Market Simulation and Trader Behavior Analysis

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February 1, 2025

Abstract

This report presents the development of a cryptocurrency market simulator over four days. The project aimed to understand market dynamics, trader behavior, and liquidation cascades. The implementation included an order book, market evolution modeling, and trader balance management. We examine price evolution, trader behaviors, and the influence of different market actors.

1 Introduction

Cryptocurrency markets are highly dynamic and influenced by multiple factors, including trader behavior, liquidity, and external financial events. The objective of this project was to build a simulated trading environment that allows for the observation of market mechanics and key economic phenomena such as price fluctuations and liquidation cascades.

The main research questions addressed in this project are:

- How do different trader types impact market stability?
- What causes liquidation cascades, and how do they affect the market price?
- How can we mitigate such phenomena ?

2 Dataset and Market Analysis (Day 1)

The initial phase of the project involved analyzing market datasets to identify patterns in trader behavior and price movements. The main focus was on liquidity distribution, order book depth, and trading volume.

2.1 Trader Profiles and Identification

Traders were categorized into three main groups:

- **Market Makers**: Provide liquidity and stabilize prices.
- **Swing Traders**: Execute trades based on market trends, often using medium leverage.
- **Degen Traders**: Engage in high-risk trading with aggressive leverage, leading to frequent liquidations.

To better understand trader influence, we assigned scores based on criteria such as trading frequency, leverage usage, and liquidity contribution. These scores helped classify traders more accurately and detect patterns of behavior in the dataset.

2.2 Modeling Influence with Graphs

To compute a graph of influence, we used a matrix X of size $n_{subaccounts} \times n_{timeblocks}$, where the coefficient for subaccount i in time block j is 1 only if the subaccount interacted within that block. By computing:

$$A = XX^T \tag{1}$$

we obtained the adjacency matrix A of a weighted graph, linking subaccounts that frequently interact within the same blocks. This metric served as our measure of "influence" between traders.

```
Subaccount 0 (0x5303d92e49a619bb29de8fb6f59c0e7589213cc8000000000000000000000001):
  Average Holding Time = 746.83 blocks
  Average Orders per Block = 2.02
  Scalper Score = 0.57
Subaccount 1 (0x21596b451da15002ebbb91661f7f5e9f2f372343000000000000000000000011):
  Average Holding Time = 758.84 blocks
  Average Orders per Block = 2.46
  Scalper Score = 0.61
Subaccount 2 (0xed8c4c43e03e24b7f12975472da771ce2f8b857c000000000000000000000000):
  Average Holding Time = 733.31 blocks
  Average Orders per Block = 4.32
  Scalper Score = 0.77
Subaccount 3 (0xbcc871dab5a507624e55afeaa93610a424c446cc000000000000000000000000):
  Average Holding Time = 785.02 blocks
  Average Orders per Block = 1.17
  Scalper Score = 0.50
Subaccount 4 (0x5303d92e49a619bb29de8fb6f59c0e7589213cc8000000000000000000000004):
  Average Holding Time = 770.18 blocks
  Average Orders per Block = 2.98
  Scalper Score = 0.66
```

Figure 1: Scalper score distribution for the first traders.

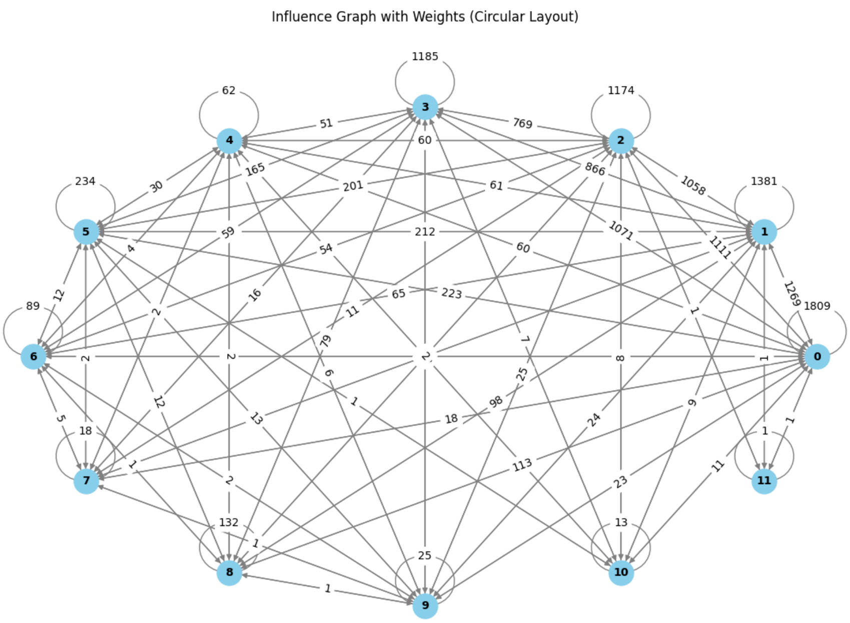

Figure 2: Graph representation of trader influence and interaction.

3 Market Simulation MVP (Day 2-3-4)

A fundamental component of this project was the development of a simulated trading environment divided into three phases:

3.1 Phase 1: Order Book Generation

This phase involved implementing the core trading infrastructure:

- **Order Class**: Represents individual trade actions.
- **Order Book**: Manages buy and sell orders in a structured queue.
- **Trader Classes**: Models different trading strategies and risk profiles.
- **Market Class**: Handles order execution and market condition updates.

	OrderHash	Block	Action	Price	Quantity	OrderType	Subaccount
0	9ee81f6117	0	EVENT_NEW	1.073359e+07	1.712	BUY	0
1	2f21c5db94	0	EVENT_NEW	1.074504e+07	0.286	BUY	2
2	2e08ada6d9	0	EVENT_NEW	1.075815e+07	1.885	SELL	3
3	1533c93e9d	0	EVENT_NEW	1.077076e+07	1.759	SELL	4
4	e5d7dcec1f	0	EVENT_NEW	1.074827e+07	0.510	SELL	5
5	26e98bdbdc	0	EVENT_NEW	1.075655e+07	0.184	SELL	6
6	7e7fd78290	0	EVENT_NEW	1.076008e+07	1.242	SELL	7
7	40b493cc84	0	EVENT_NEW	1.074158e+07	1.690	BUY	8
8	bd56ae1daf	0	EVENT_NEW	1.074451e+07	0.638	BUY	9
9	6c969ccc5f	0	EVENT_NEW	1.076583e+07	0.385	SELL	10
10	0e05b48e2c	0	EVENT_NEW	1.074404e+07	0.403	BUY	11
11	9d6893fa38	0	EVENT_NEW	1.075194e+07	1.751	SELL	12
12	c0f03d76e8	0	EVENT_NEW	1.076361e+07	1.718	SELL	1000

Figure 3: Visualization of order book generation process for a random set of traders.

3.2 Phase 2: Market Price Evolution

During this phase, we analyzed how the market price evolves over time and how buy and sell orders influence its trajectory:

$$\Delta P = \alpha \cdot \text{sign}(\text{net order flow}) \cdot \sqrt{|\text{net order flow}|} - \beta \cdot \sqrt{|\text{liquidation volume}|} \tag{2}$$

3.3 Phase 3: Trader Balances and Liquidations

In this final phase, trader balances were updated dynamically, and liquidation mechanisms were implemented:

$$P_{liq} = \begin{cases} P_{entry} \cdot \left(1 - \frac{1}{leverage^3}\right), & \text{if position} = \text{BUY} \\ P_{entry} \cdot \left(1 + \frac{1}{leverage^3}\right), & \text{if position} = \text{SELL} \end{cases} \tag{3}$$

4 Results and Discussion

Our key findings include:

- The presence of Market Makers reduces volatility and prevents liquidation cascades.
- Degen Traders amplify market instability by increasing liquidation pressure.
- Swing Traders influence price trends but do not directly trigger market crashes.

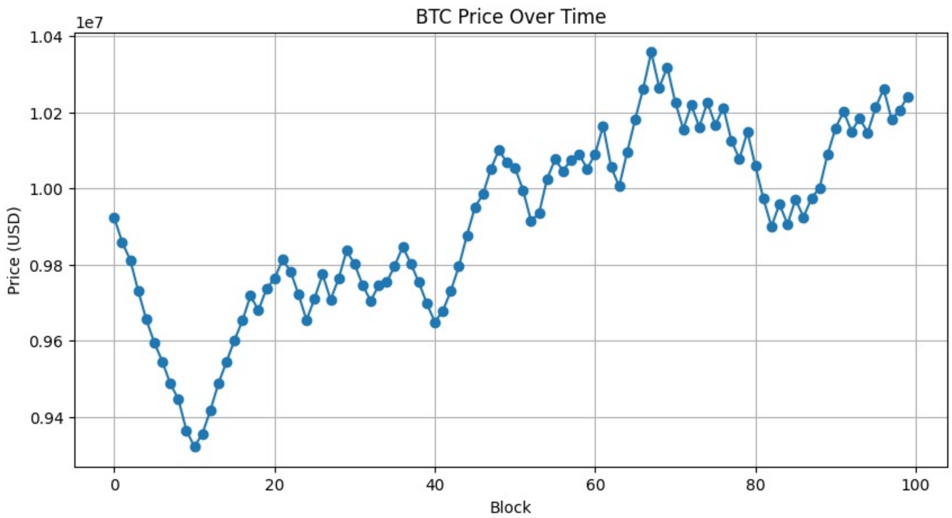

Figure 4: Market price evolution over time based on buy and sell influence.

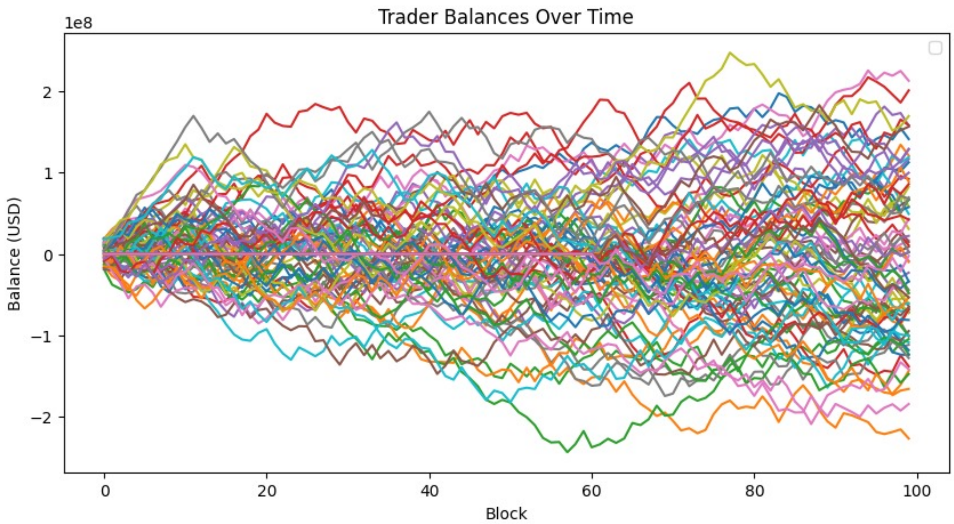

Figure 5: Trader balances over time.

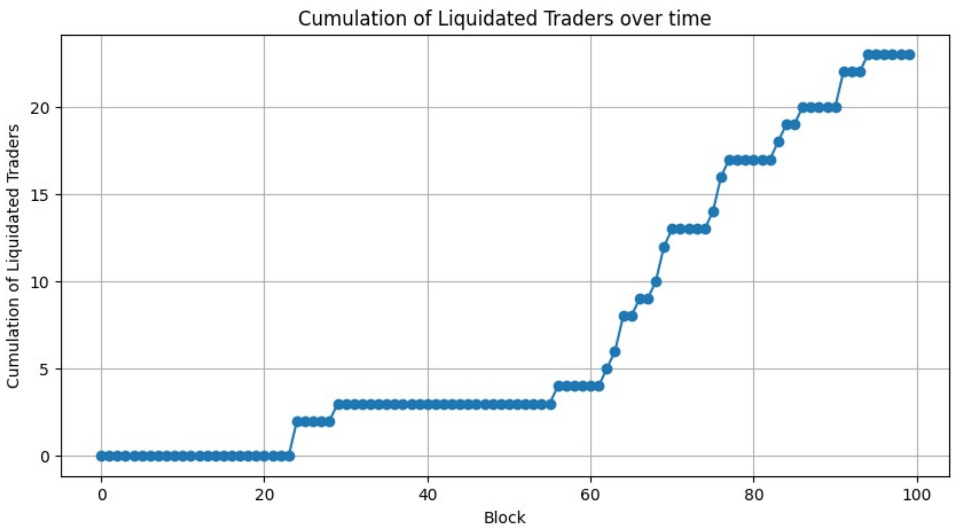

Figure 6: Liquidation on the market with the late introduction of degenerates

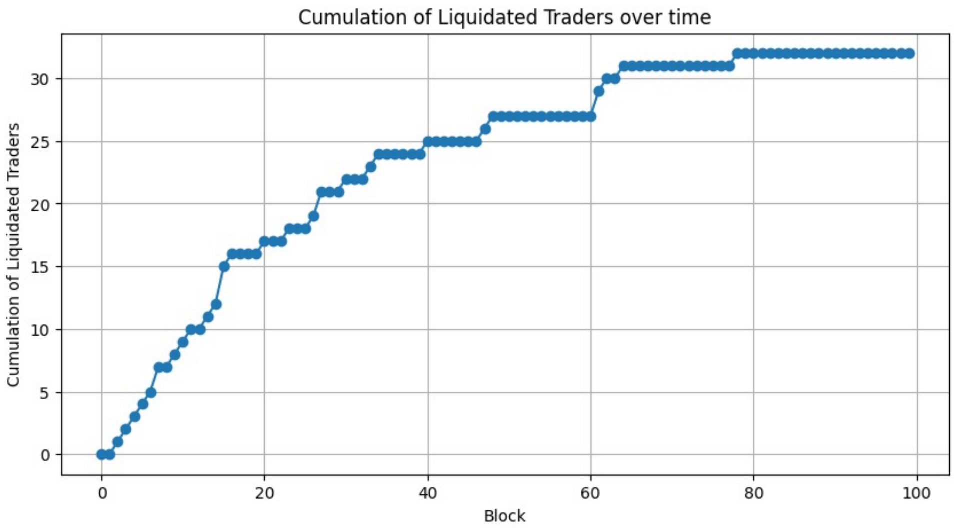

Figure 7: Liquidation on the market with the late introduction of market makers

5 Conclusion

This study successfully implemented a market simulation and analyzed different trader profiles. The model provides insights into market dynamics and liquidation events. Future work should focus on improving realism by incorporating additional financial indicators and external market influences.