# Policy Optimization in Stock Market

*An Agent-Based Model Approach*
*Integrating Evolutionary Computation*

*Interim Progress*

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2026/10/22

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# Motivation

- Financial policies aim to stabilize markets, yet individual irrationality often triggers severe policy backfires [1] .
- Example: 2016 Chinese Stock Market Circuit Breaker:
  - To curb panic after the 2015 crash, CSRC introduced a mandatory circuit breaker rule. Instead of calming investors, it accelerated panic selling, halting trading twice in four days and forcing immediate repeal [3].

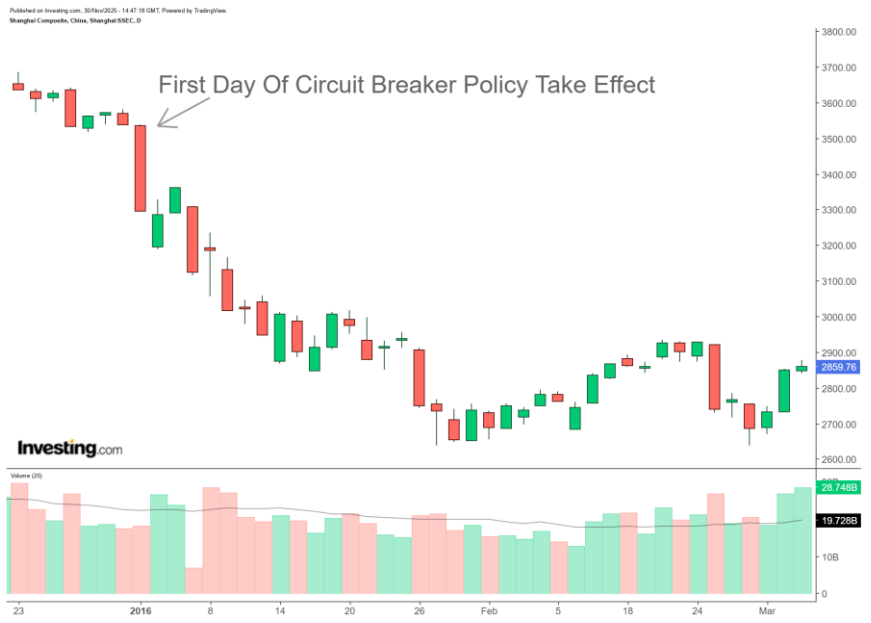



*Figure 1. SSE Market Repeatedly Triggered Circuit Breakers due to Panic.*

# 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.

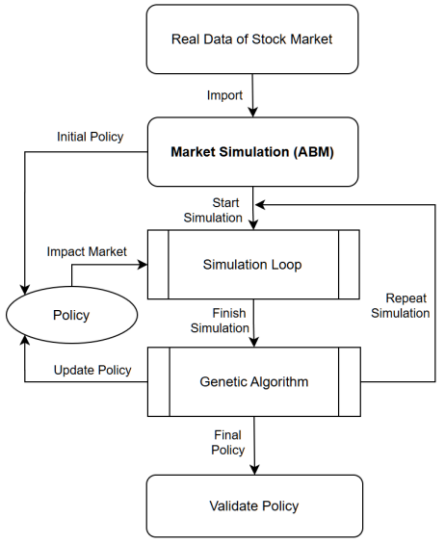



*Figure 2. A Complete Process of Policy Optimization.*

# Preliminaries

- Macroeconomic Equilibrium Models (CGE / DSGE) [4]: Rely on representative agent and homo economicus assumptions; unable to model irrational panic contagion.
- Forward Financial ABMs [6,13,14]:Reproduce market stylized facts from heterogeneous agents but focus on forward simulation rather than backward policy design.
- Static Regulatory ABMs [17]: Evaluate isolated price limits using a few manually preset parameters without automated multi-dimensional optimization.

| Research Paradigm | Micro Irrationality | Social Contagion | Magnet Effect | Automated Policy Search |
|---|---|---|---|---|
| CGE / DSGE Models [4] | No (Rational Agent) | No | No | No |
| Forward Financial ABMs [6, 13, 14] | Yes | Partial | No | No |
| Static Regulatory ABMs [17] | Yes | No | Partial | No |
| Proposed (ABM + GA) | Yes (3-Factor HAM) | Yes (Softmax) | Yes (Dynamic Weights) | Yes (GA) |

*Table 1. Comparison of Existing Research With This Research Proposal*

# Agent-Based Modeling

- Agent-Based Modeling (ABM)
  - A computational approach that simulates how individual agents interact with each other and their environment to understand how complex, large scale patterns emerge from simple local behaviors.
- Proposed ABM Framework for Stock Market.
  - Environment: Stock Market
  - Agents: Traders
  - Interactions: Trade

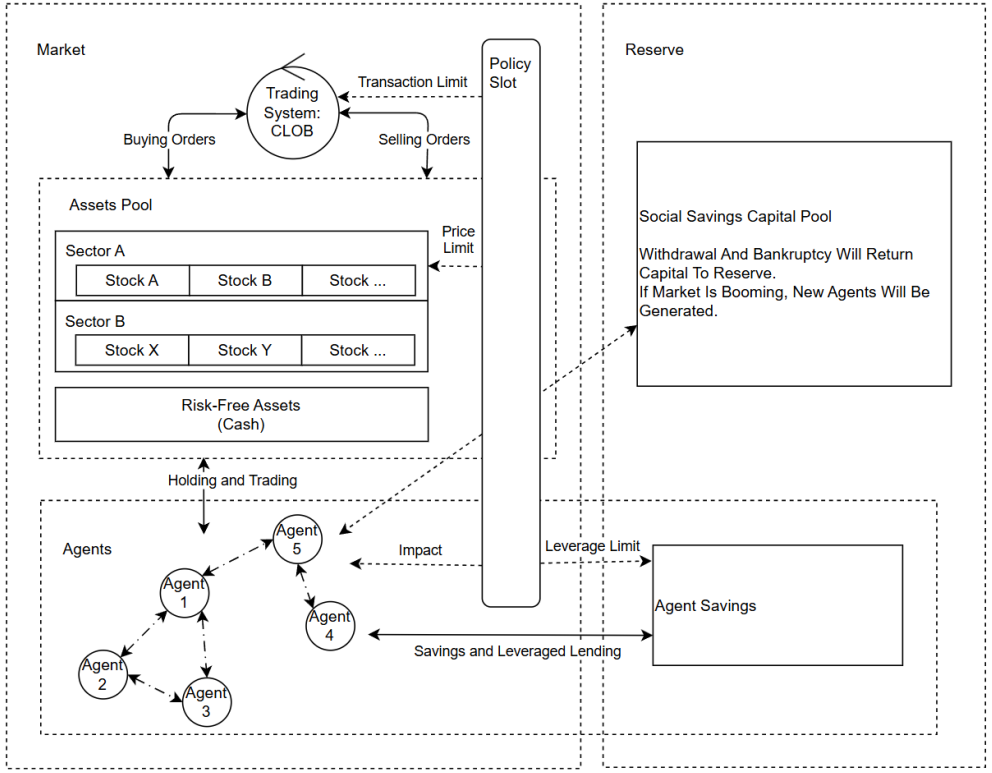



*Figure 3. Overview of Stock Market ABM Simulation.*

# 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. [15, 16]
- 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.

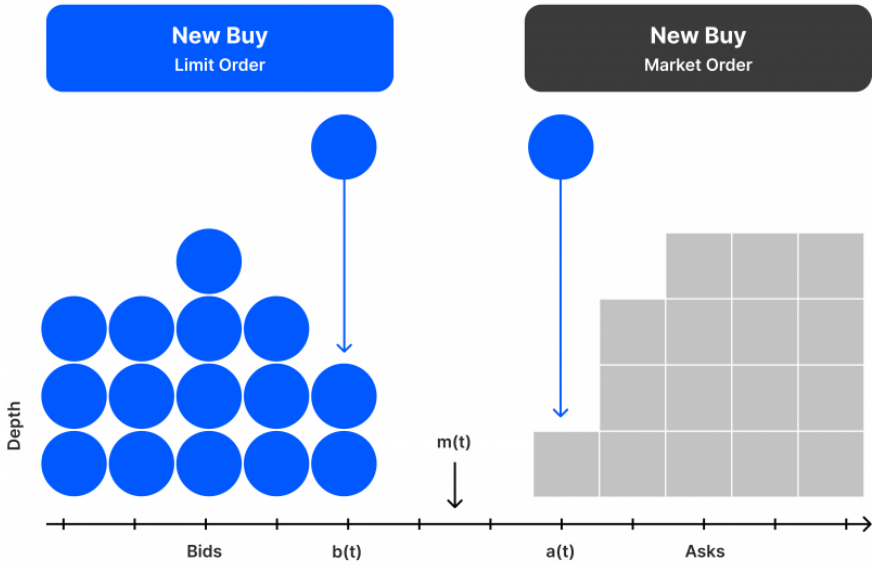



*Figure 4. Schematic of CLOB.*

# ABM Environment: 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.

# ABM Agents

- 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 $\Theta_A$: Holding count of each stock.
  - Belief [5]
    - Belief Vector $\phi_A$: Price expectations for each stock
    - Social Sensitivity $\beta$ & 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

*Model Description*

# ABM Agents

| | 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 2. Agent Composition*

# ABM 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.

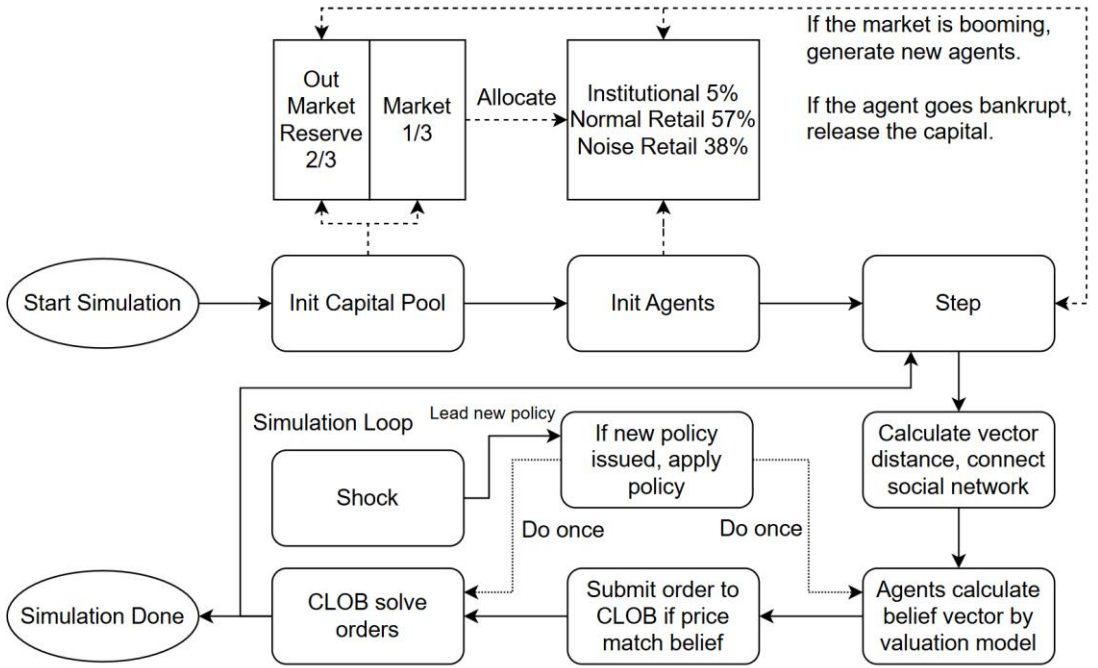



*Figure 5. Schematic of Simulation.*

# Valuation Model For Trade: 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 For Trade: Social Contagion

- To prevent portfolio homogeneity and capture realistic herding, we adapt the evolutionary discrete choice model of Brock and Hommes [8,9] and Chiarella and He [10] to a directed social network. Each agent $j$ accumulates a decayed historical performance reputation score $U_j(t)$ based on realized return rates. Agent $i$ allocates attention weights across its neighbor set $\mathcal{N}_i$ via a temperature scaled Softmax function

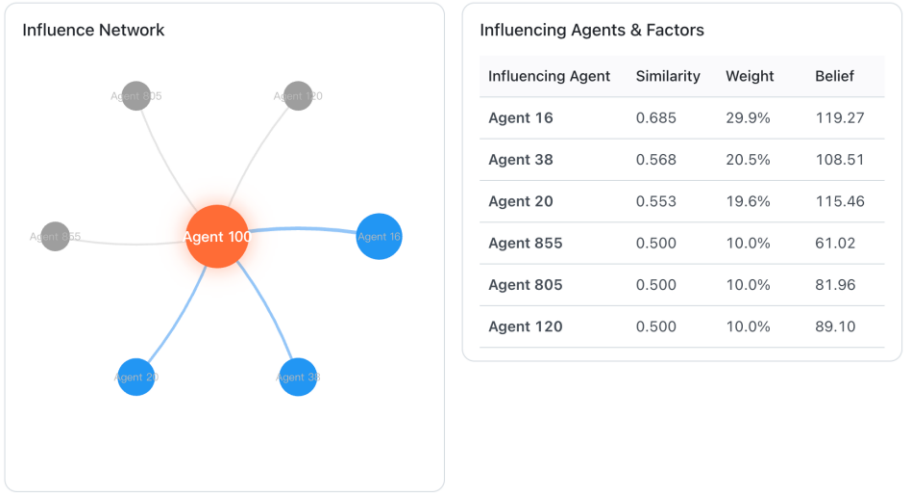



*Figure 6. Network Graph About How Social Contagion Works In A Single Trade During A Simulation.*

$$W_{ij}(t) = \frac{\exp\left(U_j(t)/\tau_s\right)}{\sum_{k\in\mathcal{N}_i}\exp\left(U_k(t)/\tau_s\right)}$$

# Valuation Model For Trade: 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 $\tau$ to time $t$, trend of price $P$ is

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

  - Valuation with extrapolation factor $\lambda$

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

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

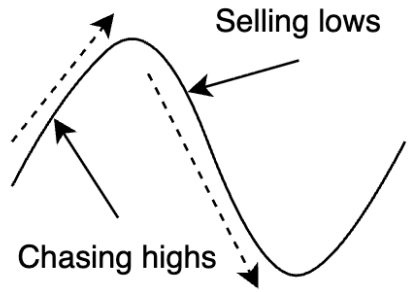



*Figure 7. Schematic of Chasing Highs, Selling Lows*

*Model Description*

# Three Factor 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 | $V_{base} = \begin{cases} \frac{(BPS_m \times PB_S) + (E_m \times PE_S)}{2} & E > 0 \\ BPS_m \times PB_S & E \leq 0 \end{cases}$ | $V_{social}^{i,m,t} = \sum_{j \in \mathcal{N}_i} W_{ij}(t)\phi_j(m,t)$ | $V_{trend} = P_t \cdot \left(1 + \lambda \cdot R_t(\tau)\right)$ |
| 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 3. Valuation Model Composition*

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

# Mean Reversion

- Mean Reversion
  - Asset prices tend to revert to their mean over time in a closed system. [6]
- Result of Proposed Framework
  - In closed baseline runs without exogenous shocks, the market composite price index starts at 3,000 and converges to an equilibrium level of approximately 2,686 around day 100. Following Day 100, the index fluctuates stably around this equilibrium mean, demonstrating clear convergence and mean reverting dynamics.

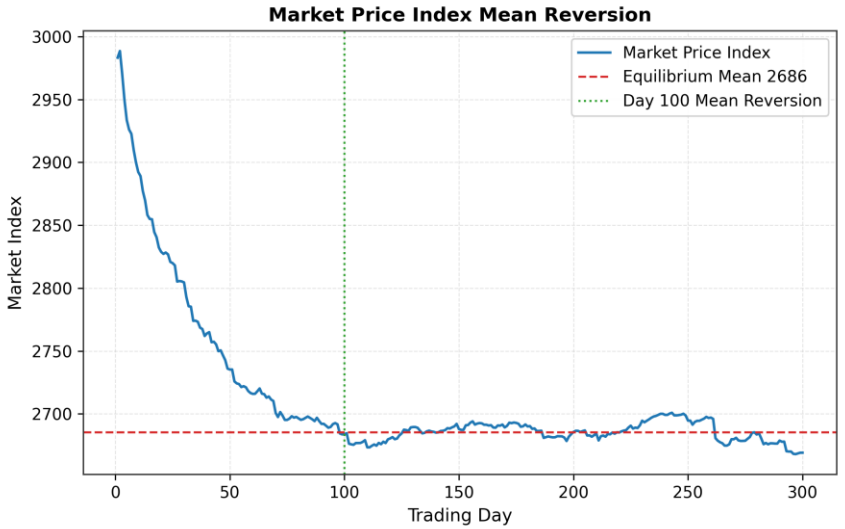



*Figure 8. Simulation converged on about day 100.*

# Heavy Tails

- Heavy Tails
  - Extreme price changes occur more often than expected under a normal distribution. [7]
- Result of Proposed Framework
  - Over 3,000 simulated trading days, excess kurtosis reaches 24.3565, with skewness of -2.9197 and a Jarque-Bera statistic of 78,390.67 ($p < 0.0001$). These results indicate strongly non-Gaussian, negatively skewed returns with pronounced heavy tails.

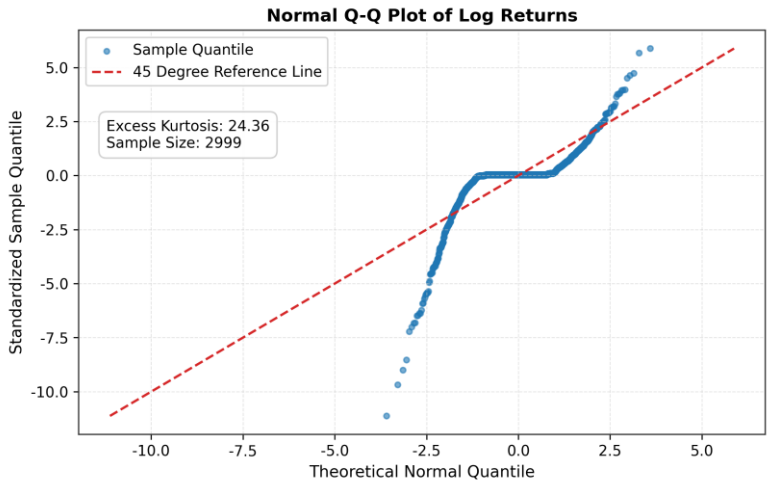



*Figure 9. Normal Quantile-Quantile Plot of Log Returns.*

# Volatility Clustering

- Volatility Clustering
  - Large price changes tend to follow large changes, while small changes tend to follow small changes.
- Result of Proposed Framework
  - The absolute return ACF at lag 1 is 0.4178, while the five lag ARCH-LM statistic is 393.27 ($p < 0.0001$). These results provide strong evidence of volatility clustering.

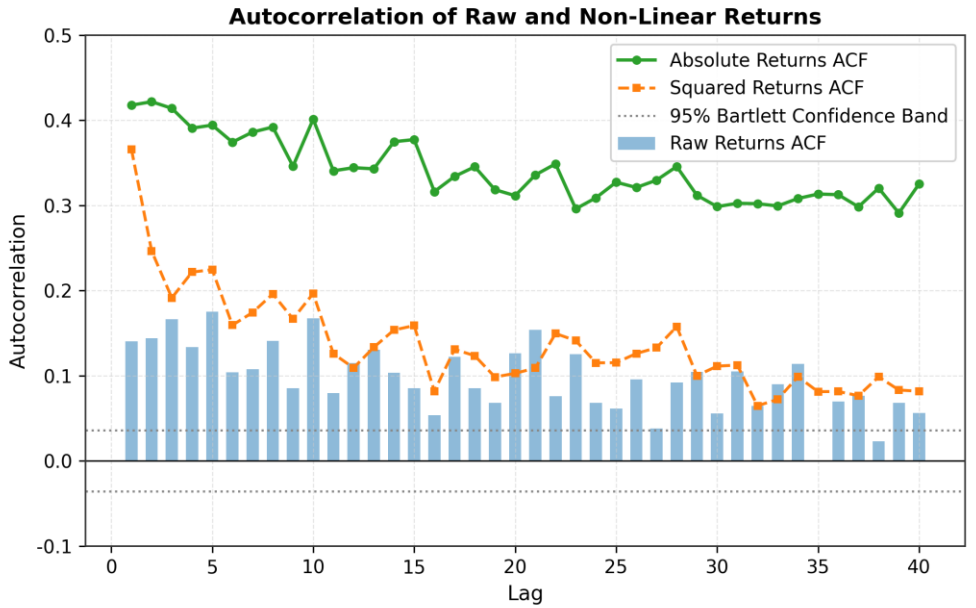



*Figure 10. Autocorrelation of Raw and Non-Linear Returns.*

# Future Work

- Integrate Genetic Algorithm
- Genetic Algorithm Validation Framework

# Genetic Algorithm

- Genetic algorithm 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
    - $F(P) = \ \&\omega_1 S_{\text{growth}}(P) + \omega_2 S_{\text{liquidity}}(P)\& - \omega_3 S_{\text{bankruptcy}}(P)$

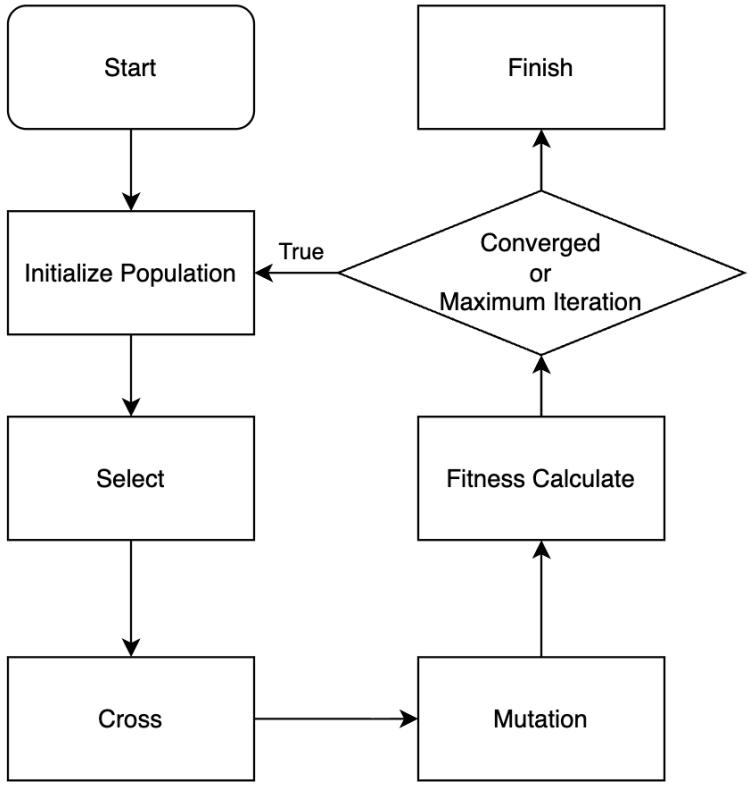



*Figure 11. Schematic of GA process*

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