Episodic Liquidity and Trading Regimes in Prediction Markets

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Abstract

Prediction markets are commonly evaluated by their forecasting accuracy at resolution, yet comparatively little is known about how trading activity and liquidity evolve over a contract's lifecycle. Using high-frequency order book data from Kalshi prediction markets spanning sports, politics, economics, and weather, this paper studies the lifecycle microstructure dynamics through which information is incorporated into prices.

We introduce a rule-based microstructure classification that partitions market activity into frozen, thin, baseline, active information, volatility burst, and resolution drift regimes. Normalizing time by contract lifecycle, we document systematic spread compression and increasing concentration of trading activity as contracts approach resolution. Modeling regime dynamics as a Markov process, we show that prediction markets are frozen by default: inactive states are highly persistent, while information-driven regimes are brief and rapidly revert to inactivity.

Taken together, our findings characterize prediction markets as episodic information-processing mechanisms rather than continuously aggregating markets, highlighting structural frictions that limit sustained price discovery.

1. Introduction

Prediction markets aggregate dispersed beliefs about uncertain future events into prices that are commonly interpreted as probabilistic forecasts. A large literature evaluates these markets by their accuracy at resolution and their ability to reflect available information in equilibrium. Recent high-frequency evidence further demonstrates that prediction market prices can respond sharply to discrete institutional and informational shocks, consistent with rapid belief updating when salient news arrives (Taillard and Zeng, 2025). However, comparatively little is known about how trading activity, liquidity, and price adjustment evolve over the full lifecycle of a contract prior to resolution. In particular, existing work largely abstracts from the temporal structure through which information is incorporated, implicitly treating belief aggregation as a continuous process rather than one potentially constrained by participation, liquidity, and coordination frictions.

Prediction markets differ from traditional financial markets along several fundamental dimensions. Contracts have finite horizons, resolution rules are discrete, and trading activity is highly uneven over time. Liquidity is not continuously supplied; instead, it emerges intermittently in response to information arrival, trader attention, and coordination among market participants, as documented in recent high-frequency evidence from event-based markets (Ng et al., 2025). These features imply that contract lifecycles are more naturally characterized by discrete regime shifts than by smooth, continuous adjustment. Understanding such dynamics is essential for interpreting prices, assessing liquidity provision, and evaluating the practical limits of information aggregation in event-driven markets. In this setting, extended periods of inactivity may simply reflect the absence of price-relevant news rather than market failure or inefficiency.

This paper studies the microstructure of Kalshi prediction markets using high-frequency order book data across multiple event categories (see Appendix B for an illustrative example of the order book interface). We focus on three empirical questions. First, how do spreads, volume, and volatility evolve as contracts progress from listing to resolution? Second, can observed trading behavior be meaningfully segmented into a small number of economically interpretable microstructure states? Third, how persistent are these states, and how do markets transition between them over time?

To address these questions, we introduce a rule-based microstructure state classification framework and normalize time by contract lifecycle to enable comparison across heterogeneous contracts. We document systematic spread compression and increasing concentration of trading activity near resolution, but also show that markets are inactive for most of their lifetimes. Modeling regime dynamics as a Markov process, we find that frozen states are highly persistent, while information-driven regimes are brief and rapidly revert to inactivity.

Taken together, these results characterize prediction markets as episodic information-processing mechanisms rather than continuously aggregating markets.

2. Institutional Setting & Data

2.1 Prediction Market Design

Kalshi is a centralized prediction market platform offering event-based contracts that settle to binary outcomes. Each contract resolves to either $1 or $0, depending on whether a clearly specified event occurs. Contract prices therefore admit a natural probabilistic interpretation under risk neutrality, though this study does not impose assumptions of full informational efficiency or rational expectations.

Contracts span multiple domains, including sports, politics, economics, weather, and culture. Each contract has a fixed resolution time and a publicly defined settlement rule. Trading occurs continuously until resolution, after which the contract settles and trading ceases.

Unlike traditional financial assets, prediction market contracts have finite horizons and do not roll over. Liquidity is therefore endogenous to both the remaining time until resolution and the arrival of event-specific information. As a consequence, trading activity is highly uneven across time and across contracts, with long periods of inactivity punctuated by brief episodes of concentrated trading.

Kalshi operates a continuous limit order book. At any point in time, traders may submit limit orders to buy or sell contracts at specified prices or execute against standing orders. The platform enforces discrete price grids and minimum tick sizes, which introduce mechanical lower bounds on bid–ask spreads and influence observed liquidity, particularly during periods of low trading activity. Appendix B provides an illustrative example of the order book interface.

2.2 Data

We use high-frequency order book data from Kalshi prediction market contracts spanning multiple event categories. The dataset contains time-stamped observations of best bid and ask prices, quoted depth, executed volume, and contract-level metadata. Observations are sampled at regular intraday intervals over each contract's active trading period, from listing until resolution.

The sample includes contracts that fully resolve within the observation window and for which complete order book histories are available. Contracts with missing resolution times, incomplete quote histories, or extremely sparse trading activity are excluded to ensure consistent measurement of microstructure dynamics across lifecycle stages.

The final sample comprises contracts from five categories: sports, politics, economics, weather, and culture, and includes several million order book observations in total. Table 1 reports summary statistics by category, highlighting substantial heterogeneity in trading activity and liquidity across contract types.

Table 1: Summary Statistics by Contract Category

Category	Contracts	Observations	Spread (¢)	Spread (%)	Volume	Volatility	Duration (hrs)
Sports	120	978,543	6.65	14.3	1,577.29	0.00729	88.4
Economics	49	3,382,530	6.82	40.8	85.10	0.00466	1,179.9
Politics	32	3,600,136	1.91	21.0	66.60	0.00272	829.3
Weather	29	337,805	6.63	64.5	69.06	0.03634	38.0
Culture	21	1,255,569	8.78	30.7	12.74	0.00849	1,127.1

Table 1 reports summary statistics by contract category. The sample includes 251 contracts spanning sports, economics, politics, weather, and culture, comprising over 9.5 million order book observations. Trading activity and liquidity conditions vary substantially across categories. Politics contracts account for the largest share of observations, while sports contracts exhibit the highest average trading volume. Economics and culture contracts tend to have much longer durations and lower per-minute activity. Bid–ask spreads are widest, in relative terms, for weather and economics contracts, reflecting both mechanical price bounds and lower liquidity. Median contract duration ranges from under two days for weather contracts to over 1,000 hours for economics and culture contracts. These differences motivate lifecycle normalization and category-level comparisons in the analysis that follows.

2.3 Lifecycle Normalization

Contracts in prediction markets vary substantially in their calendar duration, ranging from a few hours to several months. As a result, raw clock time is not a meaningful unit for comparing trading behavior across contracts: an hour before resolution represents a qualitatively different informational and strategic environment for a short-horizon weather contract than for a long-horizon economic contract. To enable coherent aggregation and comparison across heterogeneous contracts, we normalize each contract's trading history by its position in the contract lifecycle.

For each contract, let t_{list} denote the listing time and t_{res} denote the resolution time. For any observation at time $t \in [t_{\text{list}}, t_{\text{res}}]$, we define the *lifecycle ratio* as

$$\ell_t \equiv \frac{t - t_{\text{list}}}{t_{\text{res}} - t_{\text{list}}}, \qquad \ell_t \in [0, 1]. \tag{1}$$

By construction, $\ell_t = 0$ corresponds to contract listing and $\ell_t = 1$ corresponds to resolution. Observations after resolution are excluded from the analysis.

This normalization preserves the temporal ordering of market activity within each contract while rendering observations comparable across contracts with widely differing horizons. In effect, ℓ_t serves as a common time index that aligns contracts by informational maturity rather than by calendar date. This allows us to aggregate microstructure variables, such as bid–ask spreads, trading volume, and short-horizon price volatility, across contracts and categories as functions of lifecycle position.

For empirical analysis, we discretize the lifecycle into bins defined by fixed percentiles of contract duration and apply these bins consistently throughout the paper. Unless otherwise noted, lifecycle bins are constructed uniformly across contracts and categories. This discretization facilitates nonparametric visualization and comparison of liquidity, trading intensity, and regime behavior as contracts approach resolution.

2.4 Constructed Microstructure Measures

From the high-frequency order book data, we construct a set of standard microstructure measures that summarize liquidity conditions, trading activity, and short-horizon price adjustment. These include bid–ask spreads, traded volume, measures of short-horizon price volatility, and depth-based proxies for liquidity. All measures are computed at the observation frequency and are aligned with the lifecycle normalization described above.

In addition to baseline liquidity and activity measures, we construct indicators designed to capture abrupt changes in market conditions. These include measures of volatility bursts, characterized by unusually large price movements relative to recent history, and metrics capturing rapid spread dislocations. Such measures are intended to identify episodes of concentrated information arrival or sudden shifts in trading behavior that are not well summarized by averages.

All measures are computed directly from observed prices, quotes, and trades and do not rely on parametric estimation, filtering, or latent-state inference. This design choice reflects our emphasis on characterizing realized trading behavior rather than modeling underlying beliefs or equilibrium price formation. Formal definitions of these measures are provided in Section 3, where they are used to construct discrete microstructure regimes.

3. Microstructure State Classification

Trading activity in prediction markets is highly intermittent. Many contracts spend long stretches with little or no trading, punctuated by brief episodes of intense activity when new information arrives or resolution becomes salient. Averaging liquidity, volume, or volatility over an entire contract therefore obscures a central feature of these markets: discrete shifts in trading conditions rather than smooth adjustment over time.

To make these shifts measurable and comparable across contracts, we classify each observation into a small set of economically interpretable microstructure "states." The goal of this classification is descriptive rather than structural. We do not attempt to infer latent beliefs, strategic order placement, or equilibrium behavior. Instead, we partition the realized order-book and trade stream into regimes that summarize (i) liquidity conditions, (ii) trading intensity, and (iii) short-horizon price adjustment.

Throughout the analysis, an *observation* refers to a time-stamped snapshot of a contract at the sampling frequency (one minute in our baseline). Let $t = 1, 2, \ldots, T$ index observations within a contract.

3.1 Observable Inputs and Notation

For each contract and each observation t, we construct a set of observable variables summarizing prices, liquidity, trading activity, and short-horizon price movements. Throughout, an observation refers to a time-stamped snapshot at the sampling frequency (one minute in our baseline).

Prices. Let b_t and a_t denote the best bid and best ask prices (in dollars). We define the *midprice* as

$$m_t \equiv \frac{a_t + b_t}{2}. \tag{2}$$

Because Kalshi contracts settle to $\{0, 1\}$, prices are naturally bounded. This feature is important when interpreting both relative spreads and returns near the boundaries.

Spreads. We measure liquidity using both an absolute and a scale-free bid–ask spread:

$$s_t \equiv a_t - b_t, \qquad \tilde{s}_t \equiv \frac{a_t - b_t}{m_t}. \tag{3}$$

The normalized spread $\tilde{s}_t$ facilitates comparison across contracts with different price levels. Intuitively, it measures the cost of *crossing the market*, that is, the transaction cost incurred when a trader submits a marketable order that executes immediately against the best standing quote on the opposite side of the order book, relative to the current price.

Trading volume. Let v_t denote executed trading volume (number of contracts traded) within observation interval t.

Returns and short-horizon volatility. We define the one-step midprice return as

$$r_t \equiv \frac{m_t - m_{t-1}}{m_{t-1}}, \tag{4}$$

and use its absolute value $|r_t|$ as a simple measure of instantaneous price movement.

Because prediction markets often remain inactive for extended periods, we evaluate "unusual" price movements relative to a local baseline. Specifically, we compute rolling benchmarks over a window of length W (baseline $W = 20$ observations). This window length is chosen to balance two considerations: a shorter window would be overly sensitive to transient fluctuations, while a longer window would be slow to adapt to genuine regime changes. At one-minute sampling frequency, $W = 20$ corresponds to approximately 20 minutes of market history, which is short enough to capture intraday regime shifts yet long enough to provide stable baseline estimates:

$$\bar{v}_t \equiv \frac{1}{W} \sum_{k=0}^{W-1} v_{t-k}, \qquad \hat{\sigma}_t \equiv \frac{1}{W} \sum_{k=0}^{W-1} |r_{t-k}|. \tag{5}$$

We intentionally use $\hat{\sigma}_t$, based on absolute returns rather than squared returns. This choice is robust to outliers and has a straightforward interpretation: it captures the typical magnitude of recent price movements.

Volume surprise. To identify unusually high trading intensity, we standardize volume relative to recent history:

$$z_t^v \equiv \frac{v_t - \bar{v}_t}{\hat{s}_t^v}, \tag{6}$$

where $\hat{s}_t^v$ is the rolling standard deviation of volume over the same window W, computed with a small-sample safeguard (a variance floor to ensure numerical stability). Intuitively, z_t^v measures how many standard deviations current trading volume lies above its recent baseline.

Lifecycle position. Finally, let $\ell_t \in [0, 1]$ denote the normalized lifecycle ratio defined in Section 2.3, with $\ell_t = 0$ at contract listing and $\ell_t = 1$ at resolution. This variable allows us to distinguish early-stage inactivity from late-stage mechanical convergence.

3.2 Microstructure States

Each observation is assigned to one of six mutually exclusive microstructure states:

$$S_t \in \{\text{Frozen}, \text{Thin}, \text{Baseline}, \text{Active Information}, \text{Volatility Burst}, \text{Resolution Drift}\}. \tag{7}$$

An auxiliary "Unknown" label is used only for missing data; it is rare and excluded from the analysis.

The states are designed to capture distinct economic trading conditions:

- **Frozen**: Essentially no trading; price discovery is stalled.
- **Thin**: Some trading occurs, but liquidity is scarce and execution is costly.
- **Baseline**: The residual state representing non-extreme, non-information-driven trading conditions with moderate spreads, volume, and no unusual price movements.
- **Active Information**: Unusually high trading activity consistent with information arrival or rapid belief updating.
- **Volatility Burst**: Sharp price movements accompanied by elevated trading volume, indicative of sudden information shocks.
- **Resolution Drift**: Late-stage quiet trading driven by mechanical convergence as uncertainty collapses near resolution.

Below, each state is defined in terms of (i) its economic interpretation and (ii) a formal classification rule.

State 1: Frozen

Economic meaning. The market is effectively inactive. Although quotes may be posted, they are not supported by meaningful trading interest, and price discovery is largely absent.

Definition. An observation t is classified as Frozen if executed volume is negligible relative to its recent baseline:

$$S_t = \text{Frozen} \quad \text{if} \quad v_t = 0 \ \text{ or } \ v_t < \theta_F \bar{v}_t, \tag{8}$$

where $\theta_F \in (0, 1)$ is a fixed threshold (baseline $\theta_F = 0.10$). This threshold is set conservatively: a value of 0.10 means that an observation is classified as Frozen only when current volume falls below 10% of its recent rolling average, ensuring that only near-complete inactivity triggers the Frozen classification rather than modest temporary slowdowns in trading.

Rationale. A relative volume criterion ensures that "Frozen" is comparable across contracts with vastly different typical activity levels.

State 2: Thin

Economic meaning. Liquidity is scarce and costly: trades can occur, but at wide bid–ask spreads.

Definition. Conditional on not being classified as Frozen (and not satisfying higher-priority information states defined below), an observation t is classified as Thin if

$$S_t = \text{Thin} \quad \text{if} \quad \tilde{s}_t > \theta_T, \tag{9}$$

with baseline $\theta_T = 0.15$.

Interpretation. A 15% relative spread is extreme in conventional financial markets but empirically common in thin prediction market contracts. This state captures execution frictions rather than underlying uncertainty.

State 3: Baseline

Economic meaning. Baseline trading conditions: moderate spreads, moderate volume, and no extreme price movements.

Definition. Baseline is the residual state:

$$S_t = \text{Baseline} \quad \text{if no other state conditions apply.} \tag{10}$$

Rationale. Defining Baseline as a residual avoids imposing arbitrary numerical bands and ensures that it represents "nothing unusual is happening."

Baseline is a residual state representing non-extreme, non-information-driven trading conditions. Its empirical rarity reflects a core finding of the paper: prediction markets are inactive by default. Unlike continuous financial markets, stable baseline trading conditions are not prevalent.

State 4: Active Information

Economic meaning. Trading activity increases sharply relative to recent history, consistent with information arrival or rapid belief updating, but without necessarily generating extreme price jumps.

Definition. Conditional on being otherwise classified as Baseline, an observation t is classified as Active Information if

$$S_t = \text{Active Information} \quad \text{if} \quad z_t^v > \theta_A, \tag{11}$$

with baseline $\theta_A = 1.5$.

Interpretation. Volume exceeds its recent mean by more than 1.5 standard deviations, indicating unusually intense trading.

Active Information is intended to capture high-intensity trading episodes characterized by elevated participation without discontinuous repricing; observations exhibiting sharp price jumps are classified separately as Volatility Bursts.

State 5: Volatility Burst

Economic meaning. A sudden information shock: prices move sharply over a short horizon and trading volume is simultaneously elevated.

Definition. An observation t is classified as Volatility Burst if

$$|r_t| > \kappa\hat{\sigma}_t \quad \text{and} \quad v_t > \lambda\bar{v}_t, \tag{12}$$

with baseline values $\kappa = 2.5$ and $\lambda = 1.5$.

Rationale. Large price changes can arise mechanically in illiquid markets. Requiring elevated volume filters toward episodes consistent with genuine information-driven repricing.

State 6: Resolution Drift

Economic meaning. In late lifecycle stages, markets often become quiet as prices mechanically converge toward 0 or 1 and remaining uncertainty collapses. This behavior is distinct from early-stage inactivity.

Definition. An observation t is classified as Resolution Drift if

$$S_t = \text{Resolution Drift} \quad \text{if} \quad \ell_t > \ell^\star,\ \tilde{s}_t < \tilde{s}^\star,\ v_t < v^\star,\ \hat{\sigma}_t < \sigma^\star, \tag{13}$$

with $\ell^\star = 0.90$. Thresholds $\tilde{s}^\star$, $v^\star$, and $\sigma^\star$ are set using empirical quantiles (baseline: 5th percentile for spreads and 25th percentiles for volume and volatility), subject to mild floor constraints.

Interpretation. This state captures a “quiet endgame”: not dead markets, but markets whose remaining uncertainty is small and whose price discovery becomes mechanically constrained.

3.3 Priority Ordering and Assignment

Because multiple state conditions can hold simultaneously (for example, an observation may satisfy both the Volatility Burst criteria (elevated volume and large price movement) and the Thin criteria (wide spread)), we impose a strict priority ordering so that each observation is assigned exactly one microstructure state. This ensures that the state classification is mutually exclusive and rule-based: the first satisfied condition in the priority ordering determines the assigned state.

The priority ordering is:

$$\text{Frozen} \succ \text{Volatility Burst} \succ \text{Resolution Drift} \succ \text{Active Information} \succ \text{Thin} \succ \text{Baseline}. \tag{14}$$

Assignment is implemented as a rule-based mapping

$$S_t \;=\; f(v_t, \tilde{s}_t, r_t, \hat{\sigma}_t, \bar{v}_t, z_t^v, \ell_t)\,, \tag{15}$$

where $f(\cdot)$ applies the state definitions sequentially according to the priority ordering above. Each observation is evaluated in order, and the first satisfied condition determines the assigned state.

Rationale for the ordering.

- **Frozen** is given the highest priority because near-zero trading renders other diagnostics uninformative: when the market is inactive, spread and volatility measures largely reflect posted quotes rather than meaningful trading conditions.
- **Volatility Burst** is ranked above Active Information because extreme repricing accompanied by elevated volume is qualitatively distinct from high trading activity without sharp price movements. Separating these states allows us to distinguish sudden information shocks from gradual belief updating.
- **Resolution Drift** is placed above Thin and Baseline to prevent late-stage mechanical quietness near resolution from being misclassified as generic illiquidity or non-information-driven conditions.
- **Thin** is evaluated after information-driven states because bid–ask spreads may widen temporarily during news events; labeling such observations as "Thin" would conflate illiquidity with information processing.

This priority structure is not merely cosmetic. It plays a central role in ensuring that information-related regimes reflect genuine informational conditions rather than artifacts of liquidity measurement.

3.4 Regime Transitions as a Markov Process

Once each observation is assigned a microstructure state, each contract yields a discrete state sequence $\{S_t\}_{t=1}^{T}$. We summarize regime-switching behavior using a first-order Markov transition matrix, which provides a compact description of state persistence and transition patterns.

Let $\mathcal{S}$ denote the set of states. For any pair $i, j \in \mathcal{S}$, define the empirical transition probability

$$P_{ij} \;\equiv\; \Pr(S_{t+1} = j \mid S_t = i). \tag{16}$$

We estimate P_{ij} by pooling transitions across contracts and counting consecutive state realizations:

$$\widehat{P}_{ij} \;=\; \frac{\sum \mathbf{1}\{S_t = i, S_{t+1} = j\}}{\sum \mathbf{1}\{S_t = i\}}, \tag{17}$$

where the sums run over all adjacent observation pairs in the dataset and $\mathbf{1}\{\cdot\}$ denotes the indicator function. By construction, each row of $\widehat{P}$ sums to one.

Interpretation. Each row i of the transition matrix answers the question: If the market is in state i at time t, how likely is it to be in each possible state one observation later?

We do not claim that regime dynamics are strictly Markovian or stationary over time. Rather, the transition matrix serves as a descriptive summary that captures the degree of persistence within states and the relative likelihood of switching between states.

3.5 Regime Entropy

To summarize how varied a contract's microstructure is over its lifecycle, we compute a normalized Shannon entropy based on the distribution of time spent in each microstructure state. This measure provides a compact summary of regime diversity within a contract.

For a given contract, let p_k denote the fraction of observations classified into state $k \in \mathcal{S}$:

$$p_k \;\equiv\; \frac{1}{T}\sum_{t=1}^{T} \mathbf{1}\{S_t = k\}. \tag{18}$$

We define the Shannon entropy (in bits) as

$$H \;\equiv\; -\sum_{k \in \mathcal{S}} p_k \log_2(p_k). \tag{19}$$

Because the maximum attainable entropy depends on how many states are actually observed for a given contract, we normalize by the maximum possible entropy $\log_2(|\mathcal{S}_{\text{obs}}|)$, where $|\mathcal{S}_{\text{obs}}|$ denotes the number of states with nonzero occupancy:

$$H^{\text{norm}} \equiv \frac{H}{\log_2(|\mathcal{S}_{\text{obs}}|)} \in [0,1]. \tag{20}$$

Interpretation.

- $H^{\text{norm}} \approx 0$: The contract spends most of its lifetime in a single state, typically Frozen.
- $H^{\text{norm}} \approx 1$: Time is distributed across many states, indicating a highly dynamic microstructure.

Regime entropy is not a measure of forecasting accuracy, informational efficiency, or market performance. Rather, it provides a scalar measure of microstructure richness that is useful for comparing contracts and categories with respect to the diversity of trading conditions they exhibit over their lifecycles.

3.6 Practical Remarks and Robustness

Two implementation choices are worth emphasizing.

First, classification thresholds are fixed ex ante. With the exception of the Resolution Drift quantile cutoffs, which are designed to accommodate cross-contract scale heterogeneity, all thresholds are held constant across contracts and categories. This design choice ensures comparability of regime assignments and mitigates concerns about overfitting classification rules to particular contract types or market segments.

Second, rolling baselines play a central role in the construction of information-related states. Absolute trading volume and volatility levels differ by orders of magnitude across contracts; identifying information-driven episodes, therefore, requires measuring activity relative to a contract's own recent history. Rolling benchmarks convert heterogeneous raw series into comparable "surprise" indicators that are meaningful across markets with vastly different levels of baseline activity.

Across a wide range of specifications varying both the rolling window length W and the threshold values used in classification, the qualitative regime patterns (particularly the dominance of frozen states and the transience of information-driven regimes) remain stable.

4. Empirical Results

This section presents the empirical implications of the microstructure classification framework developed in Sections 2 and 3. First, we document how liquidity, trading activity, and short-horizon volatility evolve over the contract lifecycle. Second, we examine how time is allocated across microstructure regimes as a function of lifecycle position. Third, we characterize regime persistence and transition dynamics using a Markov representation and regime entropy.

All results are reported in lifecycle-normalized time, enabling aggregation and comparison across contracts with heterogeneous horizons. Unless otherwise noted, figures report pooled results across all contracts, with sports contracts highlighted where relevant.

4.1 Lifecycle Evolution of Liquidity, Volume, and Volatility

We begin by examining how core microstructure variables evolve as contracts progress from listing to resolution.

Figure 1 plots bid–ask spreads, executed trading volume, and short-horizon price volatility as functions of lifecycle position ℓ, aggregated across all contracts using lifecycle-normalized time. Bid–ask spreads are summarized using the median, while volume and volatility are summarized using the 75th percentile (p75) to characterize trading intensity conditional on activity. Category-level disaggregation is provided in Appendix C.

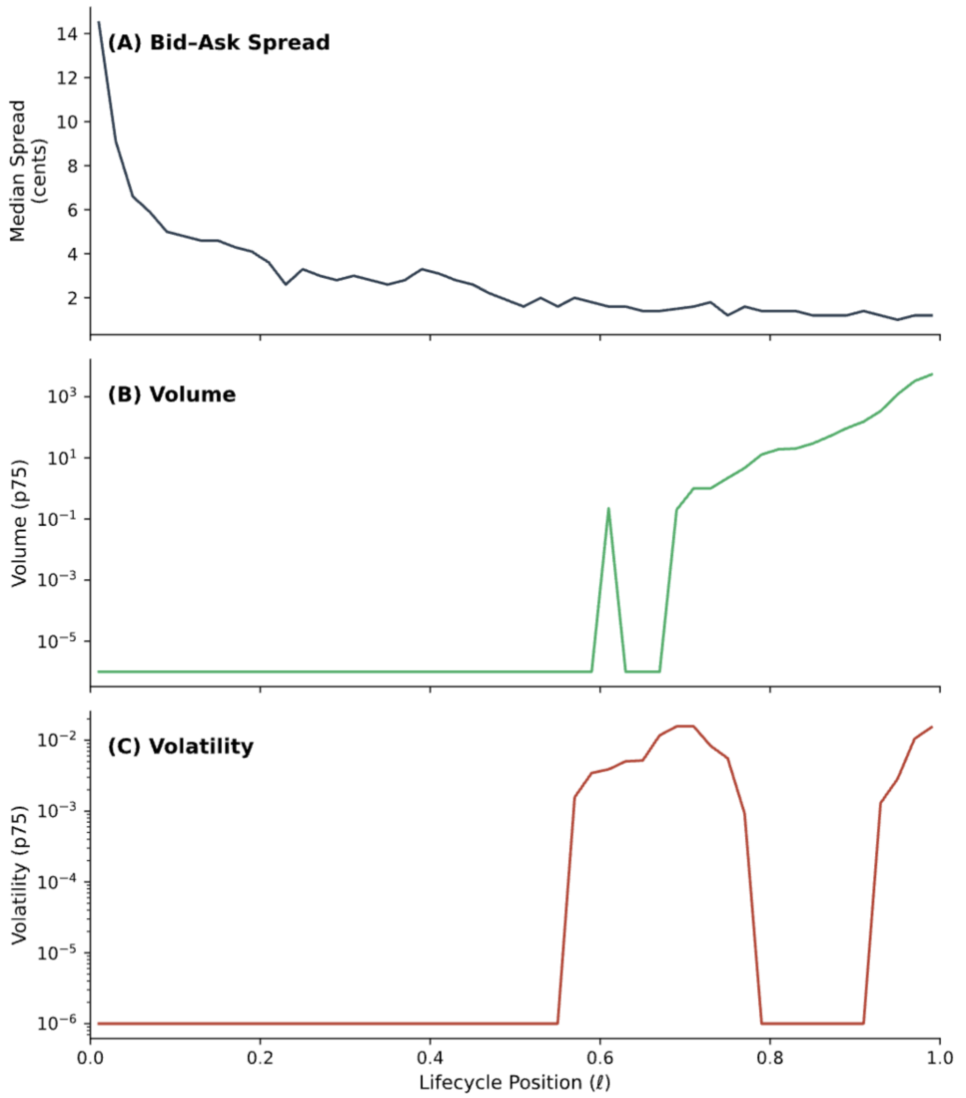

Figure 1: Lifecycle evolution of bid–ask spreads, trading volume, and short-horizon volatility. The figure plots median bid–ask spreads (Panel A), 75th-percentile trading volume (Panel B), and 75th-percentile volatility (Panel C) as functions of lifecycle position ℓ. All variables are aggregated across contracts using lifecycle-normalized time.

Two systematic patterns emerge.

First, bid–ask spreads compress monotonically over the contract lifecycle. Early in the lifecycle, spreads are wide and highly variable, reflecting sparse participation and limited coordination among traders. As ℓ increases, spreads decline steadily, reaching their narrowest levels near resolution. This pattern holds across all contract categories, although both the level and rate of compression vary substantially.

Second, trading activity is strongly concentrated in time. For much of the contract lifecycle, even relatively active contracts exhibit low levels of trading. Trading intensity increases sharply only in late-stage intervals, concentrating into narrow windows that frequently coincide with discrete information arrivals or the approach of resolution.

Short-horizon price volatility exhibits a similar episodic structure. Conditional on trading activity, price movements are modest during early lifecycle stages and increase sharply during periods of elevated trading intensity. Volatility then declines again near resolution as remaining uncertainty collapses mechanically.

Taken together, these results indicate that prediction markets do not continuously incorporate information over time. Instead, liquidity provision and price adjustment occur episodically, conditioned on both discrete information events and proximity to contract resolution.

4.2 Distribution of Microstructure States over the Lifecycle

We next examine how time is allocated across the six microstructure states defined in Section 3.

Figure 2 reports the fraction of observations classified into each state as a function of lifecycle position ℓ, aggregated across all contracts. Category-level state distributions are reported in Appendix C.

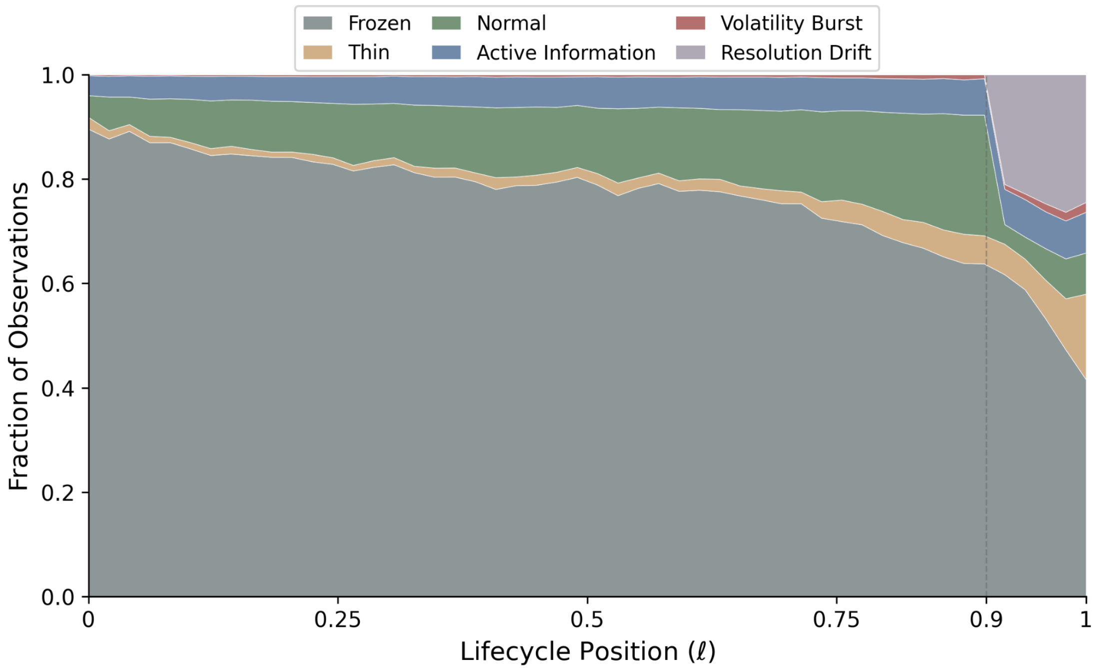

Figure 2: Distribution of microstructure states over the lifecycle. The figure plots the fraction of observations classified into each microstructure state as a function of lifecycle position ℓ, aggregated across all contracts. Fractions sum to one within each lifecycle bin.

The dominant feature across the lifecycle is the prevalence of the Frozen state. For the majority of a contract's lifetime, markets exhibit negligible trading activity and effectively stalled price discovery.

The Thin and Baseline states occupy more modest shares of the lifecycle, appearing primarily in early and mid-stage intervals. These regimes reflect limited but nonzero trading under relatively poor liquidity conditions, consistent with gradual participation buildup prior to major information events.

Information-driven regimes are rare and sharply localized in time. Active Information and Volatility Burst states occur infrequently and are concentrated in narrow lifecycle windows. Their incidence increases modestly as contracts approach resolution but remains small in absolute terms, indicating that periods of intensive information processing are brief rather than persistent.

A distinct late-stage regime emerges near resolution. In the final portion of the lifecycle, markets transition into Resolution Drift, characterized by low volatility, compressed spreads, and declining trading volume. This regime is economically distinct from early-stage inactivity: rather than reflecting informational stagnation, it arises from mechanical convergence as outcome uncertainty collapses.

These patterns are broadly consistent across contract categories, although the relative prevalence of states varies. Sports and weather contracts exhibit more frequent information-driven regimes, while economics and culture contracts spend larger fractions of their lifetimes in Frozen states.

4.3 Regime Persistence and Transition Dynamics

To characterize how markets transition between microstructure states, we model regime dynamics as a first-order Markov process. This representation allows us to quantify both the persistence of individual regimes and the likelihood of transitions between qualitatively distinct market conditions.

Figure 3 reports the estimated transition matrix pooled across contracts. Diagonal elements capture regime persistence, while off-diagonal elements capture transitions between states.

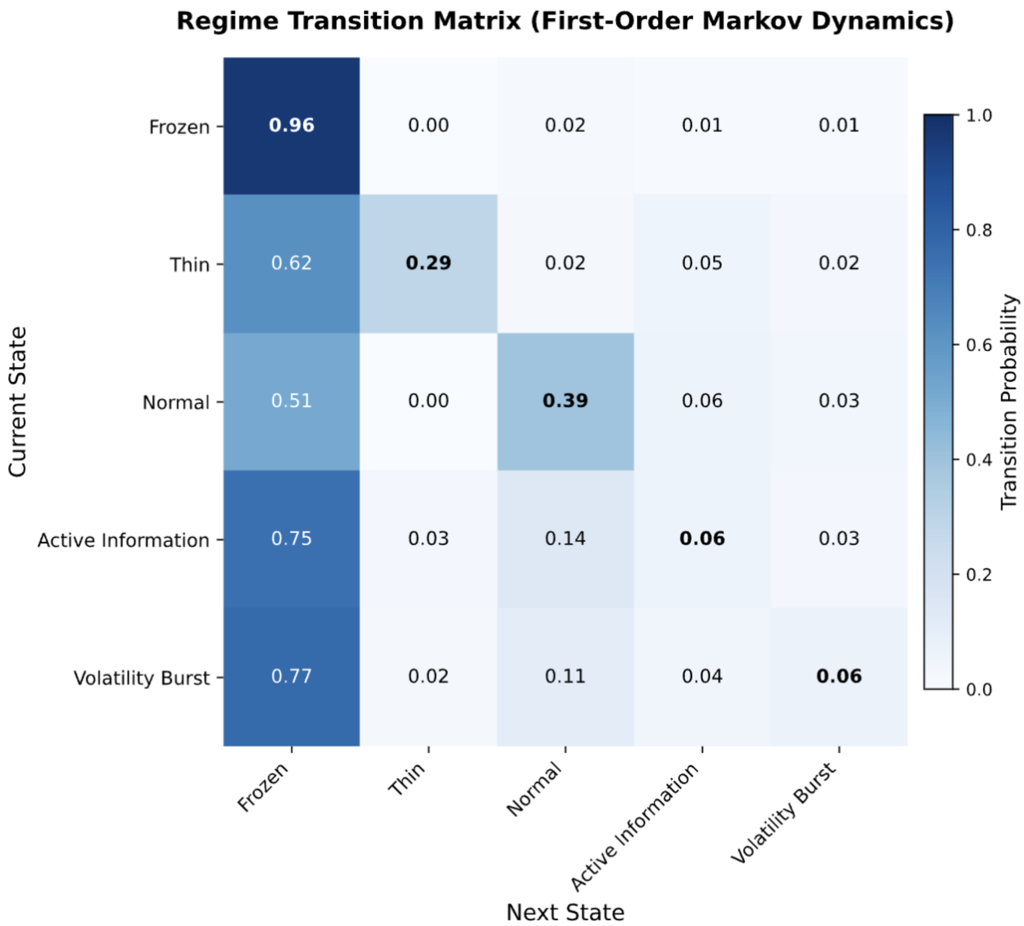

Figure 3: Regime transition matrix. Each row corresponds to the current state and each column to the subsequent state. Entries report empirical transition probabilities pooled across contracts.

The most salient feature of the matrix is the strong persistence of inactive regimes. Observations classified as Frozen exhibit a very high probability of remaining Frozen in the subsequent interval, indicating that inactivity is not transient noise but a highly persistent market condition over much of the contract lifecycle. Thin trading also displays substantial persistence, though with a greater likelihood of reverting to Frozen states than transitioning toward more active regimes.

Transitions into information-driven regimes are rare and typically short-lived. When markets enter Active Information or Volatility Burst states, self-transition probabilities are low, and observations revert quickly, most often back to Frozen or Thin states, rather than progressing smoothly into sustained Baseline trading conditions. This pattern reinforces the episodic nature of information incorporation documented in Sections 4.1 and 4.2.

Resolution Drift exhibits a distinct transition profile. Once entered, this regime displays moderate persistence, consistent with mechanical constraints imposed by diminishing outcome uncertainty as contracts approach settlement. Importantly, Resolution Drift is rarely entered from information-driven regimes, underscoring its economic distinction from both early-stage inactivity and transient information shocks.

Taken together, the transition structure confirms that prediction markets are frozen by default. Information-driven trading appears primarily as short-lived excursions away from inactivity, while late-stage convergence follows a separate mechanical path governed by contract resolution rather than ongoing information arrival.

4.4 Regime Entropy and Cross-Contract Heterogeneity

Finally, we summarize cross-contract heterogeneity in microstructure dynamics using normalized Shannon entropy of regime occupancy. This measure captures the extent to which a contract's trading activity is concentrated in a small number of regimes versus dispersed across multiple states over its lifecycle.

Figure 4 plots the distribution of regime entropy across contracts, along with category-level comparisons. Sports contracts are highlighted due to their relatively high regime diversity.

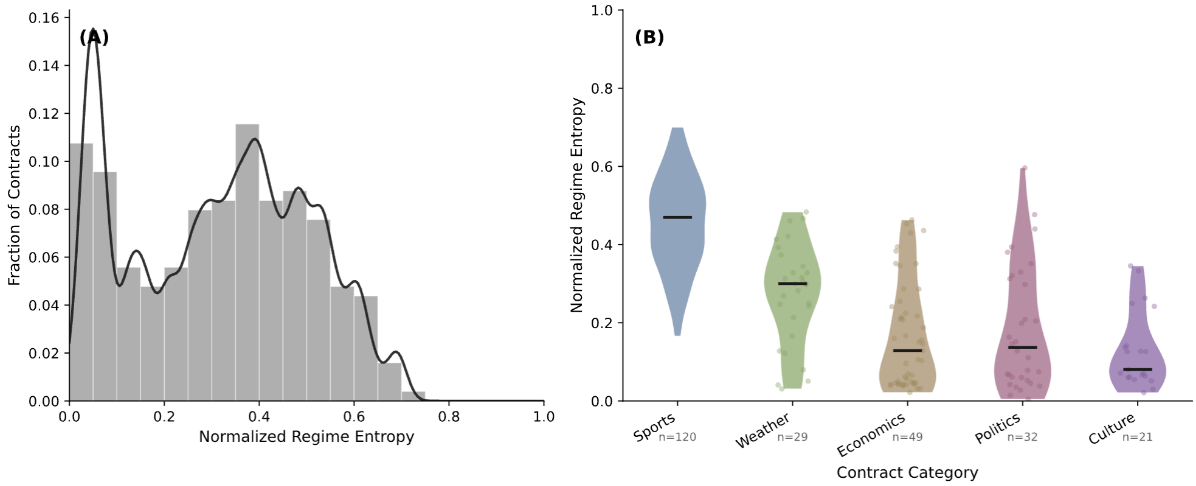

Figure 4: Distribution of normalized regime entropy across contracts. Panel A shows the pooled distribution across all contracts. Panel B reports category-level distributions with medians indicated.

The distribution is heavily right-skewed: most contracts exhibit low entropy, indicating that they spend the vast majority of their lifetimes in a small subset of regimes, most commonly the Frozen state. For these contracts, trading activity is rare and microstructure conditions are largely static.

A smaller subset of contracts displays substantially higher entropy. These contracts experience more frequent transitions between inactive and information-driven regimes, reflecting repeated episodes of trading activity and price adjustment rather than prolonged stagnation.

Regime entropy varies systematically across contract categories. Sports and weather contracts tend to exhibit higher regime diversity, consistent with more frequent information arrivals and coordinated participation. In contrast, economics and culture contracts are characterized by persistently low entropy, reflecting structural inactivity rather than intermittent trading.

Importantly, regime entropy is not mechanically related to contract duration. Long-horizon contracts often remain highly inactive, while some short- and medium-horizon contracts display substantial regime diversity. This pattern indicates that inactivity is not simply a consequence of time-to-resolution but reflects deeper structural features of participation, attention, and coordination in prediction markets.

4.5 Summary

The empirical results paint a consistent picture. Prediction markets exhibit strong lifecycle regularities in liquidity and trading activity, but these patterns are driven by discrete regime shifts rather than smooth adjustment. Markets are inactive for most of their lifetimes, punctuated by brief episodes of information-driven trading and followed by mechanical convergence near resolution.

These findings motivate a reinterpretation of prediction market prices: not as continuously updated forecasts, but as the outcomes of episodic information processing constrained by liquidity frictions.

References

[1] Taillard, J., and Zeng, L. (2025). *The Market Value of Fed Independence: High-Frequency Evidence from a Natural Experiment*. SSRN No. 5436816.

[2] Ng, K., Peng, L., Tao, Y., and Zhou, X. (2025). *Information Incorporation in Prediction Markets: Evidence from High-Frequency Order Book Data*. SSRN No. 5331995.

A. Interpretation of Mathematical Definitions and Measures

This appendix provides intuitive interpretations of all mathematical quantities used in the paper. The objective is to clarify what each object measures, why it is defined as it is, and how it supports the empirical analysis. The appendix is intentionally explanatory rather than formal, and is designed to facilitate verbal discussion of the methodology.

A.1 Prices and Midprice

Let b_t and a_t denote the best bid and best ask prices at time t. These represent the highest price a buyer is willing to pay and the lowest price a seller is willing to accept, respectively. They define the most immediate trading opportunity in the market.

The midprice is defined as

$$m_t = \frac{a_t + b_t}{2}.$$

The midprice serves as a proxy for the market's current valuation while smoothing mechanical bid–ask bounce. In prediction markets, where trades may be sparse and last-trade prices may be stale, the midprice provides a more stable and economically meaningful summary of prevailing beliefs.

Conceptually, m_t represents the most recent belief expressed by the market, conditional on available liquidity.

A.2 Bid–Ask Spreads

Liquidity is summarized using both an absolute and a relative bid–ask spread.

The absolute spread is defined as

$$s_t = a_t - b_t,$$

which measures the raw cost of immediate execution in price units.

Because prediction market prices are bounded between 0 and 1, absolute spreads are not directly comparable across price levels. We therefore define a normalized spread,

$$\tilde{s}_t = \frac{a_t - b_t}{m_t},$$

which measures the cost of immediacy relative to the current price.

The normalized spread captures liquidity scarcity and execution frictions in a scale-free manner, allowing comparison across contracts with different price levels and outcome probabilities.

A.3 Trading Volume

Let v_t denote the executed trading volume during observation interval t, measured as the number of contracts traded.

Volume captures the intensity of market participation and serves as a primary indicator of whether information is actively being processed. In prediction markets, long stretches of zero or near-zero volume indicate the absence of belief updating rather than belief convergence.

A.4 Returns and Short-Horizon Volatility

Short-horizon price movements are measured using midprice returns,

$$r_t = \frac{m_t - m_{t-1}}{m_{t-1}}.$$

We focus on absolute returns $|r_t|$ as a measure of instantaneous price movement rather than squared returns. This choice is robust to outliers and aligns with the bounded nature of prediction market prices.

To identify unusually large price movements, we construct a rolling volatility benchmark,

$$\hat{\sigma}_t = \frac{1}{W} \sum_{k=0}^{W-1} |r_{t-k}|,$$

where W denotes the rolling window length. This benchmark captures the typical magnitude of recent price changes and allows volatility to be evaluated relative to local market conditions.

A.5 Rolling Volume Benchmarks and Volume Surprise

Because baseline trading activity differs substantially across contracts, raw volume levels are not informative in isolation. We therefore construct rolling volume benchmarks,

$$\bar{v}_t = \frac{1}{W} \sum_{k=0}^{W-1} v_{t-k},$$

and corresponding rolling standard deviations $\hat{s}_t^v$.

Volume surprise is defined as

$$z_t^v = \frac{v_t - \bar{v}_t}{\hat{s}_t^v}.$$

This standardized measure captures whether current trading activity is unusually high relative to a contract's recent history. Volume surprise serves as a key indicator of information arrival or coordinated participation.

A.6 Lifecycle Normalization

Contracts vary widely in calendar duration. To make trading behavior comparable across heterogeneous contracts, we normalize time by lifecycle position.

Let t_{list} denote the listing time and t_{res} the resolution time. Lifecycle position is defined as

$$\ell_t = \frac{t - t_{\text{list}}}{t_{\text{res}} - t_{\text{list}}}, \quad \ell_t \in [0, 1].$$

Lifecycle normalization aligns contracts by informational maturity rather than clock time. Early values of ℓ_t correspond to periods of high uncertainty and low attention, while values near one correspond to imminent resolution.

A.7 Microstructure States

Each observation is assigned to one of six discrete microstructure states:

$$S_t \in \{\text{Frozen}, \text{Thin}, \text{Baseline}, \text{Active Information}, \text{Volatility Burst}, \text{Resolution Drift}\}.$$

States are defined using observable liquidity, volume, volatility, and lifecycle measures. The classification is descriptive rather than structural and does not attempt to infer latent beliefs or strategic behavior.

A.8 Regime Transitions

Given a sequence of states $\{S_t\}$, regime dynamics are summarized using a first-order Markov transition matrix,

$$P_{ij} = \Pr(S_{t+1} = j \mid S_t = i).$$

The transition matrix provides a compact description of regime persistence and switching behavior. High diagonal entries indicate persistent regimes, while off-diagonal entries characterize how markets move between inactivity, information processing, and resolution-driven states.

This representation is used as a descriptive summary rather than a structural model of trader behavior.

A.9 Regime Entropy

To quantify the diversity of trading conditions experienced by a contract, we compute normalized Shannon entropy. Let p_k denote the fraction of time a contract spends in state k. Entropy is defined as

$$H = -\sum_k p_k \log_2 p_k.$$

To ensure comparability across contracts, entropy is normalized by its maximum possible value,

$$H_{\text{norm}} = \frac{H}{\log_2(|S_{\text{obs}}|)} \in [0, 1],$$

where $|S_{\text{obs}}|$ is the number of states actually observed.

Low entropy indicates persistent inactivity, while high entropy reflects frequent transitions between regimes and richer microstructure dynamics.

A.10 Interpretive Summary

Together, these measures allow us to characterize prediction markets as episodic information-processing systems. Prices often remain unchanged not because beliefs are stable, but because information is not actively being incorporated. Information enters prices through short-lived regime shifts rather than continuous updating.

B. Kalshi Order Book Structure

Figure 5 provides an example of Kalshi's order book interface for a live sports contract. The display shows a binary contract on the outcome of a Miami–Phoenix matchup, with the "Yes" side (Miami wins) trading at a midpoint of 62 cents, implying a 62% probability under risk-neutral interpretation.

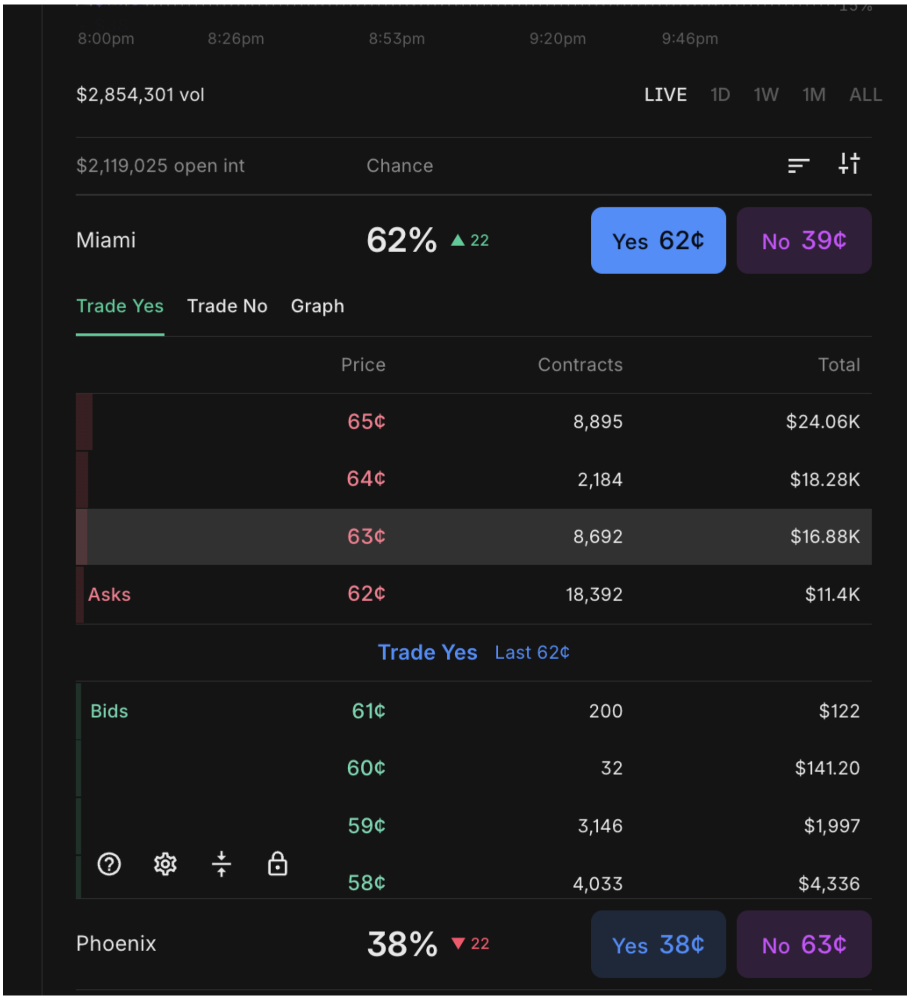

Figure 5: Kalshi order book example. The interface displays a continuous limit order book for a binary sports contract. Ask prices (sell offers) appear in the upper portion, with the best ask at 62¢ and additional depth at 63¢, 64¢, and 65¢. Bid prices (buy offers) appear below, with the best bid at 61¢ and depth extending down to 58¢. Each row reports the price, number of contracts available, and total dollar value at that price level. The spread between best bid and best ask is 1¢ in this snapshot.

The order book operates as a standard continuous double auction. Traders may submit limit orders specifying a price and quantity, which rest in the book until matched or canceled, or they may submit marketable orders that execute immediately against standing quotes. The "Yes" and "No" sides of each contract are complements: buying "Yes" at 62¢ is economically equivalent to selling "No" at 38¢, since contract payoffs sum to $1.

The displayed depth, measured in both contract counts and dollar values, reflects the cumulative liquidity available at each price level. In this example, approximately 18,400 contracts are offered at the best ask of 62¢, while only 200 contracts are bid at the best bid of 61¢, illustrating asymmetric depth that is common in prediction markets.

C. Category-Level Disaggregation

This appendix reports category-level versions of the pooled empirical results presented in Section 4. The analysis disaggregates lifecycle dynamics and microstructure state distributions by contract category, including sports, politics, economics, weather, and culture. The purpose of this appendix is to verify that the pooled patterns documented in the main text are not driven by a single category and to clarify how lifecycle and regime behavior varies across market types. No additional analysis or alternative specifications are introduced.

C.1 Lifecycle Evolution of Liquidity, Volume, and Volatility by Category

Category-level analysis of lifecycle-normalized liquidity, trading activity, and short-horizon volatility reveals patterns consistent with those documented in the pooled results. All quantities are computed using the same definitions, lifecycle normalization, and aggregation procedures described in Sections 2 and 4.

Median bid–ask spreads decline over the lifecycle across all contract categories, though absolute spread levels vary substantially. Sports and politics contracts exhibit tighter spreads throughout, while weather and economics contracts display wider spreads, particularly in early lifecycle stages. Despite these level differences, all categories exhibit declining spreads as contracts approach resolution.

Trading volume concentrates in late lifecycle intervals across all categories. Extended periods of low or zero volume characterize early and mid-lifecycle stages, with sharp increases occurring only as resolution approaches. The timing and magnitude of late-stage volume increases differ across categories—sports contracts exhibit more gradual buildup, while weather contracts show particularly concentrated bursts—but the concentration of activity near resolution is common across market types.

Short-horizon price volatility follows a similar pattern. Volatility remains low for most of the lifecycle across all categories and increases during brief intervals that coincide with elevated trading activity. Near resolution, volatility declines again as remaining outcome uncertainty collapses mechanically.

These category-level patterns confirm that the lifecycle regularities documented in Section 4.1 (including spread compression, episodic trading activity, and late-stage convergence) are present across all contract categories despite substantial heterogeneity in baseline liquidity and activity levels.

C.2 Distribution of Microstructure States by Category

Category-level analysis of microstructure state distributions confirms the patterns documented in the pooled results. Using the classification framework defined in Section 3, fractions are computed within lifecycle bins and sum to one within each bin.

Across all categories, the Frozen state accounts for the majority of observations throughout most of the contract lifecycle. The Thin and Baseline states occupy smaller shares and appear primarily in early and mid-lifecycle intervals. Information-driven states, including Active Information and Volatility Burst, occur infrequently and are concentrated in narrow lifecycle windows.

While the qualitative structure of state distributions is consistent across categories, relative state frequencies vary. Sports and weather contracts exhibit higher incidences of information-driven states, while economics and culture contracts spend larger fractions of their lifetimes in Frozen states. Resolution Drift emerges near the end of the lifecycle across categories, reflecting late-stage quiet trading and mechanical convergence.

These category-level distributions mirror the pooled patterns shown in Figure 2 and confirm that the dominance of inactive regimes and the transience of information-driven regimes are not specific to any single contract type.

C.3 Regime Persistence and Transition Dynamics by Category

Category-level regime transition matrices, estimated using the same procedure described in Section 3.4, reveal consistent patterns across contract types. Each matrix summarizes empirical transition probabilities between microstructure states at the observation frequency.

Across all categories, inactive regimes (particularly Frozen) exhibit high persistence. Observations classified as Frozen are most likely to remain Frozen in the subsequent interval. Thin and Baseline states also display persistence, though with higher probabilities of reverting to Frozen states than transitioning into information-driven regimes.

Transitions into Active Information and Volatility Burst states are rare across categories and typically short-lived. When such states occur, observations most often revert to inactive regimes rather than progressing into sustained Baseline trading conditions. Resolution Drift exhibits moderate persistence once entered and is primarily observed in late lifecycle stages.

These category-specific transition patterns are consistent with the pooled transition matrix reported in Section 4.3 and reinforce the characterization of prediction markets as exhibiting persistent inactivity punctuated by brief episodes of information-driven trading.

C.4 Summary

The category-level analysis reported in this appendix confirms that the empirical regularities documented in Section 4 are robust across contract types. While baseline liquidity, activity levels, and contract durations differ substantially across categories, the qualitative lifecycle structure (characterized by persistent inactivity, episodic information-driven trading, and late-stage convergence) appears consistently across markets.