

Liquidity Risk in Prediction Markets: A Polymarket Case Study

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ABSTRACT

This paper investigates liquidity risk in prediction markets through a case study of Polymarket, focusing on two markets: the “Jerome Powell out as Fed Chair in 2025” market and the “U.S. tariff rate on China on August 15” market. Over a two-month period, yes and no share prices, bid-ask spreads, trading volumes, liquidity pool sizes, and volatility were analyzed using Python-based data collection from the Polymarket API. Results reveal that public-interest markets, such as the Powell removal market, exhibit higher trading volume but greater volatility and wider spreads, particularly in response to unverified news. In contrast, the China tariff market displayed tighter spreads, stable liquidity depth, and more measured price adjustments, indicative of informed participation and greater market efficiency. Findings suggest that external information flow—especially the nature and credibility of news—significantly influences liquidity dynamics. The study highlights the dual role of prediction markets as both investment tools and high-frequency information aggregators, offering opportunities for market participants and researchers to evaluate event probabilities in real time.

Keywords: Prediction markets, Polymarket, Liquidity risk, Market volatility, Information flow, Public policy, Tariff rates.

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I. Introduction

1.1 Purpose

This study looked at ways to visualize data and assess liquidity risk across selected Polymarket prediction markets by analyzing bid-ask spreads, trading volume, and volatility over a two month period.

1.2 Overview of Polymarket and Prediction Markets

Polymarket is a blockchain-based information market where users trade on outcomes of future events. Prediction markets function as mechanisms to aggregate public beliefs into probability-based prices that reflect the likelihood of events. These markets allow participants to trade on future events outcomes, buy and sell shares in outcomes, as well as determine the probability of events based on public opinion. These markets cover diverse events such as elections, weather patterns, cryptocurrency prices, and public policy decisions.

1.3 Liquidity

Liquidity refers to the ease with which an asset can be converted into cash without affecting its market price. This is essential for both individuals and institutions to meet short-term financial obligations, handle unexpected expenses, as well as execute trades at fair prices. Liquidity is measured through four key metrics: bid-ask spread, market depth, volume, and slippage.

Bid–Ask Spread measures the gap between the highest price buyers are offering and the lowest price sellers are willing to accept. Smaller spreads generally signal more competitive pricing, smoother execution, and higher liquidity. On Polymarket, the “Buy Yes” and “Buy No” figures display these levels directly, letting traders gauge transaction costs at a glance.

Market Depth reflects the available volume across price points, indicating how much trading a market can sustain without sharp price shifts. In automated market maker (AMM) setups like Polymarket, the liquidity pool size acts as a proxy for depth. Larger pools can absorb heavier trades while keeping prices relatively stable.

Trading Volume tracks the quantity of shares exchanged over a set timeframe, commonly over 24 hours. Consistent high volume suggests active participation, high liquidity, stronger price discovery, and greater confidence in market probabilities. This metric is displayed on Polymarket’s market page under “Volume (24h)” and “All-Time Volume.”

Slippage captures the difference between the quoted price before a trade and the actual price once executed. High slippage, resulting from low liquidity, can make large trades costly or unpredictable, especially in thinner markets. Polymarket provides an estimated slippage figure when you input an order, which enables traders to anticipate potential price impact before committing.

II. Background

In this section, we examine the differences between trading-like platforms and traditional betting.

Odds: In traditional betting, bettors place wagers on events with fixed odds (i.e. a set chance of something occurring). In prediction markets, bettors can buy and sell “shares” that represent the odds of an event.

Prices: Traditional betting prices are set by a central authority, such as a bookmaker. However, prediction market prices are set by community consensus, reflecting odds of the events happening. As people purchase an option, the price increases, mirroring the odds of the event.

Payout Structure: Traditional bets are made against the house on a fixed ratio, while prediction market shares each pays out \$1 if that specific event occurs, no matter the price the share was purchased at.

Purpose: Traditional betting is mostly for entertainment purposes and is typically more “unofficial.” On the other hand, prediction markets are used as information markets or forecasting tools. They can be used as data to predict events (i.e. elections, foreign policy, tech, etc.)

Regulation: Traditional betting is universally classified as “gambling” and regulated by the state/country-level organizations. Prediction markets can be classified as financial or informational instruments. Legal status is often unclear or debated, especially for decentralized and anonymous platforms.

Trading-like platforms such as Polymarket can be more appealing as they allow traders to enter and exit positions at will, reflecting real-time market sentiment, and create opportunities for transparent and easy trades.

III. Methodology

3.1 Chosen Markets

This study examines two markets: (1) the potential removal of Jerome Powell as Federal Reserve Chair in 2025, and (2) U.S. tariff rates on China on August 15. These topics were selected for their high trading volumes, recent relevance, and broad relatability. The Trump presidency market was chosen in part due to ongoing controversy and public debate, while the China tariff market was selected partly because of the author’s personal connection to the U.S.–China trade dispute. As an American-born Chinese individual, the author occupies a unique position in which policy decisions directly affect both sides of their cultural background.

3.2 Data Collection Process

Data was collected using an automated Python script interfacing with Polymarket’s Gamma API. The script captured key numerical variables, including “yes” share price, “no” share price, bid–ask spread, total trading volume, 24-hour trading volume, and liquidity. Collection occurred twice daily—once in the morning and once in the evening—over a two-month period to ensure consistent time-series observations. All extracted values were cross-checked against the corresponding figures displayed on the Polymarket webpage to verify accuracy. The data was stored in CSV format and processed using Pandas, with cleaning procedures that included removing duplicate entries, filling missing values, and standardizing timestamps.

IV. Results

4.1 Key Findings

I. Price Volatility Patterns

The Powell removal market exhibited pronounced volatility spikes coinciding with major news, reflecting sensitivity to political developments and rumors. In contrast, the China tariff market followed a steadier pricing trajectory, with fewer abrupt fluctuations over the observation period.

II. Liquidity Correlations

In both markets, trading volume showed a strong positive correlation with the timing of news events, indicating that information flow was a key driver of participation.

III. Market Efficiency

The China tariff market displayed higher overall efficiency, characterized by consistently tighter spreads and deeper liquidity pools. These conditions suggest a participant base that was more data-driven and informed, enabling smoother price discovery and reduced transaction costs.

4.2 Comparative Liquidity Analysis

<i>Metric</i>	Powell Removal Market	China Tariff Market
<i>Market Size</i>	\$2.7M liquidity pool	\$1.9M liquidity pool
<i>Spread Dynamics</i>	Average 1.7% spread	Average 1.2% spread
<i>Trading Patterns</i>	Higher volume, more volatile	Lower volume, more stable

Figure 1. Comparative Market Metrics: Powell Removal vs. China Tariff Markets

The above table reveals that markets with broader public interest such as Powell removal demonstrates higher trading volumes but less efficient pricing, while more specialized markets such as tariff rates show greater price stability and narrower spreads.

4.3 Visualization

4.3.1 China Tariff Market

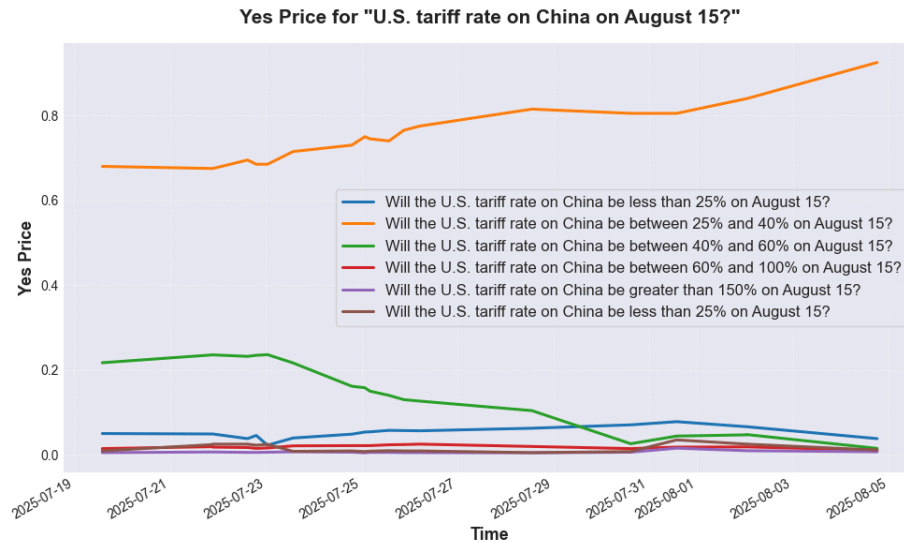


Figure 2. Yes Share Price for the China Tariff Market

The “Yes” price for the 25–40% interval showed a steady upward trend over time, reflecting consistent, data-driven market sentiment that most informed participants considered a 25–40% tariff rate the most likely outcome on August 15.

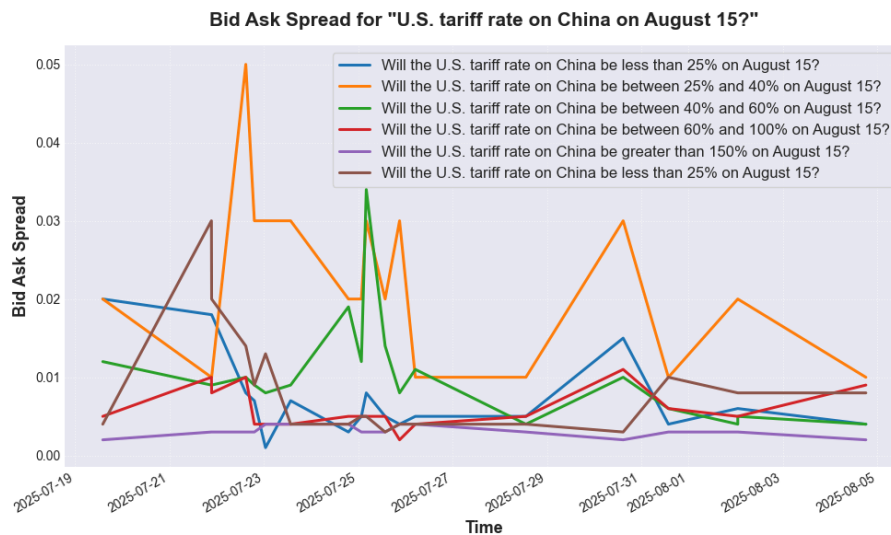


Figure 3. Bid Ask Spread for the China Tariff Market

As shown in the figure above, the bid–ask spread narrowed as the event’s resolution date drew closer.

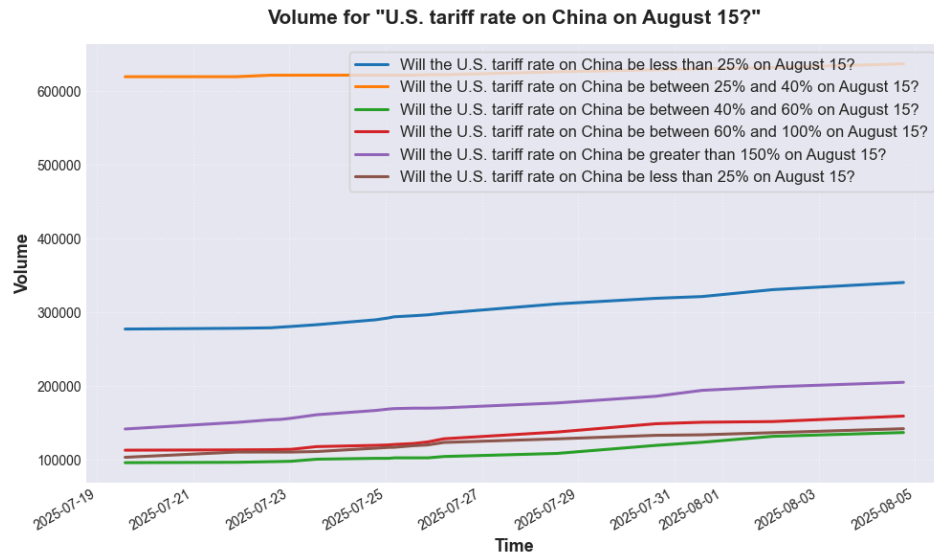


Figure 4. Volume for the China Tariff Market

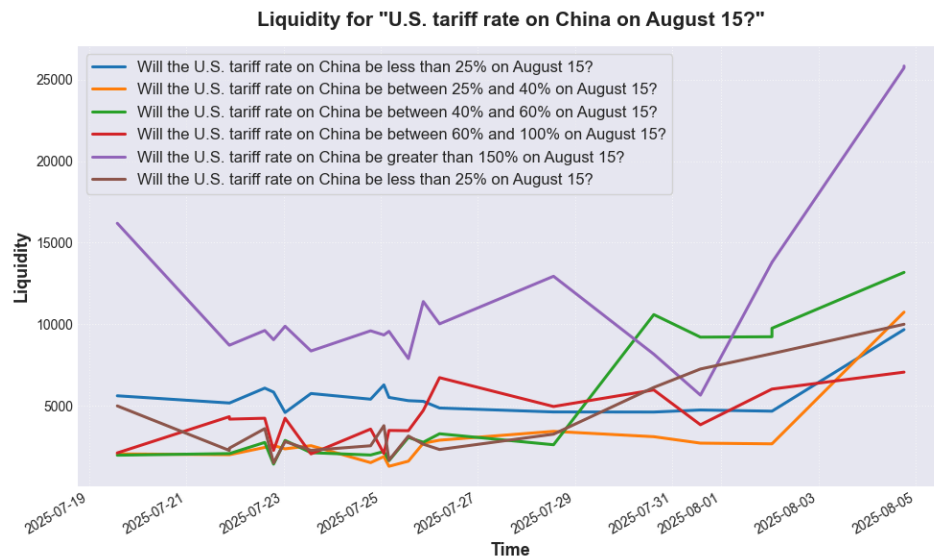


Figure 5. Liquidity for the China Tariff Market

Overall, the findings for the “U.S. tariff rate on China on August 15” market indicate a higher level of informed trading with reduced emotional response to news events. Additionally, pricing exhibited greater efficiency compared to general Polymarket trends, suggesting the presence of more sophisticated market participants.

4.3.2 Powell Removal Market

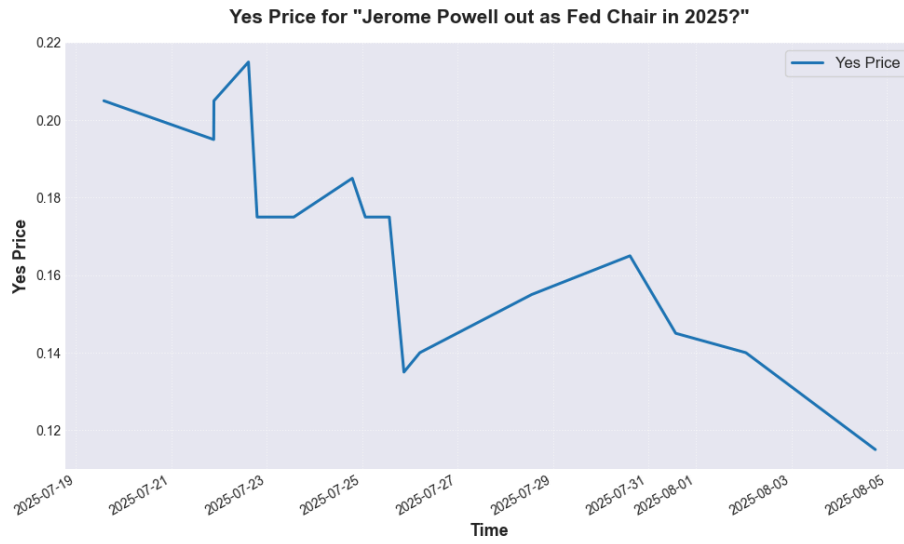


Figure 6. Yes Share Price for the Powell Removal Market

In addition to Figure 6, historical data from the Polymarket platform shows that prices underwent significant volatility in the period following Trump's election results.

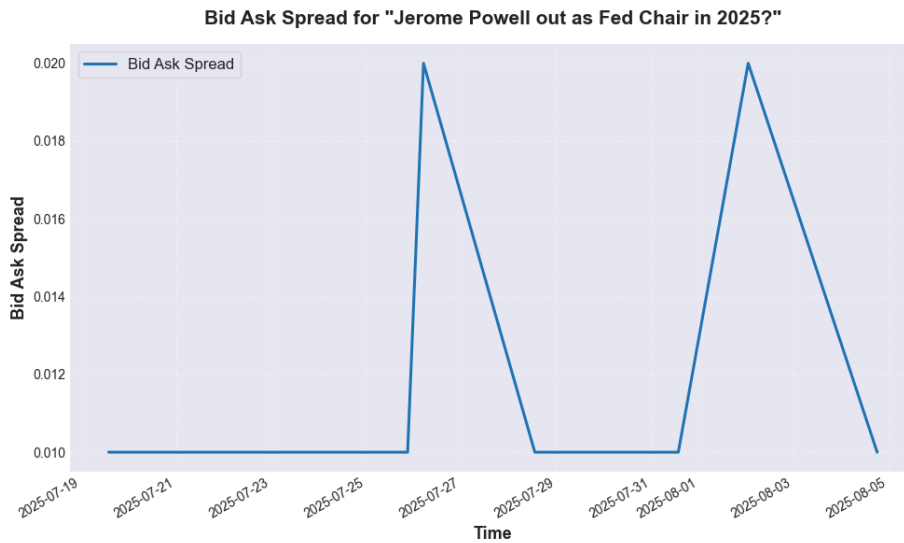


Figure 7. Bid Ask Spread for the Powell Removal Market

As shown in the above figure, bid-ask spread widened during the period of most uncertainty.

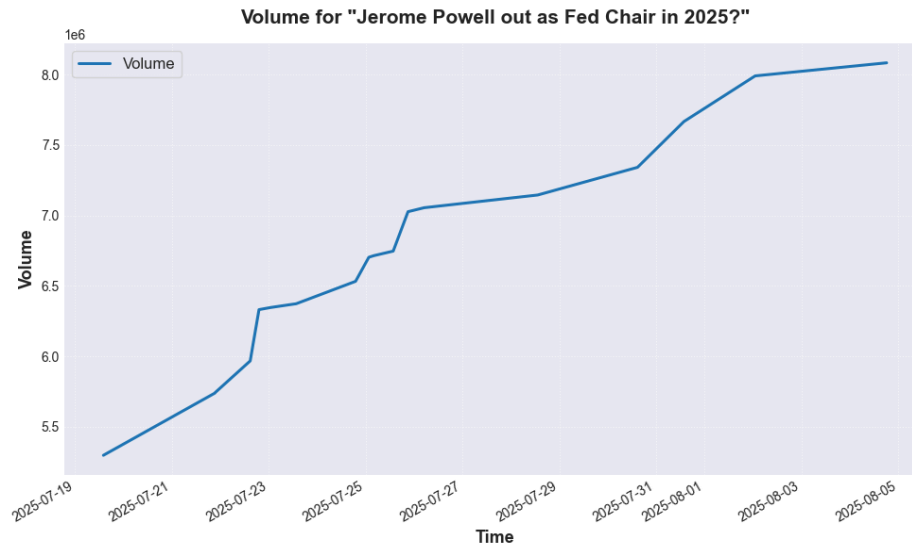


Figure 8. Volume for the Powell Removal Market

Figure 8 reveals that spikes in trading volume closely aligned with major Federal Reserve announcements.

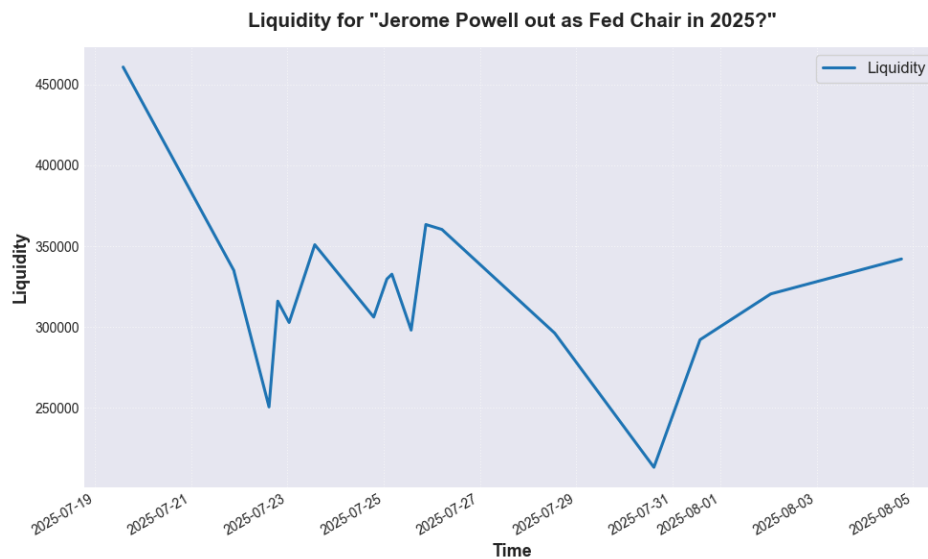


Figure 9. Liquidity for the Powell Removal Market

Overall, the “Jerome Powell out as Fed Chair in 2025” market’s implied probability of Powell’s removal has fallen from roughly 25% to about 13%, largely due to the debunking of rumors related to presidential memos. Liquidity levels tend to drop during off-market hours, while narrowing bid–ask spreads following initial opening volatility suggest growing participant confidence over time.

V. Discussion

5.1 Liquidity Risk

Liquidity risk was lower in markets with high trader participation and substantial media coverage, indicating that information flow plays a direct role in improving market efficiency. Beyond price movements alone, liquidity metrics provide deeper insight into the reliability of probability assessments for future events. Public-interest markets, such as the “Jerome Powell out as Fed Chair in 2025” market, exhibited higher volumes but greater volatility, whereas specialized markets, like the “U.S. tariff rate on China on August 15” market, demonstrated tighter pricing and greater price efficiency.

5.2 External Influences

Market behavior in both the Powell removal and China tariff contracts were notably shaped by external information shocks. For instance, in the Powell removal market, unconfirmed reports, such as alleged internal disputes regarding building costs in the Fed or leaked termination letters, generated pronounced short-term volatility, with rapid price escalations followed by quick corrections once credibility was reassessed.

In contrast, the China tariff market was more responsive to actually verified, policy-oriented disclosures. For example, detailed trade strategy announcements, such as the one during April of 2025, produced gradual and sustained price adjustments on an upwards trajectory. These patterns indicate that the nature and perceived reliability of external information directly influence liquidity flows, spread dynamics, and volatility levels within different prediction markets.

VI. Conclusion

6.1 Key Insights

This study found that market popularity, news cycles, and even the proximity to resolution can move the needle on liquidity levels in prediction markets. Traders should monitor event-related information to anticipate liquidity changes. Since participants in prediction markets have their own financial interests at stake, they are highly motivated to seek out and process the most up-to-date and reliable information. This incentive structure often leads to remarkably accurate forecasts. For this reason, prediction markets serve a dual purpose: they are powerful tools for investors aiming to make data-driven decisions, and they provide academics with rich, real-time datasets for research and analysis.

6.2 Future Research

Future studies could explore three main dimensions to deepen our understanding of prediction market dynamics. First, the information flow between traditional financial markets and prediction markets. Identifying how prediction markets mirror or do not mirror price movements

in equities, bonds, or commodities in traditional markets could clarify their role in broader price discovery.

Second, research could investigate arbitrage opportunities between related prediction markets. For instance, those with overlapping political or economic factors. Analyzing price discrepancies and the speed of correction has the potential to provide useful insights into market efficiency and sophistication of traders.

Third, we can do more deep research uncovering the major investors and bettors on these prediction markets to get a better understanding of the stakeholders in these markets.

By addressing these areas, future research can advance the understanding of prediction markets beyond just isolated ecosystems, but also as interconnected components of global information and trading networks.

REFERENCES

1. [add references]

Appendix A

“Jerome Powell out as Fed Chair in 2025” Market Statistics

<i>Statistic</i>	Yes Price	No Price	Bid-Ask Spread	Volume	24-Hour Volume	Liquidity
<i>Mean</i>	0.1653	0.8347	0.0115	6844348.27	232783.34	323318.23
<i>Median</i>	0.175	0.825	0.01	6731191.27	189920.41	325058.64
<i>Standard Deviation</i>	0.0289	0.0289	0.0037	835321.57	150966.23	48277.32
<i>Minimum</i>	0.115	0.785	0.01	5298252.65	20667.74	213166.07
<i>Maximum</i>	0.215	0.885	0.02	8083620.95	596664.65	460799.11

Appendix B

“U.S. tariff rate on China on August 15” Market Statistics

<i>Metric</i>	<i>Statistic</i>	< 25%	25%-40%	40%-60%	60%-100%	100%-150%	> 150%
Yes Price	<i>Mean</i>	0.052	0.7635	0.1386	0.0184	0.0155	0.0066
	<i>Standard Deviation</i>	0.0132	0.0776	0.0826	0.0041	0.009	0.0025
No Price	<i>Mean</i>	0.948	0.2365	0.8614	0.9816	0.9845	0.9934
	<i>Standard Deviation</i>	0.0132	0.0776	0.0826	0.0041	0.009	0.0025
Bid-Ask Spread	<i>Mean</i>	0.0077	0.021	0.01	0.006	0.0084	0.0031
	<i>Standard Deviation</i>	0.0055	0.0107	0.0068	0.0025	0.0067	0.0007
24-Hour Volume	<i>Mean</i>	4587.08	1180.74	2087.61	2275.26	2371.52	3352.66
	<i>Standard Deviation</i>	3264.04	1256.62	1768.58	2036.44	1784.2	2101.57
Volume	<i>Mean</i>	300934.63	625134.42	109397.76	129690.13	121582.9	172507.96
	<i>Standard Deviation</i>	22105.32	5732.26	14693.2	17273.91	12111.71	19489.9
Liquidity	<i>Mean</i>	5672.4	3190.84	4893.77	4415.1	4443.57	11712.21
	<i>Standard Deviation</i>	1459	2637.8	4143.48	1643.79	2804.46	5390.42