Policy Optimization in Stock Market

An Agent-Based Model Approach
Integrating Evolutionary Computation

Interim Progress

Du Yusen

2026/05/20

筑波大学
University of Tsukuba

LABORATORY OF
Evolutionary
Computation

Research Topic

- Finding optimal macroeconomic policies under **individual irrationality** to mitigate resulting policy failures. [1]
  - **Simulation**
    - Build an **ABM Simulation** for the stock market.
  - Optimization
    - Evolve the optimal policy through **Genetic Algorithm**.
  - Validation
    - Construct an **Evaluation Framework** and functions to quantify policy scores.

Figure 1. To mitigate panic following the 2015 Chinese stock market turbulence, the SSE approved a trading curb rule on the first trading day of 2016. However, the policy backfired accelerating the market crash.

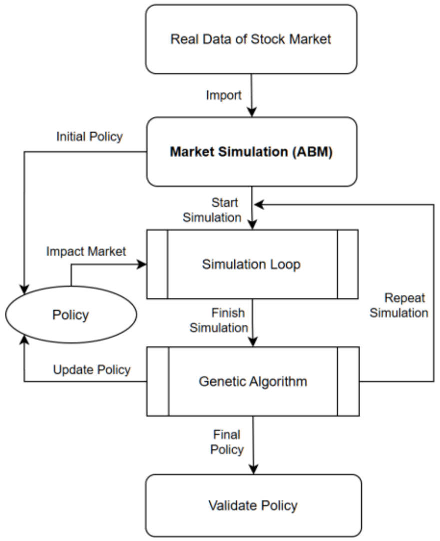


Figure 2. A complete process of policy optimization.

Simulation

- Construct a market simulation by Agent-Based Model's heterogeneity to emerge irrational trading decisions.
  - Environment: Stock Market
  - Agents: Traders
  - Interactions: Trade

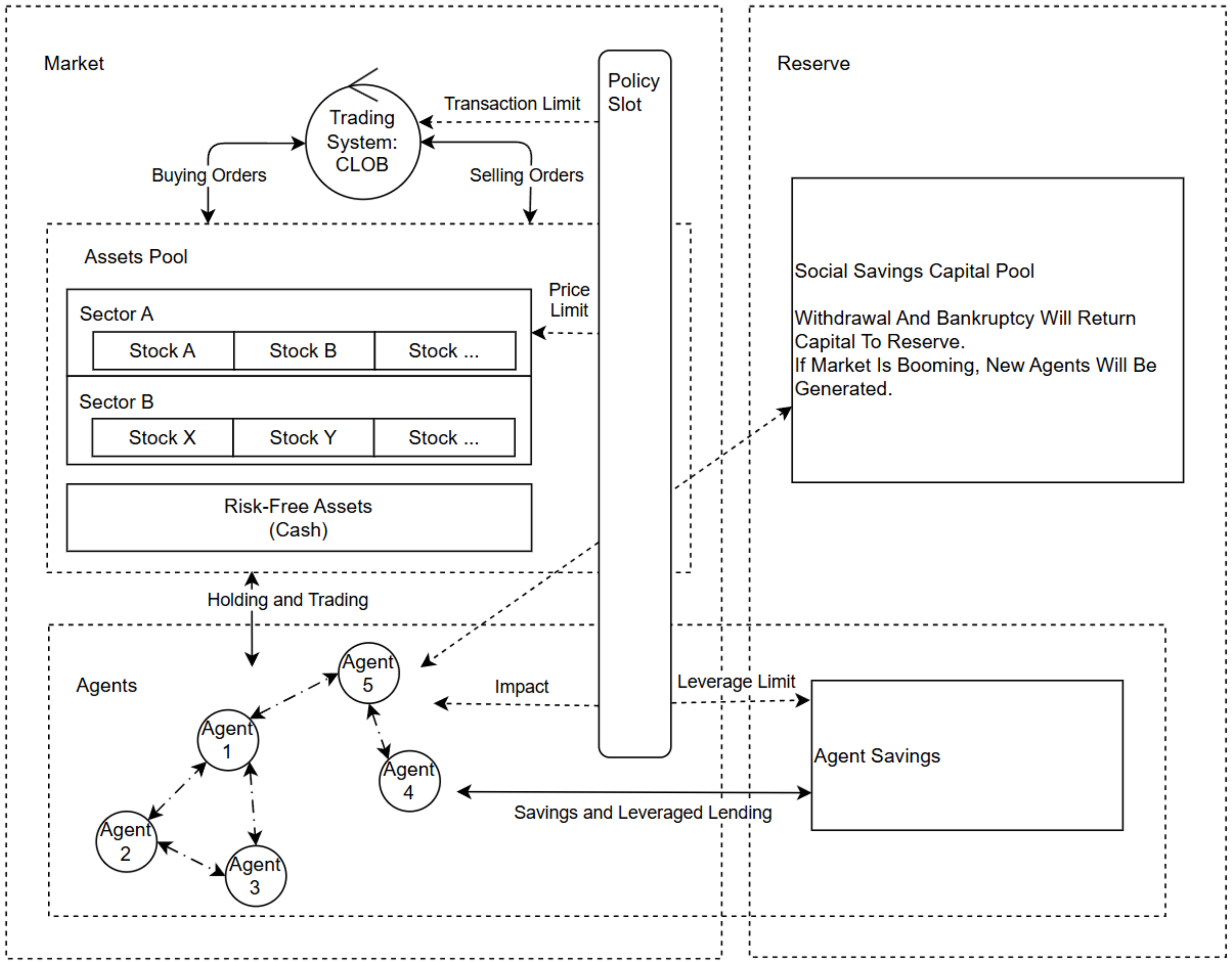


Figure 3. Overview of Simulation.

Stock Market

- Trade Object: Stocks
  - Sectors: Stocks of the same type belong to the same sector.
  - Stock
    - Intrinsic Attribute: Total Assets, Net Profit, Total Shares
    - Market Attributes: Price, Volume, Liquidity
- Matching System
  - Central Limit Order Book (CLOB)
- Policies
  - Macroeconomic regulation policies that can affect the stock market.

Policies

- Macroeconomic intervention is complex, spanning Monetary Policy, Fiscal Regulations, and Public Narrative, etc.
- However, regarding stock market volatility, Trading Regulations are the direct triggers of irrational herding behavior and panic selling. [2] [3]
- This research will focus on **Market Regulations**, specifically:
  - Limit of Price L_{price}
  - Limit of Circuit Breakers $L_{breaker}$
  - Limit of Leverage $L_{leverage}$
  - Limit of Settlement ($T + n$ Trading) L_{settle}

$$C_{policy} = \begin{bmatrix} r_{base} & r_{reserve} & M_{options} & \gamma_{credit} & \cdots \\ \tau_{stamp} & \tau_{gain} & \tau_{corp} & S_{subsidy} & \cdots \\ L_{price} & L_{breaker} & L_{leverage} & L_{settle} & \cdots \\ Freq_{news} & Sent_{bias} & I_{censorship} & U_{policy} & \cdots \\ \vdots & \vdots & \vdots & \vdots & \ddots \end{bmatrix}$$

$$P = [L_{price} \quad L_{breaker} \quad L_{leverage} \quad L_{settle}]$$

Central Limit Order Book (CLOB)

- Trade
  - Traders can submit bid (buy) and ask (sell) orders.
- Matching Logic
  - If Bid Price ≥ Lowest Ask: Executes immediately against the earliest submitted lowest ask order.
  - If Bid Price < Lowest Ask: Enters the order book as a limit order until matched or canceled.
- Priority Rule
  - Price-Time Priority: Higher bids and lower asks take precedence; earlier orders prioritize at the same price.

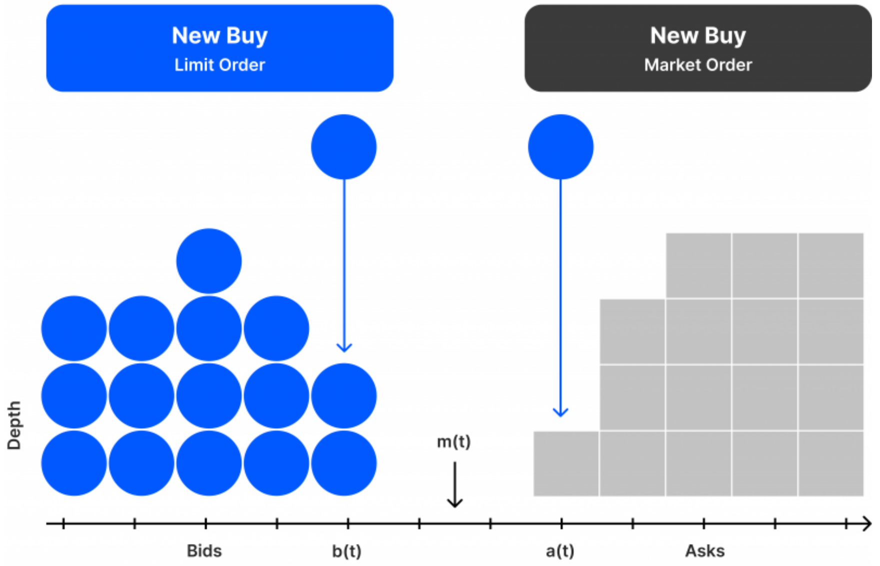


Figure 4. Schematic of CLOB.

Agent

- Agents are traders in the market; they come in different types and have different attributes.
  - Portfolio [5]
    - Reserve Capital: Capital pool outside the market
    - Active Capital: Risk-free assets, use to buying stocks.
    - Portfolio Holdings Vector Θ_A: Holding count of each stock.
  - Belief [5]
    - Belief Vector ϕ_A: Price expectations for each stock
    - Social Sensitivity β & Top Neighbors Count (K) : Used for social network
  - Constraint
    - Holding Limit: Maximum number of stocks held
    - Trading Frequency: Dormant if the minimum transaction interval is not met

Agent

	Institutional Trader	Normal Retail Trader	Noise Retail Trader
Population Ratio	5%	57%	38%
Capital Ratio	70%	18%	12%
Investment/Savings	80%/20%	20%/80%	20%/80%
Stock Limitations	20-100	5-50	5-50
Trade Frequency	3-5 Days	1-3 Days	1-3 Days
Fundamental Weight	80%	50%	10%
Bankruptcy	10% Initial Capital	20% Initial Capital	20% Initial Capital
Entrance	N/A	1% continued index increase increases the probability of generation by 5% with 1% baseline.	

Table 1. Agent Composition

Interactions

- In the market, **Trading** is the most important interaction.
  - Step 1: **Valuing Stocks** (Calculate Belief) via Fundamental Analysis, Social Network and Short-Term Price Trend.
  - Step 2: Check Cash, Decide Leveraged Investing.
  - Step 3: Submit Orders.
  - Step 4: Order Execution Or Cancellation.

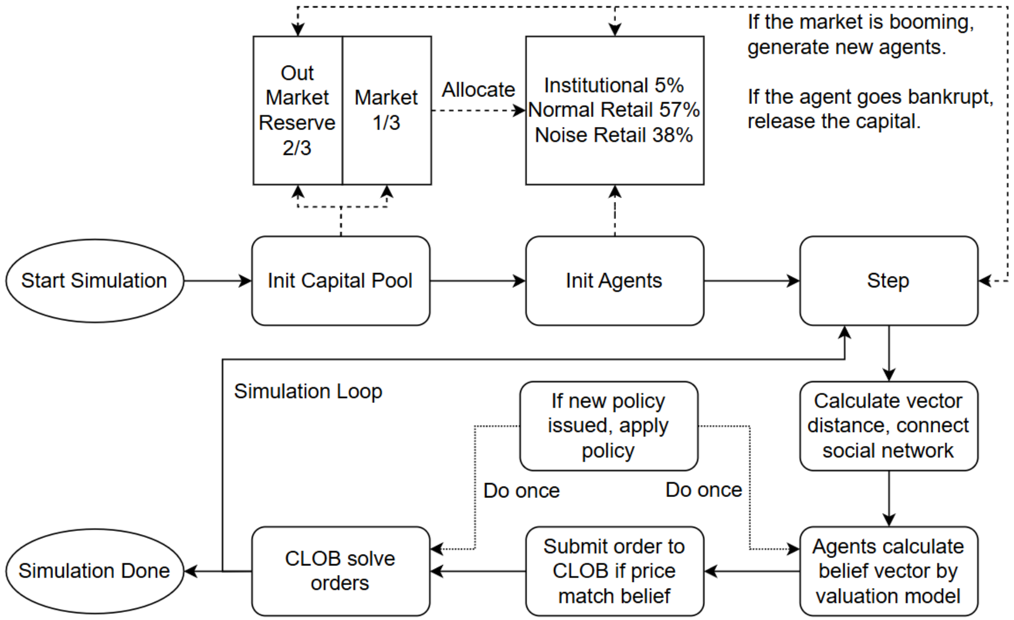


Figure 5. Schematic of simulation.

Valuation Model: Fundamental

- Shareholders' Equity (SE): $Total\ Assets - Total\ Liabilities$
- Book Value Per Share (BPS): $SE \div Number\ of\ Shares\ (NOS)$
- Earnings Per Share (EPS): $(SE - Preferred\ stock\ dividend) \div NOS$
- Price-to-Book Ratio (PB): $Price\ (P) \div BPS$
- Price-to-Earnings Ratio (PE): $Price\ (P) \div EPS$
- Sector average PB PE ($PE_S\ PB_S$): Shows average value of sector
- Earnings (E) : $Total\ Revenue\ -\ Total\ Expenses$
- Valuation: $V_{base} = \begin{cases} \frac{(BPS \times PB_S) + (E \times PE_S)}{2} & E > 0 \\ BPS \times PB_S & E \leq 0 \end{cases}$

Valuation Model: Social

- Sector Allocation Weights

  Let agents be a set $\mathcal{A} = \{1,2,\ldots,N\}$, for any agent $i \in \mathcal{A}$:

$$\mathbf{v_i} = \left[v_{i,1}, v_{i,2}, \ldots, v_{i,D}\right]^{\top} \in \mathbb{R}^{\mathbb{D}}$$

- Cosine Similarity

$$S_{ij} = \cos(\theta_{ij}) = \frac{\mathbf{v_i} \cdot \mathbf{v_j}}{\|\mathbf{v_i}\|_2 \|\mathbf{v_j}\|_2} = \frac{\sum_{d=1}^{D} v_{i,d} v_{j,d}}{\sqrt{\sum_{d=1}^{D} v_{i,d}^2}\sqrt{\sum_{d=1}^{D} v_{j,d}^2}}$$

- Valuation With Social
  - Let neighbors selected by Top-K be a set $\mathcal{N}_i = \{j \in \mathcal{A} \setminus \{i\} \mid \mathrm{rank}(S_{ij}) \le K\}$
  - For agent i

$$V_{social}^{(i)} = \sum_{j \in \mathcal{N}_i} W_{ij} \phi_j$$

  - ϕ_j is the valuation form agent j, and W_{ij} is

$$W_{ij} = \frac{S_{ij}}{\sum_{k \in \mathcal{N}_i} S_{ik}}$$

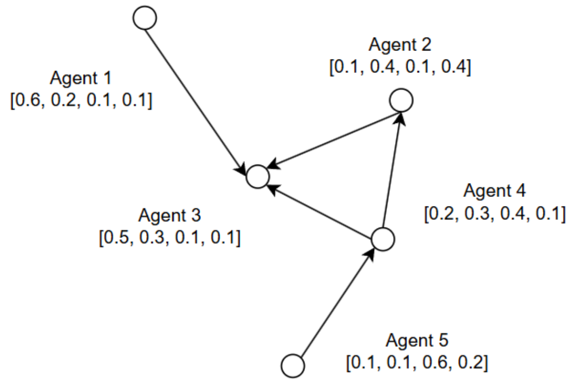


Figure 6. Schematic of Social Network

Valuation Model: Trend

- Chasing Highs, Selling lows
  - In market, everyone wants to buy stocks in the lowest price and sell them in highest price.
- Valuation By Price Trend
  - For stock m, from time τ to time t, trend of price P is

$$R_t(\tau) = \frac{P_t - P_{t-\tau}}{P_{t-\tau}}$$

  - Valuation with extrapolation factor λ

$$V_{trend} = P_t \cdot \left(1 + \lambda \cdot R_t(\tau)\right)$$

$$\lambda_i \sim \mathcal{N}\left(0.5, 0.2^2\right)$$

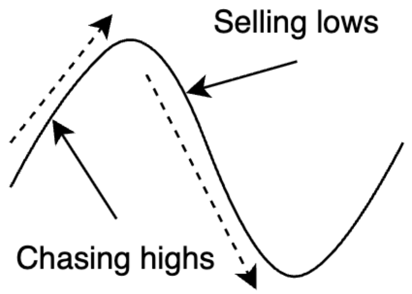


Figure 7. Schematic of Chasing Highs, Selling Lows

Valuation Model

For agent i, the price belief for stock m at time t is

$$\phi_i(m,t) = w'_{fund} \cdot V_{fund}(i,m,t) + w'_{social} \cdot V_{social}(i,m,t) + w'_{trend} \cdot V_{trend}(i,m,t) + \epsilon$$

$$w'_{fund} + w'_{social} + w'_{trend} = 1$$

	Fundamental $V_{fund}(i,m)$	**Social $V_{social}(i,m)$**	**Trend $V_{trend}(i,m)$**
Meaning	Intrinsic Value	Sentiment Contagion	Buy High, Sell Low
Method	$V_{base} = \begin{cases} \frac{(BPS_m \times PB_S) + (E_m \times PE_S)}{2} & E > 0 \\ BPS_m \times PB_S & E \le 0 \end{cases}$	$V_{social}^{i,m,t} = \sum_{j \in \mathcal{N}_i} W_{ij}\phi_j(m)$	$V_{trend} = P_t \cdot \left(1 + \lambda \cdot R_t(\tau)\right)$
Weight	w_{fund}^{base}	$w_{social}^{base} \times \left(1 + \beta \cdot \frac{\sigma}{L_{breaker}}\right)$	$w_{trend}^{base} \cdot \left(1 + \beta \cdot \frac{\lvert R_t(\tau)\rvert}{\lvert L_{price} - P_t\rvert + \epsilon}\right)$

Table 2. Valuation Model Composition

- β: Agent Social Sensitivity
- σ: Market Volatility, $\sigma_t = \sqrt{\frac{1}{T}\sum_{k=1}^{T}(R_{t-k} - \bar{R})^2}$
- ϵ: Noise that follows a normal distribution

Validation

- For ABM Simulation: Mean Reversion, Asset prices tend to revert to their mean over time in a closed system

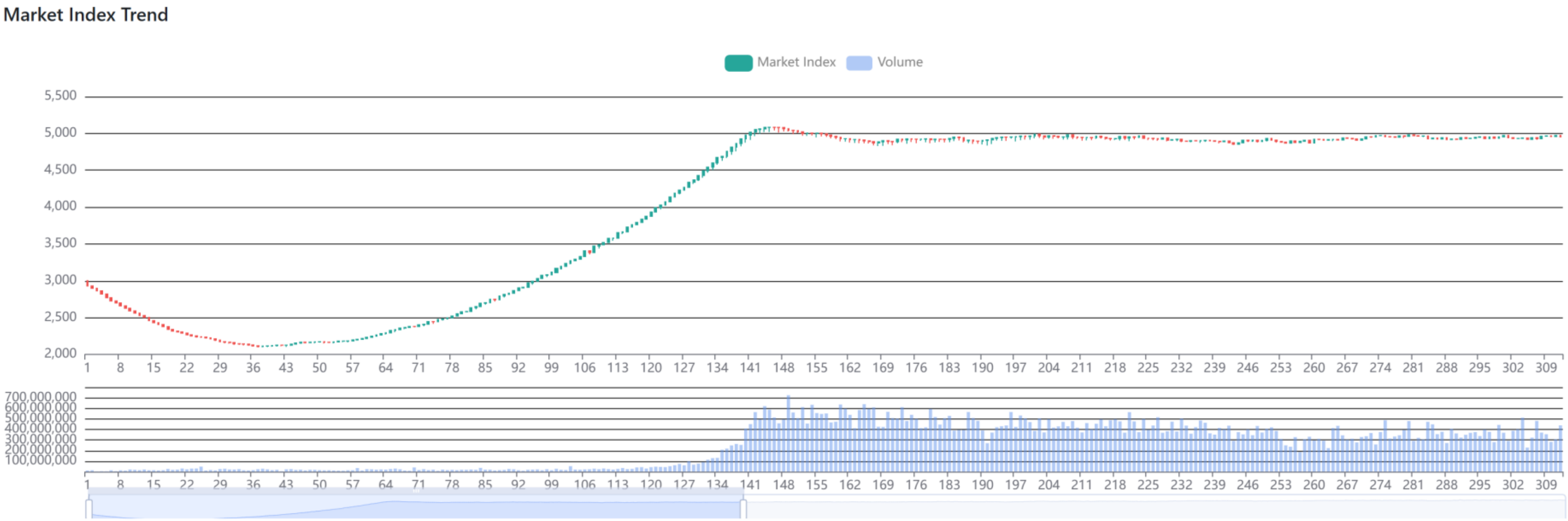


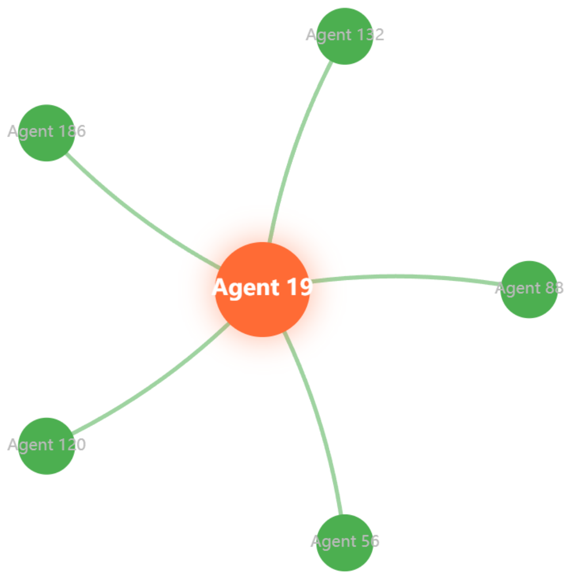
Figure 8. Simulation converged on about day 150.

Validation Problem
Social Network

- All neighbor similarity remains around 0.95-1
  - Initial portfolios too similar
  - Too few stocks
  - Too few sectors

Social Influence — Stock 21 (Day 679)

Influence Network



Neighbor Details

Neighbor	Similarity	Weight	Belief	
88	0.994	20.3%	70.02	→
56	0.980	20.1%	77.11	→
120	0.975	19.9%	76.44	→
186	0.970	19.8%	83.65	→
132	0.970	19.8%	72.01	→

Figure 9. Social network influence on a trading decision

Policy

- Compared to the simulation with other policy set without social network, market volatility has decreased after the policy was issued.

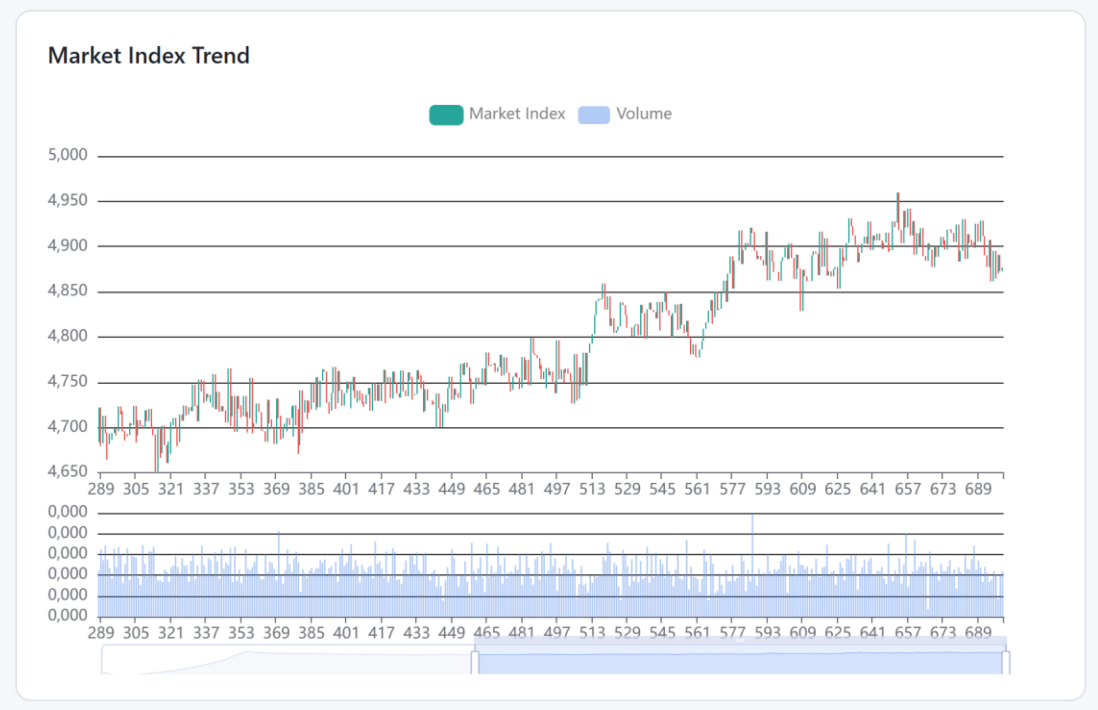


Figure 10. New policy set is not suitable for stable market

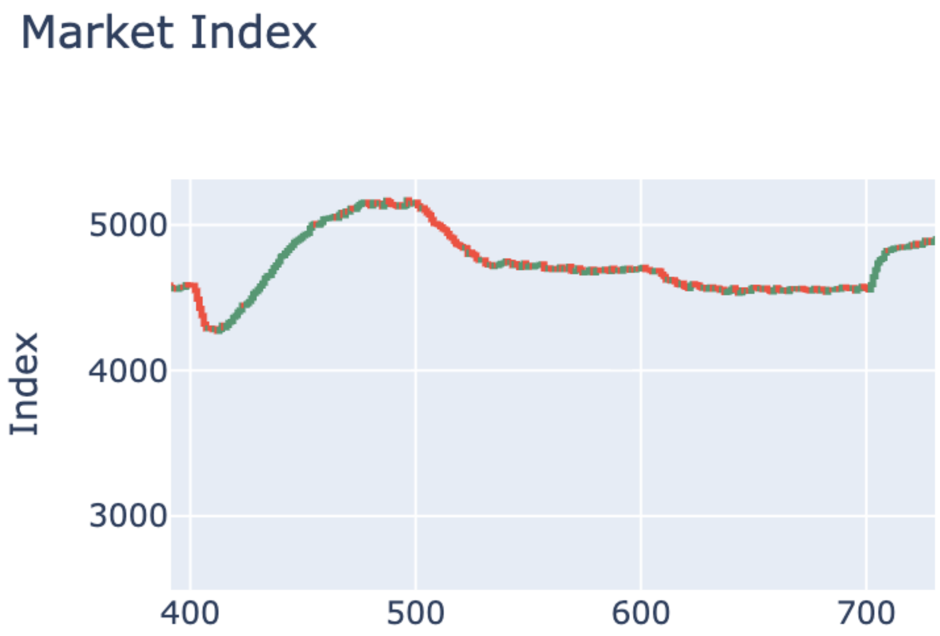


Figure 11. Index trend with previous policy set

Future Work

- Improve and Validate The Simulation
- Optimization: Genetic Algorithm
- GA Validation Framework

Improve Simulation Process

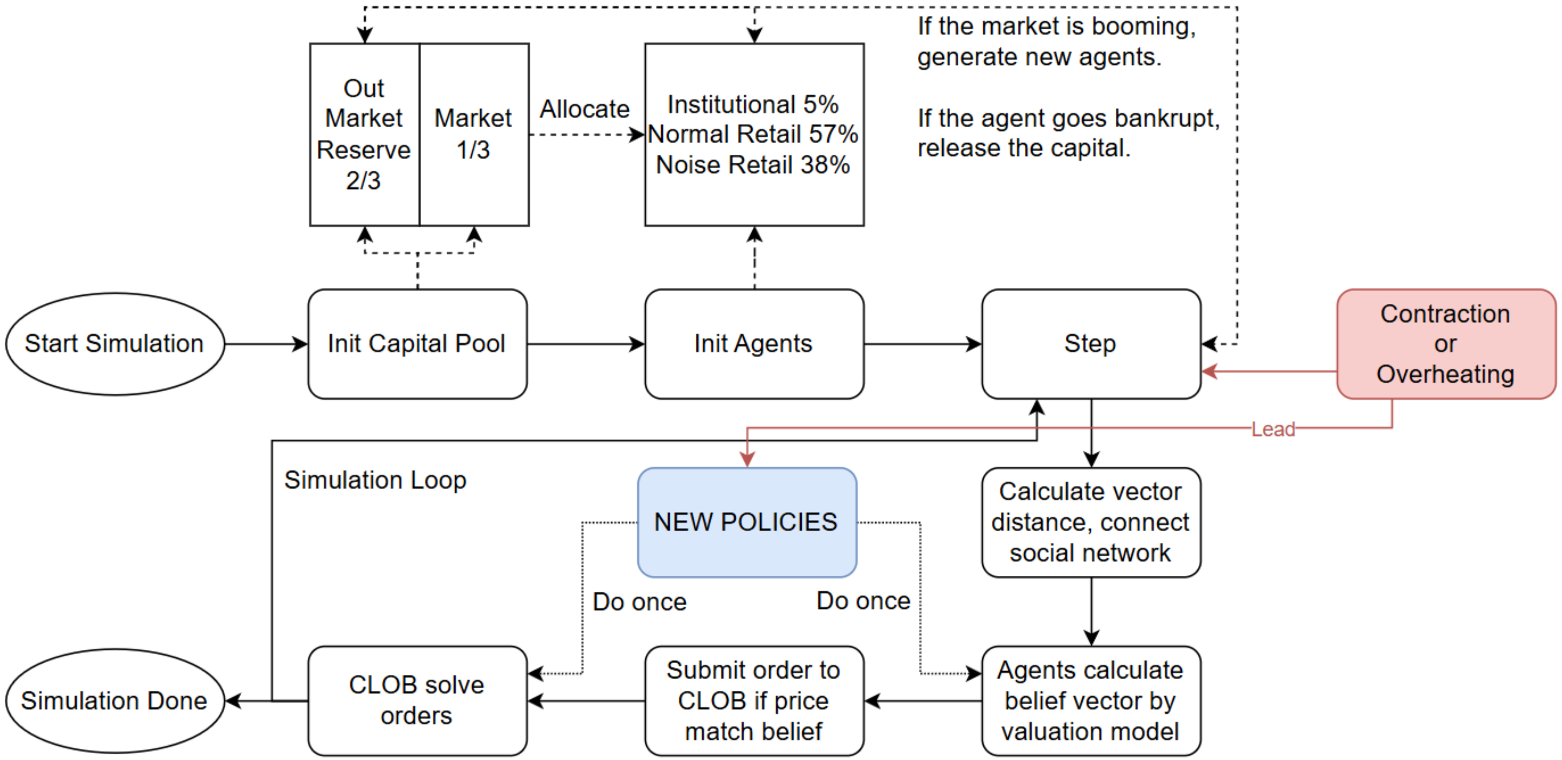


Figure 12. Pushing the market to extremes before implementing policies

Policy Optimization

- Genetic algorithm (GA) is a metaheuristic inspired by the process of nature selection.
  - Gene and Chromosome:

    $$[L_{price} \quad L_{breaker} \quad L_{leverage} \quad L_{settle}]$$

  - Select, Crossover and Mutation
    - Tournament Selection
    - Simulated Binary Crossover
    - Gaussian Mutation
  - Fitness Function
    - $Score = Stable\ Growth + Liquidity\ Preservation$ - $Bankruptcy\ Penalty$

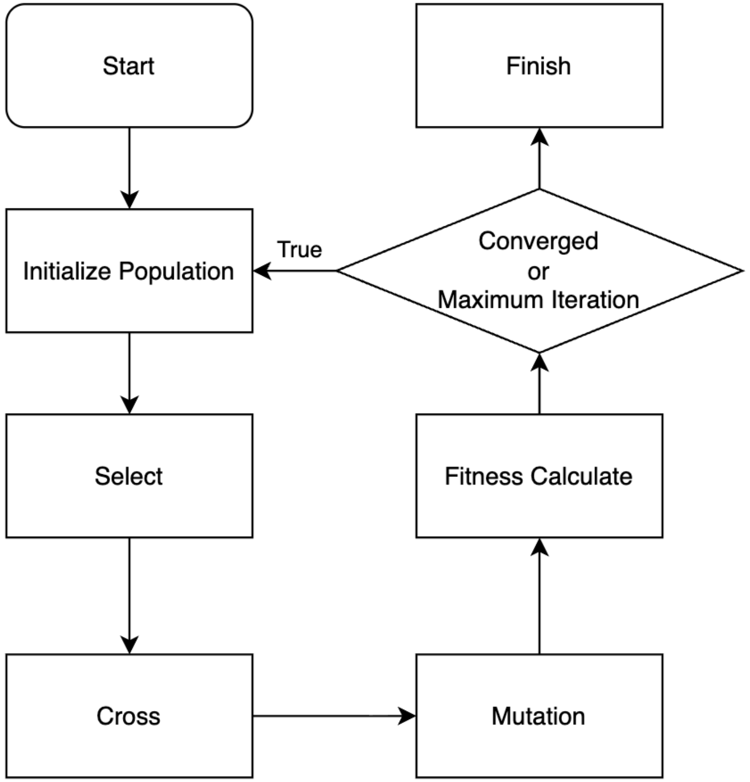


Figure 13. Schematic of GA process

Appendix 1. Reference

1. Hu, J., Jiang, G.J. and Pan, G. (2020), Market Reactions to Central Bank Interest Rate Changes: Evidence from the Chinese Stock Market*. Asia Pac J Financ Stud, 49: 803-831. https://doi.org/10.1111/ajfs.12316
2. Ackert, L.F., B. Church, and N. Jayaraman, 2001. An experimental study of circuit breakers: The effects of mandated market closures and temporary halts on market behavior, Journal of Financial Markets4, 185–208. https://doi.org/10.1016/S1386-4181(00)00020-3
3. Hu Yourou. (2023). Statistical Properties of Price Limit Hits in the Chinese Stock Markets. Advances in Applied Mathematics. 12. 4112-4121. 10.12677/AAM.2023.129403.
4. Fagiolo, G. and Roventini, A. (2012). Macroeconomic Policy in Dsge and Agent-Based Models. Revue de l'OFCE, 124(5), 67-116. https://doi.org/10.3917/reof.124.0067
5. Evan Albers, Mohammad T Irfan, and Matthew J. Botsch. 2024. Beliefs, Shocks, and the Emergence of Roles in Asset Markets: An Agent-Based Modeling Approach. In Proceedings of the 23rd International Conference on Autonomous Agents and Multiagent Systems (AAMAS '24). International Foundation for Autonomous Agents and Multiagent Systems, Richland, SC, 40–48. https://dl.acm.org/doi/10.5555/3635637.3662850