Market Efficiency in Prediction Markets - A Comparison with Derivatives*

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PRELIMINARY DRAFT - NOT FOR CIRCULATION

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Keywords: Prediction Markets, Market Efficiency, Risk-Neutral Pricing, Crypto Derivatives, Behavioral Biases, Decentralized Finance

JEL Classification Codes: G14, D84, G12, G13

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1 Introduction

Prediction markets are gaining traction as tools for forecasting, risk transfer, and belief aggregation. These platforms facilitate trading on binary outcomes of real-world events, where contract prices, ideally representing probabilities, are derived from user trades. Contracts often take the form of Arrow-Debreu securities: "Yes" or "No" bets paying $1 if an event occurs. While their resemblance to financial derivatives like binary options is well-established, the rise of decentralized platforms such as Polymarket has highlighted this connection (Liu and Bierwirth, 2025; Ng et al., 2025). However, these decentralized markets operate with distinct regulatory frameworks, user demographics, and liquidity dynamics compared to traditional derivatives markets (Hopkins, 2022). These differences raise crucial questions: Do prediction markets price event risk efficiently compared to conventional derivatives? How effectively do they aggregate information? Are their implied probabilities consistent with benchmarks from established financial markets?

This paper addresses such questions through the first systematic comparison of market-implied probabilities from Polymarket with benchmarks derived from the option-implied risk-neutral distribution in the derivatives market. We focus specifically on Bitcoin (BTC) prediction bets, leveraging the unique parallel existence of an active betting market on Polymarket and a deep, liquid BTC derivatives market on Deribit. Our analysis covers four primary bet structures: terminal value bets (*Above*, *Range*) analogous to European digital options, and path-dependent bets (*Reach*, *Dip*) resembling knock-in barrier options. We compare Polymarket's central limit order book (CLOB) prices directly against these option-implied prices (OIP).

Our empirical evidence suggests that these markets can be efficient under certain circumstances, but that they also exhibit significant and systematic biases. Specifically, while Polymarket prices generally track the option-implied benchmarks, significant and systematic deviations emerge. Pricing inaccuracy correlates strongly with bet complexity; simple *Above* and *Range* bets show high alignment (mean correlations 0.97 and 0.83, respectively), whereas more complex *Reach* and *Dip* bets exhibit weaker correlations (around 0.73-0.79), suggesting inefficiencies related to payoff structure.

Beyond bet complexity, we identify other consistent patterns in these pricing deviations. Mispricing is most pronounced at the inception and near the expiration of bets, and lower in between, suggesting that price adjustments follow a learning process but tend to overreact as expiration approaches. Deviations are also amplified during periods of lower liquidity, such as weekends. Furthermore, we find clear evidence of behavioral biases, particularly the overpricing of low-probability, tail-event bets (e.g., extreme price targets), consistent with probability overweighting or sentiment-driven speculation. These behavioral effects intensify during periods of heightened macroeconomic uncertainty or sharp market movements, where Polymarket prices tend to react more drastically and overshoot compared to the more measured responses of the options market. This overall behavior is consistent with Barber and Odean (2000, 2001, 2008), as traders on Polymarket—much like traditional investors—tend to focus on salient political or market events and trade excessively on attention-grabbing signals rather than fundamentals.

We then employ regression analysis to systematically investigate the drivers of these deviations. The regressions confirm that cross-market price discrepancies stem from a combination of underlying market dynamics (returns and volatility), platform-specific frictions (blockchain operational risks, market fragmentation), and behavioral factors (order-flow imbalances, sentiment, macroeconomic news). Crucially, we find asymmetric effects: mispricing in bullish contracts (*Above*, *Reach*) widens with positive returns (consistent with overreaction), while mispricing in bearish contracts (*Dip*) intensifies during market downturns and periods of high fear, driven more by volatility and negative sentiment.

Overall, our findings indicate that while decentralized prediction markets like Polymarket exhibit considerable informational efficiency, their pricing is also systematically shaped by market frictions, behavioral biases (akin to those documented by Barber and Odean (2000, 2001, 2008)), and platform-specific risks.

2 Literature Review

Betting markets like sportsbooks, horse racing, and Betfair have long provided real-world settings to study market efficiency. These markets trade on uncertain future events, with prices often reflecting collective beliefs. Prediction markets often yield accurate forecasts, sometimes outperforming polls—especially in elections Axén and Cortis (2020); Rothschild and Sethi (2016); Wolfers and Zitzewitz (2006). Quote-driven betting markets offer immediacy and guaranteed liquidity, boosting participation and returns when exchange liquidity is low; however, they may also attract uninformed trading, inflating volume without improving—and potentially harming—market efficiency Flepp et al. (2017).

Crypto prediction markets (e.g., Augur and Polymarket) use decentralized blockchain infrastructure to enable anonymous, transparent trading without intermediaries, lowering entry barriers and providing verifiable data for studying opinion aggregation (Chen et al. (2023, 2024)). As real-time signals of crowd beliefs, prediction markets are widely used for forecasting; Polymarket, for example, has reached up to 94% accuracy shortly before events occur (McCullough (2022)). Eichengreen et al. (2025) use Polymarket data to show that expectations of political interference with the Federal Reserve lead traders to expect lower short-term rates and higher long-term yields, reflecting concerns about reduced central bank independence and credibility.

Prediction markets show platform-specific biases: in Polymarket, low-probability outcomes may be undervalued due to user incentives Puri (2025). Inefficiencies like slow price reactions to goals create brief arbitrage windows. While markets generally respond efficiently to information shocks Gauriot and Page (2025), large shocks can trigger brief under-reactions, and longshot biases.

3 A Primer on Polymarket

Polymarket operates a hybrid-decentralized CLOB to facilitate trading in prediction markets. Unlike centralized betting platforms or automated market makers (AMMs), Polymarket's exchange infrastructure is designed around peer-to-peer trading, where market participants submit and match orders for shares representing binary event outcomes (e.g., "Yes" or "No" on a future event). The CLOB comprises an off-chain based matching engine paired with on-chain non-custodial settlement. Orders are submitted and matched off-chain, with final settlement executed on-chain on Polygon. Orders in the CLOB consist of limit prices and quantities.

Each binary market consists of two complementary outcome tokens—typically referred to as "Yes" and "No" shares. These tokens are fully collateralized, meaning that for every matched trade, the combined price paid for one "Yes" and one "No" share must total exactly 1.00 USDC. This ensures that the market is always fully backed by sufficient collateral. Upon resolution, the token corresponding to the correct outcome redeems for 1.00 USDC, while the incorrect token becomes worthless. All shares are priced in the range $[0.00, 1.00]$ USDC, and prices directly represent the market-implied probability of the associated event. For instance, a "Yes" share priced at 0.42 implies a 42% chance of the event occurring, as inferred from the balance of supply and demand. Participants can sell their shares at any time before market resolution by either accepting the current bid price via a market order or posting a limit order with their desired price and quantity.

3.1 Betting Types

Polymarket is a decentralized information market platform where users can trade on the outcomes of real-world events using the USDC stablecoin. Its prediction markets support a variety of bet structures, which function as contingent claims on cryptocurrency price movements. In the context of cryptocurrency markets, we identify four primary types of bets:

1. **Above Bets**: These are binary options structured around whether BTC will exceed a specified threshold by a fixed maturity date (e.g., "Will BTC be above $60,000 on July 31?"). These bets resolve to "Yes" if the spot price at the market's expiry exceeds the stated level, and "No" otherwise.

2. **Range Bets**: These bets specify whether BTC will lie within a predefined price interval at maturity (e.g., "Will BTC be between $50,000 and $60,000 on July 31?"). They effectively represent double-barrier digital options, with resolution contingent on the final price remaining strictly within the bounds.

3. **(Knock-In) Reach Bets**: These are forward-looking bets on whether BTC will hit or exceed a particular price at any point before the stated expiry (e.g., "Will BTC reach

$65,000 before August 1?"). They resemble American-style barrier options that activate and resolve immediately upon breach.

4. **(Knock-In) Dip Bets**: Similar in structure to the reach bets but applied to downward price movements, these markets ask whether BTC will dip below a certain price level before expiry (e.g., "Will BTC fall below $45,000 before August 1?"). These are useful for capturing market expectations of short-term downside risk.

All Polymarket markets are resolved via an on-chain oracle that references externally verifiable data sources. In the case of cryptocurrency prediction markets—such as those involving BTC/USDT pairs—the resolution criteria are explicitly defined using timestamped price data from centralized exchanges (Binance). A typical specification reads: "This market will immediately resolve to *Yes* if any Binance 1-minute candle for Bitcoin (BTC/USDT) between July 1, 2025, 00:00 and July 31, 2025, 23:59 ET has a final high price of $200,000 or higher. Otherwise, this market will resolve to *No*". This means that if any 1-minute interval during the specified period reaches the threshold, the market is resolved immediately.

4 Data

4.1 Option-Implied Information

We obtain option data through Amberdata[1], using hourly floating-delta implied volatility (IV) surfaces derived from BTC options. A floating-delta surface refers to a dataset of IVs structured by option delta, where maturity is not fixed to standardized intervals (e.g., 7 or 30 days). Instead, each observation reflects the actual time to expiration of the listed option at a given point in time—hence the term floating. The data is collected from Deribit, which is the largest exchange for trading cryptocurrency options. On Deribit, options are cash-settled and quoted directly in the respective cryptocurrency and not in USD. The surface data consists of five delta levels per call and put option.

[1] https://www.amberdata.io/

4.1.1 Risk-Neutral Densities (RND)

For each Polymarket event, we first identify the start and the end date (target maturity). Within that window, we perform hourly linear interpolation of IVs across time by identifying the two nearest maturity surfaces surrounding each target maturity.

The resulting IV surface is then used to compute the RND. Specifically, we interpolate IV across moneyness to obtain a smooth curve and apply a generalized version of the Breeden and Litzenberger (1978). Specifically, we extract the RND using

$$f_i\left(T,\ K;\ \theta\right) = e^{rT}\frac{\partial^2}{\partial K^2}Call_i\left(T,\ K,\ \widehat{\sigma}_i\left(T,\ K;\ \theta\right)\right), \quad \text{for } i = 1,\ 2,$$

where $\widehat{\sigma}_i(T, K; \theta)$ is the interpolated IV surface. It is shown in Figlewski (2018) that improved estimation of the risk-neutral density is obtained by parametrically fitting the IV smile and then differentiating the option price. Hence, we first fit a quadratic polynomial to the IVs $\sigma(K)$ observed across different strike prices K, i.e., $\sigma(K) \approx aK^2 + bK + c$. We then compute the first and second derivatives of the fitted volatility curve, denoted by $\sigma'(K)$ and $\sigma''(K)$, respectively. Using this smoothed and differentiable representation, we evaluate IVs and their derivatives on a dense grid of strikes $\{k_i\}$. The RND at each grid point k_i is then computed using the extended Breeden and Litzenberger (1978) formula:

$$p(k_i) = \frac{\partial^2 C(k_i)}{\partial K^2} + \text{Vega}(k_i) \cdot \sigma''(k_i) + \text{Volga}(k_i) \cdot \left(\sigma'(k_i)\right)^2 + 2 \cdot \frac{\partial^2 C(k_i)}{\partial K\, \partial \sigma} \cdot \sigma'(k_i),$$

where the first term corresponds to the classical second derivative of the call price w.r.t strike, while the remaining terms correct for the slope and curvature of the IV-surface. Specifically, Vega(k_i) is the option's sensitivity to volatility, Volga(k_i) captures the curvature of this sensitivity, and $\frac{\partial^2 C(k_i)}{\partial K\, \partial \sigma}$ is the cross-partial derivative with respect to strike and volatility. These adjustments improve the robustness of the density estimate in the presence of a non-flat volatility smile.

To ensure the estimated density captures the tail behavior more realistically, we append log-normal tails to both ends of the strike support. To the right, we extrapolate the density using a log-normal approximation based on the last observed IV $\sigma(k_{\max})$, generating a right tail over an extended grid $k > k_{\max}$ and scaling it as

$$p_{\text{right}}(k) = \frac{p(k_{\max})}{C_{KK}(S, k_{\max}, T, \sigma(k_{\max}))} \cdot C_{KK}(S, k, T, \sigma(k_{\max})),$$

where $C_{KK}(\cdot)$ denotes the second derivative of the Black–Scholes call price with respect to strike. Similarly, the left tail is constructed for $k < k_{\min}$ using

$$p_{\text{left}}(k) = \frac{p(k_{\min})}{C_{KK}(S, k_{\min}, T, \sigma(k_{\min}))} \cdot C_{KK}(S, k, T, \sigma(k_{\min})).$$

Finally, we concatenate the left tail, core, and right tail densities to obtain the full strike grid $\{k_i\}$ and corresponding density values. The resulting density is normalized to integrate to one.

4.1.2 Option-Implied Prices (OIP)

We use the estimated RNDs (p) to compute the OIP of exotic binary options linked to Polymarket events. For the Above Bets—such as "BTC above \$X before time T" we compute the OIP by integrating the upper part of the RND beyond the event threshold. Let K_{event} denote the strike defined by the event. The risk-neutral probability of the outcome $\{S_T \geqslant K_{\text{event}}\}$ is then approximated by summing the density above this strike:

$$OIP_{AboveBets} = \sum_{K \geqslant K_{\text{event}}} p(K) \cdot \Delta K.$$

For the Range Bets such as "BTC between \$X and \$Y before time T" we compute the OIP by integrating the RND over the corresponding strike interval. Let $K_{\text{event}}^{\text{low}}$ and $K_{\text{event}}^{\text{high}}$ denote the lower and upper strike bounds of the range. The risk-neutral probability of the event is then obtained by summing the density over that interval. In practice, if the terminal value falls exactly on a bracket boundary, the market resolves to the higher range bracket, and the integration reflects this rule.

$$OIP_{RangeBets} = \sum_{K_{\text{event}}^{\text{low}} \leqslant K < K_{\text{event}}^{\text{high}}} p(K) \cdot \Delta K.$$

For knock-in barrier events such as "BTC hits \$X before time T" we estimate the OIP using the standard reflection principle for Brownian motion.

$$OIP_{Knock-In} = 2 \cdot \Phi \left(-\frac{|\log(K_{\text{event}}/S_0)|}{\sigma(K_{\text{event}})\sqrt{T}} \right),$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function, S_0 is the current spot price, and $\sigma(K_{\text{event}})$ is the interpolated IV at the barrier level (K_{event}). The absolute value and symmetry of Brownian motion under Black–Scholes make the formula equally applicable to both Reach and Dip Knock-In Bets.

4.2 Polymarket

We collected data on prediction markets from Polymarket, operating on the Polygon blockchain that offers a variety of markets, including those related to cryptocurrency price movements. The data was retrieved via the Polymarket API: First, we query the "markets" endpoint to retrieve a list of all active and closed markets, along with associated metadata (titles, timestamps, tags, resolution status, etc.). From this list, we filter for cryptocurrency-specific markets—specifically those referencing BTC—using keyword matching and manual verification of market descriptions. For each relevant market, we used its CLOB-specific token IDs to query the "clob-token-timeseries" endpoint, which returns historical prices at hourly frequency.

For each market, we also source trade data on a tick level, which is recorded at the transaction level, where multiple rows may share the same transaction hash when a taker order matches against several makers. Each row contains the market identifier (condition ID), the outcome tokens, side (buy or sell), size, and price, and basic trader metadata (wallet address, pseudonym).

We also enrich the trade data with blockchain-level information by computing per-transaction gas costs for trades executed on Polygon, retrieved via Web3 from Infura endpoints, together with the corresponding transaction receipts. From the receipt, we obtain the actual *gas used* and the *effective gas price*. The on-chain gas fees in USD for a transaction are then calculated as follows:

$$\text{gas fee} = \text{gas used} \times \text{effective gas price}/10^{18} \times P^{\text{MATIC/USD}},$$

where $P^{\text{MATIC/USD}}$ denotes the contemporaneous MATIC–USD exchange rate; MATIC is the native token of Polygon and is used to pay transaction fees.

Table 5.1 presents summary statistics for trades placed on Polymarket, categorized by bet type. The data encompasses the raw trade data and the gas fees. Overall, the dataset contains 324,188 trades across 255 unique bets. The table reveals significant variation in trading activity across different bet types: Range (Dip) bets are the most (least) frequently traded ($104,890$ vs. $56,944$). The average fee per trade across all bet types is 0.0147 USD, indicating the low transaction costs users face when participating in these markets on Polygon.

Bet Type	Trades	Total Fees	Avg Fees	Unique Bets
Above	73,136	1,312.7944	0.0218	62
Range	104,890	889.2485	0.0085	80
Reach	89,218	955.9687	0.0167	71
Dip	56,944	677.1490	0.0127	42
All	324,188	3,835.1606	0.0147	255

Table 4.1: Bets – Summary Statistics. For each bet type, the table reports total trades, total fees, the average fee per trade (total fees divided by total trades), average fees per observation, and the number of unique bets.

Following Bollen and Whaley (2004), we construct *net buying pressure (NBP)*, which is different from volume when buy and sell orders offset. NBP is calculated by subtracting the number of contracts sold from those bought. This calculation is performed for each bet and on an hourly frequency as follows:

$$\text{NBP}_t = \frac{(\text{Buy Volume}_t - \text{Sell Volume}_t)}{\text{Total Volume}_t}.$$

We also calculate the moneyness and maturity of each bet over time: For Above bets, the moneyness is calculated as the ratio of the spot price to the strike price (S/K), treating them like call options. For range bets, the lower strike is treated like a call with moneyness S/K_1, and the upper strike is treated like a put with moneyness K_2/S; if the spot price lies between the two strikes (in the money), the average of the two is taken, while otherwise the side that is OTM is used. For Reach bets, they are treated like calls, so moneyness is again S/K. Finally, for dip bets, which behave like puts, moneyness is computed as K/S. Hence, for all bets, if moneyness moves toward 1, it indicates that the market price is approaching the strike and the bet is becoming more ATM. Maturity is measured as the number of hours remaining from the initialization of the bet until its resolution.

4.3 Blockchain Related Risk Measures – L2 Risk

To proxy operational risk on L2 networks, we use block-level data from the Polygon blockchain to construct a high-frequency measure of inter-block intervals. This measure is derived from differences in timestamps between consecutive blocks, extracted via The Graph through a subgraph indexing Polygon block metadata. These intervals are aggregated hourly, and for each hour, we record the longest block gap. To capture persistent disruptions rather than transitory spikes, we compute a smoothed version of this measure by taking the rolling average of the hourly maximum block gaps over the last 24 hours. This is the *L2 Risk*.

4.4 Macroeconomic Risks

We also construct an *Announcement* indicator that captures key policy events, specifically the tariff announcements made by President Donald Trump between November 2024 and April 2025, as well as the Federal Open Market Committee (FOMC) meetings. In doing so, we account for both FOMC meeting days and the tariff-related events documented by the American Institute for Economic Research.[2]

[2] We source the FOMC meetings from https://www.federalreserve.gov/monetarypolicy/fomccalendars.htm. The data for the announcements can be found here: https://aier.org/article/how-equity-markets-reacted-to-trumps-tariff-announcements-the-data/?

4.5 Other Risks

Polymarket employs a data feed from Binance to receive verifiable off-chain information to its smart contracts, thereby enabling the accurate resolution of bets. Deribit references prices through its proprietary feed system, drawing from multiple centralized exchanges. To capture the risk in price differences for the same underlying, we focus on the divergence in BTC prices between Binance and Deribit, reflecting valuation gaps across different exchanges. We construct an hourly relative deviation measure defined as the difference between the Binance price and the Deribit price, normalized by the Binance price. To capture short-term volatility in these deviations, we compute the rolling standard deviation over a 24-hour window. This *Diff Underlying* measure provides insight into frictions in price discovery, informational latency, and short-term market segmentation.

In our panel regressions, we control for both the return and volatility of BTC and USDC. To ensure neutrality, we rely on price data from a source independent of Polymarket, Binance, and Deribit. Specifically, we obtain hourly BTC-USD and USDC-USD prices from CryptoCompare, from which we compute the first and second moments: The variable $\Delta\,\mathrm{BTC}$ (%) denotes the percentage change in BTC (its return), while BTC Vol_{30} captures the 30-day rolling volatility of BTC. Similarly, $\Delta\,\mathrm{USDC}$ (%) measures the percentage change in USDC, and USDC Vol_{30} represents the 30-day rolling volatility of USDC.

5 Empirical Analysis

At a high level, the empirical analysis compares prediction-market prices with option-implied probabilities for BTC bets. The two markets generally move together, especially for simple directional bets, while complex or extreme outcomes show larger and more persistent pricing gaps. Mispricing is greatest early in contracts and around major news or weekend periods. We conduct a regression analysis showing that price discrepancies arise not only from returns and volatility but also from blockchain operational risks, macroeconomic news, market fragmentation, and order-flow imbalances, with asymmetric effects across bet types—bullish bets overreacting to positive returns and bearish bets to volatility and fear—highlighting both structural and behavioral sources of mispricing.

5.1 Probabilities from Betting and Option Markets

Table 5.1 summarizes the distribution and timing across the four betting types: Above, Range, Reach, and Dip. The sample comprises 255 bets, spanning from March 2024 to May 2025. Range bets are the most prevalent (80), followed by Reach (71), Above (62), and Dip (42). Maturities vary notably across types: Above and Range bets have short average maturities (which we calculate from the inception of the bet until its resolution) of roughly a week (7 and 6.7 days), respectively, indicating near-term expectations. In contrast, Reach and Dip bets are longer-dated, with average maturities of approximately a month (27.6 and 29.97 days), reflecting positions targeting more gradual or less likely price movements.

Bet Type	Number of Bets	Avg. Maturity	Start Date	End Date
Above	62	7.00	2024-03-17	2025-05-30
Range	80	6.69	2025-02-07	2025-05-30
Reach	71	27.55	2024-04-02	2025-05-31
Dip	42	29.97	2024-04-25	2025-05-31

Table 5.1: Bets – Summary Statistics. This table reports the number, the average time to maturity in days, and active date ranges of bets across the four prediction market bet types: Above, Range, Reach, and Dip. Start and end dates reflect the earliest and latest appearance of each bet in the data. The different types of bets are discussed in Section 3.1.

Figure 5.1 shows illustrative examples of price dynamics over time for the four BTC-related bet types (Section 3.1) across the two pricing sources CLOB and OIP. Panel (a) shows prices for the "BTC above 97,000" bet. Where prices first gradually decline, reflecting reduced probability of the event, before sharply rising to 1.0 as the outcome becomes increasingly likely and eventually realized. Panel (b) tracks prices for the "BTC between 97,000 and 99,000" range bet. Prices are relatively stable but exhibit a peak followed by a rapid collapse. Panel (c) displays the "BTC reach 130,000" bet, which exhibits a steady decline over time. The bet starts with a moderate probability in late December 2024 but sees continuous depreciation, consistent with diminishing expectations of such an extreme outcome. Panel (d) reports on the "BTC dip 90,000" bet, which also declines steadily from May 2025 onward, suggesting the market priced in progressively lower chances of a downside breach as time advanced. Across all panels, the CLOB and OIP pricing series track each other closely, though minor discrepancies are observable, particularly during periods of rapid price adjustments.

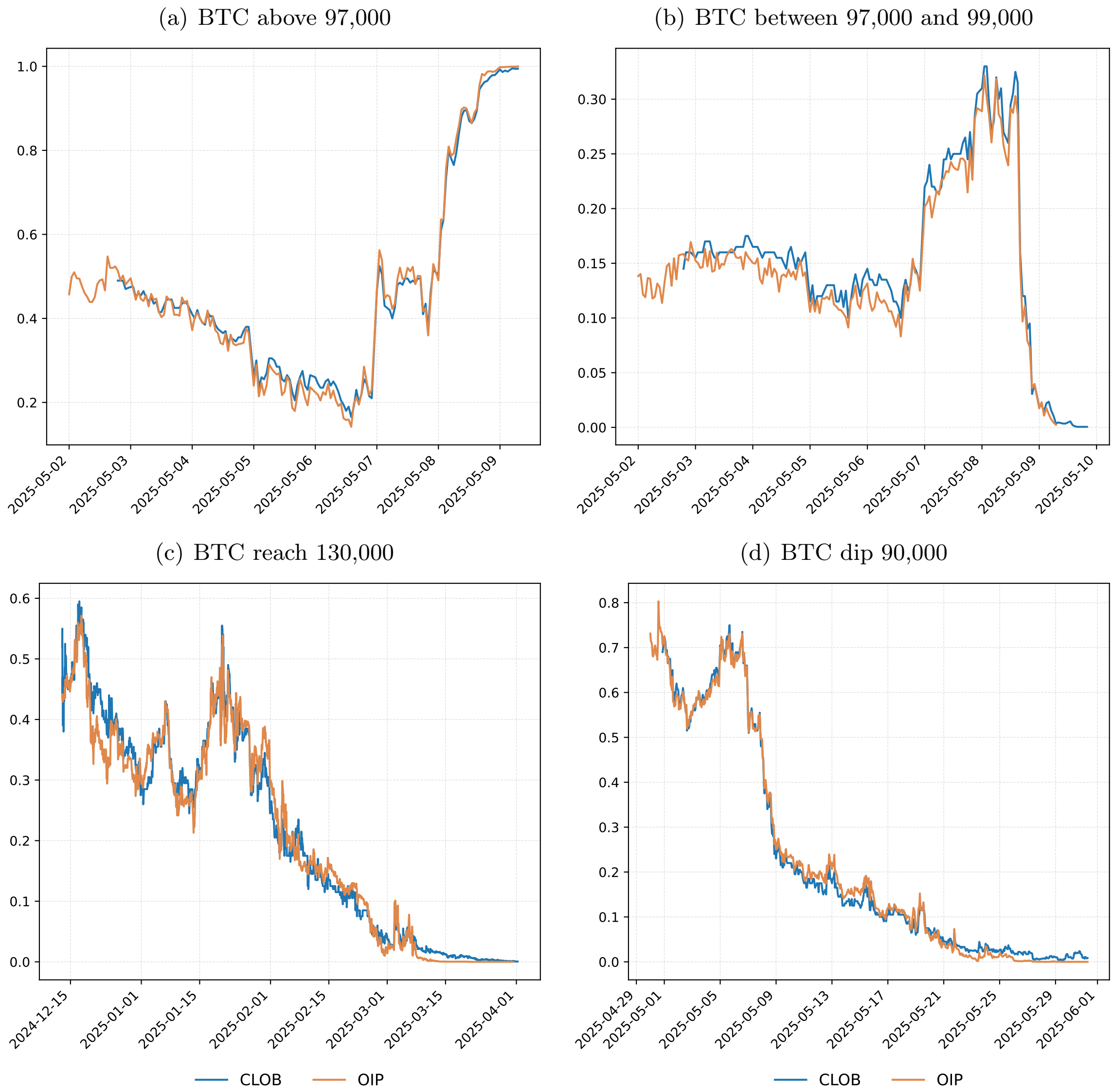


Figure 5.1: Example – Different Betting Types – CLOB vs. OIP. The figure displays time series of CLOB and OIP prices for one representative event from each of the four betting types (Above, Range, Reach, and Dip) shown in Panels (a) through (d), respectively. The different types of bets are discussed in Section 3.1.

Figure 5.2 presents histograms of average (time-series) correlations between CLOB and the OIP, for each of the four betting types. Panel (a) shows that Above bets exhibit extremely high consistency across sources, with correlations tightly concentrated near 1 and a sample mean of 0.97. This suggests near-perfect agreement between OIP and CLOB for this category. Panel (b) reports Range bets with slightly more dispersion but still high alignment, with a mean correlation of 0.83, indicating broadly consistent pricing across platforms. Panels (c) and (d), corresponding to Reach and Dip bets respectively, display wider distributions and lower means 0.79 and 0.73. These categories show greater heterogeneity in correlation values, with several bets exhibiting mid- or low-range correlation levels, and even occasional negative values. Overall, the figure reveals that correlation strength varies by bet type. Simpler directional bets (Above, Range) tend to be more aligned, while path dependent or tail-oriented bets (Reach, Dip) show more disagreement between CLOB and OIP, potentially reflecting behavioral biases, liquidity segmentation, or timing frictions in price formation.

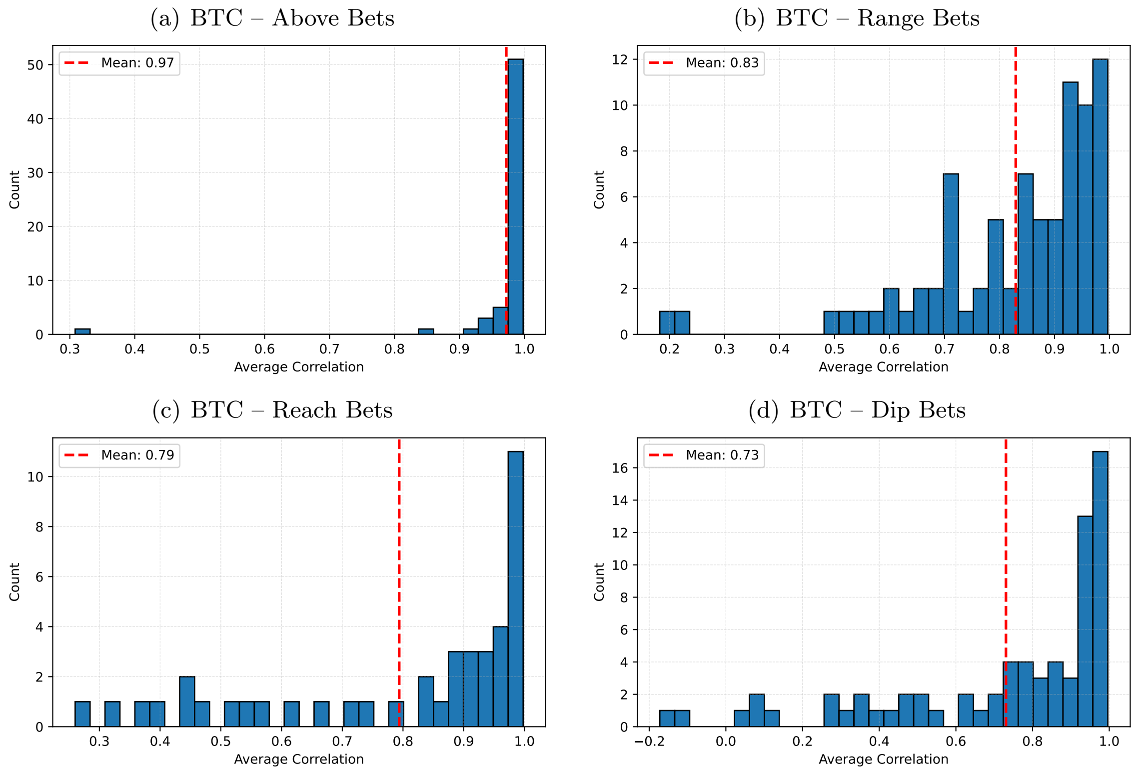


Figure 5.2: Histogram – Average Correlations per Betting Type. The figure displays the histogram of the average correlation of the CLOB and OIP for each of the four betting types (Above, Range, Reach, and Dip) shown in Panels (a) through (d), respectively. The different types of bets are discussed in Section 3.1.

Figure 5.3 presents a time series of market-implied probabilities for BTC-related Above bets, comparing the CLOB to the OIP. The figure reveals high-frequency fluctuations and sharp reversals in both series, consistent with the binary, event-driven nature of Above bets. Despite the volatility, OIP and CLOB prices track each other closely over time, suggesting strong alignment across pricing mechanisms. However, temporary divergences are evident, particularly around periods of elevated market uncertainty or near contract expiration, hinting at liquidity differences or short-term frictions in price formation. Overall, the plot underscores the responsiveness of both pricing sources to evolving market expectations, while also confirming their general consistency.

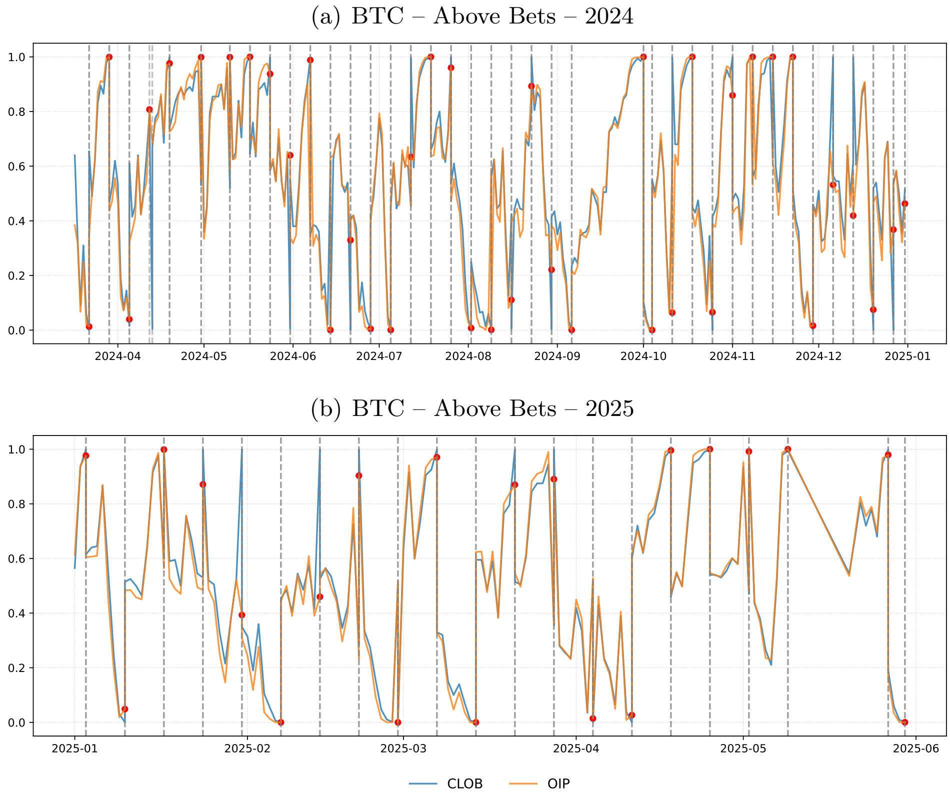


Figure 5.3: Above Bets over Time. The figure displays the time series of CLOB and OIP over time for Above bets for 2024 (Panel (a)) and 2025 (Panel (b)). A vertical line represents the beginning of a new bet (the end of an existing bet). The data is resampled to daily, taking the last available value on each day.

5.2 Behavioral Biases for Extreme Events

Figure 5.4 displays time series for the BTC Reach 200,000 and BTC Dip 40,000 bets, comparing CLOB and the OIP. Panel (a) shows that for the Reach 200,000 bet, CLOB consistently exceeds OIP throughout the entire period, with CLOB starting around 3% and gradually decaying toward zero. Several short-lived spikes in the CLOB series suggest episodic bursts of optimism or speculative trading, despite the low realized likelihood of the event. In contrast, OIP remains flat and near-zero throughout, indicating a more stable, possibly rational, valuation. Panel (b) presents a similar pattern for the dip 40,000 bet. Again, CLOB is elevated relative to OIP, with a peak exceeding 2% followed by a steady decline. OIP displays only brief, low-magnitude upticks before flattening. The divergence suggests that users on betting platforms may be more prone to overestimating tail events or exhibiting stronger behavioral biases, particularly in extreme outcome scenarios. Overall, the persistent upward bias in CLOB relative to OIP, especially for highly improbable bets, points to systematic overpricing consistent with behavioral distortions such as probability weighting or narrative-driven speculation.

(a) BTC reach 200,000 (b) BTC dip 40,000

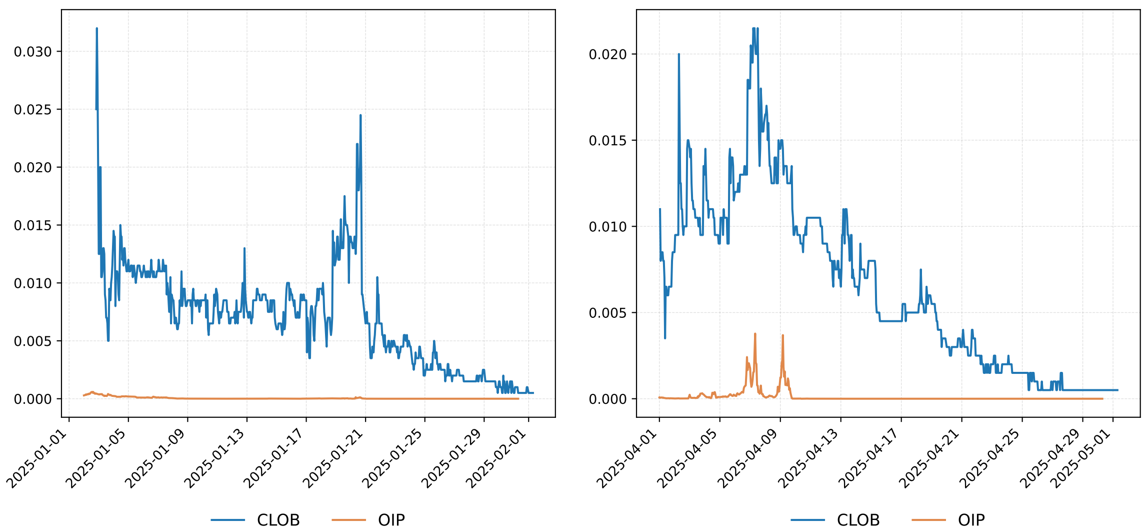


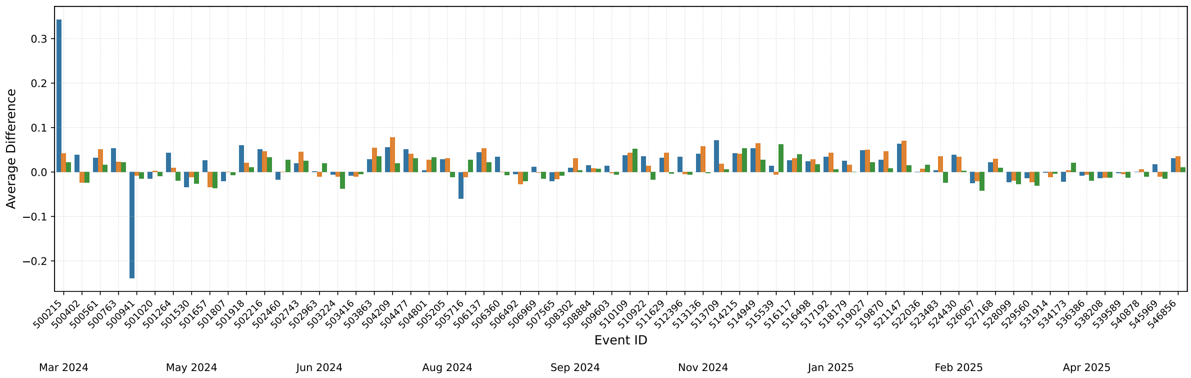
Figure 5.4: Behavioral Biases for Extreme Events. The figure displays the CLOB and OIP over time for two representative bets. In Panel (a) the event corresponds to “BTC reaches 200,000 before February 2025” and Panel (b) corresponds to “BTC dips below 40,000 before February 2025”. The different types of bets are discussed in 3.1.

5.3 Behavioral Biases over Time

Figure 5.5 displays the evolution of pricing differences between the betting market and the derivatives benchmark for each event—ordered chronologically by the bet's opening date—across three time segments: the *beginning* (first day of trading), *middle*, and *end* (final trading day). The figure reports results separately for each bet type: Above, Range, Reach, and Dip. Panels (a) and (b) focus on Above and Range bets, respectively, highlighting the evolution of pricing differences across forecast segments. In both cases, differences are largest at the beginning of the betting window (blue bars), often substantial and dispersed, particularly for Range bets in early 2025, where deviations frequently exceed 10%. These initial mispricings diminish markedly in the middle (orange) and end (green) segments, with differences converging toward zero. The consistent decline across events suggests systematic overpricing early on, followed by rapid convergence toward benchmark values as information is incorporated. Overall, these plot suggests that early misalignment between markets is progressively corrected over time as information is incorporated. Panels (c) and (d) report average pricing differences for Reach and Dip bets, respectively, across the beginning, middle, and end forecast segments. In both panels, the large differences emerge at the end of the horizon (green bars), with several events exhibiting values exceeding 60%. This pattern contrasts with the Above and Range bets, where differences tend to decline over time. Here, pricing differences widen toward resolution, with Reach and Dip bets showing larger end-segment deviations that suggest late-stage divergence driven by strategic positioning or new information.

Figure 5.6 examines the average of the difference in prices, Above, Range, Reach, and Dip, across three forecast stages: beginning, middle, and end. All reported differences are statistically significant at the 1% level (see Table 5.2). The difference in prices from the betting market vs. the derivatives market for the Above bets shows a clear downward trend: the mean declines from 0.0187 at the beginning ($p = 0.0000$) to 0.0146 in the middle and 0.0041 at the end. This suggests decreasing optimism or upward bias over time, potentially due to learning or convergence toward final outcomes. The Range bets follow a similar pattern, exhibiting a sharp early contraction from 0.0413 to 0.0147 in the middle segment, and declining further to 0.0062 by the end.

(a) BTC – Above Bets



(b) BTC – Range Bets

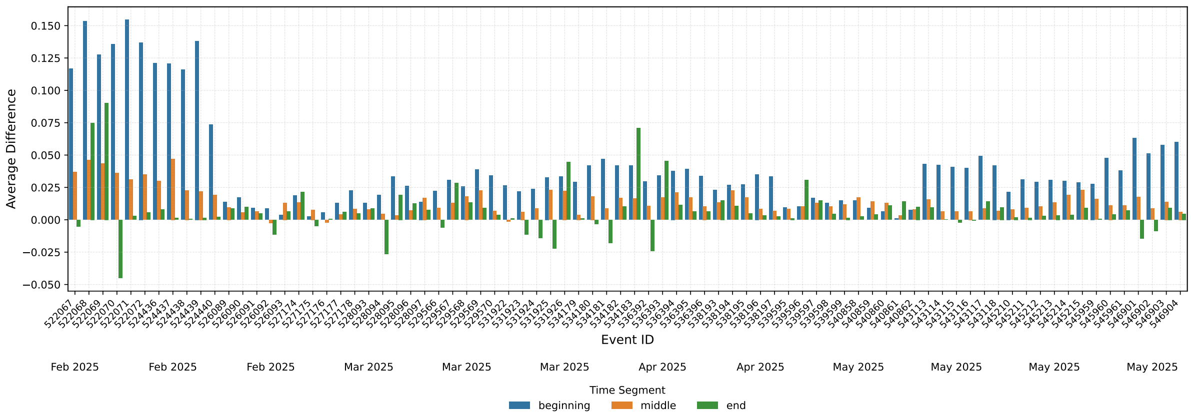
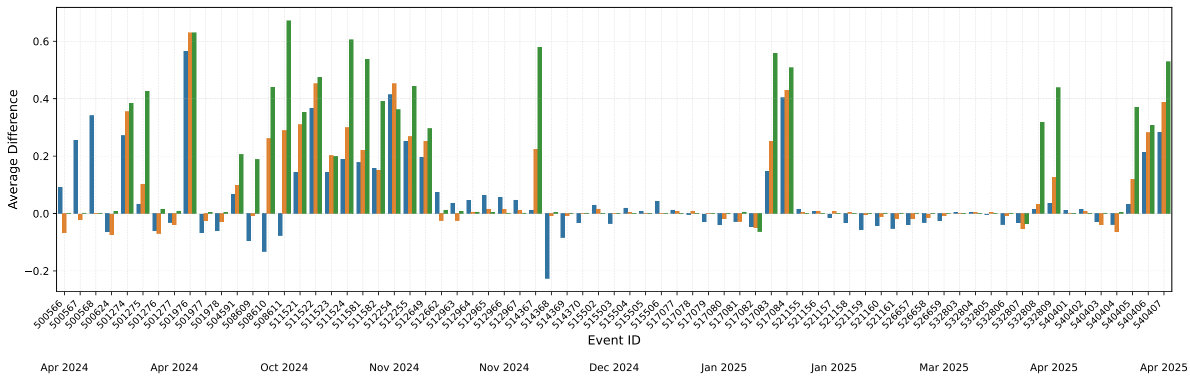


Figure 5.5: Average Difference (CLOB - OIP) per Betting Type, Event and Time Segment (Part 1). The figure displays average differences for the respective events of each betting type (Panel(a) - Panel(d)), split across three-sized temporal segments: beginning (first day of the bets release), middle, and end (last day before the bet ends). Each bar represents the mean difference between the OIP and CLOB for a given event and time segment. The different types of bets are discussed in Section 3.1. The data ranges from March 2024 to May 2025.

This points to initial mispricing in the market, followed by fast information incorporation and convergence toward reference values. In contrast, the Reach bets display a significant U-shaped pattern, with the mean declining from 0.0530 to 0.0129 before rising sharply to 0.1448 in the final segment. A similar pattern holds for the Dip bets (beginning: 0.0286, middle: 0.0098, end: 0.0884). These reversals point to a late-stage re-expansion in belief dispersion, likely reflecting delayed information arrival or strategic repositioning as resolution nears.

Table 5.3 reports average absolute price deviations between Polymarket and option-implied benchmarks, separately for weekends and weekdays, across the four bet types. Deviations tend to

(c) BTC – Reach Bets



(d) BTC – Dip Bets

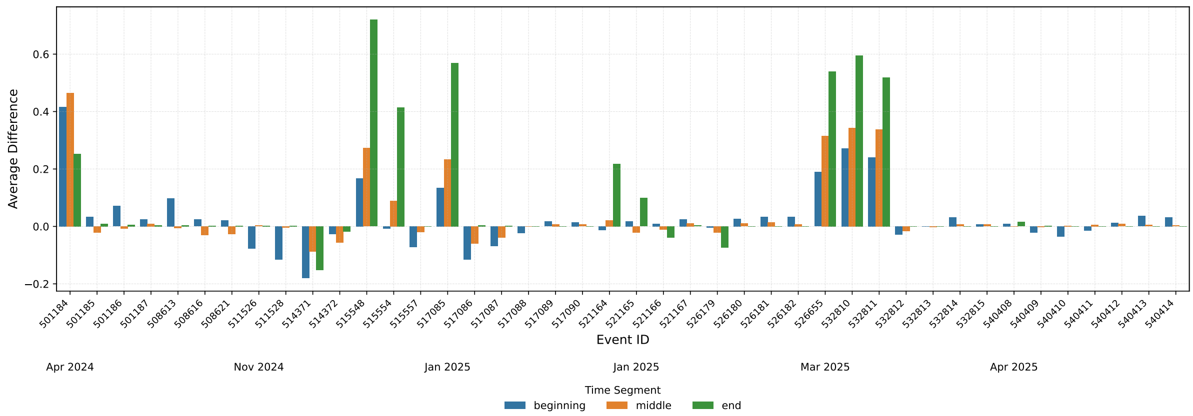


Figure 5.5: Average Difference (CLOB - OIP) per Betting Type, Event and Time Segment (Part 2). The figure displays average differences for the respective events of each betting type (Panel(a) - Panel(d)), split across three-sized temporal segments: beginning (first day of the bet's release), middle, and end (last day of the bet). Each bar represents the mean difference between the OIP and CLOB for a given event and time segment. The different types of bets are discussed in Section 3.1. The data ranges from March 2024 to May 2025.

be larger for most categories. For *Above*, *Reach*, and *Dip* bets, mean differences are significantly higher on weekends (all $p < 0.01$), suggesting reduced efficiency or thinner liquidity. In contrast, *Range* bets exhibit no statistically significant weekend effect ($p = 0.67$).

5.4 Regression Analysis

We expand on the visual evidence given by the figures to a regression framework. The goal is to explain the difference in prices (CLOB-OIP) with explanatory variables: The returns and volatilities of BTC and USDC, the VIX for BTC, blockchain operational risks (L2 Risk), the

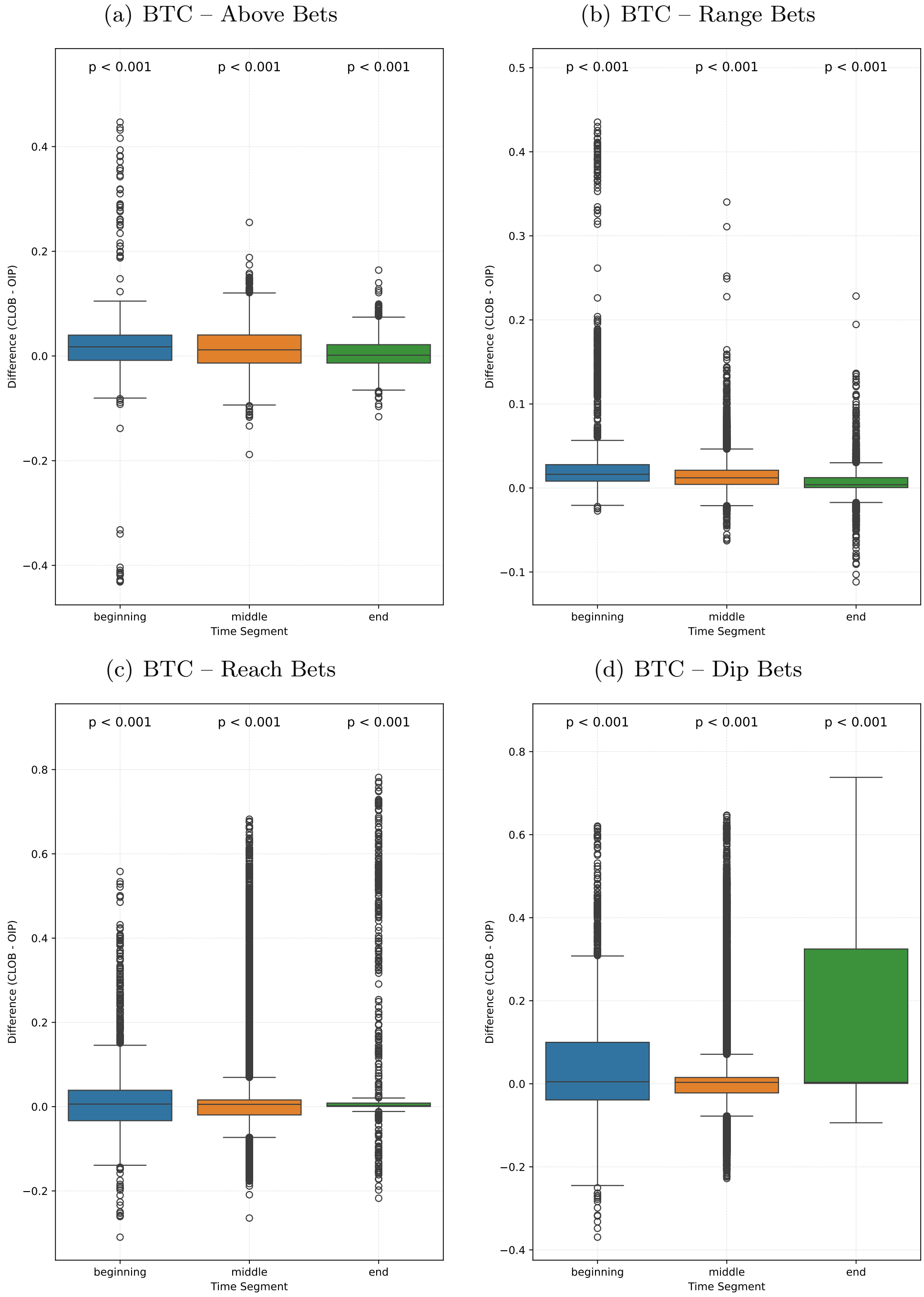


Figure 5.6: Box Plots – Difference (CLOB - OIP) per Betting Type and Time Segment. The figure displays the box plots for the respective events of each betting type (Panel(a)-Panel(d)), split across three-sized temporal segments: beginning (first day of the bet's release), middle, and end (last day of the bet). Each bar represents the mean difference between the CLOB and OIP for a given event and time segment. The different types of bets are discussed in Section 3.1. The data ranges from March 2024 to May 2025.

(a) BTC – Above Bets

Segment	Mean	p-value	Obs.
Beginning	0.0187	0.0000	1426
Middle	0.0146	0.0000	7167
End	0.0041	0.0000	1426

(b) BTC – Range Bets

Segment	Mean	p-value	Obs.
Beginning	0.0413	0.0000	1840
Middle	0.0147	0.0000	8686
End	0.0068	0.0000	1840

(c) BTC – Reach Bets

Segment	Mean	p-value	Obs.
Beginning	0.0530	0.0000	1633
Middle	0.0129	0.0000	41782
End	0.1448	0.0000	1633

(d) BTC – Dip Bets

Segment	Mean	p-value	Obs.
Beginning	0.0286	0.0000	966
Middle	0.0098	0.0000	27043
End	0.0884	0.0000	966

Table 5.2: Summary Statistics: Difference (CLOB - OIP) per Betting Type and Time Segment. Panels (a) to (d) display the average return (Mean), p-value, and number of observations (n obs) by time segment — beginning, middle, and end — for the four bet types: Above, Range, Reach, and Dip. See Section 3.1 for more details. The data ranges from March 2024 to May 2025.

	Mean				Obs.	
Bet Type	Weekday	Weekend	Diff	p-value	Weekday	Weekend
Above	0.0117	0.0184	0.0067	0.0000	7014	3005
Range	0.0174	0.0177	0.0003	0.6657	8686	3680
Reach	0.0162	0.0264	0.0101	0.0000	32024	13024
Dip	0.0109	0.0184	0.0074	0.0000	20607	8368
All	0.0143	0.0220	0.0077	0.0000	68331	28077

Table 5.3: Bets – Weekend Analysis. This table reports the average difference (CLOB-OIP) by bet type and by weekday or weekend. Differences (Diff) are computed as Weekend minus Weekday averages.

difference in the underlying from Binance and Deribit, NBP, sentiment (Fear & Greed), and announcement (Announcement).[3]

Table 5.4 analyzes the explanatory variables, revealing strong interlinkages between risk and volatility measures. In particular, BTC's 30-day volatility correlates strongly with VIX_{BTC} ($\rho = 0.535$) and USDC volatility ($\rho = 0.498$). L2 Risk aligns with Diff. Underlying ($\rho = 0.466$) and VIX_{BTC} ($\rho = 0.383$), indicating unified risk transmission across markets. The Fear

[3] Figure A.1 presents the main explanatory variables used in the panel regressions. Panel (a) plots BTC's hourly percentage change and 30-day rolling volatility, showing pronounced return fluctuations alongside periods of elevated volatility. Panel (b) shows the corresponding measures for USDC. As expected for a stablecoin, the return series is tightly centered around zero, but short volatility bursts are visible during peg stress episodes. Panel (c) shows the L2 Risk, constructed from Polygon block-level data. The measure varies substantially over time, with clear spikes that coincide with periods of congestion and higher on-chain activity.

& Greed Index aligns with volatility and risk metrics (ρ = 0.285–0.296). Conversely, short-term returns (Δ BTC and Δ USDC) exhibit near-zero correlations ($|\rho| < 0.1$) with all risk measures, suggesting price movements operate independently of contemporaneous volatility and risk conditions.

	BTC Vol_{30}	USDC Vol_{30}	VIX_{BTC}	L2 Risk	Diff Underlying	NBP	Fear & Greed	Announcement	Δ BTC (%)	Δ USDC (%)
BTC Vol_{30}	1.000	0.498	0.535	0.220	0.307	-0.094	-0.190	0.049	-0.002	0.001
USDC Vol_{30}	0.498	1.000	0.332	0.143	0.225	-0.032	0.093	-0.061	0.005	0.005
VIX_{BTC}	0.535	0.332	1.000	0.383	0.178	-0.017	0.285	-0.014	0.007	-0.002
L2 Risk	0.220	0.143	0.383	1.000	0.466	0.013	0.296	-0.028	0.003	-0.000
Diff Underlying	0.307	0.225	0.178	0.466	1.000	-0.064	0.199	-0.006	0.014	-0.000
NBP	-0.094	-0.032	-0.017	0.013	-0.064	1.000	0.001	-0.035	-0.024	0.007
Fear & Greed	-0.190	0.093	0.285	0.296	0.199	0.001	1.000	-0.056	-0.009	-0.001
Announcement	0.049	-0.061	-0.014	-0.028	-0.006	-0.035	-0.056	1.000	0.011	0.000
Δ BTC (%)	-0.002	0.005	0.007	0.003	0.014	-0.024	-0.009	0.011	1.000	0.080
Δ USDC (%)	0.001	0.005	-0.002	-0.000	-0.000	0.007	-0.001	0.000	0.080	1.000

Table 5.4: Regressors – Correlation Matrix. This table reports the unconditional correlation between the explanatory variables: BTC returns, USDC returns, BTC volatility, USDC volatility, and additional market structure variables: L2 Risk, Diff Underlying, NBP, Fear & Greed, and . The construction of the variables is explained in Section 4. The data ranges from March 2024 to May 2025.

Table 5.5 reports pooled OLS regressions of the price difference between Polymarket and Deribit (CLOB-OIP) on returns, volatility, blockchain risks, and market structure variables. We also include a *Weekend* indicator, which is one if the observation is recorded during a weekend and zero otherwise. Overall, the differences increase in moneyness (closer to ATM) and when the bet tends towards resolution. BTC and USDC volatilities load negatively and significantly, indicating that higher underlying volatility is associated with lower cross-market spreads. L2 Risk yields a strong positive and highly significant effect. The positive coefficient on Diff Underlying suggests that greater price dispersion between Binance and Deribit widens CLOB–OIP differences, indicating that spot market fragmentation spills over into prediction market pricing. Misaligned BTC prices across venues hinder arbitrage between CLOB and OIP platforms, allowing mispricing to persist. The NBP coefficient suggests that when buy volume outweighs sell volume, the Polymarket–Deribit spread widens, reflecting temporary dislocations driven by order-flow imbalances. These results highlight that structural factors (contract heterogeneity) and microstructure frictions (order-flow imbalances) jointly account for a substantial portion of the observed cross-market price differences. The coefficient on the weekend indicator is significantly positive, consistent with our previous results (Table 5.3). The same pattern holds for the Announcement indicator, which captures periods of pronounced market divergence that often coincide with major geopolitical or macroeconomic developments. As expected in high-frequency panel regressions, the adjusted R^2 values remain low. For returns and volatility, several coefficients behave as expected, while others deviate from the anticipated sensitivities to underlying price movements and volatility. In what follows, we analyze the regression framework separately for each type of bet.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Moneyness	0.037***								
	(0.004)								
Maturity	-0.143***								
	(0.004)								
BTC Vol_{30}		-0.081***							
		(0.004)							
USDC Vol_{30}			-0.025***						
			(0.003)						
$\mathrm{VIX}_{\mathrm{BTC}}$				-0.024***					
				(0.004)					
L2 Risk					0.027***				
					(0.004)				
Diff Underlying						0.023***			
						(0.004)			
NBP							-0.004	-0.004	
							(0.007)	(0.007)	
Fear & Greed								-0.064***	
								(0.009)	
Announcement									0.012***
									(0.004)
Δ BTC (%)	0.008*	0.007*	0.008**	0.008**	0.008*	0.007*	0.010	0.010	0.007*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.008)	(0.008)	(0.004)
Δ USDC (%)	0.001	0.001	0.001	0.001	0.001	0.001	-0.000	-0.001	0.001
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.005)	(0.005)	(0.004)
Weekend	0.042***	0.038***	0.040***	0.039***	0.039***	0.040***	0.150***	0.152***	0.043***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.012)	(0.012)	(0.004)
R^2 Adj	0.025	0.008	0.002	0.002	0.002	0.002	0.022	0.026	0.002
Obs.	96,408	96,408	96,408	96,382	96,408	96,408	17,950	17,950	96,408

Table 5.5: Panel Regression – All Bets – CLOB-OIP. This table reports the results from a pooled OLS panel regression of the price difference between CLOB and OIP for all bets on Moneyness, Maturity, BTC volatility, USDC volatility, and additional market structure variables: L2 Risk, Diff Underlying, NBP, and Fear & Greed. We include BTC returns, USDC returns, and a Weekend dummy as controls. The construction of the variables is explained in Section 4. The data ranges from March 2024 to May 2025. Standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All data is standardized to have a zero mean and unit root.

Table 5.6 repeats the panel regression for Above bets. Moneyness and maturity display negative coefficients, meaning that the difference increases for OTM bets and over time. BTC returns show consistently positive effects (coefficients around 0.03, $p < 0.05$). This suggests a potential overreaction in the prediction market relative to the options market. The significant positive coefficient implies that Polymarket prices increase more sharply in response to positive BTC returns than comparable options prices on Deribit. The volatility measures significantly explain variation in these differentials as well: USDC 30-day volatility (0.169, $p < 0.01$), Bitcoin VIX (0.169, $p < 0.01$). This positive relationship suggests that periods of higher volatility are associated with a larger pricing discrepancy for above bets. The positive coefficient on L2 Risk (0.134, $p < 0.01$) indicates that concerns over blockchain-specific risks, such as network congestion, smart contract vulnerabilities, or bridging security, are priced into Polymarket bets. Announcement loads positively on the difference (0.021, $p < 0.05$).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Moneyness	-0.425***								
	(0.012)								
Maturity	-0.023***								
	(0.008)								
BTC Vol_{30}		-0.007							
		(0.010)							
USDC Vol_{30}			0.169***						
			(0.010)						
VIX_{BTC}				0.169***					
				(0.015)					
L2 Risk					0.134***				
					(0.017)				
Diff Underlying						0.188***			
						(0.009)			
NBP							0.014	0.014	
							(0.017)	(0.017)	
Fear & Greed								-0.002	
								(0.017)	
Announcement									0.021**
									(0.010)
Δ BTC (%)	0.019	0.031**	0.030**	0.029**	0.032**	0.029**	-0.011	-0.011	0.031**
	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.018)	(0.018)	(0.014)
Δ USDC (%)	0.003	0.006	0.005	0.007	0.006	0.006	0.010	0.010	0.006
	(0.023)	(0.024)	(0.023)	(0.024)	(0.024)	(0.022)	(0.015)	(0.015)	(0.024)
Weekend	0.072***	0.071***	0.073***	0.080***	0.067***	0.068***	0.075***	0.075***	0.075***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.016)	(0.016)	(0.011)
R^2 Adj	0.184	0.006	0.034	0.034	0.024	0.041	0.005	0.005	0.006
Obs.	10,019	10,019	10,019	10,016	10,019	10,019	3,180	3,180	10,019

Table 5.6: Panel Regression – Above Bets – CLOB-OIP. This table reports the results from a pooled OLS panel regression of the price difference between CLOB and OIP for the above bets on Moneyness, Maturity, BTC volatility, USDC volatility, and additional market structure variables: L2 Risk, Diff Underlying, NBP, Fear & Greed, and Announcement. We include BTC returns, USDC returns, and a Weekend dummy as controls. The construction of the variables is explained in Section 4. The data ranges from March 2024 to May 2025. Standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All data is standardized to have a zero mean and unit root.

Table 5.7 repeats the panel regression for the Range bets. The difference rises with moneyness and maturity, hence for ATM bets, and decreases over time. Bitcoin and USDC returns show no significance. USDC 30-day volatility exhibits a large and highly significant positive effect (coefficient 0.105, $p < 0.01$), indicating that stablecoin volatility substantially widens mispricing. L2 Risk measures also show statistically significant positive relationships as before. Announcement loads positively on the difference (0.050, $p < 0.01$).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Moneyness	0.056***								
	(0.006)								
Maturity	0.481***								
	(0.050)								
BTC Vol_{30}		0.010							
		(0.018)							
USDC Vol_{30}			0.105***						
			(0.017)						
VIX_{BTC}				0.010					
				(0.015)					
L2 Risk					0.123***				
					(0.015)				
Diff Underlying						0.014			
						(0.016)			
NBP							0.007	0.007	
							(0.015)	(0.015)	
Fear & Greed								-0.009	
								(0.011)	
Announcement									-0.050***
									(0.016)
Δ BTC (%)	-0.012	-0.012	-0.010	-0.012	-0.011	-0.012	-0.012	-0.012	-0.010
	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.012)	(0.012)	(0.015)
Δ USDC (%)	0.009	0.010	0.011	0.010	0.011	0.010	0.005	0.005	0.010
	(0.012)	(0.013)	(0.014)	(0.013)	(0.013)	(0.013)	(0.011)	(0.011)	(0.013)
Weekend	-0.308***	0.004	0.009	0.004	-0.000	0.003	0.092***	0.093***	-0.008
	(0.041)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.015)	(0.015)	(0.015)
R^2 Adj	0.151	0.000	0.011	0.000	0.015	0.000	0.008	0.008	0.002
Obs.	12,366	12,366	12,366	12,361	12,366	12,366	4,483	4,483	12,366

Table 5.7: Panel Regression – Range Bets – CLOB-OIP. This table reports the results from a pooled OLS panel regression of the price difference between CLOB and OIP for the range bets on Moneyness, Maturity, BTC volatility, USDC volatility, and additional market structure variables: L2 Risk, Diff Underlying, NBP, Fear & Greed, and Announcement. We include BTC returns, USDC returns, and a Weekend dummy as controls. The construction of the variables is explained in Section 4. The data ranges from March 2024 to May 2025. Standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All data is standardized to have a zero mean and unit root.

Table 5.8 examines Reach bets. The positive loading on moneyness and negative loading on maturity suggest that the difference is greater for ATM bets and increases as the bet approaches its resolution date. Similar to the Above bets, Bitcoin returns demonstrate strong positive effects (significant coefficients rising from 0.025 to 0.056 across specifications), indicating that positive BTC returns substantially widen CLOB-OIP. Conversely, volatility measures exhibit consistently negative and highly significant coefficients—BTC volatility (-0.176, $p < 0.01$), USDC volatility (-0.015, $p < 0.01$), and BTC VIX (-0.066, $p < 0.01$)—indicating that higher volatility reduces pricing discrepancies. This pattern implies that during calmer, euphoric market phases characterized by low volatility, prediction markets tend to overreact and overprice bullish contracts. NBP exhibits a positive effect (0.062, $p < 0.01$). The same is true for Announcement (0.026, $p < 0.01$).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Moneyness	0.189***								
	(0.006)								
Maturity	-0.126***								
	(0.005)								
BTC Vol_{30}		-0.176***							
		(0.007)							
USDC Vol_{30}			-0.015***						
			(0.005)						
VIX_{BTC}				-0.066***					
				(0.007)					
L2 Risk					-0.004				
					(0.007)				
Diff Underlying						-0.011*			
						(0.006)			
NBP							0.062***	0.066***	
							(0.012)	(0.012)	
Fear & Greed								-0.052***	
								(0.014)	
Announcement									0.026***
									(0.007)
Δ BTC (%)	0.025***	0.024***	0.025***	0.025***	0.025***	0.025***	0.055***	0.056***	0.024***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.015)	(0.015)	(0.006)
Δ USDC (%)	0.001	0.000	0.000	0.000	0.000	0.000	-0.005	-0.006	0.000
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)	(0.006)	(0.004)
Weekend	0.044***	0.039***	0.046***	0.044***	0.047***	0.047***	0.152***	0.151***	0.052***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.018)	(0.018)	(0.007)
R^2 Adj	0.062	0.034	0.003	0.007	0.003	0.003	0.030	0.032	0.003
Obs.	45,048	45,048	45,048	45,039	45,048	45,048	5,815	5,815	45,048

Table 5.8: Panel Regression – Reach Bets – CLOB-OIP. This table reports the results from a pooled OLS panel regression of the price difference between CLOB and OIP for the reach bets on Moneyness, Maturity, BTC volatility, USDC volatility, and additional market structure variables: L2 Risk, Diff Underlying, NBP, Fear & Greed, and Announcement. We include BTC returns, USDC returns, and a Weekend dummy as controls. The construction of the variables is explained in Section 4. The data ranges from March 2024 to May 2025. Standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All data is standardized to have a zero mean and unit root.

Table 5.9 examines Dip bets. The difference increases for ATM bets and when approaching the resolution. The significant negative coefficient (coefficients ranging from -0.021 to -0.046) on BTC returns confirms that rising prices rationally reduce the value and mispricing of these bearish bets. Conversely, the positive coefficients for BTC volatility $(0.011, p < 0.05)$ indicate that market turbulence increases mispricing for these contracts, as uncertainty and fear amplify the premium participants are willing to pay for downside protection on prediction markets relative to options. The differential between underlying assets shows a large positive effect $(0.050, p < 0.01)$, indicating fundamental market discrepancies contribute significantly to Dip bet mispricing. Fear & Greed exhibits a significant negative relationship ($-0.303, p < 0.01$), which indicates that fear sentiment (negative index values) significantly increases mispricing, as panicked investors on prediction markets bid up the price of downside protection more aggressively than traders in the options market, likely due to a stronger behavioral bias toward loss aversion and disaster hedging. This highlights how retail-driven prediction markets amplify mispricing for insurance-like products during stress periods. NBP shows no significant effect.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Moneyness	0.027***								
	(0.007)								
Maturity	-0.211***								
	(0.007)								
BTC Vol_{30}		0.011***							
		(0.004)							
USDC Vol_{30}			-0.095***						
			(0.005)						
VIX_{BTC}				-0.001					
				(0.005)					
L2 Risk					0.049***				
					(0.007)				
Diff Underlying						0.050***			
						(0.005)			
NBP							-0.029**	-0.020	
							(0.014)	(0.014)	
Fear & Greed								-0.303***	
								(0.022)	
Announcement									-0.003
									(0.005)
Δ BTC (%)	-0.021***	-0.022***	-0.021***	-0.022***	-0.021***	-0.022***	-0.046**	-0.040**	-0.022***
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.021)	(0.020)	(0.006)
Δ USDC (%)	-0.000	-0.000	0.000	0.000	-0.000	0.000	0.003	0.004	-0.000
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.013)	(0.012)	(0.003)
Weekend	0.041***	0.036***	0.036***	0.036***	0.034***	0.035***	0.127***	0.097***	0.036***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.024)	(0.024)	(0.006)
R^2 Adj	0.047	0.002	0.011	0.002	0.004	0.004	0.018	0.109	0.002
Obs.	28,975	28,975	28,975	28,966	28,975	28,975	4,472	4,472	28,975

Table 5.9: Panel Regression – Dip Bets – CLOB-OIP. This table reports the results from a pooled OLS panel regression of the price difference between CLOB and OIP for the dip bets on Moneyness, Maturity, BTC volatility, USDC volatility, and additional market structure variables: L2 Risk, Diff Underlying, NBP, Fear & Greed, and Announcement. We include BTC returns, USDC returns, and a Weekend dummy as controls. The construction of the variables is explained in Section 4. The data ranges from March 2024 to May 2025. Standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. All data is standardized to have a zero mean and unit root.

Overall, the price differences between Polymarket and Deribit are primarily driven by volatility, blockchain-specific risks, and market structure variables. The influence of returns is confined to specific bet types: positive BTC returns widen mispricing in Above and Reach bets but compress it in Dip bets. Macroeconomic news increases the gap in Above, Range, and Reach bets. Structural factors, including the difference in the underlying and order-flow imbalances, systematically amplify differences, while fear sentiment exacerbates them in downside-protection bets (Dip). The *Weekend* dummy variable exhibits a positive and statistically significant effect on the difference for most bet types, except for the Range bet. These findings highlight that persistent CLOB–OIP mispricing reflects the joint impact of volatility shocks, network-level risks, frictions in market microstructure, and macroeconomic news.

6 Conclusion

This paper evaluates pricing efficiency in decentralized prediction markets by comparing market-implied probabilities from Polymarket with benchmark prices derived from option-implied risk-neutral distributions. Focusing on BTC-related bets across four distinct bet structures, *Above*, *Range*, *Reach*, and *Dip*, we document several consistent patterns in price behavior.

We find that prices from Polymarket's *CLOB* generally align well with benchmark-implied probabilities, especially for simpler directional bets. Deviations are most pronounced at the beginning of the bet's lifecycle and during weekends. In contrast, more complex bets display persistent overpricing, pointing to behavioral biases such as probability overweighting and over-attention.

Our findings suggest that while decentralized prediction markets are broadly efficient, their structure and user behavior generates systematic frictions. These insights contribute to a deeper understanding of market integration, belief formation, and the boundaries of informational efficiency in emerging decentralized financial ecosystems.

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Appendix A Additional Figures

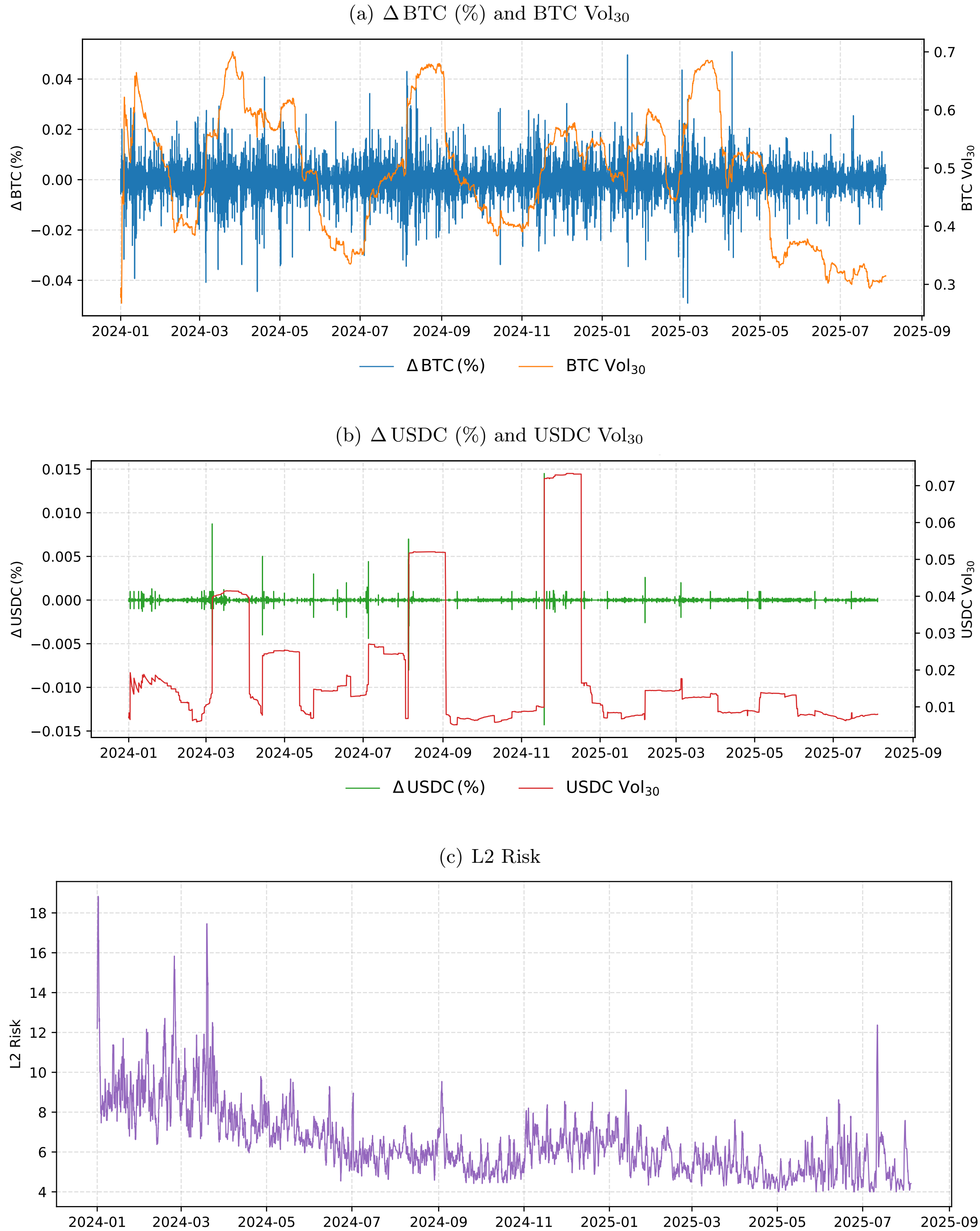

Figure A.1: BTC, USDC, and L2 Risk. The figure displays the percentage change (left-axis) and the 30-day rolling volatility (right axis) of BTC (Panel (a)) and USDC (Panel (b)). Panel (c) plots the L2 Risk as described in Section 4.3. The BTC and the USDC data are obtained from CryptoCompare, while the block information for Polygon is obtained through TheGraph. The data is resampled to an hourly frequency and ranges from March 2024 to June 2025.

Internet Appendix

I Additional Tables

Event ID	Description	Start Date	End Date	Event ID	Description	Start Date	End Date
500215	BTC above 70000	2024-03-17	2024-03-22	510109	BTC above 69000	2024-10-18	2024-10-25
500402	BTC above 65000	2024-03-22	2024-03-29	510922	BTC above 68000	2024-10-25	2024-11-01
500561	BTC above 70000	2024-03-29	2024-04-05	511629	BTC above 70000	2024-11-01	2024-11-08
500763	BTC above 70000	2024-04-05	2024-04-13	512396	BTC above 76000	2024-11-08	2024-11-15
500941	BTC above 60000	2024-04-13	2024-04-19	513136	BTC above 90000	2024-11-15	2024-11-22
501020	BTC above 60000	2024-04-17	2024-04-30	513709	BTC above 100000	2024-11-22	2024-11-29
501264	BTC above 60000	2024-04-30	2024-05-10	514215	BTC above 98000	2024-11-29	2024-12-06
501530	BTC above 60000	2024-05-10	2024-05-17	514949	BTC above 100000	2024-12-06	2024-12-13
501657	BTC above 65000	2024-05-17	2024-05-24	515539	BTC above 100000	2024-12-13	2024-12-20
501807	BTC above 68000	2024-05-24	2024-05-31	516117	BTC above 97000	2024-12-20	2024-12-27
501918	BTC above 69000	2024-05-31	2024-06-07	516498	BTC above 94000	2024-12-27	2025-01-03
502216	BTC above 71000	2024-06-07	2024-06-14	517192	BTC above 97000	2025-01-03	2025-01-10
502460	BTC above 65000	2024-06-14	2024-06-21	518179	BTC above 95000	2025-01-10	2025-01-17
502743	BTC above 65000	2024-06-21	2024-06-28	519027	BTC above 103000	2025-01-17	2025-01-24
502963	BTC above 61000	2024-06-28	2024-07-05	519870	BTC above 105000	2025-01-24	2025-01-31
503224	BTC above 57000	2024-07-05	2024-07-12	521147	BTC above 105000	2025-01-31	2025-02-07
503416	BTC above 58000	2024-07-12	2024-07-19	522036	BTC above 97000	2025-02-06	2025-02-14
503863	BTC above 65000	2024-07-19	2024-07-26	523483	BTC above 97000	2025-02-14	2025-02-21
504209	BTC above 68000	2024-07-26	2024-08-02	524430	BTC above 99000	2025-02-21	2025-02-28
504477	BTC above 65000	2024-08-02	2024-08-09	526067	BTC above 84000	2025-02-28	2025-03-07
504801	BTC above 60000	2024-08-09	2024-08-16	527168	BTC above 89000	2025-03-07	2025-03-14
505205	BTC above 60000	2024-08-16	2024-08-23	528099	BTC above 83000	2025-03-14	2025-03-21
505716	BTC above 60000	2024-08-23	2024-08-30	529560	BTC above 84000	2025-03-21	2025-03-28
506137	BTC above 60000	2024-08-30	2024-09-06	531914	BTC above 86000	2025-03-28	2025-04-04
506360	BTC above 60000	2024-09-05	2024-10-01	534173	BTC above 84000	2025-04-04	2025-04-11
506492	BTC above 55000	2024-09-06	2024-09-13	536386	BTC above 82000	2025-04-11	2025-04-18
506969	BTC above 60000	2024-09-13	2024-09-20	538208	BTC above 85000	2025-04-18	2025-04-25
507565	BTC above 63000	2024-09-20	2024-09-27	539589	BTC above 94000	2025-04-25	2025-05-02
508302	BTC above 65000	2024-09-27	2024-10-04	540878	BTC above 97000	2025-05-02	2025-05-09
508884	BTC above 62000	2024-10-04	2024-10-11	545969	BTC above 106000	2025-05-20	2025-05-27
509603	BTC above 62000	2024-10-11	2024-10-18	546856	BTC above 113000	2025-05-23	2025-05-30

Table I.1: BTC Above Bets. The table lists all the Above bets, along with their Event IDs and brief descriptions of each bet's content. The different types of bets are discussed in Section 3.1.

Event ID	Description	Start Date	End Date	Event ID	Description	Start Date	End Date
522067	BTC b/w 92000 and 94000	2025-02-07	2025-02-14	534183	BTC b/w 78000 and 80000	2025-04-04	2025-04-11
522068	BTC b/w 94000 and 96000	2025-02-07	2025-02-14	536392	BTC b/w 84000 and 86000	2025-04-11	2025-04-18
522069	BTC b/w 96000 and 98000	2025-02-07	2025-02-14	536393	BTC b/w 82000 and 84000	2025-04-11	2025-04-18
522070	BTC b/w 98000 and 100000	2025-02-07	2025-02-14	536394	BTC b/w 80000 and 82000	2025-04-11	2025-04-18
522071	BTC b/w 100000 and 102000	2025-02-07	2025-02-14	536395	BTC b/w 78000 and 80000	2025-04-11	2025-04-18
522072	BTC b/w 102000 and 104000	2025-02-07	2025-02-14	536396	BTC b/w 76000 and 78000	2025-04-11	2025-04-18
524436	BTC b/w 93000 and 95000	2025-02-21	2025-02-28	538193	BTC b/w 87000 and 89000	2025-04-18	2025-04-25
524437	BTC b/w 95000 and 97000	2025-02-21	2025-02-28	538194	BTC b/w 85000 and 87000	2025-04-18	2025-04-25
524438	BTC b/w 97000 and 99000	2025-02-21	2025-02-28	538195	BTC b/w 83000 and 85000	2025-04-18	2025-04-25
524439	BTC b/w 99000 and 101000	2025-02-21	2025-02-28	538196	BTC b/w 81000 and 83000	2025-04-18	2025-04-25
524440	BTC b/w 101000 and 103000	2025-02-21	2025-02-28	538197	BTC b/w 79000 and 81000	2025-04-18	2025-04-25
526089	BTC b/w 78000 and 80000	2025-02-28	2025-03-07	539595	BTC b/w 96000 and 98000	2025-04-25	2025-05-02
526090	BTC b/w 80000 and 82000	2025-02-28	2025-03-07	539596	BTC b/w 94000 and 96000	2025-04-25	2025-05-02
526091	BTC b/w 82000 and 84000	2025-02-28	2025-03-07	539597	BTC b/w 92000 and 94000	2025-04-25	2025-05-02
526092	BTC b/w 84000 and 86000	2025-02-28	2025-03-07	539598	BTC b/w 90000 and 92000	2025-04-25	2025-05-02
526093	BTC b/w 86000 and 88000	2025-02-28	2025-03-07	539599	BTC b/w 88000 and 90000	2025-04-25	2025-05-02
527174	BTC b/w 83000 and 85000	2025-03-07	2025-03-14	540858	BTC b/w 93000 and 95000	2025-05-02	2025-05-09
527175	BTC b/w 85000 and 87000	2025-03-07	2025-03-14	540859	BTC b/w 95000 and 97000	2025-05-02	2025-05-09
527176	BTC b/w 87000 and 89000	2025-03-07	2025-03-14	540860	BTC b/w 97000 and 99000	2025-05-02	2025-05-09
527177	BTC b/w 89000 and 91000	2025-03-07	2025-03-14	540861	BTC b/w 99000 and 101000	2025-05-02	2025-05-09
527178	BTC b/w 91000 and 93000	2025-03-07	2025-03-14	540862	BTC b/w 101000 and 103000	2025-05-02	2025-05-09
528093	BTC b/w 85000 and 87000	2025-03-14	2025-03-21	543113	BTC b/w 108000 and 110000	2025-05-09	2025-05-16
528094	BTC b/w 83000 and 85000	2025-03-14	2025-03-21	543114	BTC b/w 106000 and 108000	2025-05-09	2025-05-16
528095	BTC b/w 81000 and 83000	2025-03-14	2025-03-21	543115	BTC b/w 104000 and 106000	2025-05-09	2025-05-16
528096	BTC b/w 79000 and 81000	2025-03-14	2025-03-21	543116	BTC b/w 102000 and 104000	2025-05-09	2025-05-16
528097	BTC b/w 77000 and 79000	2025-03-14	2025-03-21	543117	BTC b/w 100000 and 102000	2025-05-09	2025-05-16
529566	BTC b/w 86000 and 88000	2025-03-21	2025-03-28	543118	BTC b/w 98000 and 100000	2025-05-09	2025-05-16
529567	BTC b/w 84000 and 86000	2025-03-21	2025-03-28	545210	BTC b/w 100000 and 101000	2025-05-16	2025-05-23
529568	BTC b/w 82000 and 84000	2025-03-21	2025-03-28	545211	BTC b/w 101000 and 102000	2025-05-16	2025-05-23
529569	BTC b/w 80000 and 82000	2025-03-21	2025-03-28	545212	BTC b/w 102000 and 103000	2025-05-16	2025-05-23
529570	BTC b/w 78000 and 80000	2025-03-21	2025-03-28	545213	BTC b/w 103000 and 104000	2025-05-16	2025-05-23
531922	BTC b/w 88000 and 90000	2025-03-28	2025-04-04	545214	BTC b/w 104000 and 105000	2025-05-16	2025-05-23
531923	BTC b/w 86000 and 88000	2025-03-28	2025-04-04	545215	BTC b/w 105000 and 106000	2025-05-16	2025-05-23
531924	BTC b/w 84000 and 86000	2025-03-28	2025-04-04	545959	BTC b/w 101000 and 103000	2025-05-20	2025-05-27
531925	BTC b/w 82000 and 84000	2025-03-28	2025-04-04	545960	BTC b/w 103000 and 105000	2025-05-20	2025-05-27
531926	BTC b/w 80000 and 82000	2025-03-28	2025-04-04	545961	BTC b/w 105000 and 107000	2025-05-20	2025-05-27
534179	BTC b/w 86000 and 88000	2025-04-04	2025-04-11	546901	BTC b/w 106000 and 108000	2025-05-23	2025-05-30
534180	BTC b/w 84000 and 86000	2025-04-04	2025-04-11	546902	BTC b/w 108000 and 110000	2025-05-23	2025-05-30
534181	BTC b/w 82000 and 84000	2025-04-04	2025-04-11	546903	BTC b/w 110000 and 112000	2025-05-23	2025-05-30
534182	BTC b/w 80000 and 82000	2025-04-04	2025-04-11	546904	BTC b/w 112000 and 114000	2025-05-23	2025-05-30

Table I.2: BTC Range Bets. The table lists all the Range bets, along with their Event IDs and brief descriptions of each bet's content. The different types of bets are discussed in Section 3.1.

Event ID	Description	Start Date	End Date
500566	BTC reach 80000	2024-04-02	2024-05-01
500567	BTC reach 90000	2024-04-02	2024-05-01
500568	BTC reach 100000	2024-04-02	2024-05-01
500624	BTC reach 75000	2024-04-02	2024-05-01
501274	BTC reach 65000	2024-04-30	2024-05-06
501275	BTC reach 70000	2024-04-30	2024-05-20
501276	BTC reach 75000	2024-04-30	2024-06-01
501277	BTC reach 80000	2024-04-30	2024-06-01
501976	BTC reach 70000	2024-05-31	2024-06-04
501977	BTC reach 75000	2024-05-31	2024-06-30
501978	BTC reach 80000	2024-05-31	2024-06-30
504591	BTC reach 65000	2024-08-06	2024-08-25
508609	BTC reach 70000	2024-10-01	2024-10-29
508610	BTC reach 67000	2024-10-01	2024-10-15
508611	BTC reach 65000	2024-10-01	2024-10-14
511521	BTC reach 72000	2024-11-01	2024-11-06
511522	BTC reach 75000	2024-11-01	2024-11-06
511523	BTC reach 77000	2024-11-01	2024-11-10
511524	BTC reach 80000	2024-11-01	2024-11-10
511581	BTC reach 85000	2024-11-01	2024-11-11
511582	BTC reach 90000	2024-11-01	2024-11-13
512254	BTC reach 82000	2024-11-07	2024-11-11
512255	BTC reach 87000	2024-11-07	2024-11-11
512649	BTC reach 95000	2024-11-11	2024-11-21
512662	BTC reach 105000	2024-11-11	2024-12-02
512963	BTC reach 110000	2024-11-13	2024-12-02
512964	BTC reach 120000	2024-11-13	2024-12-02
512965	BTC reach 130000	2024-11-13	2024-12-02
512966	BTC reach 140000	2024-11-13	2024-12-02
512967	BTC reach 150000	2024-11-13	2024-12-02
514367	BTC reach 105000	2024-12-02	2024-12-16
514368	BTC reach 110000	2024-12-02	2025-01-01
514369	BTC reach 120000	2024-12-02	2025-01-01
514370	BTC reach 130000	2024-12-02	2025-01-01
515502	BTC reach 200000	2024-12-13	2025-04-01
515503	BTC reach 150000	2024-12-13	2025-04-01
515504	BTC reach 130000	2024-12-13	2025-04-01
515505	BTC reach 120000	2024-12-13	2025-04-01
515506	BTC reach 110000	2024-12-13	2025-04-01
517077	BTC reach 200000	2025-01-02	2025-02-01
517078	BTC reach 150000	2025-01-02	2025-02-01
517079	BTC reach 140000	2025-01-02	2025-02-01
517080	BTC reach 130000	2025-01-02	2025-02-01
517081	BTC reach 120000	2025-01-02	2025-02-01
517082	BTC reach 110000	2025-01-02	2025-02-01
517083	BTC reach 105000	2025-01-02	2025-01-17
517084	BTC reach 100000	2025-01-02	2025-01-06
521155	BTC reach 200000	2025-01-31	2025-03-01
521156	BTC reach 150000	2025-01-31	2025-03-01
521157	BTC reach 140000	2025-01-31	2025-03-01
521158	BTC reach 130000	2025-01-31	2025-03-01
521159	BTC reach 120000	2025-01-31	2025-03-01
521160	BTC reach 115000	2025-01-31	2025-03-01
521161	BTC reach 110000	2025-01-31	2025-03-01
526657	BTC reach 95000	2025-03-03	2025-04-01
526658	BTC reach 100000	2025-03-03	2025-04-01
526659	BTC reach 105000	2025-03-03	2025-04-01
532803	BTC reach 200000	2025-04-01	2025-05-01
532804	BTC reach 150000	2025-04-01	2025-05-01
532805	BTC reach 120000	2025-04-01	2025-05-01
532806	BTC reach 110000	2025-04-01	2025-05-01
532807	BTC reach 100000	2025-04-01	2025-05-01
532808	BTC reach 95000	2025-04-01	2025-04-25
532809	BTC reach 90000	2025-04-01	2025-04-22
540401	BTC reach 200000	2025-04-30	2025-05-31
540402	BTC reach 150000	2025-04-30	2025-05-31
540403	BTC reach 125000	2025-04-30	2025-05-31
540404	BTC reach 115000	2025-04-30	2025-05-31
540405	BTC reach 110000	2025-04-30	2025-05-22
540406	BTC reach 105000	2025-04-30	2025-05-12
540407	BTC reach 100000	2025-04-30	2025-05-08

Table I.3: BTC Reach Bets. The table lists all the Reach bets, along with their Event IDs and brief descriptions of each bet's content. The different types of bets are discussed in Section 3.1.

Event ID	Description	Start Date	End Date
501184	BTC dip 60000	2024-04-25	2024-05-01
501185	BTC dip 55000	2024-04-25	2024-06-01
501186	BTC dip 50000	2024-04-25	2024-06-01
501187	BTC dip 45000	2024-04-25	2024-06-01
508613	BTC dip 57000	2024-10-01	2024-11-01
508616	BTC dip 55000	2024-10-01	2024-11-01
508621	BTC dip 52000	2024-10-01	2024-11-01
511526	BTC dip 65000	2024-11-01	2024-12-02
511528	BTC dip 60000	2024-11-01	2024-12-02
514371	BTC dip 90000	2024-12-02	2025-01-01
514372	BTC dip 85000	2024-12-02	2025-01-01
515548	BTC dip 90000	2024-12-13	2025-01-13
515554	BTC dip 80000	2024-12-13	2025-02-28
515557	BTC dip 70000	2024-12-13	2025-04-01
517085	BTC dip 90000	2025-01-02	2025-01-13
517086	BTC dip 85000	2025-01-02	2025-02-01
517087	BTC dip 80000	2025-01-02	2025-02-01
517088	BTC dip 70000	2025-01-02	2025-02-01
517089	BTC dip 60000	2025-01-02	2025-02-01
517090	BTC dip 50000	2025-01-02	2025-02-01
521164	BTC dip 90000	2025-01-31	2025-02-25
521165	BTC dip 85000	2025-01-31	2025-02-26
521166	BTC dip 75000	2025-01-31	2025-03-01
521167	BTC dip 60000	2025-01-31	2025-03-01
526179	BTC dip 75000	2025-02-28	2025-04-01
526180	BTC dip 60000	2025-02-28	2025-04-01
526181	BTC dip 50000	2025-02-28	2025-04-01
526182	BTC dip 40000	2025-02-28	2025-04-01
526655	BTC dip 80000	2025-03-03	2025-03-10
532810	BTC dip 80000	2025-04-01	2025-04-06
532811	BTC dip 75000	2025-04-01	2025-04-07
532812	BTC dip 70000	2025-04-01	2025-05-01
532813	BTC dip 60000	2025-04-01	2025-05-01
532814	BTC dip 50000	2025-04-01	2025-05-01
532815	BTC dip 40000	2025-04-01	2025-05-01
540408	BTC dip 90000	2025-04-30	2025-05-31
540409	BTC dip 85000	2025-04-30	2025-05-31
540410	BTC dip 80000	2025-04-30	2025-05-31
540411	BTC dip 75000	2025-04-30	2025-05-31
540412	BTC dip 70000	2025-04-30	2025-05-31
540413	BTC dip 60000	2025-04-30	2025-05-31
540414	BTC dip 50000	2025-04-30	2025-05-31

Table I.4: BTC Dip Bets. The table lists all the Dip bets, along with their Event IDs and brief descriptions of each bet's content. The different types of bets are discussed in Section 3.1.