Research Progress

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Outline

1. Current Work
2. Research Proposal
3. Open Questions

Current Work

Agent-Based Model

The SEIR model is a classical model for describing infectious diseases.

It divides the population into four compartments: **Susceptible**, **Exposed**, **Infectious**, and **Recovered**.

Although it can effectively describe disease transmission at the macro level, the SEIR model still has several limitations.

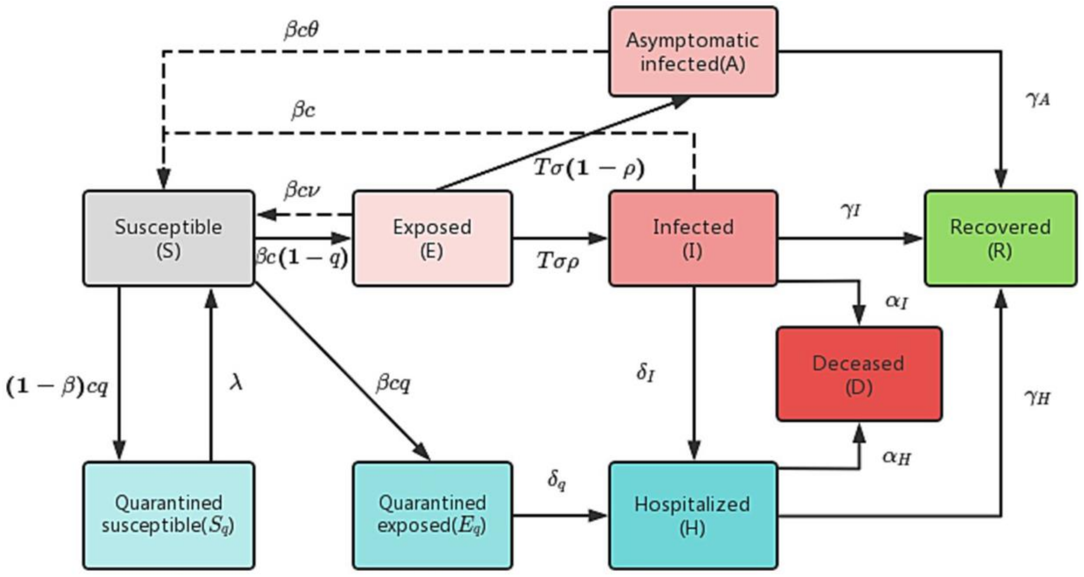

Figure 1. A variant of the SEIR model. Ref. https://doi.org/10.3389/fpubh.2023.1223039

$$\frac{dS}{dt} = -\beta\frac{SI}{N} \qquad \frac{dI}{dt} = \sigma E - \gamma I$$

$$\frac{dE}{dt} = \beta\frac{SI}{N} - \sigma E \qquad \frac{dR}{dt} = \gamma I$$

Agent-Based Model

- ABM is a **bottom-up** modeling approach in which a system is represented by autonomous agents following simple individual rules. When the system is simulated, **complex**, **emergent** patterns can be observed at the macro level. Core Components:
  - **Agents**
  - **Behaviors (Rules)**
  - **Environment**
  - **Interaction**

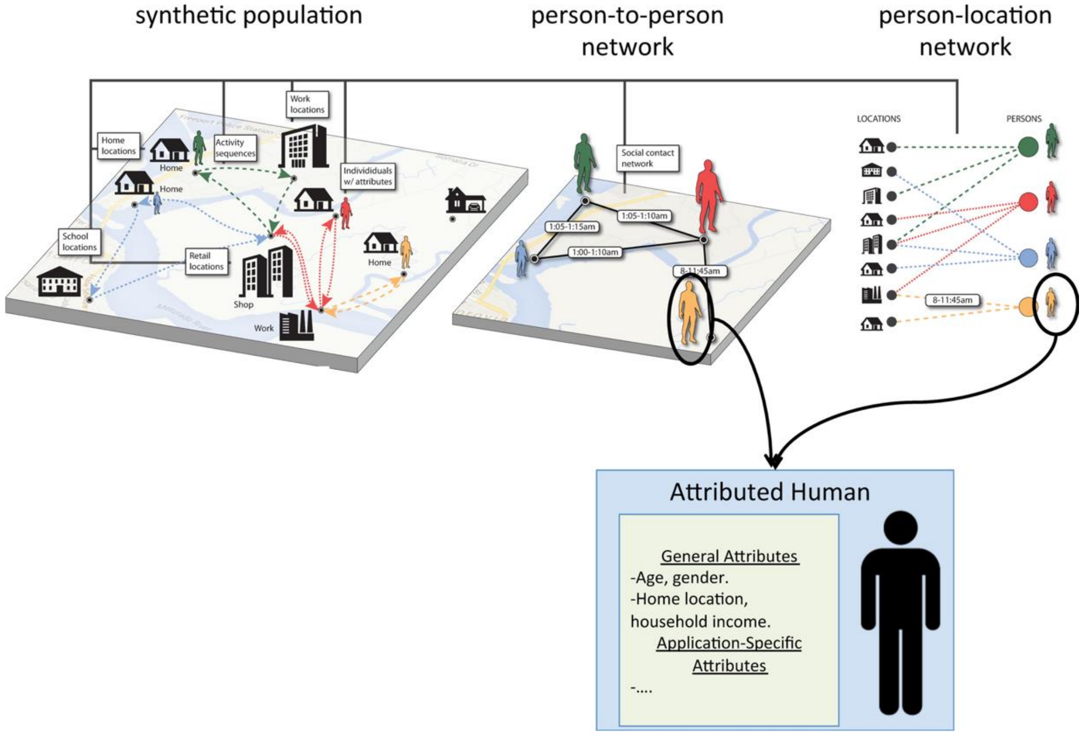

Figure 2. An ABM network for Computational Epidemiological. Ref. https://doi.org/10.1007/s41745-021-00260-2

Koudou Next

Koudou Next is a general real map based ABM simulation engine. It allows anyone to build agent-based simulations for various scenarios, such as disaster or infectious disease situations, etc., simply through JSON configuration files or front-end UI, even without any programming experience.

https://github.com/UtopiaXC/Koudou-Next

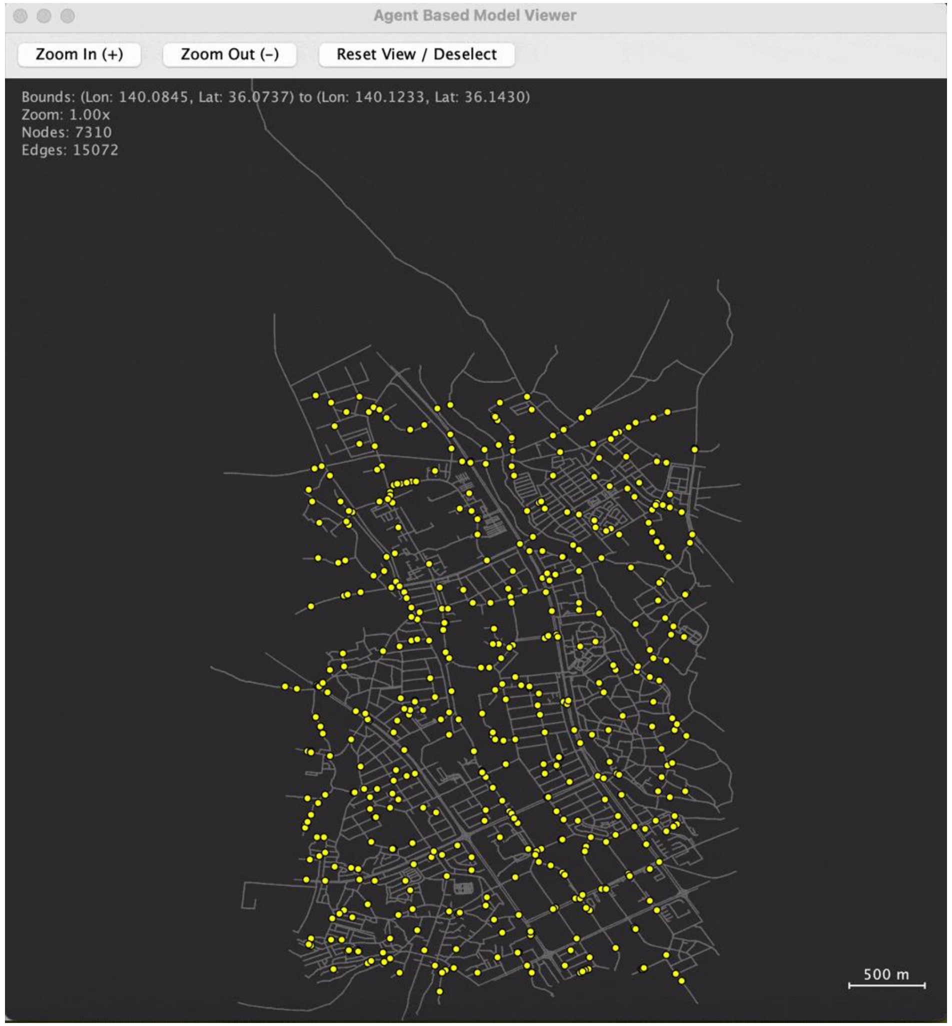

Figure 3. A simple demo for Koudou Next

Koudou Next

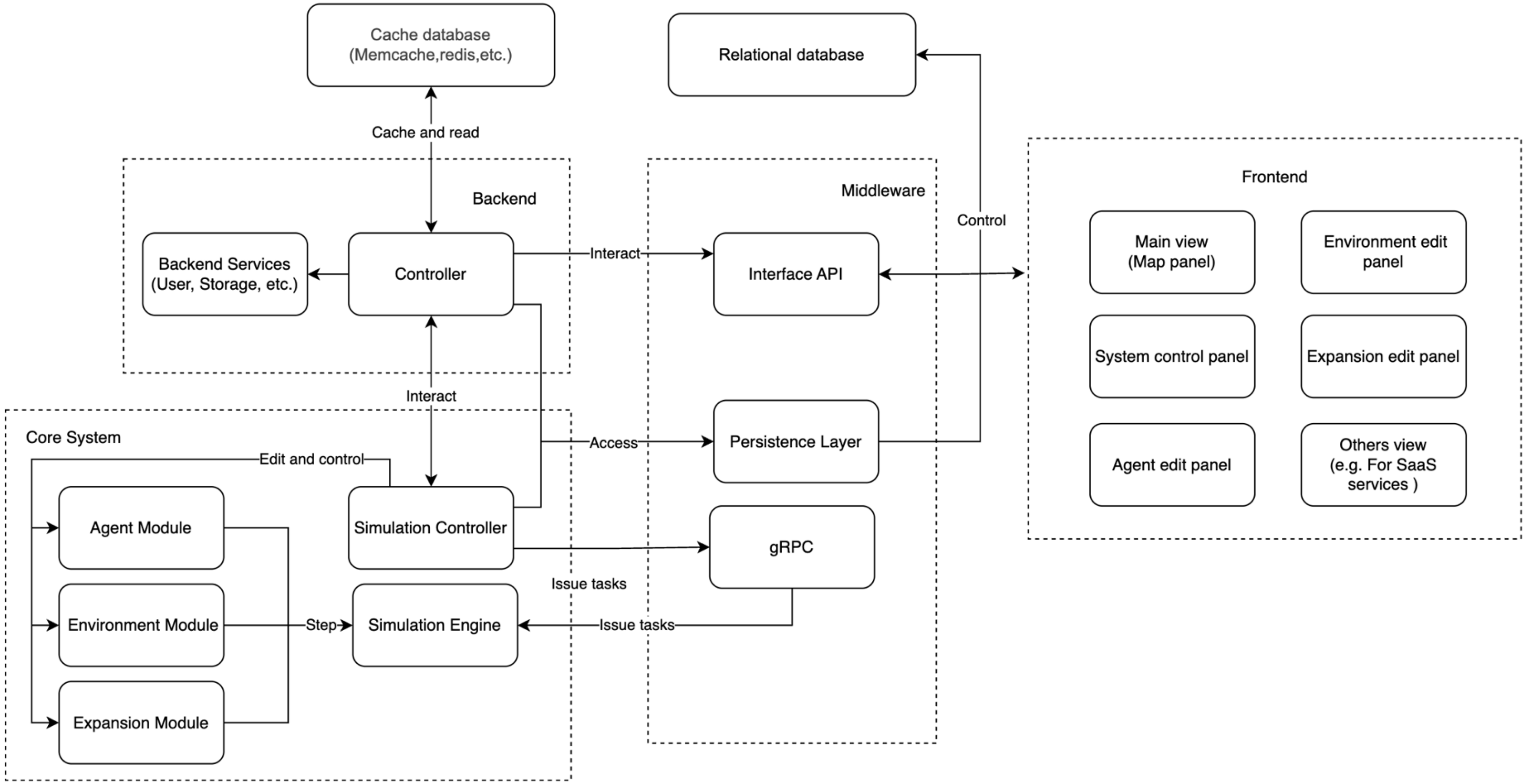

Figure 4. Architecture Design of Koudou Next

Koudou Next

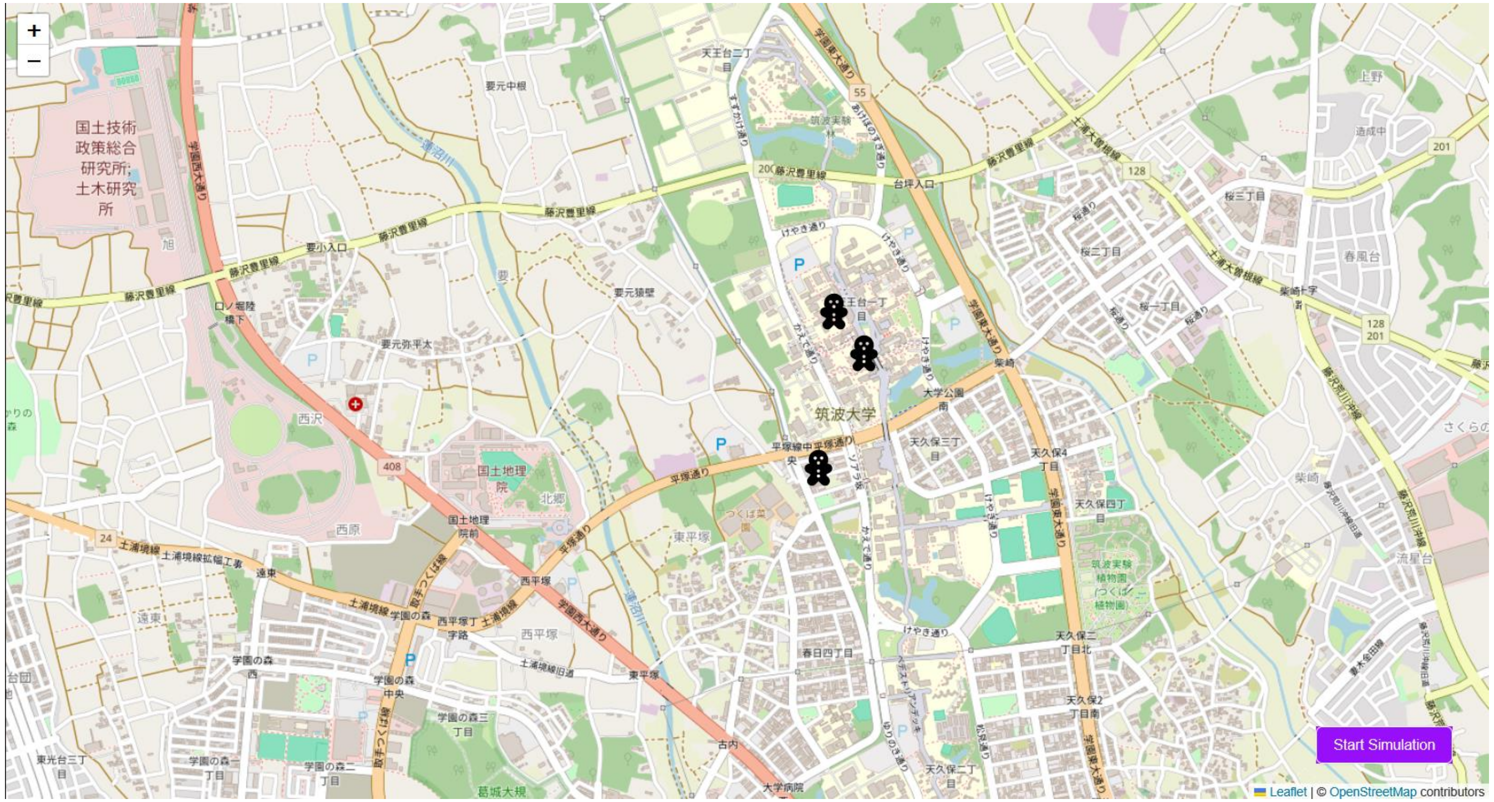

Figure 5. Prototype of front-end UI (By Julia)

Research Proposal

Policy Optimization in Stock Market: An Agent-Based Model Approach Integrating Evolutionary Computation

Background

- Economically, it is generally believed that interest rate and reserve requirement cuts tend to stimulate market growth. However, this is not always the case. [1]
- Different market participants, such as small investors, institutions, etc., have different levels of risk tolerance and total assets, etc. This is one of the main reasons for the failure of macroeconomic regulation, which called **individual irrationality**.

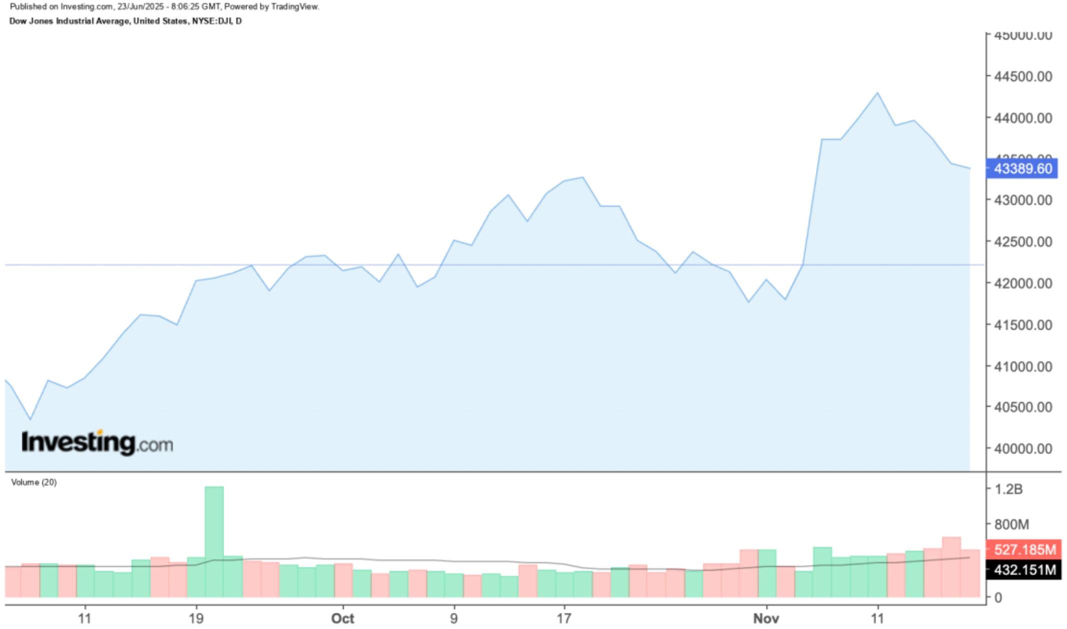

Figure 6. Dow Jones Industrial Average. The index rose by 4% during the two interest rate cuts between 2024/09/24 and 2024/11/08.

Methodology [2]

- Computable General Equilibrium Model (CGE)
  - Assess the static impact of a specific policy on various industrial sectors via real economic data.
- Dynamic Stochastic General Equilibrium Model (DSGE)
  - Simulates the economy's dynamic equilibrium response to random shocks, based on rational agent hypothesis.
- Agent-Based Model (ABM)
  - Simulates the simple interactions of a large amount of different agents to find how macro-level phenomena emerge.

Methodology [2]

Table 1. Three Algorithms for Economic Policy Analysis

Feature	CGE	DSGE	ABM
Concept	**Top-Down**	**Bottom-Up**	**Bottom-Up**
Modeling Agents	**Macroeconomic sectors**	**Rational agent**	**Every investor**
Real Data Requirements	High: require social accounting matrix	Middle, require	Low, only for validation
Solution Method	Solves algebraic equations	Solves dynamic systems	Simulation-based
Stochasticity	Deterministic	Via stochastic shocks	Native support
Computational Cost	Low	Middle	High
Key Advantage	Numerical analysis and experience base	Based on logic and policy transmission	Heterogeneity, interaction, and emergence

Related Research: Beliefs, Shocks, and the Emergence of Roles in Asset Markets: An Agent-Based Modeling Approach [3]

- In their 2024 study, Evan Albers et al. used the Capital Asset Pricing Model (CAPM) and Tobin's separation theorem to construct an ABM model based on investor beliefs.
- The simulation results were compared with the CAPM benchmark and converged to a single equilibrium investment portfolio, confirming the model’s validity.

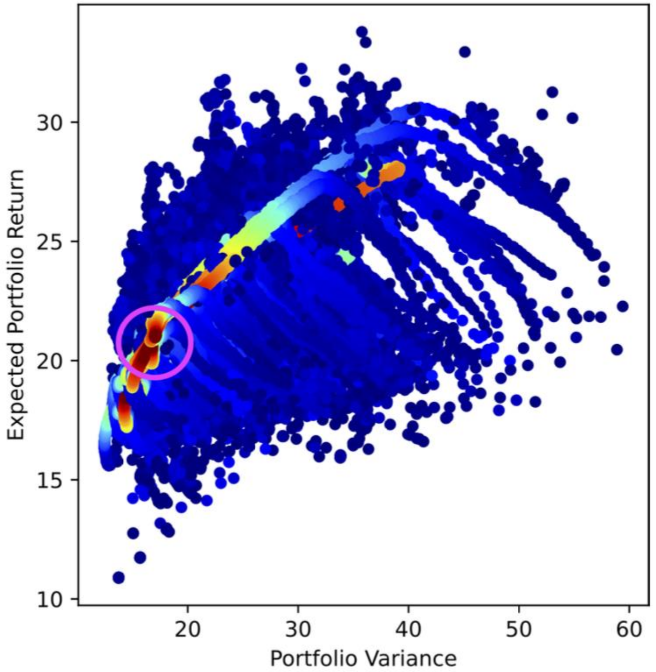

Figure 7. The mean-variance characteristics of 500 different agents’ portfolios over the course of a trading period, as predicted by CAPM and Tobin’s separation theorem.

Related Research: Agents

- **Investors (Traders)** in stock market, contains attributes:
  - **Portfolio ($\boldsymbol{\Theta_A}$):** An array of numbers for holding of each share
  - **Belief ($\boldsymbol{\phi_A}$):** An array of quantified belief for each share. Belief is the agent's psychologically expected price, which adjusts according to real-time transaction prices.
    - When transaction succeed: $\phi_A(i)$ is the price of share
    - When transaction failed: $\phi_A(i)$ gets up when it is buyer or gets down when it is seller
  - **Risk Coefficient ($\boldsymbol{r_A}$):** Risk aversion. The higher the more aversion.
  - **Risk-free Asset ($\boldsymbol{\tau_A}$)**: Number of risk-free assets (such as cash)

Related Research: Environment

- The environment is the **asset market** where agents trade, contains:
  - **Risky Assets**: A set of tradable assets. Each asset has two basic attributes:
    - P_i: Expected payoff
    - σ_i^2: Variance of payoff in squared
  - **Risk-free Asset**: An asset with zero risk and a fixed return.
  - **Decentralized Mechanism**: No central market maker, prices emerge from agent interactions.

Related Research: Interactions

- Interactions between agents and agents or agents and environment is **trading assets** by ways:
  - **Submitting Orders:** Agents submit buy or sell limit orders to the market.
  - **Executing Trades:** A trade occurs when buy and sell orders overlap.
  - **Adjusting Prices:** If an order doesn't execute, agents adjust their beliefs and resubmit.
  - **Updating Information:** A trade price becomes new market information that can influence other agents' beliefs.

Related Research: Behaviors (Rules)

- Core: **Utility function** $\boldsymbol{U(\sigma,\mu) = \mu - \frac{1}{2}r\sigma^2}$
  - μ: The expected return of the agent‘s portfolio (based on CAPM)
  - σ: The standard deviation of the portfolio's return (based on CAPM)
- Utility is positively related to expected return, and negatively related to risk, to get the maximum utility:
  - Calculate Optimal Allocation: Determine the optimal portfolio weight w for the risky market portfolio using the formula $w = \frac{ER_M - R_f}{r\sigma_M^2}$ (based on CAPM)
  - Compare and Act: Compare the optimal w to their current portfolio. If they don't match, submit buy or sell orders to adjust the portfolio towards the optimal state.

Related Research: Shock

- Two impacts were applied on asset 2
  - Negative payoff shock of 10% at timestamp 5000
  - Positive payoff shock of 11.11% at timestamp 10000

- Conclusion: A large shock on a single asset can cause a “ripple effect” that causes the value of all assets in the market to move in the same direction.

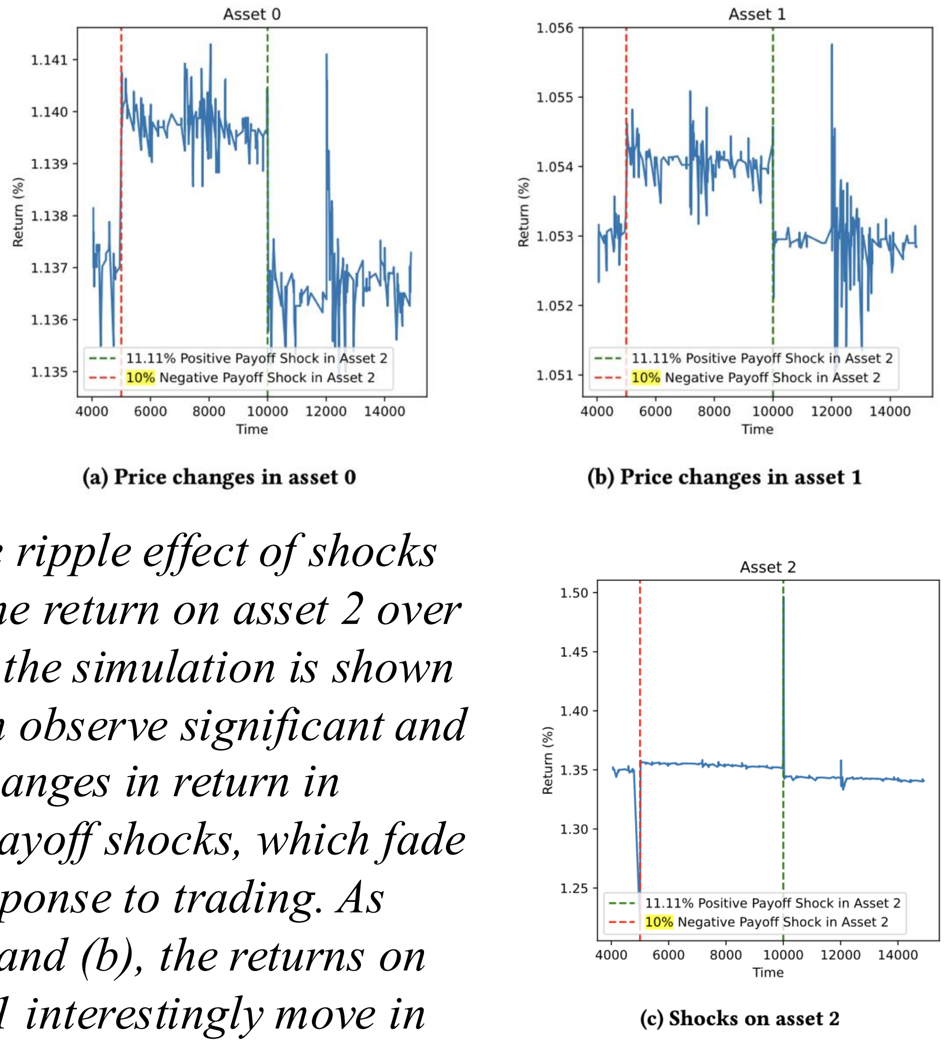

Figure 8. The ripple effect of shocks on asset 2. The return on asset 2 over the course of the simulation is shown in (c). We can observe significant and immediate changes in return in response to payoff shocks, which fade quickly in response to trading. As shown in (a) and (b), the returns on assets 0 and 1 interestingly move in the same direction as asset 2 (after shocks).

Related Research: Noise

- A noise trader is an individual with imperfect information about the true value of the assets they are trading. In this research:
  - An alternative set of beliefs: expected payoff set 10% higher. That means individual irrationality.
  - Give these beliefs to 5 agents in 30 agents.
- As a result:
  - Two equilibrium market portfolios formed that against the Tobin's Separation Theorem.
  - Noise traders converge to another portfolio with a higher expected return.

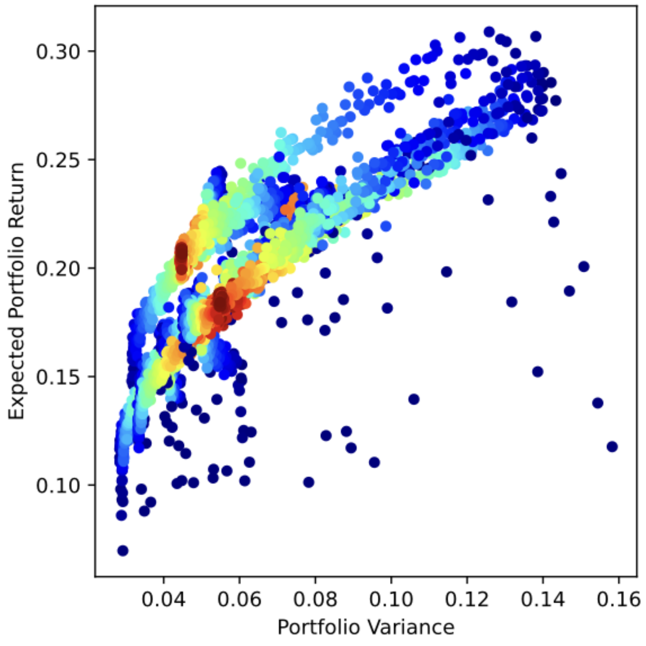

Figure 9. The mean-variance characteristics of portfolios of 30 agents, five of whom are noise traders. There are two distinct equilibria.

My Research

- Based on the mature stock market ABM solutions of others, add policies as environmental factors, then construct a quantitative optimal policy drafting model using genetic algorithms.
  - Gene: Macroeconomic regulation tools, such as interest rate, reserve requirement ratio, tariff, quantitative easing, etc.
  - Chromosome: A combination of macroeconomic regulation tools.
  - Fitness Function: Constructing a market health function using a series of market indicators

Validation

- For the ABM, whether it can truly reflect some statistical characteristics of the financial market is a very important question.
- We can use the logarithmic return series to verify the degree of fit between the model and the real data:
  - $R_t = \ln(P_t) - \ln(P_{t-1})$
- And use Fitting GARCH Models to verify whether their volatility is clustered:
  - $\sigma_t^2 = \omega + \alpha R_{t-1}^2 + \beta\sigma_{t-1}^2$

Validation

- For the policy
  - Find some historically recognized optimal policies, and use our model to find the best economic policy at that time point, compare them with real policies to verify the degree of fit.
  - Create an Effectiveness Score Function based on Performance, Risk and Stability:
    - $E_{policy} = w_P \cdot P - w_R \cdot R - w_S \cdot S$

Open Questions

Open Questions

- Different types of investors respond differently to macroeconomic policies. One of the key challenges is how to quantify and model these reactions in the simulation.
- Defining the fitness function for the genetic algorithm is difficult. How to accurately measure the "health" of a assets market by balancing growth, stability, and liquidity remains an open question.
- From a macroeconomic opinion, policies should not only serve the stock market but also consider broader impacts such as social stability, employment levels, and consumer confidence. Incorporating these factors into the simulation is another open question.

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
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3. 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
4. Evans, B. P., & Ganesh, S. (2024). _Learning and calibrating heterogeneous bounded rational market behaviour with multi-agent reinforcement learning_. In _Proceedings of the 23rd International Conference on Autonomous Agents and Multiagent Systems (AAMAS '24)_ (pp. 534–543). International Foundation for Autonomous Agents and Multiagent Systems. https://dl.acm.org/doi/10.5555/3635637.3662904