in financial markets actively learn from Polymarket prices. To do this, we track a portfolio of "Trump trades" in the traditional asset classes, such as stocks, bonds, currencies, and commodities. This portfolio is based on a systematic review of media coverage and sell-side research reports identifying assets that are flagged as being sensitive to Trump's election outcome and his policy priorities. The portfolio is supposed to increase in value when the probability of Donald Trump winning the election increases. Our analysis explores the relation between returns of this Trump-trade portfolio and changes in the Polymarket prices which reflect probabilities of Trump winning the election.

As a first step, we document a robust lead-lag relationship from variations in Polymarket prices to traditional assets' returns. This relationship is consistent with cross-market learning, whereby traders in the traditional financial markets learn from the prices in prediction markets and trade accordingly. The magnitude is sizeable: a one-percentage-point increase in Polymarket probability is associated with 13 basis points of next-day returns of Trump trades in the pooled sample. A trading strategy based on this signal earns an annualized Sharpe ratio of 1.95 and a total return of 16.45% from April 2024 through the election date. In addition, we find that these patterns are stronger among assets that are more sensitive to the U.S. presidential election outcome.

A likely alternative to learning is passive reflection, according to which both the Polymarket prices and the returns of the Trump-trade assets are moving in response to fundamentals which are the underlying developments throughout the election cycle. The fact that Polymarket probabilities are moving first is not necessarily an indication of a causal effect. For this reason, identifying an active learning channel is notoriously difficult. To make more progress we rely on a strategy that has been employed in the literature on the "feedback effect" of financial markets—tracking the effect of noise or non-fundamental changes in the price. This empirical strategy goes back to Edmans, Goldstein, and Jiang (2012) and Dessaint, Foucault, Frésard, and Matray (2019) and is reviewed in surveys of the feedback effect literature by Bond et al. (2012) and Goldstein (2023).

The idea behind this empirical strategy is as follows. When traders in financial markets learn from changes in Polymarket probabilities, they will inevitably be affected by price movements driven by both informed and uninformed trades. This is an unintended consequence of learning:

traders in traditional markets cannot distinguish in real time between price changes in Polymarket that reflect genuine information and those that originate from noise. As researchers, however, we can identify, after the fact, trades that are more likely driven by noise and trace their effect on the traditional financial markets. If such Polymarket-specific noise propagates to the returns of Trump-trade assets, this constitutes evidence of an active learning channel. Crucially, because this noise originates within Polymarket and is unrelated to any fundamental developments in the election, the alternative explanation—that both Polymarket prices and Trump-trade returns move in response to the sequential arrival of the same underlying information—does not apply. Non-fundamental price changes in Polymarket have no reason to predict returns in traditional asset markets unless traders in those markets are actively extracting and acting on signals from Polymarket prices.

Our first piece of evidence exploits variation in retail traders' attention to Polymarket. The logic follows directly from the identification strategy described above: because retail traders are less equipped to distinguish informed from uninformed price movements, periods of heightened retail attention to Polymarket should transmit more of Polymarket's noise into traditional assets. Using daily mentions of "Polymarket" across Reddit forums where retail traders exchange views, we show that the pass-through from Polymarket price changes to Trump-trade returns is significantly stronger when retail attention to Polymarket is elevated. Importantly, this amplified spillover is entirely transitory—it reverses within two days, and the cumulative three-day effect is indistinguishable from zero—which confirms that what heightened retail attention transmits is predominantly noise from Polymarket prices rather than information. The lead-lag relationship from such noise transmission cannot be explained by the sequential arrival of the same information to both markets. The exercise therefore establishes an active channel of learning: traders in traditional markets extract signals from the Polymarket price, inadvertently importing noise along with genuine information.

To directly distinguish information from noise in Polymarket, we exploit the unique transparency of Polymarket's blockchain ledger, which offers a granular dataset of a kind typically unavailable in traditional financial markets. The ledger provides an immutable, trader-level (wallet-level) audit trail of every transaction, allowing us to classify traders as informed or uninformed based on their performance. We designate a trader as informed if their trades consistently generate profits, or equivalently, if the Polymarket price tends to move, on average, in the direction of their trades, and classify all remaining traders as uninformed.

We first verify that the trader classification meaningfully separates information from noise by examining the price impact of each group's market orders. We regress Polymarket price changes on the net order flows of informed and uninformed traders and find that, while both groups move prices on the day they trade, their effects diverge sharply thereafter. The price impact of informed flow persists and accumulates over the following days, consistent with the gradual incorporation of fundamentals, whereas the impact of uninformed flow partially reverses. This pattern confirms that our partition isolates genuine noise from informed trading. Importantly, this is not a test the classifier was designed to pass: we build it from first principles, flagging wallets with consistent trading profits, without reference to whether their price impact persists or reverses.

Next, we decompose the change of Polymarket price into a component driven by informed trading and a component driven by uninformed trading (the noise component) and show that both components predict Trump-trade returns on the next day. Consistent with the distinction between information and noise, the impact associated with informed trading on the Trump-trade returns persists into the second and third days, whereas the effect of the noise trading fades, with the cumulative coefficient statistically indistinguishable from zero. Taken together, these results provide consistent evidence of both information transmission and noise spillovers from Polymarket to the broader financial system. The presence of noise spillover isolates an active learning channel from the alternative explanation of sequential information arrival.

One might still object that a common, non-fundamental sentiment shock could hit all markets sequentially—reaching Polymarket first because of its greater retail participation—so that the lead-lag relationship reflects the sequential arrival of a shared sentiment shock rather than genuine cross-market learning. To rule this out, we augment our predictive regressions with a rich set of controls that capture the information and sentiment shocks common to all markets. We extract principal components from a daily panel that combines Trump-win contract prices across prediction-market venues with the full cross section of Trump-trade asset returns, so that these components absorb the common variation and isolate the information and noise specific to Polymarket. The results are robust to including these controls: the informed component remains economically large and statistically significant, while the noise component still fades to insignificance over three days. Therefore, we conclude that Polymarket-specific information and noise are what drive the spillover.

We corroborate these findings with a complementary specification that measures each group's footprint through net order flow rather than the price change it generates. Regressing future Trump-trade returns directly on the informed and uninformed traders' order flows yields the same pattern: informed trading predicts Trump-trade returns on the next day and continues to do so on the second and third days, accumulating to a sizable three-day effect, while uninformed trading predicts returns at first but fades into insignificance over the three-day horizon.

These two channels of information and noise transmission play distinct and complementary roles in our thesis. The informed channel carries the substance of what is being learned: traders in traditional markets respond to informed Polymarket trading because genuine information about the presidential election is being revealed there. The uninformed channel provides the identification: because Polymarket-specific noise is orthogonal to fundamentals, its transmission cannot be explained by the sequential arrival of common information across markets, and it therefore pins down cross-market learning as the operative mechanism. The granularity of Polymarket's wallet-level transaction records is what makes this separation possible, allowing us to establish cross-market learning through the two channels jointly—one supplying the content, the other the proof.

We next sharpen the characterization of what is being learned by showing that information transmission intensifies precisely around resolution events. During an election cycle, polls arrive in waves, and the days just before a cluster of major polls are when informed traders are most likely to hold a temporary informational advantage. We capture this with the number of A-rated national polls scheduled for release over the following five days and interact it with informed and uninformed Polymarket trading. The lead-lag relationship from informed trading to next-day Trump-trade returns strengthens when poll releases are imminent, while the interaction for uninformed trading remains insignificant. In other words, traditional-market participants place more weight on informed Polymarket activity precisely when near-term information arrival is anticipated. This pattern reinforces the interpretation that part of what crosses from Polymarket to traditional markets in these windows is genuine information.

To gain more insight into this interdependence, we develop a simple model of learning in financial markets, most directly building on the framework in the recent review article of Goldstein et al. (2025), and going back to a long line of literature starting from Grossman and Stiglitz (1980) and Hellwig (1980). 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 is transmitting noise alongside information. The model provides an intuitive account of our empirical findings and generates additional implications that we take to the data. One prediction is that learning, which generates transmission of information and noise from the prediction market to traditional markets, is expected to be stronger when traditional-asset investors face greater uncertainty over the event, in our case, the U.S. presidential election result. Intuitively, when their belief is less precise, as 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 information. This is exactly what we find empirically.

Another prediction is that transmission of noise and information is stronger precisely when prediction-market prices more accurately reflect the underlying event outcome. When prediction-market signals are perceived as generally more precise, investors place greater weight on them, and then when price variation happens to be 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, as 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 changes, exhibit a statistically significant impact on subsequent Trump-trade returns.

Overall, our paper provides strong evidence that traders in the main financial markets are looking at prediction markets for signals, and using these signals in their trading decisions, so that whatever happens in the prediction market spills over to financial markets. On the one hand, this is an expected outcome given that prediction markets are designed and often praised for their ability to aggregate information. On the other hand, one might be surprised that a prediction market ends up having an effect on much larger and more liquid financial markets. Finally, a key theme that we emphasize throughout the paper and that plays a key role in our empirical strategy is that with the transmission of information comes also transmission of noise. Hence, people should be mindful of the consequences of having noise generated in the process of prediction-market trading spill over outside the boundaries of the prediction market.

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 (Black, 1986; De Long et al., 1990; Shleifer and Vishny, 1997; 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 contributes to the empirical literature on decentralized finance (DeFi) and financial technology by exploiting the wallet-level transparency of an on-chain prediction market to construct a direct, ex-post trader classification—informed versus uninformed—over the full universe of Trump-YES transactions (Bartlett et al., 2022; Makarov et al., 2022). To our knowledge, this is the first paper to provide trader-level evidence on the cross-market transmission of noise from a prediction market to traditional financial assets.

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 wallet classification, decomposes Polymarket price changes into informed and uninformed components, documents the within-Polymarket persistence asymmetry, traces both components into cross-market spillover, 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 Institutional Background

In this section, we provide institutional background on Polymarket and the Trump trade during the 2024 U.S. Presidential Election cycle. We also describe our sample and document several 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.[1] 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 is Polymarket. During 2024, Polymarket became the dominant venue for predicting the outcome of U.S. presidential election, attracting widespread media attention and interest from traditional financial institutions.[2] Unlike traditional centralized exchanges, it runs on the Polygon network—a Layer-2 scaling solution of Ethereum, a blockchain-based decentralized ledger. This architecture makes all trading activities publicly verifiable and immutable and eliminates concerns about data manipulation or traders' selective disclosure of

[1] 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.

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

transactions.[3] 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.[4] 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 52.7% with a standard deviation of 6.4%. The table also reports the corresponding statistics for the daily change in the probability under three timing windows: midnight-to-midnight ET (our baseline), 9am-to-9am ET, and 4pm-to-4pm ET.[5] Daily probability changes exhibit mean reversion with positive skewness and excess kurtosis, indicating occasional

[3] Screenshots of the platform interface appear in Internet Appendix Figures A.1 and A.2.

[4] This represents a shift from earlier decentralized automated market makers (AMMs) in December 2022.

[5] For brevity, we use $\Delta\mathcal{P}(Trump)$ and $\Delta\mathcal{P}$ interchangeably to denote the change in Polymarket price of Trump-YES contract throughout the paper.

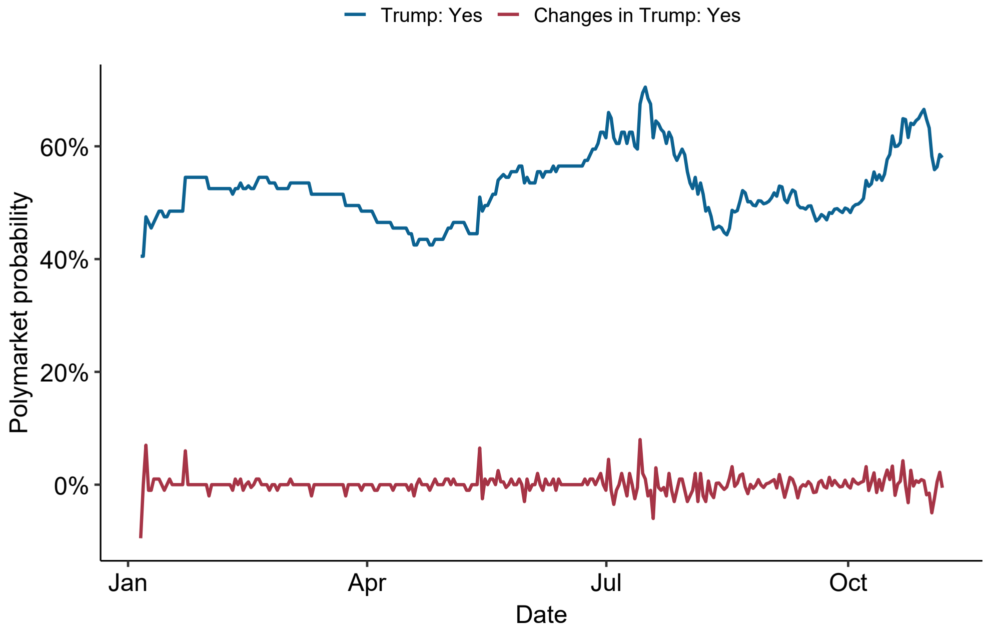


Figure 1 Polymarket Trump Winning Probability Over Time

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.

large movements superimposed on typical gradual adjustments. Trading volume varies, clustering around major 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

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	52.731	6.424	44.290	48.500	52.500	55.500	63.650
$\Delta\mathcal{P}(Trump)$	306	0.184	2.593	-2.000	-0.338	0.000	0.488	2.675
$\Delta\mathcal{P}(Trump)^{9AM-9AM}$	307	0.162	2.641	-2.000	-0.200	0.000	0.500	2.420
$\Delta\mathcal{P}(Trump)^{4PM-4PM}$	306	0.035	1.490	-2.000	-0.300	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`
Connected	`DJT, PHUN, TSLA`

Panel C: Trump Trade Daily Returns

	nobs	mean	sd	p5	p25	median	p75	p95
All	8,062	0.093	3.501	-2.516	-0.436	0.041	0.608	2.500
By category:								
Stock ETF	2,240	0.108	1.195	-1.769	-0.516	0.128	0.748	1.811
Bank	1,320	0.173	1.643	-2.120	-0.660	0.149	1.017	2.414
Currency & Commodity	2,238	0.078	1.663	-2.153	-0.323	0.035	0.428	2.478
Bond	1,604	0.003	0.522	-0.787	-0.259	-0.020	0.220	0.897
Connected	660	0.149	11.368	-10.913	-3.718	-0.321	2.950	14.431

Trump-sensitive. This approach captures real-time market participant perceptions rather than 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, and a set of "Connected" stocks. We specify the expected directional relationship for each asset: "long" positions benefit from Trump's victory, "short" positions benefit from his defeat. Complete directional definitions appear in Internet Appendix Table A.1. Bank stocks comprise a leading category due to deregulation benefits. Traditional energy represents another major category benefiting from pro-fossil fuel policies. Renewable energy assets face potential headwinds. Currency exposures reflect trade policies, with dollar strength anticipated under Trump's tariff policies. The "Connected" category comprises stocks directly tied to Trump himself—his family, his businesses, and his campaign supporters—namely Trump Media & Technology Group (`DJT`), Phunware (`PHUN`), and Tesla (`TSLA`); the asset-by-asset rationale is detailed in Internet Appendix Table A.1. 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.[6] 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. The mean daily return across all Trump trades is 0.09% (9 bps) with a standard deviation of 3.5%. 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 a systematic lead-lag relationship between prediction market prices and traditional asset returns and a partial reversal. Our findings suggest that participants in the traditional financial markets draw inference from variations in the prediction-market prices.

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.

Let $\Delta\mathcal{P}_t(\text{Trump})$ denote daily changes in Trump's winning probability on Polymarket. We examine whether prediction-market price changes lead traditional assets' returns through predictive regressions across multiple horizons:

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

Here $r^{TT}_{i,h}$ is the signed log return of Trump trade asset i at horizon h: the single-day return on day $t+1$, $t+2$, or $t+3$, and, where indicated, the cumulative three-day return $r^{TT}_{i,t+1\to t+3} = \sum_{j=1}^{3} r_{i,t+j}$.

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

For each asset, its signed return $r_{i,t}^{TT} = d_i r_{i,t}$ encodes trading direction ($d_i \in \{+1, -1\}$) based on exposure to Trump's policy initiatives. The coefficient β_h captures horizon-dependent predictive power for $h = 1, 2, 3$ trading days. We align signals to the timing of U.S. markets' opening hours, ensuring signals, i.e., $\Delta\mathcal{P}_t$(Trump), are available before the next trading day.

We sign the Trump-trade returns so that positive coefficients ($\beta_h > 0$) consistently indicate an increase in Trump winning probability leads an increase in returns of assets that benefit from Trump presidency. Our primary specification pools all Trump trades to capture the average lead-lag effects. This pooling result averages out Trump-trade assets' time-varying sensitivities to Trump's policies and the shifting policy priorities throughout the 2024 presidential campaign. We also conduct analysis by category to explore the heterogeneity across Trump-trade assets and demonstrate the robustness of the lead-lag relationships.

Panel A of Table 2 presents results from pooled regressions spanning January 2024 through the election date. Given the structure of our data—particularly the fact that we have the same predictor for all assets on a given day—to account for both the cross-sectional and time-series dependence in the error term, we report standard errors following the procedure of Driscoll and Kraay (1998), which is robust to general forms of cross-sectional and serial correlation. Polymarket price changes systematically predict Trump-trade returns on the following day, with the coefficient on $\Delta\mathcal{P}_t$(Trump) positive and statistically significant at $h = 1$. The magnitude is economically meaningful: a one-percentage-point increase in Trump's Polymarket probability predicts approximately 13 basis points of next-day return in the pooled sample. The effect is roughly four times larger on assets we identify as "connected" to the Trump campaign (about 42 bps next-day), reflecting their more direct exposure, and roughly 10 bps on non-connected Trump-trade assets. At $h = 2$, the day-after coefficient is negative and statistically significant for connected assets (-23.5 bps), showing a partial reversal of an initial overreaction. By $h = 3$, the coefficients are close to zero and statistically insignificant in all three subsamples, so the lead-lag is short-lived. The combined pattern—a next-day spillover effect followed by a partial reversal concentrated in the connected subset—indicates that initial response partly reflects the transmission of noise.

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 signed return for Trump trades on day $t + 1$, $t + 2$, or $t + 3$, where returns are signed to align with expected directional relationships. $\Delta\mathcal{P}_t$(Trump) is the daily change in Trump's Polymarket probability (in percentage points). Standard errors following the Driscoll-Kraay procedure are reported in parentheses. Panel A, B and C use the full sample, the sample beginning April 1, 2024 and the sample after Biden withdrawal, respectively. Within each panel, columns 1–3 pool all Trump trades; columns 4–6 restrict to assets identified as "Connected"; columns 7–9 use the remaining "Not Connected" Trump trades. *, **, *** denote significance at 10%, 5%, and 1% levels, respectively.

	Full sample			Connected			Not Connected		
	$r^{TT}_{i,t+1}$ (1)	$r^{TT}_{i,t+2}$ (2)	$r^{TT}_{i,t+3}$ (3)	$r^{TT}_{i,t+1}$ (4)	$r^{TT}_{i,t+2}$ (5)	$r^{TT}_{i,t+3}$ (6)	$r^{TT}_{i,t+1}$ (7)	$r^{TT}_{i,t+2}$ (8)	$r^{TT}_{i,t+3}$ (9)
Panel A: Full sample									
Constant	0.001	0.001	0.001	0.002	0.002	0.002	0.001*	0.001*	0.001*
	(0.001)	(0.001)	(0.001)	(0.004)	(0.005)	(0.004)	(0.000)	(0.000)	(0.000)
$\Delta\mathcal{P}_t(Trump)$	0.131***	-0.018	0.009	0.418***	-0.235***	0.068	0.104***	0.003	0.003
	(0.009)	(0.019)	(0.017)	(0.123)	(0.088)	(0.106)	(0.013)	(0.014)	(0.012)
R^2	0.011	0.000	0.000	0.011	0.004	0.000	0.050	0.000	0.000
Observations	7,618	7,618	7,618	633	633	633	6,985	6,985	6,985
Panel B: 2024-04-01 onwards									
Constant	0.000	0.001	0.001	-0.001	0.000	0.000	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)
$\Delta\mathcal{P}_t(Trump)$	0.133***	-0.013	0.003	0.399***	-0.197*	0.006	0.108***	0.004	0.003
	(0.009)	(0.022)	(0.018)	(0.104)	(0.103)	(0.068)	(0.011)	(0.016)	(0.014)
R^2	0.033	0.000	0.000	0.037	0.009	0.000	0.067	0.000	0.000
Observations	5,512	5,512	5,512	459	459	459	5,053	5,053	5,053
Panel C: 2024-07-21 onwards (post-Biden withdrawal)									
Constant	0.000	0.001	0.001	0.001	0.002	0.003	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.006)	(0.007)	(0.006)	(0.001)	(0.001)	(0.001)
$\Delta\mathcal{P}_t(Trump)$	0.137***	-0.018	0.008	0.417***	-0.219**	0.027	0.110***	0.001	0.006
	(0.009)	(0.021)	(0.018)	(0.123)	(0.100)	(0.068)	(0.011)	(0.015)	(0.014)
R^2	0.051	0.001	0.000	0.057	0.015	0.000	0.109	0.000	0.000
Observations	2,731	2,731	2,731	228	228	228	2,503	2,503	2,503

Panels B and C of Table 2 confirm the results across alternative sample periods that begin on April 1, 2024—when the attention to the election and Polymarket trading volume significantly increased—and after Biden's withdrawal. The next-day pooled coefficient is stable across sample periods (approximately 13–14 bps per percentage point of $\Delta\mathcal{P}$). What varies is the explanatory power: the R^2 for $h = 1$ in the pooled sample rises from 1.1% (Panel A) to 3.3% (Panel B) and to

5.1% (Panel C), with higher R^2 in the Not-Connected subsample, indicating Polymarket changes explain meaningful variation in the returns of traditional assets over the next day. The day-2 reversal on connected assets (-19.7 bps in Panel B and -21.9 bps in Panel C) emerges again in the later sample periods. The combination—a next-day lead-lag effect of comparable magnitude across sample periods and a partial reversal concentrated in the subset of connected assets—reinforces our interpretation that prediction-market price variations contain both information and noise.

Table A.2 in the Internet Appendix presents the results of our placebo tests. We run predictive regressions using two sets of assets that have relatively small exposure to Trump's policies, such as taxation, 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 Table A.7. Large banks' stocks exhibit the strongest effect, with coefficients about twice the pooled estimate, consistent with their heightened sensitivity to potential regulatory changes. Stock ETFs and currencies & commodities also show significant lead-lag relationships, while bonds exhibit weaker effects. These cross-sectional differences align with plausible policy exposures and thus support our interpretation that participants in traditional financial markets draw inference from prediction-market price variations. Since our main results are a panel of individual assets, we further demonstrate the robustness of our results using the equally-weighted portfolio returns of all Trump-trade assets (Table A.5 in the Internet Appendix) and the equally-weighted portfolio returns within each asset category—equities, bonds, FX, banks, and connected stocks (Table A.6 in the Internet Appendix).

The baseline series of daily Polymarket price changes in Table 2 uses a midnight-to-midnight Eastern Time window. Our results hold under alternative timing conventions. Table A.3 in the Internet Appendix uses a 9am-to-9am ET window covering the 24-hour period immediately before the opening of U.S. markets for traditional assets. Table A.4 uses a 4pm-to-4pm ET window that ends at the close of the previous U.S. trading day. The 4pm-to-4pm specification is particularly important. Because Polymarket trades around the clock while traditional markets operate only during discrete sessions, one may argue that a portion of the daily Polymarket change measured midnight to midnight occurs while the traditional market is closed, so next-day predictability could simply reflect the traditional market mechanically catching up to news that Polymarket already incorporated overnight rather than genuine cross-market learning. This concern does not apply to the 4pm-to-4pm window: it ends precisely when the previous trading day closes, so to the extent any such catch-up exists, it should have already occurred during that prior session.

3.2 Economic significance: A trading strategy approach

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 market-structure noise. 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:

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

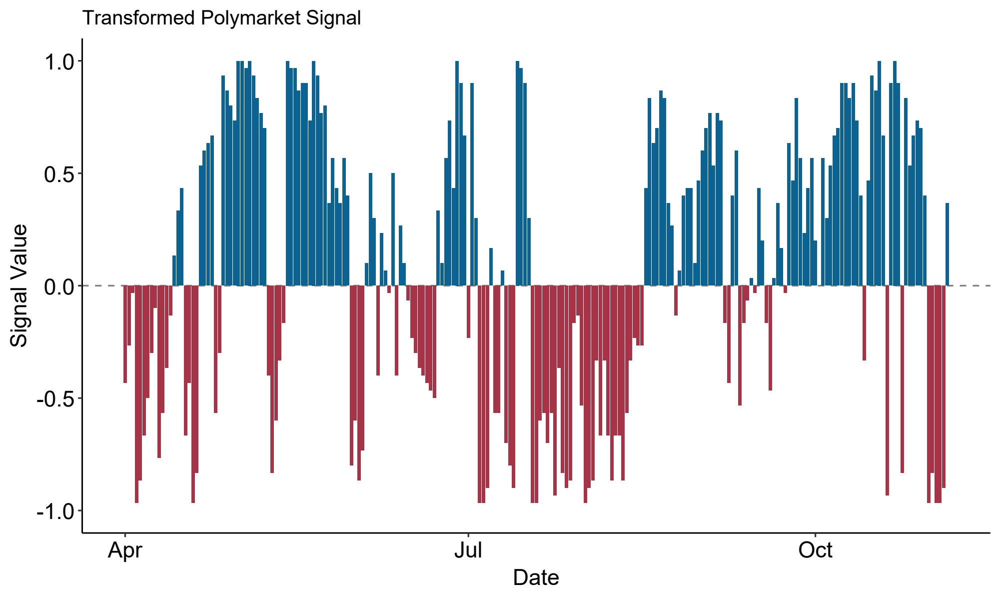


Figure 2 Transformed Polymarket Trading Signal

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.

Figure 2 plots our processed signal based on Trump's winning probability on Polymarket. The 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: median reversion over extended horizons, persistence over shorter periods, and reasonable turnover avoiding excessive costs while remaining event-responsive.

The strategy achieves an 18.93% annualized return with 9.72% volatility, yielding a 1.95 Sharpe ratio, and a 16.45% total return over the sample period from April 1 to the election day in 2024.[7] The 4.58% 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.8 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,

[7]The evaluation window begins on April 1, 2024, later than the regression sample, because the signal requires a burn-in: the 60-trading-day rolling window underlying the percentile ranks is first fully populated at the end of March 2024.

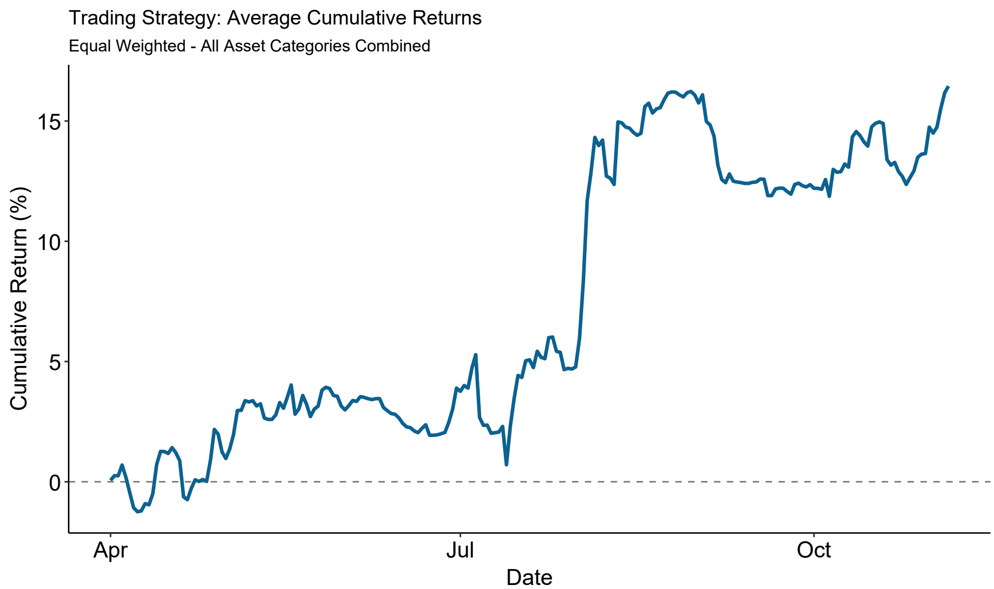


Figure 3 Cumulative Returns of Polymarket Trading Strategy

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.

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 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.

3.3 Retail attention and noise transmission

The lead-lag relationship indicates that participants in traditional markets learn from Polymarket price variations, while the subsequent reversal suggests that at least part of what is transmitted constitutes noise. Noise transmission is noteworthy for two reasons. First, the fact that noise originating in Polymarket—a relatively new market with far smaller volume—can move prices in traditional financial markets of vastly greater magnitude is striking in itself. Second, and more importantly, because Polymarket-specific noise is orthogonal to fundamentals, its transmission provides compelling evidence that cross-market learning takes place. By contrast, lead-lag relationships driven by fundamental news may simply reflect the sequential arrival of the same information—first to Polymarket and subsequently to traditional markets—rather than genuine learning across venues.

Next, we identify noise transmission from Polymarket to traditional assets by exploiting the variation in retail traders' attention to Polymarket. When their attention to Polymarket is high, it is more likely that they extract signals from Polymarket price variations and, due to their lack of expertise in discerning the source of price variation, transmit noise from Polymarket to traditional assets. We proxy for attention with internet search activity (Da et al., 2011; Ben-Rephael et al., 2017), specifically on Reddit. Since the 2021 meme-stock episode Reddit has become a principal forum on which retail traders share information. The meme-stock episodes also show that their correlated trades move asset prices (Pedersen, 2022), making them plausible transmitters of Polymarket noise into traditional assets. We collect the daily number of submissions and comments mentioning "Polymarket", denoted by n_t, across a set of finance- and politics-oriented subreddits—r/wallstreetbets, r/stocks, r/investing, r/options, r/Economics, and r/politics.[8]

Following the specification of Da et al. (2011) closely, we separate spikes in attention from its slow-moving trend by constructing a daily *abnormal* attention measure,

$$\text{AbnAttentionReddit}_{t-1} \;\equiv\; \log\left(1+n_{t-1}\right) \;-\; \log\left(1+\text{median}\left\{\,n_s\,\right\}_{s=t-61}^{t-2}\right), \tag{4}$$

the log mention count less the log of its trailing 60-day median. Differencing against the median, rather than the mean, removes the pronounced upward trend and low-frequency seasonality in attention over the 2024 cycle while remaining robust to the series' own large spikes; a positive value indicates the mention of Polymarket above its recent baseline. We lag the measure by one day so that attention is predetermined relative to the price change whose transmission it modulates. Figure 4 plots the series: it is stationary and displays sharp spikes around major election-related events, and retail attention rose as the presidential election approached.

[8] The counts are drawn from the Arctic Shift archive of Reddit, a successor to Pushshift; a mention is any submission or comment whose text contains "polymarket" (case-insensitive). The six subreddits are chosen for their large and active user bases, their focus on finance and politics, and their consistent availability in the archive. The Reddit mention counts series is highly correlated with Google search trends for the term "Polymarket." We choose Reddit over Google Trends because the former is more granular and more directly tied to active engagement with financial content.

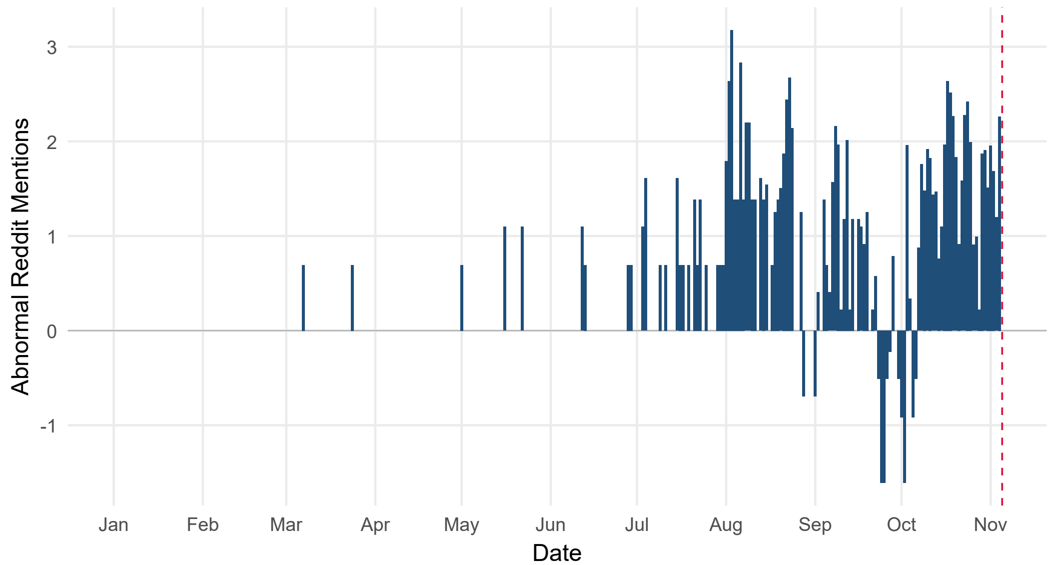


Figure 4 Abnormal Reddit Attention to Polymarket

This figure plots the daily abnormal Reddit attention measure, $\text{AbnAttentionReddit}_{t-1}$ (Equation (4)): the log number of submissions and comments mentioning "Polymarket" across the six fixed subreddits, less the log of its trailing 60-day median. The series begins on March 2, 2024, the first date for which the 60-day window is available. The dashed vertical line marks election day, November 5, 2024.

We extend the specification of the lead-lag regression in (1) by incorporating abnormal attention and its interaction with the Polymarket price change:

$$r^{TT}_{i,h} = \alpha_h + \beta_h \, \Delta\mathcal{P}_t + \gamma_h \left(\Delta\mathcal{P}_t \times \text{AbnAttentionReddit}_{t-1}\right) + \delta_h \, \text{AbnAttentionReddit}_{t-1} + \varepsilon_{i,h}, \quad (5)$$

where $h \in \{t+1,\ t+2,\ t+3,\ t+1 \to t+3\}$. As in the previous specifications, we report Driscoll–Kraay standard errors. We include day-of-week and day-of-month fixed effects to control for remaining seasonality in the attention series. The coefficient of interest is γ_h: a positive value means that the cross-market transmission of Polymarket price changes is stronger when retail attention is higher. We normalize $\text{AbnAttentionReddit}_{t-1}$ to unit standard deviation, so that γ_h measures the change in pass-through per one-standard-deviation increase in abnormal attention.

Table 3 reports the estimates. The interaction is positive and significant on the next day: in column (1), a one-standard-deviation increase in abnormal attention raises the next-day pass-through of the Polymarket price change from 0.082 to 0.141, an increase of roughly 70%. The interaction reverses sign at $t + 2$ (-0.081), and the cumulative three-day interaction is indistin-

Table 3 Retail Investor Attention and Cross-Market Noise Transmission

This table reports predictive regressions of signed Trump-trade returns on the lagged total daily Polymarket price change interacted with abnormal retail attention, following Eq (5). The dependent variables are the signed log Trump-trade returns over horizons $t+1$, $t+2$, $t+3$, and cumulatively over $t+1 \rightarrow t+3$. $\Delta\mathcal{P}_t$ is the total daily Polymarket price change. AbnAttentionReddit$_{t-1}$ is the abnormal Reddit attention measure of Eq (4)—the log count of Polymarket mentions across the six fixed subreddits at $t-1$ minus the log of its trailing 60-day median—normalized to unit standard deviation, so that its coefficients are expressed per one standard deviation of abnormal attention. All specifications include day-of-week and day-of-month fixed effects. The sample is March 2 to November 4, 2024; the start date is set by the 60-day window required to construct the abnormal-attention measure. Driscoll–Kraay standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels.

	$r^{TT}_{i,t+1}$	$r^{TT}_{i,t+2}$	$r^{TT}_{i,t+3}$	$r^{TT}_{i,t+1\rightarrow t+3}$
	(1)	(2)	(3)	(4)
$\Delta\mathcal{P}_t(Trump)$	0.082*	0.168***	0.008	0.257***
	(0.048)	(0.049)	(0.060)	(0.096)
AbnAttentionReddit$_{t-1}$	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
$\Delta\mathcal{P}_t(Trump) \times$ AbnAttentionReddit$_{t-1}$	0.059*	-0.081**	0.016	-0.006
	(0.035)	(0.038)	(0.038)	(0.050)
R^2	0.024	0.026	0.018	0.033
Observations	6,077	6,077	6,077	6,077
DOW FE	✓	✓	✓	✓
DOM FE	✓	✓	✓	✓

guishable from zero. Retail attention amplifies the transitory part of the spillover (i.e., noise in Polymarket prices); it does not strengthen the part that persists. [9] Throughout, the standalone attention term is statistically and economically zero, confirming that attention does not forecast Trump-trade returns on its own—it operates only by scaling the pass-through of Polymarket price movements.

This test delivers two important messages. First, variation in Polymarket prices predicts future returns of traditional assets more strongly during periods of heightened retail attention to Polymarket, consistent with our broader theme of cross-market learning. Second, what retail

[9] The level coefficients on $\Delta\mathcal{P}_t$ in Table 3—including the positive coefficient at $t+2$ and the significant cumulative effect—measure the pass-through at *mean* abnormal attention, on the shorter sample dictated by the 60-day attention window and with day-of-week and day-of-month fixed effects, and are therefore not directly comparable to the unconditional estimates of Table 2. That the pass-through at mean attention persists while the attention-scaled increment reverses is precisely the mechanism at work: the baseline pass-through carries the persistent information component, and heightened attention adds the transitory noise component.

attention transmits is predominantly noise, as the cumulative predictive power fully reverses within three days. Together, these findings demonstrate that the lead-lag relationship arises from cross-market learning and that part of what is transmitted is noise specific to Polymarket. The Polymarket-specific nature of this noise is critical: it rules out the alternative explanation that the lead-lag relationship reflects the sequential arrival of the same information, first to Polymarket and then to other assets, leaving cross-market learning as the only viable channel. Next, we exploit the information available from Polymarket's blockchain infrastructure to directly construct measures of noise in Polymarket prices from the transaction records of informed and uninformed traders.

4 Prediction-Market Information and Noise Spillover

This section exploits features of Polymarket's blockchain infrastructure to identify the sources of information and noise at the trader level. Specifically, we classify Polymarket traders into informed ones and the rest and analyze the impact of their trading activities. After classifying traders, we establish the transmission of both information and noise from Polymarket to traditional assets.

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. Our data cover the full universe of on-chain Polymarket transactions in the Trump-YES contract from January 5 to November 4, 2024, comprising approximately 1.6 million transactions (combined buys and sells). We validate the largest trades against records on Polymarket's official website to verify the accuracy of the on-chain data accessed via the API.

Table 4 presents summary statistics of the trades. The trade-size distribution is highly skewed: the full sample contains roughly 815,000 buys and 813,000 sells; the mean buy size (421 contracts) is more than ten times the median (31 contracts), with maximum trades in the millions of contracts.

Table 4 Summary Statistics of Polymarket Trades

This table presents summary statistics for the full universe of Polymarket trades on the 2024 U.S. presidential election contract. Trade size is measured in number of contracts (signed: positive for buys, negative for sells), 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.

	nobs	mean	sd	min	p25	median	p75	max
Panel A: Full Sample								
buy	814,678	421.014	5,689.601	0.009	10.900	31.020	169.710	1,999,294.357
sell	812,661	-338.425	4,322.987	-1,251,424.364	-162.985	-36.520	-11.668	-0.005
Panel B: Before First Poll Opening on the Election Day								
buy	787,187	375.688	3,875.300	0.009	11.000	31.480	169.460	760,906.596
sell	784,163	-287.432	2,892.125	-1,087,820.765	-160.742	-36.176	-11.847	-0.005
Panel C: Excluding November								
buy	615,363	386.224	3,847.281	0.009	12.120	46.810	181.000	760,906.596
sell	621,045	-296.189	2,803.994	-1,087,820.765	-174.682	-44.910	-17.074	-0.005

As a reminder, the payout of each contract is $1 when its event materializes. 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 4 present summary statistics for trades executed before the first poll opening on election day (November 5, 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.

Figure 5 plots aggregate daily volume for buys and sells. The volumes exhibit substantial variation over time, with pronounced clustering around major events and sustained growth approaching the election. Figure 6 displays the highly skewed distribution of traders by their total transaction volume, with relatively few large traders accounting for disproportionately large shares.[10] Note that we avoid double counting: when tallying transactions, we only count market orders.

[10]Figure A.10 in the appendix provides an alternative visualization using the top and bottom 50% partitions.

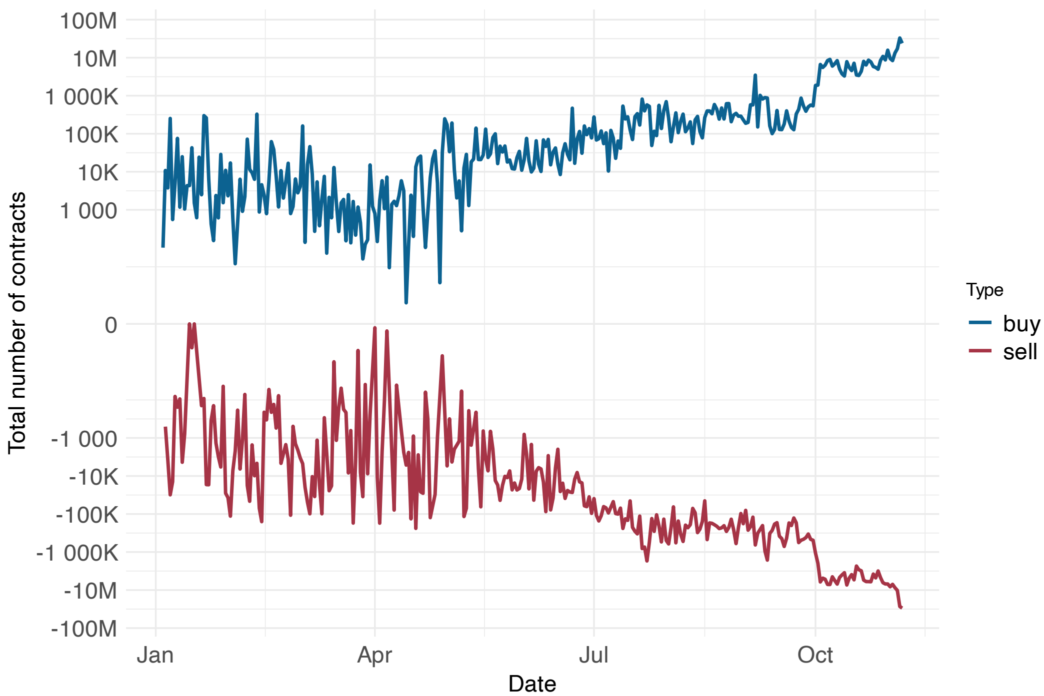


Figure 5 Daily Signed Volume on Polymarket

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.

Trader classification. We screen out informed traders (wallets) through their post-trade trading performance.[11] Informed traders on the buy and sell sides are separately identified as a trader can be asymmetrically informed about news favorable versus unfavorable regarding the Trump campaign.

We impose three criteria. The first is a minimum-activity criterion for statistically reliable performance evaluation: a wallet must have placed at least 20 market orders on the buy (or sell) side. We focus on market orders because a trader paying the liquidity premium to get filled immediately is acting on a signal they're unwilling to wait on—that urgency is exactly what we want to capture.

Our second criterion requires the wallet's total transaction volume on the buy (or sell) side to be above the median.[12] A high volume arises either from frequent trading or occasional large trades, both of which are consistent with the trader having consistent access to proprietary information.

Finally, we examine whether a wallet's trades are followed by meaningful price movements

[11]Throughout the paper, we use wallet and trader interchangeably. However, we acknowledge that a trader may own multiple wallets. Pinning multiple wallets to one trader has long been a technical challenge in the blockchain area.

[12]Since our sample contains the full universe of trades, 50th percentile ($129 for buy / $309 for sell) is a mild restriction, which screens out smaller trades. Our results are robust to thresholds ranging from 50th to 90th percentiles.

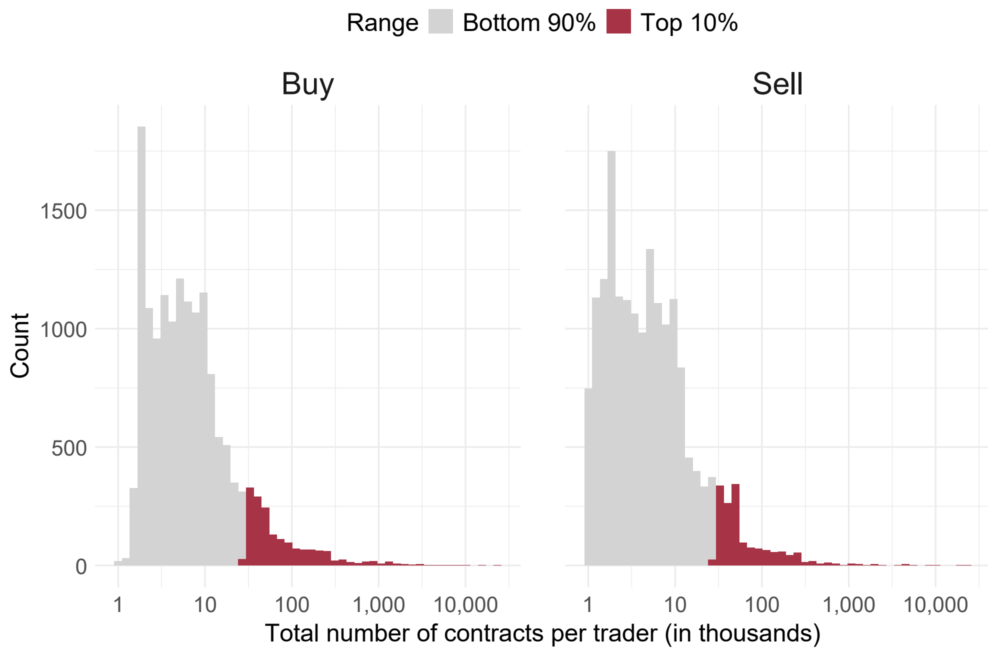


Figure 6 Distribution of Traders by Total Transaction Volume

This figure shows a histogram of the total transaction volume per trader over the sample period, in log scale. Traders are partitioned into a top 10% and a bottom 90% by total transaction volume. The sample is the full universe of Polymarket trades on the Trump-YES contract.

in the same direction—that is, whether the trader generates significant profits. We take three steps. First, for trade i, we compute the signed cumulative return at horizon h, $r_{i,h} \equiv \sigma_i \left(\mathcal{P}_{t_i+h} - \mathcal{P}_{t_i}\right)/\mathcal{P}_{t_i}$, where t_i is the execution time and σ_i equals $+1$ for buys and -1 for sells, so that a trade earns a positive return when the Polymarket price of Trump-YES contract subsequently moves in its direction. Next, we average $r_{i,h}$ over the five horizons $h \in \{24, 30, 36, 42, 48\}$ hours, denoted by $\bar{r}_i$. This variable captures average trade performance across horizons, with emphasis on the next-day window where our empirical analysis (Section 3) shows the lead-lag relationship between Polymarket and traditional assets most clearly. In the last step, we compute the trade size-weighted average of $\bar{r}_i$ as the wallet-level performance measure. The criterion requires a wallet's performance to exceed the average by at least 200bps—where the benchmark is the trade size-weighted mean of $\bar{r}_i$ across all wallets on the same side. This benchmarking removes the passive return earned simply by holding a buy or sell position on Trump-YES until the election outcome is revealed.

Informed buyers and sellers together account for 33.4% of total trading volume. While their volumes are roughly balanced with an informed buy-to-sell dollar volume ratio of 1.3,[13] the populations are starkly asymmetric: 529 informed buyers versus 3,019 informed sellers. Informed buyers, in other words, trade in larger sizes but are far fewer in number. This asymmetry aligns with the event's eventual resolution in buyers' favor—Trump winning the 2024 presidential election. Informed buyers are more likely to have possessed genuine information whose effects are persistent and content not undermined by subsequent developments in the election cycle. Informed sellers, by contrast, have acted on signals that eventually reversed. Buyers with more reliable information naturally trade with higher conviction, taking larger and more aggressive positions, while sellers trade more conservatively. The scarcity of informed buyers also reflects the nature of their edge: true information is difficult to obtain, whereas noise-like signals whose effects are transient, are more widely available, giving rise to a larger but less precisely informed seller population.

Having identified the informed traders, we classify the rest as uninformed.[14] Both groups move the Polymarket price, and traditional-market participants read the resulting price move as a signal, which is the source of the lead-lag relationship and the eventual partial reversal of the effect.

Traders' price impact. We document the price impact of traders' market orders by regressing Polymarket price changes on the informed traders' net volume (informed buy minus informed sell) and uninformed traders' net volume. Table 5 reports regression results with the dependent variables being the contemporaneous, next-day, and two-day-cumulative changes in the Trump-YES price.

Both informed and uninformed order flows move the price on the day they trade, consistent with each carrying price impact, but the two impacts diverge thereafter. The informed-trade impact persists into the one-day-ahead change and accumulates over the two-day window, whereas the uninformed-trade impact does not: it partially reverses, with the coefficient on $UninformedTrade_t$

[13] Informed traders contribute an almost equal share of each side's own total dollar volume: 14.0% of all buy-side dollar volume and 13.5% of all sell-side dollar volume. The 1.3 ratio compares informed buy and sell dollar volumes directly; it differs from the ratio of these two shares because the buy and sell sides have different totals.

[14] Figure A.8 in the Internet Appendix displays the daily aggregated trading volume of uninformed traders over time, and Table A.9 reports summary statistics for both informed and uninformed traders, including their post-trade returns and total trade size. Informed traders earn positive average post-trade profitability—3.9% on buys and 4.2% on sells—while uninformed traders earn essentially zero (−0.2% on buys and 0.2% on sells), confirming that the Polymarket price tends to move in informed traders' direction after they trade.

Table 5 Price Impact of Informed and Uninformed Trades on Polymarket

This table reports panel regressions of the change in the Trump-YES Polymarket price on contemporaneous informed and uninformed net trade flows. The dependent variables are the daily change $\Delta\mathcal{P}_t$(Trump) (column 1), the one-day-ahead change $\Delta\mathcal{P}_{t+1}$(Trump) (column 2), and the two-day cumulative change $\mathcal{P}_{t+1}$(Trump) $-$ $\mathcal{P}_{t-1}$(Trump) (column 3), measured in probability units. The independent variables, $InformedTrade_t$ and $UninformedTrade_t$, are the daily net market-order volumes (buys minus sells, in millions of contracts) from informed and uninformed wallets, respectively. The sample period is January 5, 2024, to November 4, 2024. Newey-West standard errors with optimal lag lengths are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	$\Delta\mathcal{P}_t(Trump)$	$\Delta\mathcal{P}_{t+1}(Trump)$	$(\mathcal{P}_{t+1} - \mathcal{P}_{t-1})\,(Trump)$
	(1)	(2)	(3)
Constant	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)
$InformedTrade_t$	1.006**	0.733*	1.739**
	(0.467)	(0.385)	(0.805)
$UninformedTrade_t$	0.257**	-0.203*	0.054
	(0.115)	(0.123)	(0.202)
R^2	0.043	0.060	0.074
Observations	301	302	301

negative and significant at the one-day horizon (column (2)). This is the signature pattern that distinguishes information from noise. Informed flow moves the price as the underlying fundamentals are gradually incorporated, and that movement persists; uninformed flow generates transitory pressure that later corrects—exactly what we would expect if the partition between informed and uninformed traders allows us to distinguish the genuinely noise-driven trade from that driven by information. A caveat on what this exercise does and does not validate: because the classifier selects wallets on their 24-to-48-hour post-trade returns, the persistence of the informed group's price impact is partly built into its construction. The informative content of the table lies in the *uninformed* group's partial reversal, and, in the next subsection, the cross-market horizon profiles—which are diagnostics the partition was not constructed to deliver.

4.2 Cross-market learning: Information and noise

In Section 3, we show that Polymarket price variation leads returns on traditional assets. Section 4.1 establishes that Polymarket price variation is driven by both informed and uninformed trading, the former with a persistent impact and the latter with a transitory one. Next, we connect informed and uninformed trading in Polymarket directly to the future returns on traditional assets. The results corroborate the finding of noise transmission in Section 3.3 with a more direct identification of noise (and information) in Polymarket and thereby offer more evidence on cross-market learning.

In the first exercise, we decompose Polymarket price variation into a component driven by informed trading and a component driven by uninformed trading. We find that both components lead returns on traditional assets, but as the horizon extends, only the informed component retains a significant and persistent effect. The regressions are close to those in Section 3, except that the single regressor—Polymarket price change—is replaced by the informed and uninformed components. In the second exercise, we regress future traditional-asset returns directly on the net order flows of informed and uninformed traders on Polymarket and obtain similar results.

We decompose daily Polymarket price changes into components driven solely by informed versus uninformed trades. We segment each trading day into 10-minute intervals and, within each interval, separately aggregate informed and uninformed traders' market orders. We attribute the interval's price change as follows. If the price change is in the same direction as only one type of trade (the net order flow of informed or uninformed traders), we attribute it entirely to that type. To attribute price changes unambiguously, we discard intervals in which the price moves with both types or with neither.[15] Summing across the 10-minute intervals yields the daily price changes attributed to informed and uninformed trades, denoted $\Delta\mathcal{P}_t^{Informed}$ and $\Delta\mathcal{P}_t^{Uninformed}$, respectively.

We run the predictive regressions of pooled Trump-trade returns on these Polymarket price-change components:

$$r_{i,h}^{TT} = \alpha_h + \beta_h^i \cdot \Delta\mathcal{P}_t^{Informed} + \beta_h^u \cdot \Delta\mathcal{P}_t^{Uninformed} + \gamma_h \cdot \text{Controls}_t + \varepsilon_{i,h}, \tag{6}$$

where the dependent variable, $r_{i,h}^{TT}$, as in Section 3, is the signed log return of Trump trade i over the next day ($h = t + 1$), the second day ($h = t + 2$), the third day ($h = t + 3$), and the cumulative

[15] Among 10-minute intervals, those in which the Polymarket price moves with neither type constitute approximately 27%, and those in which it moves with both types constitute 9%; these intervals are excluded for cleaner alignment with informed and uninformed trading. As a result, $\Delta\mathcal{P}_t^{Informed} + \Delta\mathcal{P}_t^{Uninformed}$ does not exactly equal the total daily Polymarket price change, $\Delta\mathcal{P}_t(Trump)$.

Table 6 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 $t+1$, $t+2$, $t+3$, and the three-day cumulative horizon $t+1 \rightarrow t+3$. 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. These 10-minute components are then summed to the daily level. Columns (1)–(4) report the baseline specification; columns (5)–(8) add as controls the first nine principal components of a daily panel of cross-venue Trump-win price changes (Polymarket, PredictIt, and Kalshi) and the Trump-trade cross-section—the fewest explaining at least 80% of its variance—to absorb common information and sentiment shocks. The sample period is January 5, 2024, to November 4, 2024. Driscoll-Kraay standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	$r^{TT}_{i,t+1}$	$r^{TT}_{i,t+2}$	$r^{TT}_{i,t+3}$	$r^{TT}_{i,t+1\rightarrow t+3}$	$r^{TT}_{i,t+1}$	$r^{TT}_{i,t+2}$	$r^{TT}_{i,t+3}$	$r^{TT}_{i,t+1\rightarrow t+3}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.001	0.001	0.001	0.002	0.001	0.001*	0.001	0.003*
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
$\Delta\mathcal{P}_t^{Informed}$	0.196***	0.030	0.047	0.274*	0.218***	0.035	0.063	0.317**
	(0.062)	(0.063)	(0.075)	(0.140)	(0.073)	(0.079)	(0.078)	(0.153)
$\Delta\mathcal{P}_t^{Uninformed}$	0.074**	-0.008	0.010	0.076	0.091**	-0.015	0.008	0.084
	(0.036)	(0.031)	(0.034)	(0.055)	(0.040)	(0.035)	(0.032)	(0.052)
PC included					✓	✓	✓	✓
R^2	0.002	0.000	0.000	0.002	0.007	0.001	0.001	0.005
Observations	7,544	7,544	7,544	7,518	7,544	7,544	7,544	7,518

return over next three days ($h = t+1 \rightarrow t+3$). In the regression in Section 3, the coefficient of interest is β_h on $\Delta\mathcal{P}_t(Trump)$; now that the impact of $\Delta\mathcal{P}_t(Trump)$ is decomposed into those of $\Delta\mathcal{P}_t^{Informed}$ and $\Delta\mathcal{P}_t^{Uninformed}$, the coefficients of interest are β_h^i and β_h^u, respectively.

Table 6 presents the results. The price changes attributed to both informed and uninformed trades positively and significantly predict next-day Trump-trade returns, with the informed-trade effect substantially larger in magnitude than the uninformed-trade effect. On the second and third days, the predictive coefficients are not statistically significant for either component. Over the cumulative three-day horizon, however, the informed-trade effect remains statistically significant and large in magnitude, whereas the uninformed trade's effect fades into statistical insignificance.

Our results once again point to the transmission of both information and noise from Polymarket to traditional assets. As previously discussed, the transmission of Polymarket-specific noise plays a critical role in differentiating cross-market learning from the sequential arrival of information, because noise can be market-specific whereas fundamental information is relevant to and attended to by participants across all markets. While our construction of the noise component in Polymarket prices is based directly on Polymarket traders' transaction records, one may still argue that all markets—including traditional ones and Polymarket—could be responding to a common, non-fundamental sentiment shock sequentially, with Polymarket leading due to its greater retail participation. The lead-lag relationship would then merely reflect the sequential arrival of the same sentiment shock across markets rather than cross-market learning.

To address this concern, we augment the regressions with a large set of controls that capture the information and sentiment environment common to all markets. Specifically, we construct a set of principal components from a daily panel comprising Trump-win contract price changes across prediction-market venues (Polymarket, PredictIt, and Kalshi) and the entire cross section of Trump-trade assets' returns. Intuitively, these principal components capture the common information and sentiment shocks affecting all markets, so including them as controls should absorb the common variation and isolate information and noise specific to Polymarket. In columns (5)–(8) of Table 6, we add the first nine principal components—the fewest that cumulatively explain at least 80% of the panel's total variance—as controls. The results are robust: the informed-trade effect remains statistically significant and economically large, whereas the uninformed-trade effect still fades to insignificance over the three-day horizon. Overall, these results indicate that the lead-lag relationship is not purely driven by a common shock; Polymarket-specific information and noise are important.

Next, we directly test whether informed and uninformed trading activity on Polymarket predict Trump trade returns. We define $\Delta\mathcal{P}_t^{Informed}$ and $\Delta\mathcal{P}_t^{Uninformed}$ as the net market-order volume (buy minus sell) from informed and uninformed traders in day t (i.e., the trading activities behind Polymarket price pressure) and run the following predictive regressions:

$$r_{i,h}^{TT} = \alpha_h + \beta_h^i \cdot InformedTrade_t + \beta_h^u \cdot UninformedTrade_t + \gamma_h \cdot \text{Controls}_t + \varepsilon_{i,h}, \quad (7)$$

Table 7 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 $t+2$, day $t+3$, and cumulatively over days $t+1$ to $t+3$, 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. Columns (1)–(4) report the baseline specification; columns (5)–(8) add the same principal-component controls as in Table 6. All specifications include day-of-week and day-of-month fixed effects. The sample period is January 5, 2024, to November 4, 2024. Driscoll-Kraay standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	$r^{TT}_{i,t+1}$	$r^{TT}_{i,t+2}$	$r^{TT}_{i,t+3}$	$r^{TT}_{i,t+1\to t+3}$	$r^{TT}_{i,t+1}$	$r^{TT}_{i,t+2}$	$r^{TT}_{i,t+3}$	$r^{TT}_{i,t+1\to t+3}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$InformedTrade_t$	0.599**	0.519**	0.227	1.345***	0.512**	0.480**	0.234	1.227***
	(0.249)	(0.207)	(0.157)	(0.394)	(0.244)	(0.223)	(0.168)	(0.396)
$UninformedTrade_t$	0.117**	0.046	0.054	0.216	0.095*	0.016	0.043	0.154
	(0.050)	(0.059)	(0.066)	(0.144)	(0.054)	(0.056)	(0.062)	(0.129)
PCs included					✓	✓	✓	✓
DOW FE	✓	✓	✓	✓	✓	✓	✓	✓
DOM FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.013	0.013	0.010	0.018	0.017	0.014	0.012	0.020
Observations	7,623	7,623	7,623	7,597	7,623	7,623	7,623	7,597

where, as in the previous regression, the dependent variable, $r^{TT}_{i,h}$, is the signed return of Trump trade i over the next day ($h = t+1$), the second day ($h = t+2$), the third day ($h = t+3$), and cumulatively over the next three days ($h = t+1 \to t+3$). The results in Table 7 corroborate the analysis based on Polymarket price decomposition. Informed trading predicts Trump-trade returns on the next day ($t+1$) and continues to predict returns on day $t+2$, accumulating to a sizable effect over the three-day horizon. Uninformed trading also predicts Trump-trade returns at $t+1$, but its effect fades at $t+2$, with the cumulative effect over three days fading into statistical insignificance. Such patterns are robust to controlling for the same principal components from Table 6.

The specifications in Table 6 and 7 measure the informed and uninformed traders' footprint through different variables—the Polymarket price change attributed to informed and uninformed trading in Table 6 versus informed and uninformed traders' net order flows in Table 7—but deliver the same message. The significant first-day effect of both informed and uninformed trading is critical for establishing cross-market learning. The participants in traditional asset markets learn from Polymarket price variation because information is being revealed in Polymarket, which is what the effect of informed Polymarket trading shows. The identification challenge—the lead-lag relationship between informed Polymarket trading and Trump-trade returns may reflect the sequential arrival of the same information rather than cross-market learning—is addressed by the uninformed-trade effect, i.e., the transmission of Polymarket-specific noise.

This Polymarket setting, and in particular, the availability of granular transaction records at the trader (wallet) level, allows us to identify informed and uninformed trading separately and to establish cross-market learning through two complementary channels: the informed channel carries the substance of what is being learned, while the uninformed channel provides the identification. In the next subsection, we provide more evidence on the information channel.

4.3 Additional evidence on information transmission

As previously discussed, we rely on the transmission of Polymarket-specific noise to establish cross-market learning, so, next, we focus on information transmission. Specifically, we sharpen the characterization of what is being learned by documenting that information transmission from Polymarket to traditional assets intensifies precisely around resolution events (poll releases).

During a presidential election cycle, polls arrive in waves, and each release temporarily resolves uncertainty about the candidates' relative prospects. The days just before a cluster of major polls are therefore when informed traders are most likely to hold a temporary informational advantage. In those windows, informed trading should move Polymarket prices more, and traditional-market participants should act on the resulting signal more strongly.

To measure this, we define $NPolls_t$ as the number of "A-rated" national polls scheduled for release over the following 5 days. We take the polling data compiled by Nate Silver, which runs from June 28, 2024 through Election Day, and set $NPolls_t$ to zero on days with no release and on dates before June 28, which Nate Silver's data do not cover. Figure 7 plots the series and shows pronounced clustering as the election approaches. In the regressions below, we center

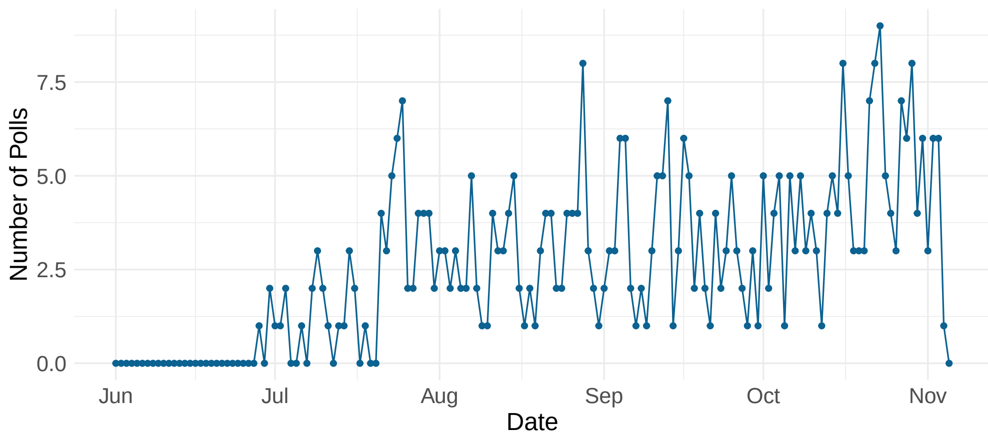


Figure 7 Number of National Polls Over Time

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

$NPolls_t$ and scale it to unit standard deviation (one standard deviation corresponds to roughly nine upcoming polls), so that interaction coefficients measure the change per one standard deviation of poll intensity and level coefficients are evaluated at mean poll intensity.

Table 8 augments the trading-volume specification of Table 7 with $NPolls_t$ and its interactions with informed and uninformed Polymarket volume. Columns (1)–(4) report the next-day, second-day, third-day, and cumulative three-day horizons; columns (5)–(8) repeat these horizons with the principal-component controls of Table 7.

The interaction in Column (1) of Table 8 shows that when news is imminent—proxied by the count of national polls due the next 5 days—the lead-lag from informed Polymarket trading to next-day Trump-trade returns strengthens: a one-standard-deviation increase in poll intensity raises the next-day pass-through of informed volume by 0.770, an increment larger than the unconditional informed coefficient in Table 7, and the interaction survives the principal-component controls. By contrast, the interaction for uninformed trading is essentially zero at the next day. Indeed, the level coefficient on informed volume—its pass-through at mean poll intensity—is statistically indistinguishable from zero, so the next-day transmission of informed activity is concentrated in information-rich windows. Traditional-market participants appear to weight informed Polymarket activity more, and to discount uninformed activity, when near-term information arrival is anticipated.

Table 8 Cross-Market Transmission of Information: Poll Releases

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 over the following 5 days. The dependent variables are the signed log returns of the Trump trade on day $t+1$, day $t+2$, day $t+3$, and cumulatively over days $t+1$ to $t+3$, following trading on day t. Columns (1)–(4) report the baseline specification; columns (5)–(8) add the same principal-component controls as in Table 7. We use the count of national polls over the following 5 days, $NPolls_t$, as a proxy for the imminence of information revelation. $NPolls_t$ is centered and scaled to unit standard deviation within the estimation sample, so interaction coefficients are expressed per one standard deviation of $NPolls_t$ and level coefficients are evaluated at mean poll intensity. Trump trade returns are signed to reflect their expected sensitivity to Trump's electoral prospects. All specifications include day-of-week and day-of-month fixed effects. The sample period is January 5, 2024, to November 4, 2024. Driscoll-Kraay standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	$r^{TT}_{i,t+1}$	$r^{TT}_{i,t+2}$	$r^{TT}_{i,t+3}$	$r^{TT}_{i,t+1\to t+3}$	$r^{TT}_{i,t+1}$	$r^{TT}_{i,t+2}$	$r^{TT}_{i,t+3}$	$r^{TT}_{i,t+1\to t+3}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$InformedTrade_t$	-0.493	-0.193	1.851***	1.165	-0.490	-0.024	1.858***	1.342
	(0.441)	(0.473)	(0.508)	(1.105)	(0.385)	(0.496)	(0.527)	(1.067)
$UninformedTrade_t$	0.096	0.199	0.458***	0.751**	0.077	0.157	0.384***	0.617*
	(0.126)	(0.163)	(0.152)	(0.349)	(0.141)	(0.169)	(0.148)	(0.335)
$NPolls_t$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
$NPolls_t \times InformedTrade_t$	0.770***	0.485	-1.126***	0.129	0.694***	0.334	-1.134***	-0.103
	(0.271)	(0.313)	(0.294)	(0.577)	(0.264)	(0.325)	(0.340)	(0.606)
$NPolls_t \times UninformedTrade_t$	0.041	-0.086	-0.276***	-0.319*	0.028	-0.084	-0.235**	-0.290
	(0.070)	(0.088)	(0.092)	(0.188)	(0.074)	(0.091)	(0.102)	(0.188)
PCs included					✓	✓	✓	✓
DOW FE	✓	✓	✓	✓	✓	✓	✓	✓
DOM FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.014	0.014	0.012	0.019	0.017	0.015	0.014	0.021
Observations	7,623	7,610	7,610	7,597	7,623	7,610	7,610	7,597

The interactions are insignificant for second-day returns (Column (2)) and do not accumulate over the three-day horizon (Column (4)): higher poll intensity accelerates the next-day incorporation of informed Polymarket activity rather than adding to its cumulative effect, consistent with information whose value is short-lived around its public release. At longer horizons, the interaction for uninformed volume turns negative (columns (3)–(4)), so, if anything, participants discount uninformed Polymarket activity precisely when genuine information is about to arrive. Because $NPolls_t$ enters the specification in interactions, the level coefficients in Table 8 measure pass-through at mean poll intensity and are not directly comparable to the unconditional estimates of Table 7. Taken together, traditional-market participants seem to distinguish informed from uninformed Polymarket traders mainly in the days just before major poll releases; outside those windows they pay less attention to this distinction.

5 A Simple Framework and Additional Predictions

Our empirical analysis establishes a link from informed and uninformed trading in Polymarket to price movements in traditional financial markets. In this section, we present a simple theoretical framework that formalizes the mechanisms underlying cross-market learning and noise transmission. Our goal is not to provide a new theory but simply to offer a conceptual framework that generates additional predictions in our setting and guides our subsequent empirical analysis.

5.1 A simple model of information and 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 in 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, a 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.,

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

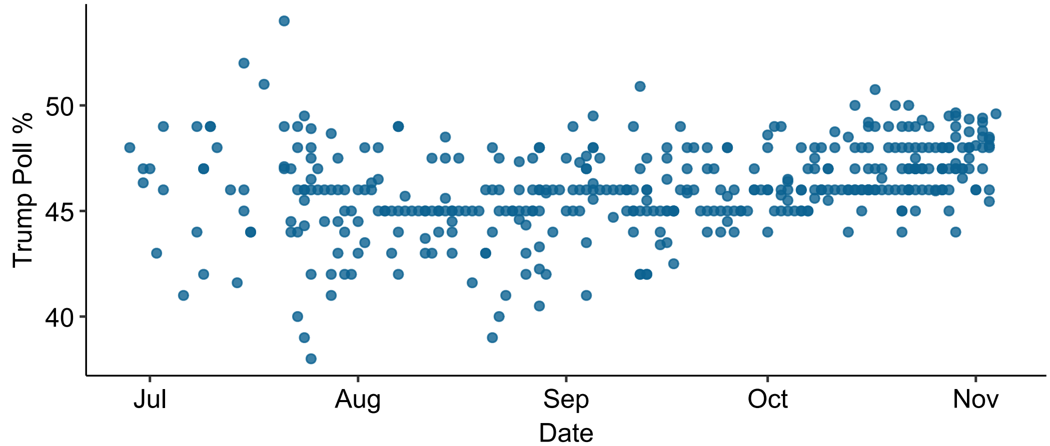
where $\frac{\beta_v}{\beta_v^2 + \beta_x^2 \tau_i / \tau_x}$ is the covariance between v and q scaled by the variance of q under the investors' prior. Thus, we obtain a causal chain that underpins our empirical findings:

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

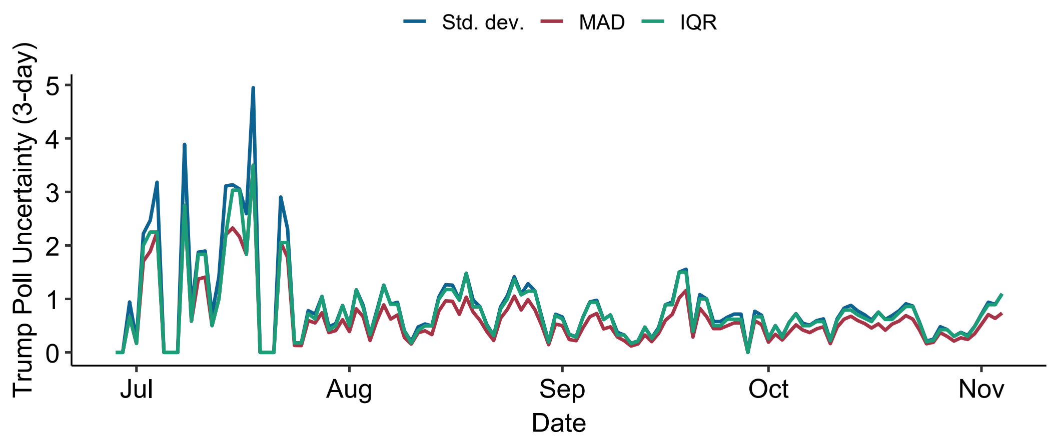
That is, variation in the prediction-market noise trade, Δx, generates price impact, Δq, which, through cross-market learning, generates variation in the price of the traditional asset.

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 expectations 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 contracts (with maximum payout of \$1.2 million) were traded in 2024 on the U.S. election outcome, while the traditional 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



(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 three measures of poll dispersion computed over the trailing three-day window: the standard deviation, median absolute deviation, and interquartile range of Trump winning probabilities across polls in the window. The series are filled with zero on pre-poll days; the x-axis is truncated to start at the first polling date. Sample period: June 28, 2024, through the election date.

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.

Table 9 Noise Spillover Effects and Polling Uncertainty

This table tests Prediction 1 by examining whether the Polymarket-to-Trump-trade lead-lag is stronger on days with greater poll dispersion. The dependent variable is the next-day Trump trade return. $\Delta\mathcal{P}_t$ is the daily change in Trump's Polymarket-implied winning probability. The three poll-dispersion measures (columns 1–3) are the trailing three-day standard deviation ($\text{PollSD}_{t-3,t}$), median absolute deviation ($\text{PollMAD}_{t-3,t}$), and interquartile range ($\text{PollIQR}_{t-3,t}$) of Trump winning probabilities across the polls reported in the window. Sample period: June 1, 2024 through the election date, with poll dispersion set to zero on pre-poll days. Driscoll-Kraay standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	$r^{TT}_{i,t+1}$		
	(1)	(2)	(3)
Constant	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)
$\Delta\mathcal{P}_t$	0.074	0.071	0.066
	(0.068)	(0.069)	(0.070)
$PollSD_{t-3,t}$	0.000		
	(0.001)		
$\Delta\mathcal{P}_t \times PollSD_{t-3,t}$	0.068*		
	(0.039)		
$PollMAD_{t-3,t}$		0.001	
		(0.001)	
$\Delta\mathcal{P}_t \times PollMAD_{t-3,t}$		0.099*	
		(0.055)	
$PollIQR_{t-3,t}$			0.000
			(0.001)
$\Delta\mathcal{P}_t \times PollIQR_{t-3,t}$			0.083*
			(0.049)
R^2	0.009	0.009	0.009
Observations	3,897	3,897	3,897

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 three measures of poll dispersion over the trailing three-day window ending at t: the standard deviation $\text{PollSD}_{t-3,t}$, the median absolute deviation $\text{PollMAD}_{t-3,t}$, and the interquartile range $\text{PollIQR}_{t-3,t}$ of the Trump's winning probabilities reported across polls in that three-day window. The regression sample begins on June 1, 2024, with the dispersion measure set to zero on pre-poll days. Figure 8 shows the considerable variation in these dispersion measures across the polling period. We test the prediction of our model by interacting each measure with the contemporaneous change in the Polymarket price. Table 9 reports positive and statistically significant interaction terms across all three measures, confirming that on days with greater poll dispersion, variations in the Polymarket price lead the Trump-trade returns more strongly, consistent with our model's prediction.

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

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 10 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. The dependent variable is the next-day Trump-trade return; columns (1)–(3) measure the Polymarket change over the midnight-to-midnight, 9am-to-9am, and 4pm-to-4pm windows. H2 indicates the later, higher-liquidity period and H1 the earlier period. Driscoll-Kraay standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	$r^{TT}_{i,t+1}$		
	(1)	(2)	(3)
Constant	0.001	0.001	0.001*
	(0.001)	(0.001)	(0.001)
$\Delta\mathcal{P}_t \times$ H1	0.098		
	(0.078)		
$\Delta\mathcal{P}_t \times$ H2	0.133***		
	(0.008)		
$\Delta\mathcal{P}_t^{9AM-9AM} \times$ H1		0.115	
		(0.093)	
$\Delta\mathcal{P}_t^{9AM-9AM} \times$ H2		0.129***	
		(0.009)	
$\Delta\mathcal{P}_t^{4PM-4PM} \times$ H1			-0.003
			(0.036)
$\Delta\mathcal{P}_t^{4PM-4PM} \times$ H2			0.180***
			(0.064)
R^2	0.011	0.011	0.003
Observations	7,618	7,618	7,618

τ_q, June-November 2024). Table 10 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 speaks more directly to informed traders' capacity. Consider a decrease in γ, which, as shown in Goldstein et al. (2025), leads to a decrease in β_x.[16] When the prediction market has recently been more informative—when informed traders have been more active, or have driven a greater share of price movements—traditional-market participants rationally place greater weight on its price as a signal. The theory then makes a sharp prediction about noise transmission: precisely because the prediction-market price has grown more credible, a move driven by noise is transmitted to traditional markets *more* strongly, not less. The interaction between recent

[16]This result holds under both the rational expectations equilibrium and the cursed equilibrium of Eyster et al. (2019).

Table 11 Information Hangover: Noise Spillover Effects Following Recent Informed Trading

This table tests Prediction 2 by examining whether recent informed-trading intensity amplifies the predictive power of Polymarket price changes for next-day Trump-trade returns. The dependent variable is the next-day Trump-trade return. In each column we interact the daily change in Trump's Polymarket probability, $\Delta\mathcal{P}(Trump)_t$, with a measure of recent informed intensity. Column (1) is the baseline with no interaction. Columns (2)–(3) use volume-based measures: $|InformedTrade|_{t-1}$, the absolute informed net market-order volume on day $t-1$, and $\overline{|InformedTrade|}_{t-1}$, its five-day moving average ending on day $t-1$. Columns (4)–(5) use price-impact-share measures constructed from the informed/uninformed price-change decomposition: $\left|\Delta\mathcal{P}^{Inf}/\Delta\mathcal{P}\right|_{t-1}$, the absolute share of the daily Polymarket price change attributable to informed flow on day $t-1$, and $\overline{\left|\Delta\mathcal{P}^{Inf}/\Delta\mathcal{P}\right|}_{t-1}$, its five-day moving average ending on day $t-1$. The price-share measures are set to zero on days with a near-zero price change (for which the share is undefined). All measures are lagged so as to be predetermined, and all columns are estimated on a common sample. Driscoll-Kraay standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The sample period is January 5, 2024, through November 4, 2024.

	Dependent Variable: $r^{TT}_{i,t+1}$				
Informed Intensity		$\lvert InformedTrade\rvert_{t-1}$	$\overline{\lvert InformedTrade\rvert}_{t-1}$	$\left\lvert\Delta\mathcal{P}^{Inf}/\Delta\mathcal{P}\right\rvert_{t-1}$	$\overline{\left\lvert\Delta\mathcal{P}^{Inf}/\Delta\mathcal{P}\right\rvert}_{t-1}$
	(1)	(2)	(3)	(4)	(5)
Constant	0.001	0.001	0.001	0.001	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\Delta\mathcal{P}_t$	0.129***	0.083*	0.055	0.073	0.036
	(0.045)	(0.047)	(0.046)	(0.051)	(0.050)
Informed Intensity		-0.115	-0.178	0.000	-0.001
		(0.078)	(0.181)	(0.002)	(0.002)
$\Delta\mathcal{P}_t$ × Informed Intensity		22.839***	52.641***	0.170**	0.326***
		(5.833)	(10.013)	(0.082)	(0.101)
R^2	0.002	0.004	0.004	0.003	0.004
Observations	7,474	7,474	7,474	7,474	7,474

informed trading and the prediction-market price change should therefore be positive. We call this channel—past informativeness amplifying current noise spillover—"information hangover".

We measure recent informed intensity in two complementary ways, each lagged to be predetermined. The first is volume-based: $|InformedTrade|_{t-1}$, the absolute informed net market-order volume on the prior day, and $\overline{|InformedTrade|}_{t-1}$, its five-day moving average. These capture how much informed trading has recently occurred. The second is price-impact-based, built from the informed/uninformed decomposition of the daily price change introduced earlier: $\left|\Delta\mathcal{P}^{Inf}/\Delta\mathcal{P}\right|_{t-1}$, the absolute share of the prior day's Polymarket price change attributable to informed flow, and $\overline{\left|\Delta\mathcal{P}^{Inf}/\Delta\mathcal{P}\right|}_{t-1}$, its five-day moving average. These capture how much of the recent price movement informed flow accounts for, based on a measure of recent informed price impact rather than volume.

On the small number of days with a near-zero price change, for which the share is undefined, we set the price-share measure to zero; all columns are estimated on a common sample.

Table 11 reports the results, and they confirm our model's prediction. Across all four measures of recent informed intensity—the two volume-based measures in columns (2)–(3) and the two price-impact-share measures in columns (4)–(5)—the interaction with the prediction-market price change is positive and statistically significant. The sign holds whether intensity is measured by the quantity of recent informed trading or by the share of recent price movement that informed flow drives, and whether measured over a single day or a five-day window; the amplification reflects the recent informativeness of the prediction market, not any one construction of informed activity. Intuitively, investors lean more on the prediction-market price when it has lately looked more informative, and because they lean on it more, the noise in that price is transmitted more potently.

Taken together, these tests sharpen the mechanism of cross-market learning. The evidence shows that the magnitude of information and noise transmission is not constant; rather, it varies with the market 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 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-trade assets. This relationship reflects both information transmission and noise spillovers.

Informed trading's price impact persists into subsequent days; uninformed trading's does not—it is contemporaneous and fades. We document this asymmetry directly, using the full universe of on-chain transactions and a wallet-level classification, and find it both within Polymarket and in the cross-market spillover to Trump-trade returns. The transmission of Polymarket-specific noise is what allows us to identify an active cross-market learning channel: because such noise cannot reflect the sequential arrival of common fundamentals, its spillover cannot be explained by the same information reaching two markets in turn. Even relatively small, new markets influence much larger ones through cross-market learning, and the same channel carries both information and noise.

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 strengthened by greater perceived quality of the prediction-market signal.

Finally, our paper demonstrates the power of blockchain-based data for economic research. The wallet-level transparency of an on-chain prediction market makes possible ex-post trader classifications and price-change decompositions that traditional market data cannot support. These tools can address long-standing questions about who moves prices and how information and noise travel across markets. As decentralized markets grow, understanding their spillovers to traditional markets will only become more important.

References

Arrow, Kenneth J., Robert Forsythe, Michael Gorham, Robert Hahn, Robin Hanson, John O Ledyard, Saul Levmore, Robert Litan, Paul Milgrom, Forrest D Nelson, et al., 2008, The promise of prediction markets, *Science* 320, 877–878.

Bartlett, Robert, Adair Morse, Richard Stanton, and Nancy Wallace, 2022, Consumer-lending discrimination in the FinTech era, *Journal of Financial Economics* 143, 30–56.

Ben-Rephael, Azi, Zhi Da, and Ryan D Israelsen, 2017, It depends on where you search: Institutional investor attention and underreaction to news, *Review of Financial Studies* 30, 3009–3047.

Berg, Joyce, Forrest Nelson, and Thomas Rietz, 2008, Results from a dozen years of election futures markets research, *Handbook of experimental economics results* 1, 742–751.

Black, Fischer, 1986, Noise, *Journal of Finance* 41, 529–543.

Bond, Philip, Alex Edmans, and Itay Goldstein, 2012, The real effects of financial markets, *Annual Review of Financial Economics* 4, 339–360.

Bond, Philip, and Itay Goldstein, 2015, Government intervention and information aggregation by prices, *Journal of Finance* 70, 2777–2812.

Chernov, Mikhail, Vadim Elenev, and Dongho Song, 2025, The comovement of voter preferences: Insights from us presidential election prediction markets beyond polls, Technical report, National Bureau of Economic Research.

Da, Zhi, Joseph Engelberg, and Pengjie Gao, 2011, In search of attention, *Journal of Finance* 66, 1461–1499.

De Long, J Bradford, Andrei Shleifer, Lawrence H Summers, and Robert J Waldmann, 1990, Noise trader risk in financial markets, *Journal of Political Economy* 98, 703–738.

DellaVigna, Stefano, and Ethan Kaplan, 2007, The Fox news effect: Media bias and voting, *Quarterly Journal of Economics* 122, 1187–1234.

Dessaint, Olivier, Thierry Foucault, Laurent Frésard, and Adrien Matray, 2019, Noisy stock prices and corporate investment, *Review of Financial Studies* 32, 2625–2672.

Diercks, Anthony M, Jared Dean Katz, and Jonathan H Wright, 2026, Kalshi and the rise of macro markets, Working Paper 34702, National Bureau of Economic Research.

Driscoll, John C, and Aart C Kraay, 1998, Consistent covariance matrix estimation with spatially dependent panel data, *Review of economics and statistics* 80, 549–560.

Edmans, Alex, Itay Goldstein, and Wei Jiang, 2012, The real effects of financial markets: The impact of prices on takeovers, *Journal of Finance* 67, 933–971.

Eyster, Erik, Matthew Rabin, and Dimitri Vayanos, 2019, Financial markets where traders neglect the informational content of prices, *The Journal of Finance* 74, 371–399.

Goldstein, Itay, 2023, Information in financial markets and its real effects, *Review of Finance* 27, 1–32.

Goldstein, Itay, Chong Huang, and Liyan Yang, 2025, Fragility of financial markets, *Annual Review of Financial Economics* .

Gomez Cram, Roberto, Yunhan Guo, Theis Ingerslev Jensen, and Howard Kung, 2025, Financial prediction markets: A new measure of earnings expectations, *Available at SSRN 5933475* .

Grossman, Sanford J., and Joseph E. Stiglitz, 1980, On the impossibility of informationally efficient markets, *The American Economic Review* 70, 393–408.

Hasbrouck, Joel, 1995, One security, many markets: Determining the contributions to price discovery, *Journal of Finance* 50, 1175–1199.

Hayek, Friedrich A., 1945, The use of knowledge in society, *The American Economic Review* 35, 519–530.

Hellwig, Martin F., 1980, On the aggregation of information in competitive markets, *Journal of Economic Theory* 22, 477–498.

King, Mervyn A, and Sushil Wadhwani, 1990, Transmission of volatility between stock markets, *Review of Financial Studies* 3, 5–33.

Makarov, Igor, Antoinette Schoar, et al., 2022, Cryptocurrencies and decentralized finance, *NBER Working Paper* 30006.

Ng, Hunter, Lin Peng, Yubo Tao, and Dexin Zhou, 2025, Price discovery and trading in prediction markets, *Available at SSRN 5331995* .

Ottaviani, Marco, and Peter Norman Sørensen, 2012, The wisdom of crowds: Aggregating information in prediction markets and other mechanisms, *American Economic Journal: Microeconomics* 4, 90–130.

Page, Lionel, and Christoph Siemroth, 2017, The favorite-longshot bias in european football betting markets, *Journal of Sports Economics* 18, 802–821.

Pedersen, Lasse Heje, 2022, Game on: Social networks and markets, *Journal of Financial Economics* 146, 1097–1119.

Pástor, Ľuboš, and Pietro Veronesi, 2012, Uncertainty about government policy and stock prices, *Journal of Finance* 67, 1219–1264.

Pástor, Ľuboš, and Pietro Veronesi, 2013, Political uncertainty and risk premia, *Journal of Financial Economics* 110, 520–545.

Shleifer, Andrei, and Robert W Vishny, 1997, The limits of arbitrage, *Journal of Finance* 52, 35–55.

Snowberg, Erik, Justin Wolfers, and Eric Zitzewitz, 2007, Partisan impacts on the economy: evidence from prediction markets and close elections, *Quarterly Journal of Economics* 122, 807–829.

Wolfers, Justin, and Eric Zitzewitz, 2004, Prediction markets, *Journal of Economic Perspectives* 18, 107–126.

Internet Appendix

Learning from Prediction Markets: The Transmission of Information and Noise to Traditional Assets

This Internet Appendix provides supplementary material in six sections. Section A.I documents Polymarket's institutional setting and the media context around large prediction-market trades. Section A.II details the construction and validation of our Trump-trade portfolio, including the asset-level directional rationale and a placebo falsification test. Section A.III reports robustness checks for the lead-lag predictability result from Section 3, including alternative intra-day timing of the Polymarket-change variable, equally-weighted aggregations of the portfolio, and asset-category breakdowns. Section A.IV provides the full performance statistics and per-category decomposition of the Polymarket-based trading strategy. Section A.V provides additional descriptive evidence on the wallet-level informed/uninformed classification underlying Section 4. Section A.VI reports a robustness variant of the poll-release interaction analysis of Section 4.3.

A.I Polymarket Institutional Background

This section provides institutional context that supports two analytic choices in the main text: our use of Polymarket as the empirical setting (Section 2) and our wallet-level trader classification (Section 4.1). Two features of the platform are particularly relevant. First, Polymarket settles on the Polygon blockchain, producing an immutable, wallet-level audit trail that is unavailable in traditional financial markets and enables our ex-post trader classification. Second, the absence of significant entry frictions during the 2024 election cycle—no KYC barrier for many users and a low effective minimum bet size—attracted both small retail bettors and several large “whale” wallets whose trading attracted substantial media attention.

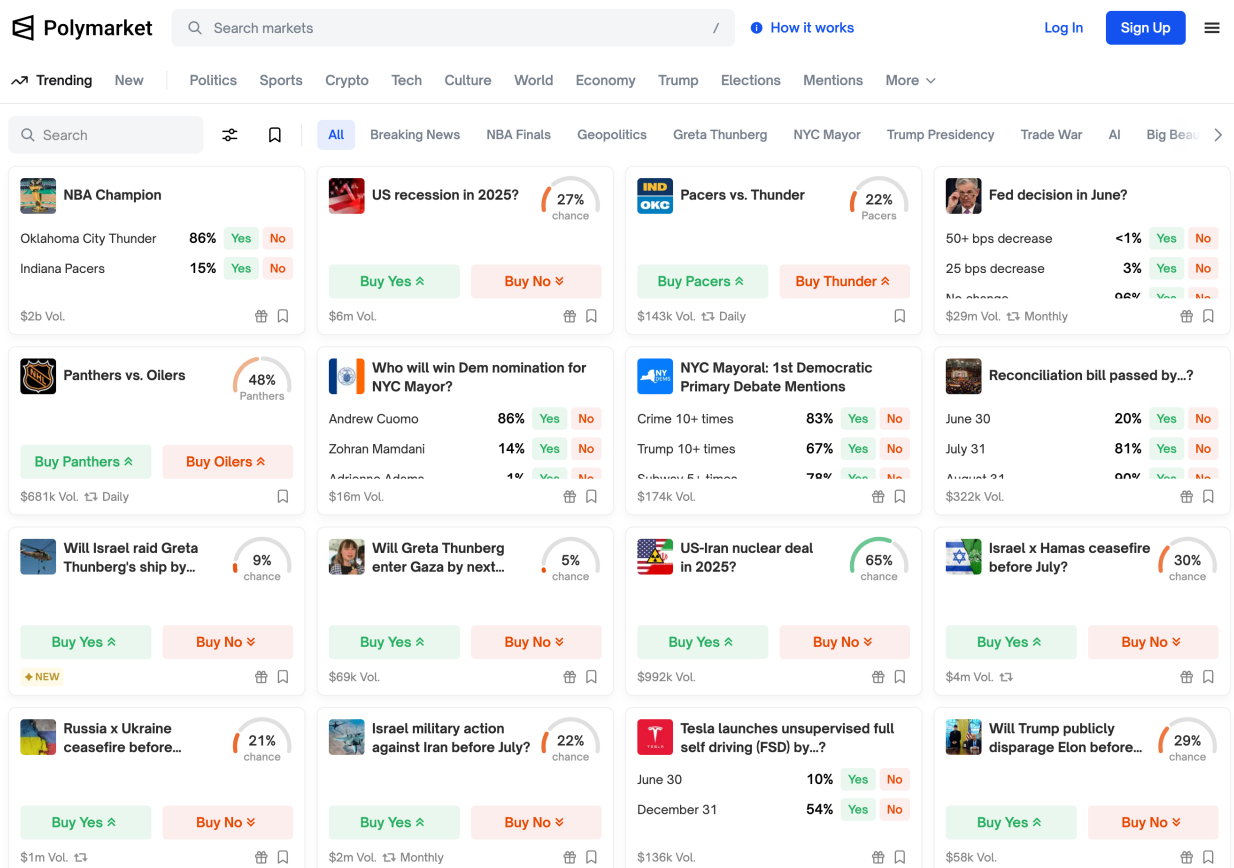


Figure A.1 Polymarket Homepage

Screenshot of the Polymarket homepage during our sample period, illustrating the variety of prediction markets available beyond our 2024 presidential-election focus.

Polymarket platform and the 2024 election contract. Figure A.1 shows the Polymarket homepage during our sample window; the platform offers contracts on a wide range of political, economic, and cultural events. Figure A.2 shows the specific 2024 U.S. presidential-election contract that anchors our analysis. The contract pays \$1 if Trump wins the election and \$0 otherwise, so its market price directly translates to a market-implied probability that we use as $\mathcal{P}_t(\text{Trump})$ throughout the paper.

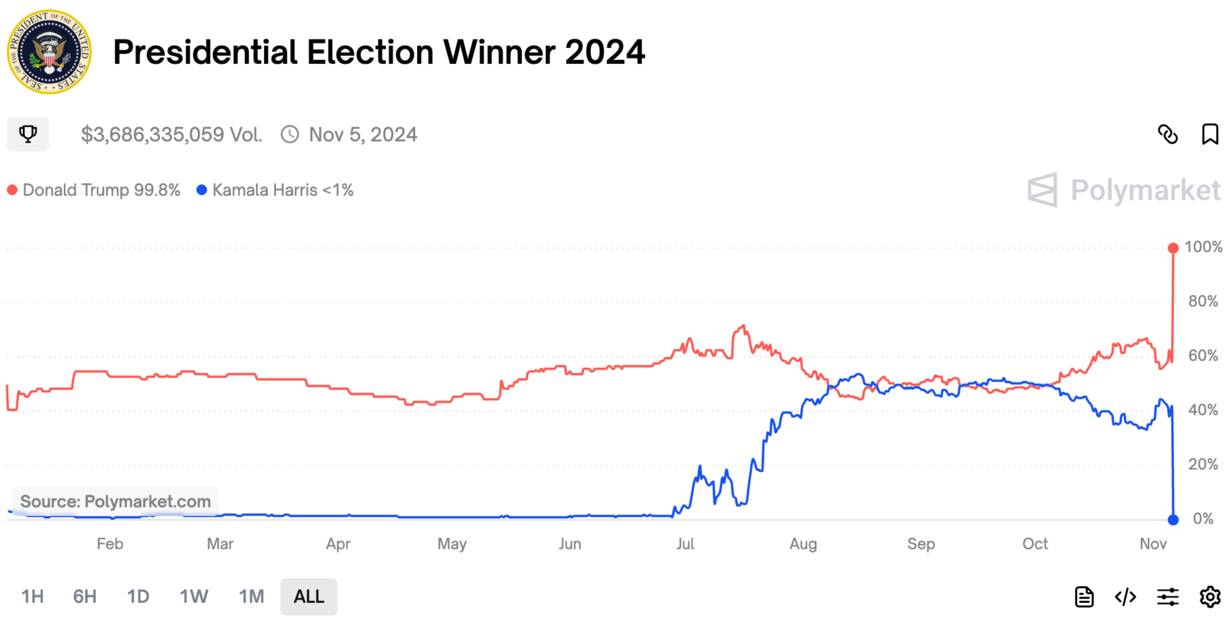


Figure A.2 Polymarket 2024 U.S. Presidential Election Contract

Screenshot of the 2024 U.S. presidential-election contract on Polymarket, the specific event contract underlying our empirical analysis, showing the price (market-implied probability), 24-hour volume, and contract specifications.

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 a Polymarket Whale Trader

Wall Street Journal coverage of the large Polymarket trader known as "Fredi9999," whose individual trades were sufficiently large to move the market price visibly in the days surrounding their execution.

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 a Polymarket Whale Trader

Bloomberg's coverage of the same Polymarket trader, illustrating the broad media attention attracted by individual participants with substantial trading volume on the platform.

Media attention on whale traders. Figures A.3 and A.4 document the substantial media attention attracted by individual large wallets on Polymarket during the 2024 cycle, with the trader known as "Fredi9999" as the most prominent example. This media coverage is itself part of the cross-market-learning channel we study: traders in traditional markets followed not only the aggregate Polymarket price but also reports about who was driving particular price moves. The salience of named traders also informs our classifier design in Section 4.1: a meaningful informed/uninformed partition must accommodate the fact that a small set of high-volume wallets accounts for a disproportionate share of price impact.

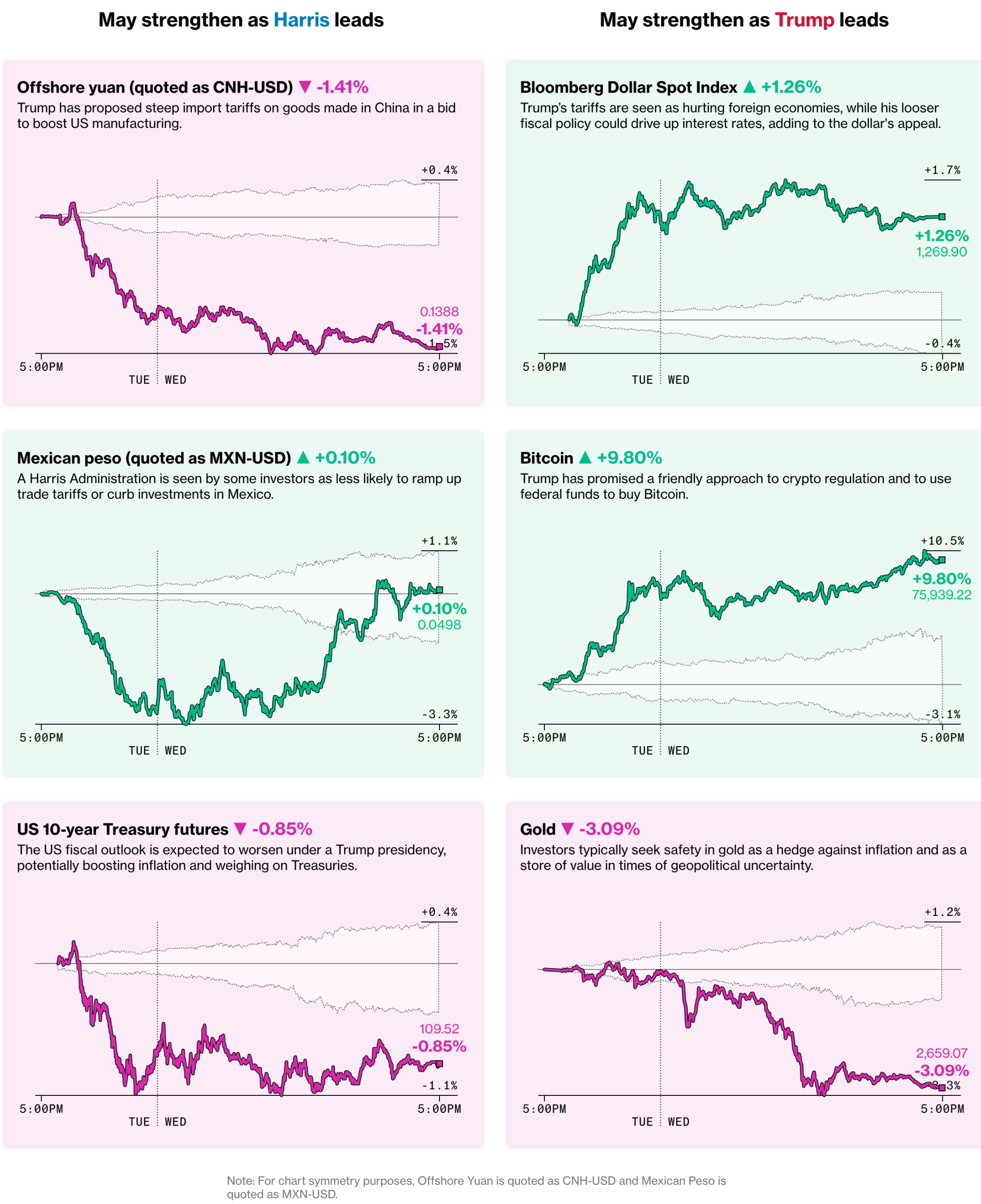


Figure A.5 Bloomberg Coverage of the "Trump Trades"

Real-time Bloomberg coverage of asset movements linked explicitly to Trump's electoral prospects during the 2024 cycle. This media framing is the basis for our narrative-driven identification of the Trump-trade portfolio (Section 2.3).

Real-time media framing of "Trump trades". Figure A.5 reproduces Bloomberg's real-time coverage of the "Trump trades" theme. Coverage of this kind, repeated across major outlets through 2024, is the contemporaneous market commentary on which our narrative-based portfolio construction in Section 2.3 draws. The figure documents that the directional bets we encode—bank stocks long, renewable energy short, and so on—reflect market participants' real-time framing rather than an ex-post relabeling of return outcomes.

A.II Trump Trades: Identification and Validation

This section reports three additional exhibits on the Trump-trade portfolio defined in Section 2.3: a complete asset-level directional rationale (Table A.1), the category-average cumulative return pattern that motivates the portfolio (Figure A.6), and a placebo falsification test (Table A.2). The placebo test addresses the natural alternative explanation that Polymarket changes might co-move with returns of any broad equity portfolio, rather than specifically with assets identified as policy-sensitive. If true, our headline lead-lag relationship would lack content. We show below that the same predictive regression run on (i) a portfolio of low-policy-sensitivity ETFs and (ii) the equal-weighted top-5,000 US-stock universe yields no significant predictability at any horizon.

Asset-level directional specifications. Table A.1 provides the complete asset-level directional specifications referenced in Section 2.3. The rationale column documents the specific policy channel—tax, regulation, trade, energy, or fiscal—through which each asset's expected exposure to a Trump victory is constructed. Two patterns are worth noting. First, the directional bets are concentrated in categories with the most direct policy link (large banks long, traditional energy long, renewables short, certain foreign currencies short under tariff exposure). Second, the directional sign for several assets is asymmetric across categories (e.g., the dollar strengthens but Treasuries weaken), reflecting the differential exposure of each asset class to specific Trump policy priorities.

Table A.1 Trump Trade Directional Specifications

This table lists the assets in our Trump-trade portfolio together with their expected directional response to a higher probability of Trump winning. Up arrows indicate "long" assets expected to benefit from Trump's policy platform; down arrows indicate "short" assets expected to be harmed. The rationale column summarizes the policy channel underlying each directional bet, drawing on financial-media coverage and sell-side research 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
Connected	Trump Media & Technology Group Corp	DJT	↑	Connections to Trump family business
	Phunware Inc	PHUN	↑	Connections to Trump campaign
	Tesla Inc	TSLA	↑	Connections to Trump campaign; a favorable regulatory environment; federal government contracts

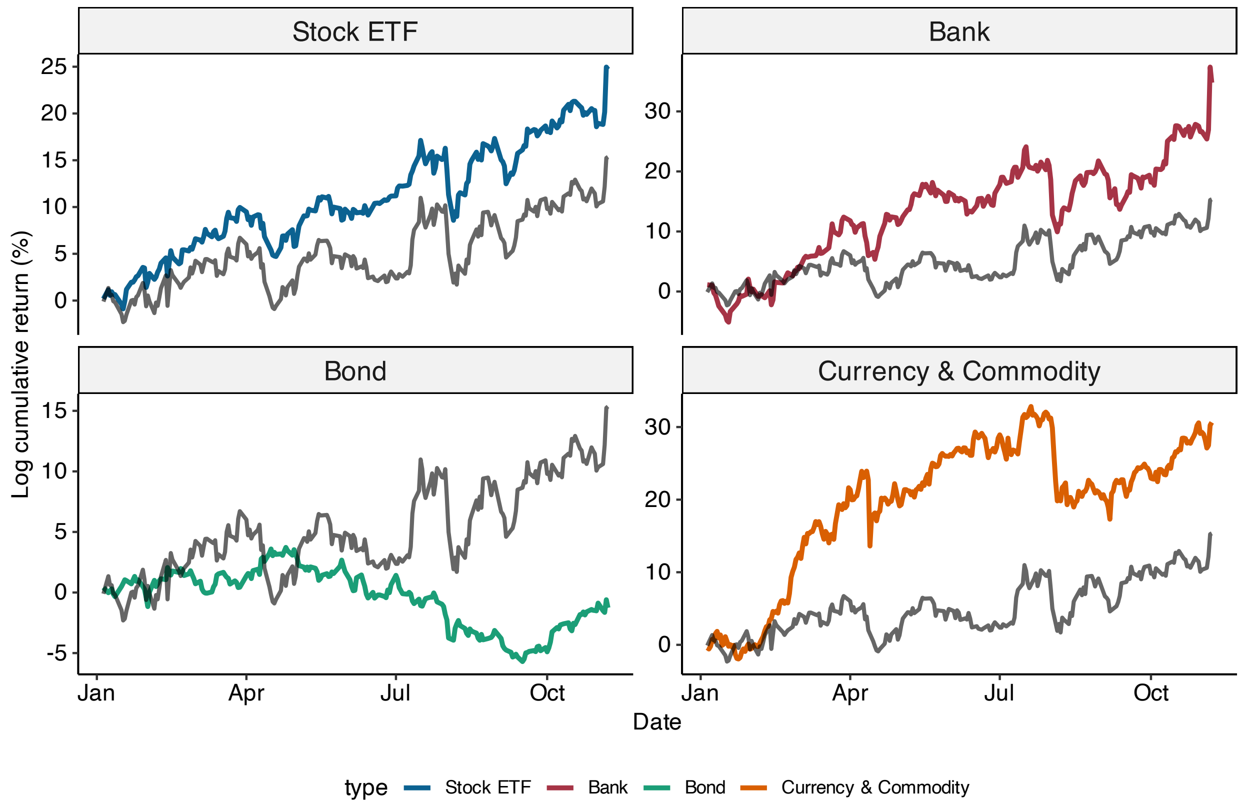


Figure A.6 Trump Trades: Category-Average Cumulative Returns

Cumulative returns averaged within each major Trump-trade category over the sample period, signed in the expected direction of exposure to Trump's electoral prospects.

Category-average cumulative returns. Figure A.6 plots category-average cumulative returns of the signed Trump-trade portfolio. The figure documents two features that motivate the cross-market-learning analysis. First, all categories share a broadly comparable trajectory through the second half of 2024, consistent with a common factor—changing electoral expectations—driving the portfolio. Second, the connected and bank categories exhibit the largest end-of-sample levels, foreshadowing the cross-sectional heterogeneity we document in Section 3.

Table A.2 Placebo Test: Polymarket Change Does Not Predict Low-Sensitivity Asset Returns

This table reports the placebo version of the headline predictive regression. The dependent variable is the h-day-ahead return on placebo assets that should have minimal sensitivity to Trump's electoral prospects. $\Delta\mathcal{P}_t$(Trump) is the daily change in Trump's Polymarket probability (in percentage points). Placebo 1 (columns 1–3) is a portfolio of five low-policy-sensitivity ETFs: XLU (Utilities), XLP (Consumer Staples), VNQ (REITs), MUB (Municipal Bonds), and USMV (Minimum Volatility). Placebo 2 (columns 4–6) 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 Driscoll-Kraay for columns 1–3 and Newey-West with optimal lags for columns 4–6. ***, **, * denote significance at 1%, 5%, and 10%.

	Placebo 1: Low-Sensitivity ETFs			Placebo 2: Average U.S. Stock		
	$r^{TT}_{i,t+1}$ (1)	$r^{TT}_{i,t+2}$ (2)	$r^{TT}_{i,t+3}$ (3)	$r^{TT}_{i,t+1}$ (4)	$r^{TT}_{i,t+2}$ (5)	$r^{TT}_{i,t+3}$ (6)
Constant	0.001**	0.001**	0.001**	0.001	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
$\Delta\mathcal{P}_t(Trump)$	-0.003	0.006	-0.009	0.030	-0.005	-0.046
	(0.015)	(0.014)	(0.009)	(0.055)	(0.051)	(0.044)
R^2	0.000	0.000	0.000	0.002	0.000	0.004
Observations	1,055	1,055	1,055	211	211	211

Placebo falsification test. Table A.2 reports the placebo version of our headline lead-lag regression. We use two placebo asset sets: a portfolio of five low-policy-sensitivity ETFs (Placebo 1, columns 1–3) and the equal-weighted return on the top 5,000 U.S. stocks by market capitalization (Placebo 2, columns 4–6). The first set should have minimal exposure to Trump-specific policy channels; the second represents a broad, diversified U.S. equity portfolio with no systematic Trump-policy tilt. Across both sets and all horizons, the predictive coefficient on $\Delta\mathcal{P}_t$(Trump) is statistically insignificant, in sharp contrast with the strong positive predictability we document for the Trump-trade portfolio in Table 2. The result supports our narrative-based portfolio construction: the predictability we document is specific to assets that the contemporaneous market commentary identified as Trump-sensitive, rather than an artifact of generic equity-market co-movement.

Table A.3 Lead-Lag Predictability under 9am-to-9am ET Polymarket Change

This table replicates Table 2 with the daily Polymarket change measured from 9am ET to 9am ET on the next day (i.e., the Polymarket move that occurs before the U.S. stock-market open). The dependent variable is the h-day-ahead signed return for Trump trades. $\Delta\mathcal{P}_t$ (Trump) is in percentage points. Standard errors are Driscoll-Kraay. Panel A, B and C use the full sample, the sample beginning April 1, 2024, and the sample after Biden's withdrawal, respectively. ***, **, * denote significance at 1%, 5%, and 10%.

	Full sample			Connected			Not Connected		
	$r^{TT}_{i,t+1}$ (1)	$r^{TT}_{i,t+2}$ (2)	$r^{TT}_{i,t+3}$ (3)	$r^{TT}_{i,t+1}$ (4)	$r^{TT}_{i,t+2}$ (5)	$r^{TT}_{i,t+3}$ (6)	$r^{TT}_{i,t+1}$ (7)	$r^{TT}_{i,t+2}$ (8)	$r^{TT}_{i,t+3}$ (9)
Panel A: 2024-01-01 onwards									
Constant	0.001	0.001	0.001	0.002	0.002	0.002	0.001*	0.001*	0.001*
	(0.001)	(0.001)	(0.001)	(0.004)	(0.005)	(0.004)	(0.000)	(0.000)	(0.000)
$\Delta\mathcal{P}_t(Trump)^{9AM-9AM}$	0.122***	-0.020	0.012	0.404***	-0.254***	0.085	0.096***	0.002	0.005
	(0.012)	(0.017)	(0.014)	(0.110)	(0.071)	(0.103)	(0.017)	(0.013)	(0.010)
R^2	0.010	0.000	0.000	0.011	0.004	0.000	0.045	0.000	0.000
Observations	7,653	7,653	7,653	636	636	636	7,017	7,017	7,017
Panel B: 2024-04-01 onwards									
Constant	0.000	0.001	0.001	-0.001	0.000	0.000	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)
$\Delta\mathcal{P}_t(Trump)^{9AM-9AM}$	0.128***	-0.015	0.004	0.385***	-0.226***	0.019	0.104***	0.005	0.002
	(0.009)	(0.021)	(0.017)	(0.093)	(0.081)	(0.063)	(0.012)	(0.016)	(0.013)
R^2	0.032	0.000	0.000	0.035	0.012	0.000	0.064	0.000	0.000
Observations	5,512	5,512	5,512	459	459	459	5,053	5,053	5,053
Panel C: 2024-07-21 onwards (post-Biden withdrawal)									
Constant	0.000	0.001	0.001	0.001	0.002	0.003	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.006)	(0.007)	(0.006)	(0.001)	(0.001)	(0.001)
$\Delta\mathcal{P}_t(Trump)^{9AM-9AM}$	0.135***	-0.021	0.007	0.428***	-0.265***	0.041	0.107***	0.002	0.004
	(0.009)	(0.019)	(0.017)	(0.130)	(0.062)	(0.065)	(0.012)	(0.016)	(0.013)
R^2	0.050	0.001	0.000	0.061	0.022	0.001	0.103	0.000	0.000
Observations	2,731	2,731	2,731	228	228	228	2,503	2,503	2,503

A.III Robustness for the Lead-Lag Predictability

This section establishes three robustness checks for the headline lead-lag relationship from Section 3. First, the predictability survives under two alternative intra-day timing conventions for the Polymarket-change variable (Tables A.3 and A.4). The 4pm-to-4pm specification is particularly informative: any news arriving in the window between two consecutive 4pm marks should already be priced into the same day's stock-market close, so the predictability of the next-day return reads naturally as noise transmission from the prediction market rather than as a delayed response to common news. Second, the result holds under two alternative aggregations of the Trump-trade portfolio: an equally-weighted average across all assets (Table A.5) and equally-weighted averages within each asset category (Table A.6). Third, the result holds in the asset-category cross-section, with the largest effects on bank stocks (Table A.7).

Table A.4 Lead-Lag Predictability under 4pm-to-4pm ET Polymarket Change

This table replicates Table 2 with the daily Polymarket change measured from 4pm ET to 4pm ET on the next day (i.e., the Polymarket move that occurs entirely within U.S. stock-market trading hours). The dependent variable is the h-day-ahead signed return for Trump trades. $\Delta\mathcal{P}_t$ (Trump) is in percentage points. Standard errors are Driscoll-Kraay. Panel A, B and C use the full sample, the sample beginning April 1, 2024, and the sample after Biden's withdrawal, respectively. ***, **, * denote significance at 1%, 5%, and 10%.

	Full sample			Connected			Not Connected		
	$r^{TT}_{i,t+1}$ (1)	$r^{TT}_{i,t+2}$ (2)	$r^{TT}_{i,t+3}$ (3)	$r^{TT}_{i,t+1}$ (4)	$r^{TT}_{i,t+2}$ (5)	$r^{TT}_{i,t+3}$ (6)	$r^{TT}_{i,t+1}$ (7)	$r^{TT}_{i,t+2}$ (8)	$r^{TT}_{i,t+3}$ (9)
Panel A: 2024-01-01 onwards									
Constant	0.001*	0.001	0.001	0.003	0.002	0.002	0.001*	0.001*	0.001*
	(0.001)	(0.001)	(0.001)	(0.004)	(0.005)	(0.005)	(0.000)	(0.000)	(0.000)
$\Delta\mathcal{P}_t(Trump)^{4PM-4PM}$	0.109**	0.040	-0.045	0.403*	-0.141	-0.015	0.083*	0.056	-0.048
	(0.049)	(0.053)	(0.043)	(0.231)	(0.362)	(0.283)	(0.048)	(0.040)	(0.033)
R^2	0.002	0.000	0.000	0.003	0.000	0.000	0.008	0.004	0.003
Observations	7,618	7,618	7,618	633	633	633	6,985	6,985	6,985
Panel B: 2024-04-01 onwards									
Constant	0.001	0.001	0.001	0.000	-0.001	0.000	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)
$\Delta\mathcal{P}_t(Trump)^{4PM-4PM}$	0.172***	0.056	-0.072	0.650**	-0.175	-0.029	0.129**	0.077	-0.076*
	(0.058)	(0.069)	(0.054)	(0.282)	(0.334)	(0.306)	(0.060)	(0.055)	(0.043)
R^2	0.010	0.001	0.002	0.018	0.001	0.000	0.018	0.006	0.006
Observations	5,512	5,512	5,512	459	459	459	5,053	5,053	5,053
Panel C: 2024-07-21 onwards (post-Biden withdrawal)									
Constant	0.001	0.001	0.001	0.002	0.001	0.003	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.006)	(0.007)	(0.006)	(0.001)	(0.001)	(0.001)
$\Delta\mathcal{P}_t(Trump)^{4PM-4PM}$	0.231***	0.120	-0.087	0.888**	-0.129	-0.064	0.171*	0.143*	-0.089
	(0.083)	(0.105)	(0.088)	(0.374)	(0.533)	(0.468)	(0.091)	(0.080)	(0.071)
R^2	0.018	0.005	0.002	0.030	0.001	0.000	0.031	0.021	0.008
Observations	2,731	2,731	2,731	228	228	228	2,503	2,503	2,503

Alternative intra-day timing of the Polymarket change. Tables A.3 and A.4 report the lead-lag regression with the Polymarket change measured over the 9am-to-9am and 4pm-to-4pm ET windows, respectively, instead of the midnight-to-midnight benchmark used in Table 2. The 9am-to-9am specification captures Polymarket information arriving before the U.S. market open; the 4pm-to-4pm specification captures information arriving within trading hours. The next-day predictability is statistically significant and quantitatively comparable across all three timing conventions. The 4pm-to-4pm result is particularly informative for our interpretation: the relevant Polymarket window is bracketed by two stock-market closes, so news arriving in that window should already be priced into the closing price—making the next-day predictability a clean signature of noise transmission from the prediction market rather than a delayed response to common news.

Equally-weighted aggregations. Tables A.5 and A.6 report the lead-lag regression under two alternative weighting schemes for the Trump-trade portfolio. Table A.5 uses the equally-weighted average across all Trump-trade assets, confirming that the headline result is not driven by a handful of high-weight assets. Table A.6 uses category-level equally-weighted averages, with one series per category (equities, bonds, FX, banks, and connected stocks). The category-level results show the predictability is concentrated in the bank and connected categories, consistent with these categories' direct policy exposure documented in Table A.1.

Table A.5 Lead-Lag Predictability: Equally-Weighted Average of All Trump-Trade Returns

This table reports the lead-lag regression where the dependent variable is the equally-weighted average signed return across all Trump-trade assets at each horizon. The right-hand-side variable is $\Delta\mathcal{P}_t$(Trump) measured midnight-to-midnight ET, identical to Table 2. Aggregating to an equally-weighted portfolio confirms the predictability is not driven by a small number of large-weight assets. Standard errors are Newey-West with optimal lag selection. Sample period: January 5, 2024 through the election date.

		$r^{TT}_{i,t+1}$			$r^{TT}_{i,t+2}$			$r^{TT}_{i,t+3}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: 2024-01-01 onwards									
Constant	0.002*	0.002*	0.002**	0.001	0.001	0.001	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\Delta\mathcal{P}_t(Trump)$	0.122***			0.000			0.033		
	(0.022)			(0.046)			(0.028)		
$\Delta\mathcal{P}_t(Trump)^{9AM-9AM}$		0.132***			-0.002			0.050*	
		(0.021)			(0.044)			(0.030)	
$\Delta\mathcal{P}_t(Trump)^{4PM-4PM}$			0.270***			0.001			-0.044
			(0.081)			(0.055)			(0.106)
R^2	0.034	0.040	0.056	0.000	0.000	0.000	0.002	0.005	0.001
Observations	306	306	306	306	306	306	306	306	306
Panel B: 2024-04-01 onwards									
Constant	0.001	0.001	0.001	0.000	0.000	0.000	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\Delta\mathcal{P}_t(Trump)$	0.125***			0.018			0.016		
	(0.016)			(0.054)			(0.020)		
$\Delta\mathcal{P}_t(Trump)^{9AM-9AM}$		0.130***			0.020			0.032*	
		(0.015)			(0.054)			(0.018)	
$\Delta\mathcal{P}_t(Trump)^{4PM-4PM}$			0.333***			0.036			-0.145
			(0.095)			(0.061)			(0.115)
R^2	0.051	0.056	0.090	0.001	0.001	0.001	0.001	0.003	0.017
Observations	219	219	219	219	219	219	219	219	219
Panel C: 2024-07-21 onwards (post-Biden withdrawal)									
Constant	-0.001	-0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\Delta\mathcal{P}_t(Trump)$	0.138***			-0.024			0.008		
	(0.017)			(0.023)			(0.023)		
$\Delta\mathcal{P}_t(Trump)^{9AM-9AM}$		0.134***			-0.018			0.023	
		(0.016)			(0.025)			(0.018)	
$\Delta\mathcal{P}_t(Trump)^{4PM-4PM}$			0.362***			0.045			-0.247
			(0.116)			(0.107)			(0.199)
R^2	0.100	0.094	0.101	0.003	0.001	0.001	0.000	0.003	0.043
Observations	108	108	108	108	108	108	108	108	108

Table A.6 Lead-Lag Predictability: Equally-Weighted Average within Each Asset Category

This table reports the lead-lag regression where the dependent variable is the equally-weighted average signed return within each major Trump-trade category (equities, bonds, FX, banks, connected) at each horizon. The right-hand-side variable is $\Delta\mathcal{P}_t$(Trump) measured midnight-to-midnight ET. Standard errors are Newey-West with optimal lag selection. Sample period: January 5, 2024 through the election date.

		$r^{TT}_{i,t+1}$			$r^{TT}_{i,t+2}$			$r^{TT}_{i,t+3}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: 2024-01-01 onwards									
Constant	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\Delta\mathcal{P}_t(Trump)$	0.169***			-0.042			0.019		
	(0.017)			(0.031)			(0.027)		
$\Delta\mathcal{P}_t(Trump)^{9AM-9AM}$		0.162***			-0.046*			0.026	
		(0.016)			(0.027)			(0.025)	
$\Delta\mathcal{P}_t(Trump)^{4PM-4PM}$			0.186***			0.013			-0.044
			(0.062)			(0.078)			(0.074)
R^2	0.019	0.018	0.006	0.001	0.001	0.000	0.000	0.000	0.000
Observations	1,157	1,162	1,157	1,157	1,162	1,157	1,157	1,162	1,157
Panel B: 2024-04-01 onwards									
Constant	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\Delta\mathcal{P}_t(Trump)$	0.169***			-0.031			0.004		
	(0.015)			(0.037)			(0.025)		
$\Delta\mathcal{P}_t(Trump)^{9AM-9AM}$		0.166***			-0.036			0.008	
		(0.014)			(0.034)			(0.022)	
$\Delta\mathcal{P}_t(Trump)^{4PM-4PM}$			0.271***			0.028			-0.090
			(0.070)			(0.089)			(0.086)
R^2	0.055	0.054	0.028	0.002	0.002	0.000	0.000	0.000	0.003
Observations	835	835	835	835	835	835	835	835	835
Panel C: 2024-07-21 onwards (post-Biden withdrawal)									
Constant	0.000	0.000	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\Delta\mathcal{P}_t(Trump)$	0.177***			-0.045			0.009		
	(0.019)			(0.030)			(0.025)		
$\Delta\mathcal{P}_t(Trump)^{9AM-9AM}$		0.177***			-0.052**			0.012	
		(0.020)			(0.025)			(0.022)	
$\Delta\mathcal{P}_t(Trump)^{4PM-4PM}$			0.349***			0.085			-0.126
			(0.097)			(0.145)			(0.141)
R^2	0.091	0.091	0.043	0.006	0.007	0.002	0.000	0.000	0.005
Observations	413	413	413	413	413	413	413	413	413

Table A.7 Lead-Lag Predictability by Asset Category

This table reports the lead-lag regression by asset category. Each column block corresponds to one category of Trump-trade assets (equities, bonds, FX, banks, connected). Within each column block, we report the regression coefficient on the lagged Polymarket change at multiple horizons. Standard errors are Driscoll-Kraay. Sample period: January 5, 2024 through the election date.

	$r^{TT}_{i,t+1}$	$r^{TT}_{i,t+2}$	$r^{TT}_{i,t+3}$	$r^{TT}_{i,t+1}$	$r^{TT}_{i,t+2}$	$r^{TT}_{i,t+3}$	$r^{TT}_{i,t+1}$	$r^{TT}_{i,t+2}$	$r^{TT}_{i,t+3}$	$r^{TT}_{i,t+1}$	$r^{TT}_{i,t+2}$	$r^{TT}_{i,t+3}$	$r^{TT}_{i,t+1}$	$r^{TT}_{i,t+2}$	$r^{TT}_{i,t+3}$
	Stock ETF			Bank			Currency & Commodity			Bond			Connected		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Panel A: 2024-01-01 onwards															
Constant	0.001*	0.001*	0.001*	0.001	0.002	0.002*	0.001	0.001	0.001	0.000	0.000	0.000	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.005)	(0.004)
$\Delta\mathcal{P}_t(Trump)$	0.118***	0.005	0.004	0.244***	-0.013	-0.015	0.059***	0.018	0.023**	0.026***	-0.009	-0.008	0.418***	-0.235***	0.068
	(0.014)	(0.013)	(0.017)	(0.031)	(0.043)	(0.029)	(0.014)	(0.012)	(0.009)	(0.005)	(0.008)	(0.006)	(0.123)	(0.088)	(0.106)
R^2	0.082	0.000	0.000	0.185	0.000	0.001	0.010	0.001	0.001	0.023	0.002	0.002	0.011	0.004	0.000
Observations	2,110	2,110	2,110	1,266	1,266	1,266	2,132	2,132	2,132	1,477	1,477	1,477	633	633	633
Panel B: 2024-04-01 onwards															
Constant	0.001	0.001	0.001	0.001	0.002	0.002	0.000	0.000	0.000	0.000	0.000	0.000	-0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.004)	(0.004)	(0.004)
$\Delta\mathcal{P}_t(Trump)$	0.123***	0.004	0.004	0.251***	-0.012	-0.017	0.062***	0.025*	0.020***	0.024***	-0.009	-0.007	0.399***	-0.197*	0.006
	(0.012)	(0.013)	(0.017)	(0.027)	(0.043)	(0.030)	(0.012)	(0.014)	(0.007)	(0.005)	(0.008)	(0.006)	(0.104)	(0.103)	(0.068)
R^2	0.112	0.000	0.000	0.231	0.001	0.001	0.015	0.002	0.002	0.027	0.003	0.002	0.037	0.009	0.000
Observations	1,530	1,530	1,530	918	918	918	1,534	1,534	1,534	1,071	1,071	1,071	459	459	459
Panel C: 2024-07-21 onwards (post-Biden withdrawal)															
Constant	0.001	0.001	0.002	0.001	0.002	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.002	0.003
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)	(0.007)	(0.006)
$\Delta\mathcal{P}_t(Trump)$	0.121***	0.004	0.011	0.253***	-0.019	-0.009	0.068***	0.017*	0.022**	0.028***	-0.006	-0.009	0.417***	-0.219**	0.027
	(0.013)	(0.015)	(0.018)	(0.026)	(0.044)	(0.034)	(0.009)	(0.009)	(0.009)	(0.004)	(0.010)	(0.005)	(0.123)	(0.100)	(0.068)
R^2	0.158	0.000	0.001	0.318	0.002	0.000	0.031	0.002	0.003	0.064	0.003	0.006	0.057	0.015	0.000
Observations	760	760	760	456	456	456	755	755	755	532	532	532	228	228	228

Asset-category breakdown. Table A.7 reports the lead-lag regression separately for each major Trump-trade category. The largest next-day coefficient is on bank stocks (consistent with their direct regulatory exposure to a Trump administration), followed by the connected category (companies and their family-linked equities), with smaller but still significant effects on the broader equity ETFs and currency baskets. Bonds exhibit the weakest predictability, consistent with their lower direct policy sensitivity.

Table A.8 Polymarket-Based Trading Strategy: Performance Statistics

This table reports performance statistics for the Polymarket-based trading strategy. Mean Daily Return and Daily Volatility are annualized. Sharpe Ratio is the annualized ratio of mean excess return to volatility. Max Drawdown is the maximum peak-to-trough drawdown over the strategy period. Statistics are in-sample, gross of transaction costs and gross of bid-ask spread. The strategy applies to the equally-weighted Trump-trade portfolio; per-category cumulative returns are in Figure A.7.

	Main Strategy
Start Date	2024-04-01
End Date	2024-11-05
Trading Days	219
Mean Daily Return (ann.%)	18.93
Daily Volatility (ann.%)	9.72
Sharpe Ratio	1.95
Total Return (%)	16.45
Max Drawdown (%)	4.58

A.IV Trading Strategy Details

This section reports the full performance statistics and per-category decomposition of the Polymarket-based trading strategy introduced in Section 3.2. The strategy converts the daily Polymarket change into a long/short signal on each Trump-trade asset via a rolling-percentile-rank transformation of a five-day exponential moving average of $\Delta\mathcal{P}_t(\text{Trump})$. We report the strategy not as a deployable investment recommendation but to quantify the economic magnitude of the lead-lag predictability documented in Section 3.

Strategy performance. Table A.8 reports the full performance statistics for the strategy summarized in Section 3.2. The strategy delivers a Sharpe ratio of 1.95 over the April 2024 through election date window, with a maximum drawdown of 4.58% and total return of 16.45%. The economic magnitude is meaningful but the focus is on the per-category decomposition that follows.

Per-category strategy performance. Figure A.7 plots cumulative returns of the strategy applied to each asset category separately. The pattern aligns with the predictability heterogeneity documented in Table A.7: bank and connected-asset categories deliver the largest cumulative strategy returns, while bonds contribute least. The visualization confirms that the strategy's aggregate performance is driven by the categories with the most direct policy exposure, not by spurious gains on weakly-exposed assets.

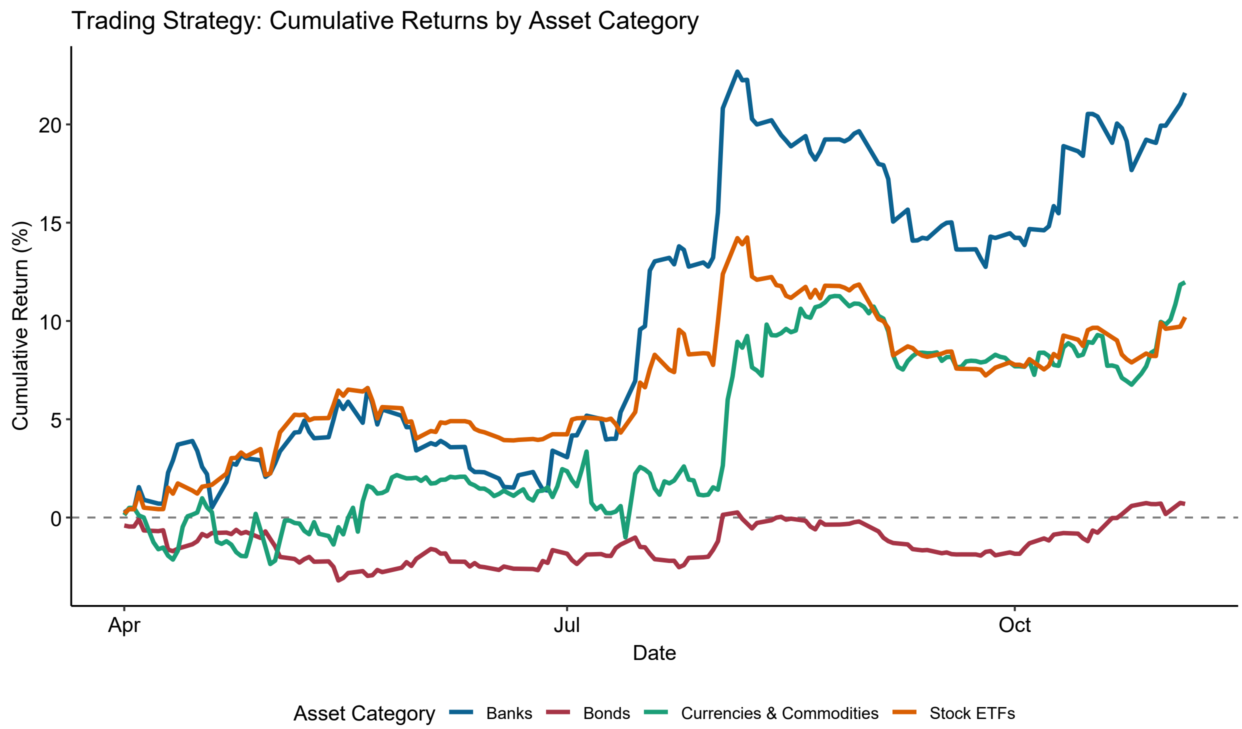


Figure A.7 Strategy Performance by Asset Category

Cumulative returns of the Polymarket-based trading strategy by asset category. Each line plots the strategy applied to one category in isolation. Sample period: January 5, 2024 through the election date.

Table A.9 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. Per the construction in Section 4.1, informed wallets satisfy (i) at least 20 market-order transactions on the side; (ii) a top-half ranking in total trade size; and (iii) volume-weighted 24-to-48h post-trade return exceeding the cross-sectional drift by at least 200 basis points. The cohort comprises 529 informed buyers and 3,019 informed sellers; the remaining eligible wallets are classified as uninformed.

	n	mean	sd	p5	p25	median	p75	p95
Uninformed Traders: Buys								
Average profitability	122,746	-0.002	0.035	-0.064	-0.023	0.002	0.019	0.057
Average post-trade price movement	122,746	-0.004	0.045	-0.090	-0.031	0.004	0.025	0.060
Total trade size	122,746	1,832.279	43,912.158	1.490	35.000	125.225	733.447	4,861.938
Informed Traders: Buys								
Average profitability	529	0.039	0.012	0.024	0.029	0.037	0.045	0.060
Average post-trade price movement	529	0.046	0.015	0.026	0.037	0.043	0.052	0.074
Total trade size	529	24,126.203	61,230.068	738.236	4,384.390	6,999.450	25,911.000	127,053.950
Uninformed Traders: Sells								
Average profitability	89,123	0.002	0.037	-0.059	-0.020	-0.003	0.024	0.066
Average post-trade price movement	89,123	0.003	0.047	-0.060	-0.026	-0.006	0.033	0.093
Total trade size	89,123	1,952.778	44,194.245	6.272	52.659	260.296	853.028	5,319.747
Informed Traders: Sells								
Average profitability	3,019	0.042	0.017	0.019	0.032	0.035	0.055	0.074
Average post-trade price movement	3,019	0.053	0.026	0.022	0.026	0.048	0.072	0.099
Total trade size	3,019	3,282.402	39,699.485	318.998	354.144	1,264.622	1,907.686	4,393.170

A.V Trader-Classification Descriptive Statistics

This section provides descriptive evidence on the wallet-level informed/uninformed classification introduced in Section 4.1. Three items support the partition. Table A.9 reports performance metrics for both groups within the eligible-wallet cohort, confirming the partition is economically meaningful. Figure A.8 plots the daily aggregated trading volume of uninformed traders over time, showing the volume base on which the cross-market spillover regressions are estimated. Figure A.9 documents the concentration of total trading volume among the largest wallets, which motivates the top-half-volume threshold in the classifier definition.

Performance metrics of classified traders. Table A.9 compares informed and uninformed wallets on three metrics. By construction, the informed cohort exhibits a higher volume-weighted 24-to-48h return: the median informed buyer's return on this metric is 3.7%, against a median uninformed buyer of 0.2%, and the analogous gap for sellers is 3.5% vs −0.3%. The 48-hour profit-per-dollar metric tracks the same pattern. The trade-size distributions are heavy-tailed in both groups, but the gap in post-trade returns is the more substantive partition characteristic.

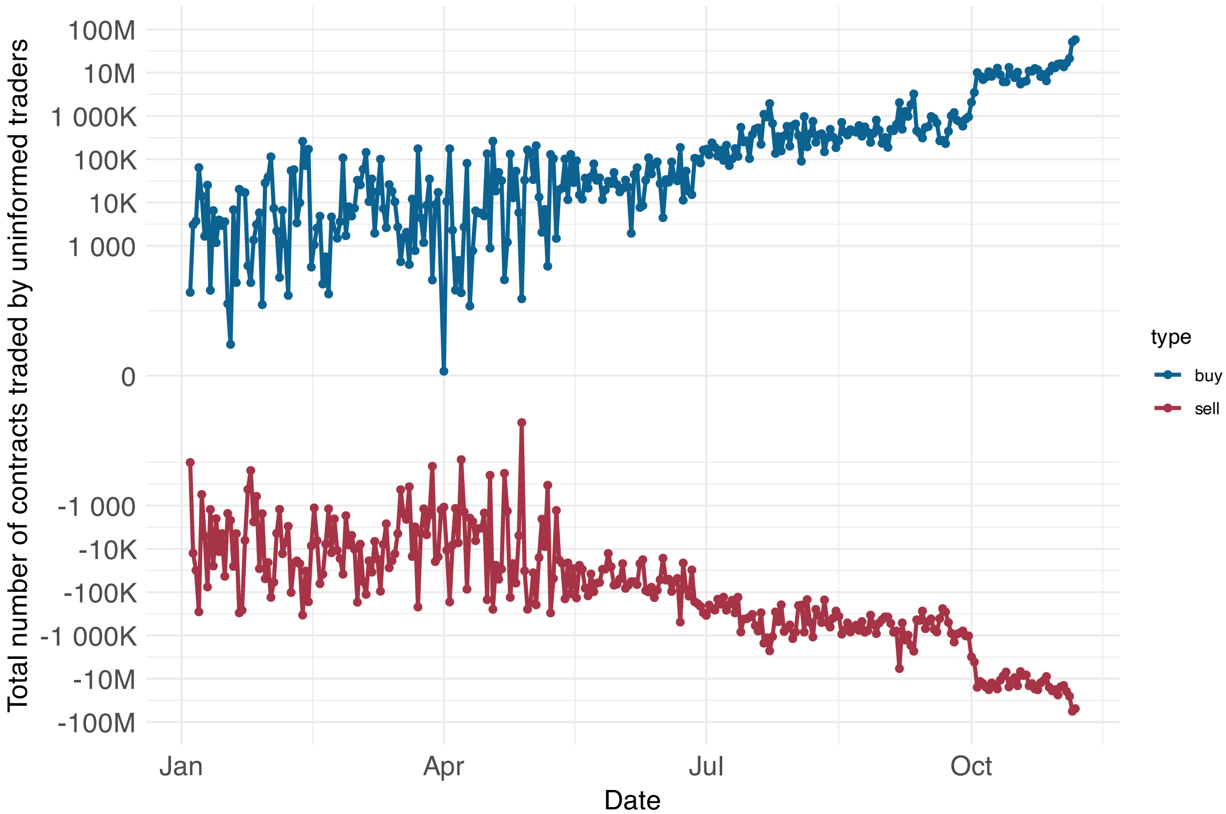


Figure A.8 Daily Signed Volume of Uninformed Trades: Buys and Sells

Daily aggregated buy and sell volume of uninformed wallets, signed by direction, from January through November 2024. The plotted series is the volume base for the cross-market spillover regressions in Section 4.

Daily aggregated uninformed flow. Figure A.8 plots the daily aggregated buy and sell volume of uninformed wallets, signed by direction, over the sample window. The series exhibits substantial day-to-day variation and a pronounced run-up toward the election date. This series is the empirical volume base for the cross-market spillover regressions reported in Table 7.

Volume concentration among large traders. Figure A.9 plots the total trading volume of wallets that traded at least one million contracts during the sample period. A small number of wallets account for a disproportionately large share of total volume, and this concentration motivates the top-half-volume eligibility threshold in our classifier definition: requiring a wallet to be in the top half of total trade size on its side ensures the classifier evaluates performance on wallets with enough volume for the post-trade return metric to be informative.

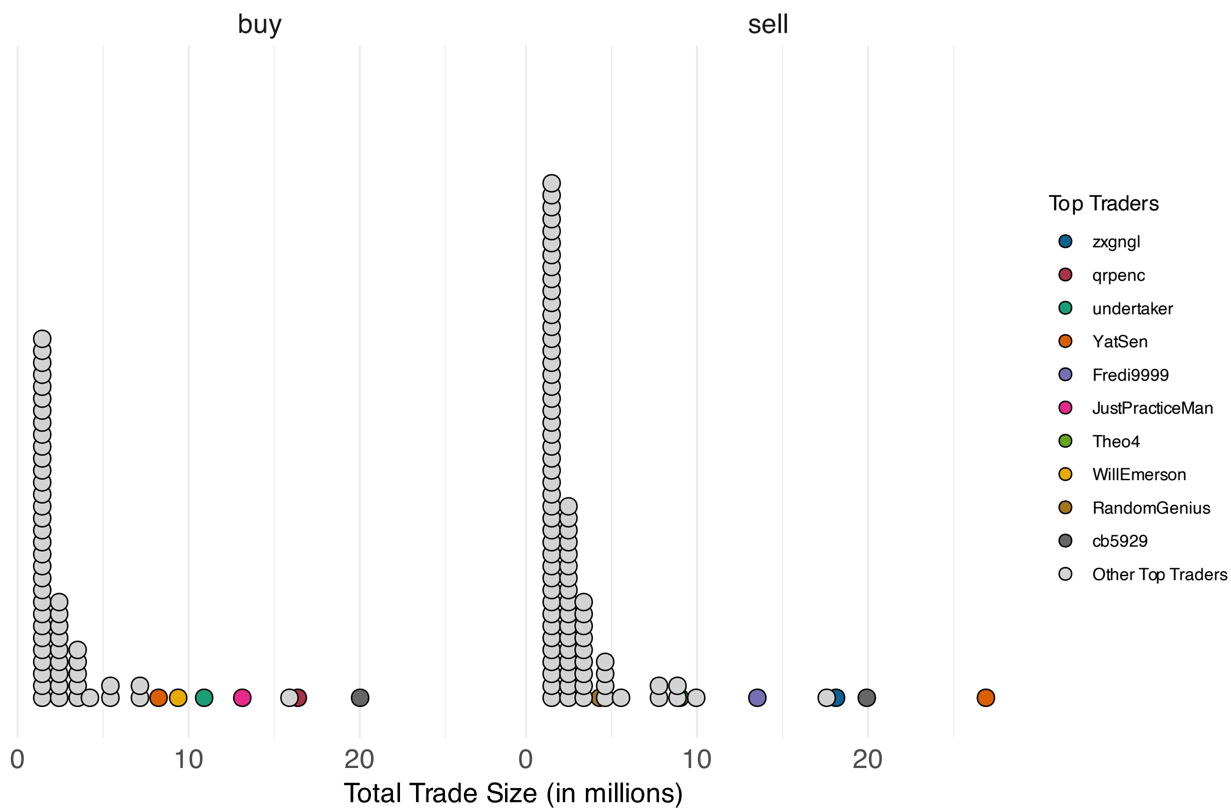


Figure A.9 Total Trading Volume of Wallets above One Million Contracts

Dot plot of total trading volume (in millions of contracts) for wallets with at least one million contracts of cumulative volume during the sample period. The figure documents the extreme concentration of total volume among a small number of large wallets, which motivates the top-half-volume eligibility criterion in our classifier definition (Section 4.1).

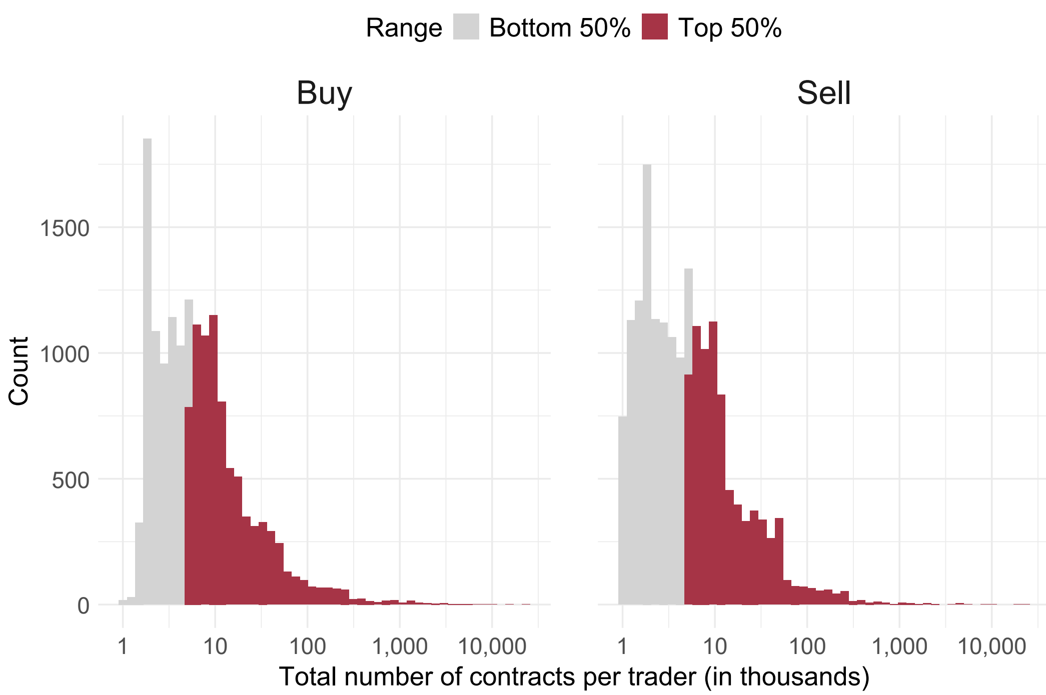


Figure A.10 Distribution of Traders by Total Transaction Volume

This figure shows a histogram of the total transaction volume per trader over the sample period, in log scale. Traders are partitioned into a top 50% and a bottom 50% by total transaction volume. The sample is the full universe of Polymarket trades on the Trump-YES contract.

Table A.10 Cross-Market Transmission of Information: Poll Releases, Active Polling Window

This table re-estimates the specification of Table 8 on the sample restricted to the active polling window: June 28, 2024—the first date covered by the Nate Silver polling data—through October 31, 2024, so that no zero-filling of $NPolls_t$ is required. The dependent variables are the signed log returns of the Trump trade on day $t+1$, day $t+2$, day $t+3$, and cumulatively over days $t+1$ to $t+3$, following trading on day t. Columns (1)–(4) report the baseline specification; columns (5)–(8) add the same principal-component controls as in Table 7. $NPolls_t$ is the count of "A-rated" national polls scheduled for release over the following 5 days, centered and scaled to unit standard deviation within this estimation sample, so interaction coefficients are expressed per one standard deviation of $NPolls_t$ and level coefficients are evaluated at mean poll intensity. All specifications include day-of-week and day-of-month fixed effects. Driscoll-Kraay standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	$r^{TT}_{i,t+1}$	$r^{TT}_{i,t+2}$	$r^{TT}_{i,t+3}$	$r^{TT}_{i,t+1\to t+3}$	$r^{TT}_{i,t+1}$	$r^{TT}_{i,t+2}$	$r^{TT}_{i,t+3}$	$r^{TT}_{i,t+1\to t+3}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$InformedTrade_t$	-0.020	0.011	0.493***	0.480	-0.145	0.002	0.512***	0.369
	(0.244)	(0.223)	(0.146)	(0.414)	(0.183)	(0.200)	(0.170)	(0.322)
$UninformedTrade_t$	0.251***	0.203**	0.269***	0.722***	0.085	0.180**	0.320***	0.584***
	(0.058)	(0.094)	(0.068)	(0.145)	(0.072)	(0.088)	(0.101)	(0.141)
$NPolls_t$	0.000	0.001	0.000	0.001	0.001	0.001	0.000	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
$NPolls_t \times InformedTrade_t$	0.869***	0.370*	-0.640**	0.598	0.654***	0.258	-0.650**	0.262
	(0.241)	(0.213)	(0.255)	(0.427)	(0.192)	(0.265)	(0.308)	(0.474)
$NPolls_t \times UninformedTrade_t$	-0.063	-0.143	-0.173**	-0.380**	-0.055	-0.159**	-0.171**	-0.385***
	(0.057)	(0.087)	(0.076)	(0.158)	(0.058)	(0.079)	(0.076)	(0.139)
PCs included					✓	✓	✓	✓
DOW FE	✓	✓	✓	✓	✓	✓	✓	✓
DOM FE	✓	✓	✓	✓	✓	✓	✓	✓
R^2	0.052	0.049	0.053	0.082	0.066	0.057	0.062	0.098
Observations	3,169	3,165	3,165	3,161	3,169	3,165	3,165	3,161

A.VI Additional Results on Information Transmission

This section reports a robustness variant of the poll-release interaction analysis of Section 4.3. In the baseline specification (Table 8), $NPolls_t$ is set to zero on dates before June 28, 2024, which the Nate Silver polling data do not cover. Table A.10 instead restricts the estimation sample to the active polling window, dropping the pre-poll dates rather than zero-filling them.