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

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1 Introduction

When central banks around the world announce new financial policies by adjusting macroeconomic regulation tools such as reserve requirements, interest rates, and tariffs, they often have a significant impact on the stock market.

For example, from September 24, 2024, when the Federal Reserve announced a 50 basis point federal funds rate cut, to November 8, when the US announced another rate cut, the Dow Jones Industrial Average rose 4

Economically, it is generally believed that cuts to the interest rate and reserve requirement tend to stimulate market growth, whereas hikes usually lead to market downturns. However, this is not always the case. For example, according to Hu et al., 2020 ”Contrary to theoretical expectations and empirical evidence in developed markets, the Chinese stock market reacts positively (negatively) to interest rate increases (cuts) by the central bank”[1].

Different economic agents such as market makers, financial institutions, retail investors, and state-owned enterprises may respond to policy changes with different investment strategies. These strategies are not always aimed at maximizing profit, a phenomenon referred to as individual irrationality, which is considered a major cause of macroeconomic regulatory failure (Fagiolo et al., 2012)[2].

One of the roles of government is to define macroeconomic regulation policies such as reserve requirements and interest rates. These decisions of macroeconomic policies depend on how the participants in the economic react.

Current economic models such as Computable General Equilibrium (CGE) or Dynamic Stochastic General Equilibrium (DSGE) can’t take into account individual decisions very well (Fagiolo et al., 2012)[2].

Therefore, this research propose the development of an agent-based model in which the agents represent market participants who react differently to such policies. Through this model, governments can better predict the outcome of policies and formulate more effective policies.

2 Motivation

In traditional policy research, the CGE model is widely used in macroeconomics. It views the national economy as a system of interactions among sectors, production factors, and entities. It can explain structural effects well. However, since the CGE model is a top-down model based on macroeconomic aggregates rather than microeconomic theory, it cannot explain well the impact of individual irrational decisions.

On the other hand, the Dynamic Stochastic General Equilibrium (DSGE) model commonly used in microeconomics adopts a bottom-up approach. However, its reliance on the economic man assumption leads to an oversimplified representation of agent behavior. The economic man assumption refers to the idea that individuals are fully rational, have complete information, and always make decisions to maximize their own utility.

According to Fagiolo et al., 2012 ”DSGE models presume a very peculiar and unrealistic framework, where agents endowed with rational expectations (RE) take rational decisions by solving dynamic programming problems”[2]. Since the agents' behavior in the DSGE model follows the economic man assumption of classical economics, the model also fails to fully reflect the role of individual irrationality in macroeconomic regulation.

Unlike CGE and DSGE models, the Agent-Based Model (ABM) is a bottom-up model based entirely on agents. It does not necessarily assume agents based on the economic man assumption.(Fagiolo, 2012)[2]. Different agents can make different decisions when facing policy changes and risk fluctuations.

Therefore, when using ABM to research the impact of different policies on the stock market, it can well reflect the impact of irrational decisions of different individuals. Based on the ABM model, I can simulate the impact of economic policies on the stock market and use evolutionary algorithms to continuously iterate different economic policies to find the best quantifiable strategy under a specified environment.

3 Related Research

In their 2024 research, 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 and designed an asset flow network to visualize the model.

They treat market investors as agents and set portfolio, belief, risk coefficient and risk-free asset as attributes. The portfolio is an array of numbers for holding of each share. The belief is the agent's psychologically expected price, which adjusts according to real-time transaction prices. The risk coefficient is risk aversion, which the higher means the more aversion. The risk-free asset is the number of risk-free assets, such as cash.

Then they set an asset market as environment with risky assets, risk-free asset. Agents can trade assets here following utility function that provide trading decision logic. The simulation results were compared with the CAPM benchmark and converged to a single equilibrium investment portfolio, confirming the model's validity.

Next, they tried to give the market certain shocks such as impairment of assets. They found that 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.

Finally, they added noise traders to the system. A noise trader is an individual with imperfect information about the true value of the assets they are trading. Because these traders were overly optimistic about asset prospects, the market no longer converged to a single equilibrium portfolio. Instead, it settled into two distinct equilibrium points that against the Tobin's Separation Theorem.

Their research clearly demonstrated the practical value of the ABM in assets market simulation and showed that it can effectively simulate the impact of policy changes and market interventions with individual irrationality.

4 Proposed Approach

My research aims to develop an ABM simulation that can be used to improve macroeconomic policy.

To reach this goal, first I would develop an ABM simulation system based on Evan Albers et al. research that represents market actors with their irrational decision making. I would treat investors as agents and macroeconomic regulation tools as attributes for environment, and build this simulation by importing real stock market data from various countries.

Next, I would use a genetic algorithm to optimize the decision making of the governmental policies in the model. For example, I would defined a combination of macroeconomic regulation tools as a chromosome. Each macroeconomic regulation tool in this combination such as reserve requirement rate and interest rate would be treated as a gene. Therefore, a chromosome represents a complete macroeconomic policy.

Then, create an initial population consisting of different chromosomes, whose genes are initialized within a reasonable range. After the population is created, start the ABM simulation, with each simulation lasting one fiscal year.

Once a simulation is completed, use a fitness function to evaluate the effectiveness of the policy. At the same time, designing and verifying this fitness function is also one of the core tasks of this research. This function calculates a score that quantitatively assesses the overall health of the assets market, and incorporating multiple key performance indicators such as total trading volume, turnover rate and market volatility.

Based on fitness scores, the algorithm selects chromosomes to reproduce. Through genetic operators such as crossover and mutation, continuously creates new generations of policy combinations and selects those with high scores.

After numerous iterations, the algorithm is expected to converge on a chromosome with the highest fitness score, which represents the optimal macroeconomic policy combination in a simulated market environment.

Finally, I would do the validation for the results. For the ABM simulation, in order to verify whether it can reflect the real market with individual irrationality, I believe that comparing simulation with real data is a good approach. 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 Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Models to verify whether their volatility is clustered.

$$\sigma_t^2 = \omega + \alpha R_{t-1}^2 + \beta \sigma_{t-1}^2$$

Then, for the policy validation, find some historically recognized optimal policies and use my model to find policies at that time point and compare them with their policies to verify the degree of fit.

At the same time, create an effectiveness score function based on performance, risk and stability of the assets market in order to quantitatively compare each policy.

$$E_{policy} = w_P \cdot P - w_R \cdot R - w_S \cdot S$$

5 Summary

This research proposes an Agent-Based Model approach integrating evolutionary computation to optimize macroeconomic policy. I think that this model could provide important advice during governments formulating macroeconomic regulation policy.

Although there are several challenges remain, such as how to define an appropriate fitness function, and how to incorporate the impact of policies on overall social stability, employment rate and international trade exception into this model, further research is expected to resolve these issues, and making ABM a valuable tool in macroeconomic regulation research.

References

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