# Kalshi Market Analysis: Retail vs Institutional Trading Behaviors in 2024 U.S. Election Contracts

Lucy Zhao
Michigan Finance and Mathematics Society
University of Michigan, Ann Arbor

May 8, 2025

## 1. Introduction

Kalshi is the first exchange regulated by the CFTC that is dedicated to trading on the outcomes of future events. Its trading platform was launched in July 2021, allowing participants to speculate on a wide range of topics, including inflation, interest rate decisions, unemployment rates, and government shutdowns.

The 2024 U.S. presidential election drew significant public attention, with numerous polls released in the lead-up to the vote. Kalshi offered a market titled *Who will win the Presidential Election*, which ran from October 4, 2024, to January 20, 2025, when Donald Trump was inaugurated as President. This market allowed users to trade based on their expectations of the election outcome and, in some cases, provided more objective signals than traditional political polls, which are often subject to bias.

According to Kalshi's own analysis, there are three main types of traders on the platform: directional traders, hedgers, and market makers. Most participants are retail traders, typically falling into the first two categories. On the other hand, institutions such as Kalshi Trading (a separate entity from Kalshi Exchange) and Susquehanna (the first institutional market maker to participate on Kalshi) engage in all three roles, though primarily as market makers. Given that liquidity remains one of Kalshi's key challenges, analyzing retail and institution's trading behaviors is crucial for understanding how retails institutions shape the platform's market structure together.

## 2. Data Overview

The trade data was accessed through the Kalshi Trading API, specifically the GetTrades endpoint. I converted the created_time from UTC to US Eastern Time for consistency. The final datasets used are KH.csv and DT.csv.

In the Kalshi market, when Trader A buys 1 KH YES contract at \$0.78 and Trader B buys 1 KH NO contract at \$0.22, these orders are matched (one KH YES and one KH NO contract, with the combined price summing to \$1). This occurs because after the market closes, if the outcome of the event KH wins is YES, the YES contract will be worth \$1, while the NO contract will be worth \$0. Typically, a market maker places the initial orders, which are added to the order book, and a market taker later matches these orders, resulting in a trade. It's important to note that buying 1 KH YES contract at \$0.78

is equivalent to selling 1 KH NO contract at $0.22, and conversely, selling 1 KH YES contract at $0.78 is the same as buying 1 KH NO contract at $0.22. For DT contracts, it's the same.

An example row in the dataset looks like the following(Table 1): It indicates that a market maker placed an order to buy 93 KH NO contracts at $57 at some point before the recorded timestamp (exact time unknown), and a market taker subsequently placed an order to buy 93 KH YES contracts at $43. When the taker's order matches the maker's, the trade is executed at the created_time.

Table 1: Sample Trade Record

| trade_id | ticker | count | created_time | yes_price | no_price | taker_side |
|---|---|---|---|---|---|---|
| e3c324f0-9d79... | PRES-2024-KH | 93 | 2024-11-05 14:23:01.932159-05:00 | 43 | 57 | yes |

# 3. Key Findings

## 3.1 Phases of Market Activity

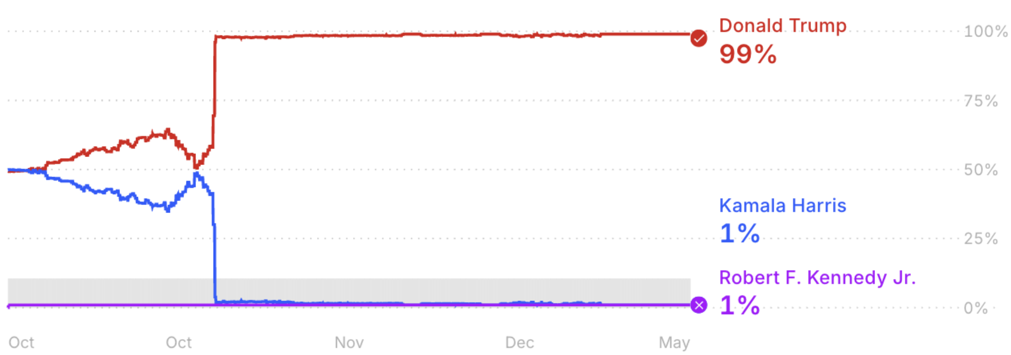


Figure 1: Winning Odds from Oct 4 to Jan 20

Based on the probability trend displayed on Kalshi (Figure 1), I divided the entire timeline into five distinct phases (Table 2):

- **Oct 4–10:** The market had just launched, and the probability remained relatively flat.
- **Oct 11–29:** The probability of Donald Trump (DT) winning began to increase.
- **Oct 30–Nov 3:** DT's probability declined to a level nearly equal to Kamala Harris (KH).
- **Nov 4–6:** The final election results were released.
- **Nov 7–Jan 20:** The post-election period leading up to the presidential inauguration.

Table 2: Avg Trades per Day, Count Mean & Median in Each Period

| **Period** | **KH-Trades/Day** | **Count Mean** | **Count Median** | **DT-Trades/Day** | **Count Mean** | **Count Median** |
|---|---|---|---|---|---|---|
| 10/04–10/10 | 298 | 1,018 | 104 | 362 | 1,118 | 104 |
| 10/11–10/29 | 1,455 | 1,668 | 172 | 2,171 | 1,280 | 125 |
| 10/30–11/03 | 6,337 | 1,183 | 200 | 9,155 | 965 | 161 |
| 11/04–11/06 | 47,300 | 1,050 | 222 | 55,173 | 641 | 137 |
| 11/07–01/20 | 142 | 3,629 | 256 | 432 | 1,742 | 166 |

Periods with low Trades/Day but high Count Mean typically indicate institutional dominance. Institutions, especially market makers, tend to place large-volume orders and provide liquidity during less active periods. Conversely, periods with high Trades/Day but low Count Mean suggest strong retail activity. Retail traders usually submit smaller orders, but their cumulative effect drives up trading frequency when market interest is high.

From Nov 4 to Nov 6, the market shows high Trades/Day but low Count Mean, indicating increased retail participation. This aligns with the timing of the presidential election, when news and results attracted widespread public attention. The relatively high Count Median suggests retail traders were also willing to place larger bets, likely driven by increased confidence from media exposure.

From Nov 7 to Jan 20, the period saw a significant drop in Trades/Day but a sharp increase in Count Mean, reflecting institutional dominance during the post-election phase.

When comparing KH and DT datasets, DT contracts exhibit higher Trades/Day but lower Count Mean and Median. This indicates stronger retail engagement with DT contracts, likely due to higher visibility and public discussion. In contrast, KH contracts show higher institutional participation. Aside from these distinctions, the overall trading dynamics are similar. Thus, the following analysis focuses on KH data to explore retail vs institutional activity in greater depth.

## 3.2 Intraday Trading Patterns of Retail vs Institutional

To analyze trading behavior throughout the day, I grouped all KH trades (from Oct 4 to Jan 20) into hourly bins (Eastern Time), calculating the average Trades/Day, Count Mean, and Count Median for each hour(Table 3).

Table 3: Intraday Trading Activity by Hour (Eastern Time)

| **Hour (ET)** | **8** | **9** | **10** | **11** | **12** | **13** | **14** | **15** | **16** | **17** | **18** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Trades/Day** | 60 | 78 | 86 | 83 | 77 | 81 | 82 | 82 | 85 | 84 | 83 |
| **Count Mean** | 2049 | 1236 | 1602 | 1593 | 1385 | 1819 | 1220 | 1244 | 1415 | 1018 | 1514 |
| **Count Median** | 232 | 232 | 232 | 204 | 204 | 196 | 177 | 178 | 163 | 131 | 131 |

| **Hour (ET)** | **19** | **20** | **21** | **22** | **23** | **0** | **1** | **2** | **3** | **4** | **5** | **6** | **7** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Trades/Day** | 104 | 117 | 160 | 203 | 173 | 124 | 78 | 43 | 16 | 9 | 12 | 18 | 26 |
| **Count Mean** | 828 | 776 | 850 | 941 | 1204 | 1519 | 1613 | 1850 | 1347 | 1557 | 1549 | 1591 | 1663 |
| **Count Median** | 138 | 143 | 161 | 224 | 256 | 300 | 303 | 256 | 282 | 242 | 285 | 256 | 238 |

Based on the data, we can categorize the trading day into four time blocks: 3–7, 8–18, 19–22, and 23–2.

The Kalshi exchange is closed daily from 3 AM to 8 AM (with the exception of November 4–9, when it remains open 24 hours due to the election). As a result, Trades/Day is quite low (fewer than 30) during Hours 3 to 7. However, the Count Mean (above 1,300) and Median (above 230) remain high, suggesting that nearly all trades during this window are placed by institutional participants.

During Hours 19 to 22 (7 PM – 11 PM), Trades/Day is relatively high (over 100), while the Count Mean drops below 1,000. This indicates that a significant number of retail traders are active during this time. This suggests that most retail users are part-time participants who place bets on Kalshi contracts after typical working hours.

In the Hours 23 to 2 window (11 PM – 2 AM), Trades/Day gradually decreases as time progresses, but the Count Mean (above 1,200) and Median (above 250) remain elevated. This pattern suggests that institutions are absorbing orders placed by retail traders earlier in the evening. As these institutional participants fulfill more of the remaining liquidity, the number of trades naturally declines.

From Hours 8 to 18 (8 AM – 6 PM), Trades/Day remains moderate (around 60–90), with a high Count Mean (over 1,200) and a medium Count Median (130–250). This indicates that institutions are actively trading during this period, likely alongside some retail participants. The presence of mixed order sizes results in a Count Median that is lower than those observed in the 23–2 and 3–7 intervals.

In summary, retails are most active in the evening (7 PM–11 PM), which is after typical work hours. Institutions maintain a more consistent presence throughout the day via automated systems, trading whenever the Kalshi exchange is open.

## 3.3 Retail Reactions to News and Subsequent Price Movements

There were three significant shifts in contract price (i.e., winning probability) prior to Presidential Election Day. I reviewed major news events and social media discussions that occurred during these periods.

At the beginning of the observation window, the probabilities for KH and DT were nearly equal. Starting from October 11, however, DT's probability began to rise steadily. This aligns with the timing of Hurricane Milton's impact on Florida. KH and the Democratic Party were widely criticized for their response to the event. As related coverage gained traction on social media, public sentiment turned negative toward KH and the Democratic Party, which likely contributed to the steady increase in DT's probability.

On October 30, U.S. Q3 GDP data was released, showing the economy remained strong and did not experience a significant downturn under Democratic Party governance. Additionally, on November 1, the unemployment rate was reported to be stable. These indicators were favorable for KH and the Democratic Party, resulting in a notable drop in DT's probability.

Trades/Day remained low before the first major news event. However, after each significant piece of news, trading activity increased substantially. This suggests that retail traders are highly responsive to information on social media, and their activity can materially influence contract price trends.

## 3.4 Retail vs Institutional Trading Behavior After the Election Result

After 2 AM on Nov 6, the KH YES price stabilized at \$0.01, and the KH NO price stabilized at \$0.99. If someone buys KH YES at \$0.01 and it settles to \$0, they will incur a loss of \$0.01 (actually more, considering transaction fees). On the other hand, if someone buys KH NO at \$0.99 and it settles to \$1, they will gain \$0.01 (actually less, considering transaction fees). Rationally, they should buy KH NO at \$0.99 and hold it until the market closes. However, in reality, there are not only buyers of KH NO, but also buyers of KH YES. To analyze this further, let's look at the Count Mean and Percentiles from Nov 7 to Jan 20 for both taker_side = yes and taker_side = no (Table 4).

Table 4: Count Data for single taker side from Now 7 to Jan 20

| **Percentile** | **Mean** | **10%** | **20%** | **30%** | **40%** | **50%** | **60%** | **70%** | **80%** | **90%** | **99%** | **100%** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **taker_side = yes** | 10,351 | 16 | 35 | 79 | 147 | 250 | 584 | 1,500 | 5,000 | 15,031 | 249,923 | 500,000 |
| **taker_side = no** | 2,045 | 25 | 63 | 116 | 200 | 256 | 368 | 624 | 1,112 | 2,500 | 21,790 | 1,000,000 |

Buyers of KH NO have a significantly lower mean trade size than those buying KH YES. Although medians are nearly identical, KH YES trades are underrepresented below the 50th percentile but dominate above it. The 99th percentile for KH NO is only 21,790 contracts—affordable for retail traders (requiring just \$200 margin). This indicates most KH NO orders come from retail, while KH YES is largely driven by institutions, though some retail participation exists.

But why instituions still buy KH YES when they know they will lose greater than \$ 0.01 per contract? There is a Kalshi Volume Incentive Program that helps institutions get reward for large volume traded. That helps them profit and also provides more liquidity for Kalshi market!

# 4. Improvements

## 4.1 Enhanced Order Book Data Analysis

At present, we can only observe the timestamp when a taker executes an order, as indicated by the `created_time` field. However, we lack information about when makers place their orders. This missing data limits our ability to fully understand institutional trading behavior—particularly whether institutions position themselves ahead of retail participants in response to significant news events.

To address this gap, I propose utilizing the GetMarketOrderbook endpoint to obtain more granular order book snapshots. Access to this data would provide deeper insights into maker-side activity, including order placement timing, size, and positioning in the spread. This could reveal whether institutions anticipate directional market movements and adjust their liquidity provision accordingly before retail traders react.

## 4.2 Establishing a More Precise Timeline for News Impact and Retail Reactions

With more detailed order book data, we could construct a finer-grained timeline capturing how quickly different market participants respond to information shocks. Specifically, we aim to measure the latency between a news release, institutional market-making adjustments, and retail order flow reactions. Understanding this sequence would enhance our ability to model market dynamics.

Incorporating Natural Language Processing (NLP) techniques—

such as news sentiment analysis or topic classification—could help automate the detection of impactful news events in real time. By combining these signals with observed order flow responses, we could train predictive models to estimate likely retail behavior. If our system can react faster than typical institutional market makers, it may be possible to strategically place maker orders that will promptly be taken by retail flow, capturing favorable spread opportunities.

# 5. Acknowledgments

I would like to thank the Michigan Finance and Mathematics Society (MFAMS) for providing the opportunity to work on this project. I am especially grateful to Dominic Wydeven for his insightful guidance throughout the research process, and to Ivan Dashkevich for providing the data and engaging in valuable discussions that shaped the direction of this work.