Research Article

Financial Revolution through Agent-based Artificial Simulation Computational Models for Predicting Market Behavior

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Abstract.
The fundamental theory of the Efficient market hypothesis (EMH), which states that market participants are rational, has received a lot of criticism. The complexity of behavior in the capital market is still a black box, especially when psychological biases influence aggressively on decision-making amid uncertainty. Experimental research on finance and capital markets in the form of AI using machine learning seeks to predict the results of more complex interactions. This multidisciplinary approach offers efforts to explain social phenomena from the micro level to macro descriptions which are built artificially through the computational world. The processing modeling approach is preferred because it includes the complexes that emerge from the behavior and interactions of individuals in the real world. Agent Based Model (ABM) is an AI approach in the form of computational simulation that performs a bottom-up approach by combining irrational–rational agent interactions through networks in microenvironments. Using the ABM approach through Netlogo computing, this study proves that AI can be used to analyze investor behavior in the capital market.

Keywords: Agent Based Model, artificial intelligence, investor behavior

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1. Introduction

Efficient Market Hypothesis (EMH) has dominated financial theory since the 1960s with the three premises that investors set security prices rationally. Investors systematically review all relevant information before making decisions. Finally, investors making investment decisions are always motivated by personal interests [1]. However, study shows that investors do not think and behave rationally [2]. Instead, driven by greed and fear, investors speculate amid unrealistic volatility [3].

In other words, investors are misled by extreme emotions, subjective thinking and the desires of large numbers of people who consistently form crowds, irrational expectations for future performance and the economy as a whole so that stock prices swing above and below fundamental values [4]. So the financial revolution based on psychology and finance shakes traditional theories, one of which is through a computational experimental-based artificial intelligence (AI) approach to prove investor behavior (OECD, 2021) [5].

Experimental research on finance and capital markets in the form of AI using machine learning seeks to predict the results of more complex interactions [6]. This multidisciplinary approach offers efforts to explain social phenomena from the micro level to macro descriptions which are built artificially through the computational world [7]. Macal & North (2008) stated that the computational modeling approach is preferred because it explicitly incorporates the complexity that arises from the behavior and interactions of individuals in the real world [8].

Agent Based Model (ABM) is an AI approach in the form of computational simulation that performs a bottom-up approach by combining irrational rational agent interactions through networks in microenvironments [9,10]. Agents are adaptive in responding to their environment and interact all the time in an adapted environment [10]. The nature of complex agent interactions captures the properties of the real financial system, in particular the emergence of heterogeneity and limited rationality [11].

The ABM approach is popular among social sciences for analyzing financial markets because it is built from heuristic rules of agent behavior [12,13]. Agents are able to control goals, circumstances, and behavior during the simulation [10]. Agents are adaptive so that through their character in behaving and interacting they can capture a series of behaviors that give rise to phenomena [14, 15]. Meanwhile, ABM is used in several studies such as population studies [16], contemporary sociology [17], and financial economic systems [7]. Thus, this study seeks to reconstruct an agent-based computational simulation model (investor behavior) as a tool in making investment strategy decisions on the LQ-45 index.

The study conducted observations of investor psychology bias using an artificial approach in the form of computational simulations. By investigating the Inter-agent interaction attributes factors (basic strategy and agent's power of influence) and wealth attribute (capital, ownership and risk expectations), the research seeks to produce psychological configurations of investor (agent) behavior in making investment decisions. The next objective is to study the behavior patterns formed in the capital market through exploring the relationship between investor strategy and market response.

The social phenomenon of the stock market from the micro level to the macro description in terms of investor psychology, using an artificial approach in the form of ABM computational simulations is still quite limited in Indonesia. The traditional approach that has been used so far has not been able to optimally open the psychology "black box" of market behavior. This article presents the results of a study that through an artificial intelligence approach, market behavior can be constructed to analyze the extent to which the type of investor influences the market.

2. Literature Review

2.1. Artificial Intelligence & Computational Approach

It is agreed that the financial revolution occurred between 1960 and 1970 which gave rise to various concepts and approaches. The financial crises (the dot-com bubble, the subprime and financial crises and the European debt crisis) provide very different study results, especially regarding irrational behavior. Mainstream financial theory has received criticism and censure from some behavioral experts [18]. Conventional financial theory, based on the efficient market hypothesis and the rational paradigm [19], has been subject to widespread criticism [20]. Behaviorists challenge assumptions of rationality and reflection of all available information in current stock prices. The behaviorist theory says that irrational investors are normal.

Artificial Intelligence (AI) with higher sophistication is able to meet the needs of analysis in the financial sector as computer computing power increases. AI is increasingly being used in investment management, loan fraud detection, insurance underwriting and others [6]. This shows a form of financial revolution in which complex markets can be translated more accurately and exploratively reduce traditional paradigms [21]. When investors make investment decisions, analysis and predictions are carried out to understand and interpret increasingly complex rules [5].

In an effort to maximize profits, investment experts apply a variety of investment analysis and data mining methods to the vast amount of publicly available stock market data. Market and non-market factors interact with each other, making it difficult to construct an accurate internal interaction model. AI techniques applied in investment management for stock selection utilize machine learning to identify income signals and investment decision risks. The use of AI techniques is also implemented by investment managers and institutional investors in trading analysis in the form of learning algorithms programmed on computers [22]. It is capable of identifying and executing trades in the market by dynamically optimizing order size, duration, and size, based on market conditions [23]. Investors can also apply AI for risk management and order flow management purposes to streamline execution and generate efficiencies.

Model predictions generated by AI seek to open a “black box” using machine learning for stock market forecasting. One of the things that AI offers to simplify complex economic behavior systems is to provide a computational platform known as an agent-based model [24].

2.2. Agent-Based Model

Lux & Westerhoff (2009) emphasized the importance of modeling economic interactions because most of the global financial market phenomena stem from complex societies [25]. ABM can see problems from a micro perspective through the interaction of a set of agents that lead to the emergence of dynamics in the macro environment [26]. Most ABMs start with a set of ideas, techniques and tools to implement complex adaptive computing model systems. The development of Santa Fe’s stock market modeling work as the pioneer of the ABM model has confirmed that asset prices can display bubbles, crashes, and volatility clustering [13].

ABM was developed to study social phenomena which shows the benefits of the model in the development of social theory. Epistemologically, this method can solve problems from different perspectives and interests by involving many actors [27]. ABM is well-known as the study of systems compared to real phenomena [28]. Thus, if there are similarities between the two then the hypothesized mechanism and decision rules are sufficient to be claimed because they are capable of producing the real observed phenomena.

Market simulation through ABM is believed to be able to replicate various phenomena with artificial intelligence algorithms that present stock market simulation results. ABM consists of agents, interactions, and environments. Each agent represents one individual in the population of the study area. Agents behave and interact with other agents repeatedly in the form of simulations through computational models.

This computational model makes the agent based model the basis for investment strategy decisions. There are 2 Inter-agent interaction attributess that will be used, namely the basic strategy and the power of agent influence. Meanwhile, there are wealth attributeconsisting of capital and share ownership. Micro-structural approach to view and study the complexity of market systems through analysis of various market simulation models and market actors (economic agents) [29]. Prices are changes that are nonlinear in nature where changes are caused by responses from market participants who act as economic agents through the interaction processes of selling, in-active and buying [30].

The premise built into the behavior of the computed capital market is that the premise of the current era capital market system has implications for the development of capital market analysis through a macro-structure (top-down) approach [13]. This approach views changes in stock prices based on changes on a macro-structural scale and is linear in nature. This has a relationship between stock time-series data and financial economic data.

In contrast, the micro-structure (bottom-up) approach views changes in stock prices as non-linear in nature and can also be caused by responses from market participants. The complexity of the capital market system is carried out by market actors who act as economic agents and interact with each other to give rise to bottom-up analysis with various forms of simulation modeling on artificial markets [7, 30].

Meanwhile, the second premise of economic agent simulation modeling (ABM) is a form of micro-structural approach (bottom-up). This model performs artificial market reconstruction to understand the behavior characteristics of market participants by using Inter-agent interaction attributess and wealth attribute [31].

3. Methods

This study uses the models where all construction is carried out in the form of models and initial scenarios which are then simulated using the NetLogo computation program. The computing program is a multi-agent programming language. This modeling platform makes it possible to simulate natural and social processes. NetLogo has a comparative advantage over other software because it provides a grid environment that facilitates local agent-based interactions resulting in easy modeling. Market construction involves stocks where agents make selling, inactive or buying decisions, with a constant P_{t+1} of the excess demand function (X_t). This construction was adopted from Situngkir and Surya (2004); (Situngkir, 2011); (Surya & Situngkir, n.d.) [7, 29, 32] as follow:

$D_t = \Sigma_i X_t^{(i)}$

Price volatility is proportional to excess demand by value:

$p_{t+1} - p_t \sim D_t$

The stages of model construction are as follows:

Collecting LQ-45 index data from 2012-2021 as a control group obtained from the Indonesia Stock Exchange. Meanwhile experimental or simulation data is the LQ-45 index from agent-based activation results model.

Constructing the Inter-agent interaction attributess of the agent where the agent chooses selling, inactive or buying strategies ($x_t^{(i)}$ ϵ {-1,0,1}). The model will observe three basic strategies:

Fundamentalist strategy, behavior which has f_t reference value will make a purchase if $p_t \leq f_t$, and sell if $p_t > f_t$. Changes in reference values are random and determined during the simulation process.

Chartis strategy, investors will sell if the moving average value of stock returns:

$x_t^{(j)}$=x

m_t (h) = 1/hΣ p $_{t'}$

t′ =t- h

$x_t^{(j)}$=x = buy, sell and inactive decisions with h a larger time horizon than price:

p_t^+ (δ) = p_t + p_t δ

whereas δ = (0,1) as input parameter

noisy strategy, investors buy at random with a probability of 0.5 and sell if they feel safe with the value:

1/$n_t^{(i)}$Σ$p_{t.j}$ < p_t

whereas t > 1, and t.j < t , p_j

Construction of Power of Influence, Agent influencing each other expressed as s $^{(i)}$. Each decisions, $x_t^{(i)}$ ϵ {-1,0,1}, depend on the strategy of each agent which is normalized from a value between -1, 0, 1 and can be seen from the probability value of the decision weight with the maximum value spectrum of the effect coefficient of 0.5.

Other wealth attributeand are random (change) during the simulation, namely:

Sources of funding or capital for investment in the capital market $c_t^{(i)}$

The number of lots of investors' shares in the market $n_t^{(i)}$. At each iteration, the total wealth of each agent is denoted by: $k_t^{(i)}$ = $n_t^{(i)}$ p_t + $c_t^{(i)}$

Investment strategy construction symbolized as $x_t^{(i)}$ ϵ {-1,0,1}). During the transaction process, agents have the option of buying or selling shares. Next, an iterative process of alternative program inputs and manual configuration iterations is carried out.

4. Results and Discussion

Netlogo software used to activate the computational simulation model program has produced a visual output of purple line graphs. The graph reflects the data results in the form of time series data from the control group for the 7year transaction observation period 2016 – 2022. During that period 1074 transactions occurred with the visual graph as follows:

Figure 1: LQ45 index chart pattern for 2016 – 2022.

Through observation of the control group from 2016 to 2022 a set of information data was obtained as follows: transactions during the observation period occurred for 1074 days which is the accumulated number of transactions in 2016 as many as 246 transaction days, in 2017 as many as 238 transaction days, in 2018 as many as 240 transaction days , in 2019 as many as 245 transaction days, in 2020 as many as 242 transaction days, in 2021 as many as 247 transactions and in 2022 as many as 246 transaction days. The highest value of the LQ–45 index during the 7 year observation period is 1.132,92 which is in the position of the 1204th observation period (circle sign) namely on January 24 2018. Meanwhile, the LQ–45 index is at its lowest position on the 26th March 2020 of 566,05. Manual iteration was carried out repeatedly to obtain a visual graph close to the model index scale with the LQ–45 index scale.

Next, 12 scenarios out of hundreds of scenarios that were carried out manually were discussed to obtain maximum results. The composition of investors according to the first scenario for the initial iteration is 25 – 35 – 40 with an influence coefficient of 0,5 and a risk coefficient of 1 – 10. The scenario forms a visual chart with two types of red and purple charts reflecting the market index and model index as follows:

The second scenario is to change the coefficient of influence and risk coefficient to 0,3 and 5 with the number of investor composition which is still the same and the number and types of shares are fixed, namely 5. The form of graphic visualization is as follows:

The figure above shows a different pattern on both the purple and red color lines caused by the scale change of the model index value which becomes much larger and very different from the LQ–45 index, namely 2.744.640.000 for the model index and 1.203for the LQ–45 index. The third scenario is to change the number of shareholdings

Figure 2: Graph Pattern of Scenario I Simulation Model LQ45 Index for 2016-2022.

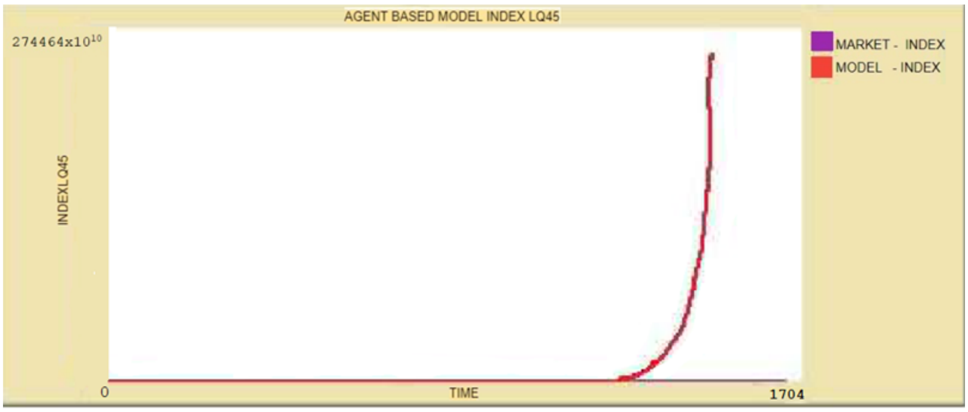

Figure 3: Graph Pattern of Scenario II Simulation Model LQ45 Index for 2016-2022.

to 25 with a correlation coefficient of 0,3 and an expectation coefficient of risk of 5. In this third scenario, the composition of investors remains the same, namely 25 – 35 – 40. This scenario produces a graphical visual output as follows:

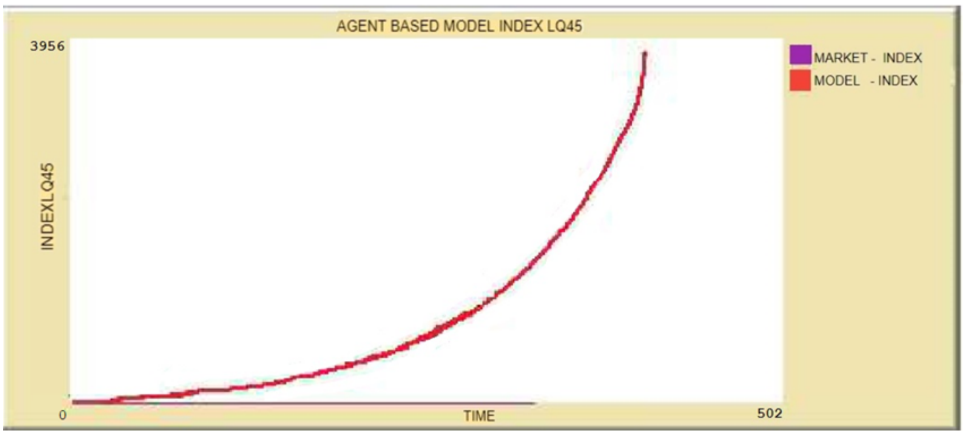

Figure 4: Graph Pattern of Scenario III Simulation Model LQ45 Index for 2016-2022.

The third scenario results in a change in the visual shape of the graph as shown in the figure above both on the red color chart which shows the LQ–45 index line and the purple line for the model index. This change was caused by a change in the value scale of the model index far beyond the LQ–45 index, namely 39.456 for the model index scale and 1.203 for the LQ–45 scale. The iteration procedure ended in the observation time span on the 502nd transaction day. The fourth scenario is carried out through manual iteration by changing the composition of investors to 75 – 10 – 15 with an influence coefficient of 0,5 and an expected risk coefficient of 10 and the number of shares is 5. This scenario produces visual output from the graph as follows:

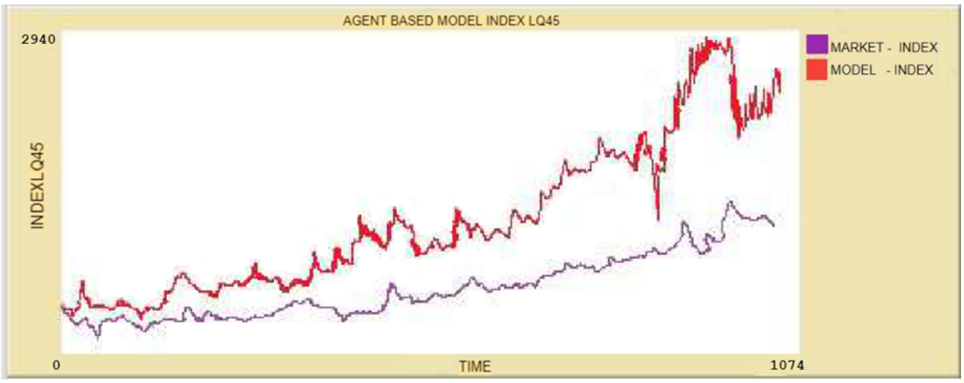

Figure 5: Graph Pattern of Scenario IV Simulation Model LQ45 Index for 2016-2022.

The visual output figure of the graph above shows changes in the shape of the model index line and the LQ–45 index scale due to changes in index values that are still far apart from one another. The value scale of the model index is 2.940 while the LQ–45 index is only on a scale of 1.203 The fifth scenario is carried out by changing the composition of the coefficient of influence to 0,3 and the coefficient of risk expectation is 5. Meanwhile, the composition of investors remains at 75 – 10 – 15 and the number of shares also remains at 5. This scenario produces changes in the visual output in graphic form as follows:

Figure 6: Graph Pattern of Scenario V Simulation Model LQ45 Index for 2016-2022.

The sixth scenario is carried out by changing the number of types of share ownership to 25 while the composition of investors remains at 75 – 10 – 15. The coefficient of influence remains at 0,3 and the risk expectation coefficient is 5. This configuration produces graphical visual output as follows:

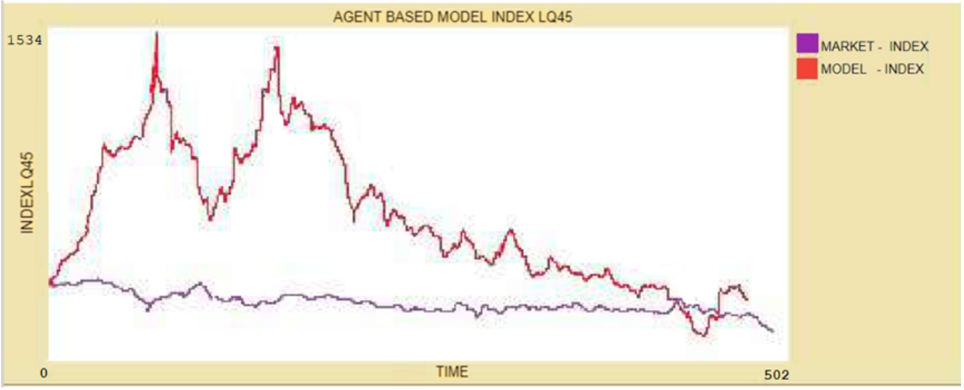

Figure 7: Graph Pattern of Scenario VI Simulation Model LQ45 Index for 2016-2022.

The figure above shows a very irregular graph, both the purple line for the LQ–45 index scale and the red line for the model index. The iteration procedure was stopped on the 502nd transaction day due to the large difference between the model index scale value and the LQ–45 index scale value. The seventh scenario is carried out by changing the composition of investors in an extreme way, namely 15 – 75 – 10. Meanwhile, the number of shares is 5, the impact coefficient is 0,5 and the risk expectation coefficient is 10. The change in scenario produces the graphical visual output below:

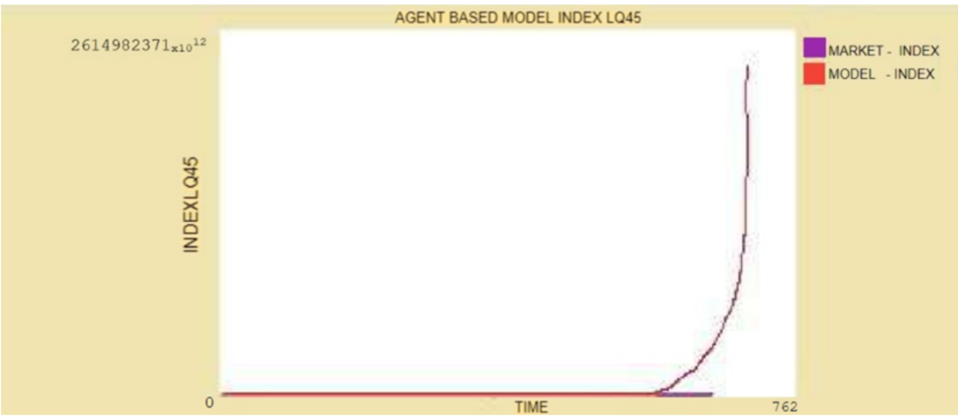

Figure 8: Graph Pattern of Scenario VII Simulation Model LQ45 Index for 2016-2022.

The figure above shows a very reactionary change in the line pattern, both the line showing the model scale and the LQ–45 scale line. This is caused by an extreme change in the model scale value to 2.614.982.371.200 while the LQ–45 index scale is at 1.203. The iteration procedure ends with transaction observation on the 762nd day. The eighth scenario remains with the investor composition of 15 – 75 – 10 but by changing the risk expectation coefficient to 5 and the impact coefficient to 0,3. This new construction produces the following graphical visual figure:

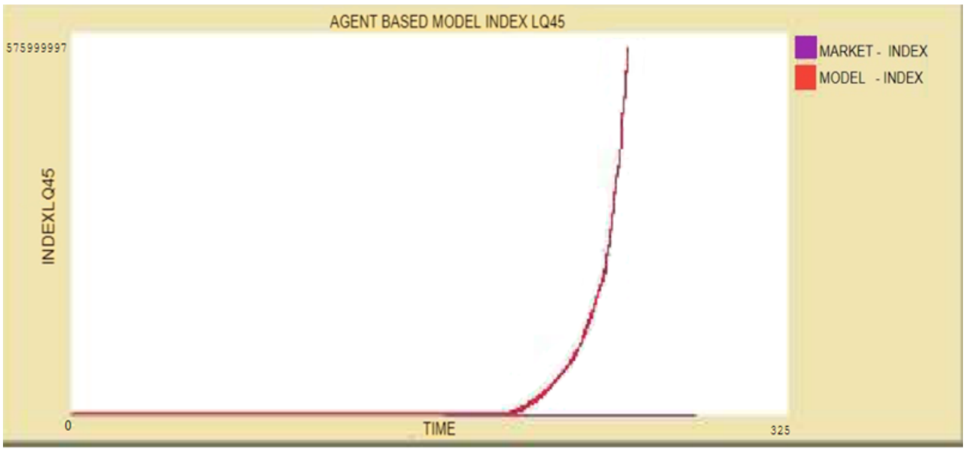

Figure 9: Graph Pattern of Scenario VIII Simulation Model LQ45 Index for 2016-2022.

Just as in the previous section, the construction changes produce visual graphs that also change both the red line and the purple line which represent the model index scale and the LQ–45 index scale. This is due to the very extreme scale range between the model index scale and the LQ–45 index scale, namely 575.999.997 on the model index and 1.203 on the LQ–45 index scale. This iteration process was finally stopped on the 325th transaction day observation. The ninth scenario remains the same as the eighth scenario both on the composition of investors, the impact coefficient and the risk expectation coefficient. It's just that the number of shares that was previously 5 was changed to 25. This produces a graphic visual output that is different from the previous scenario as follows:

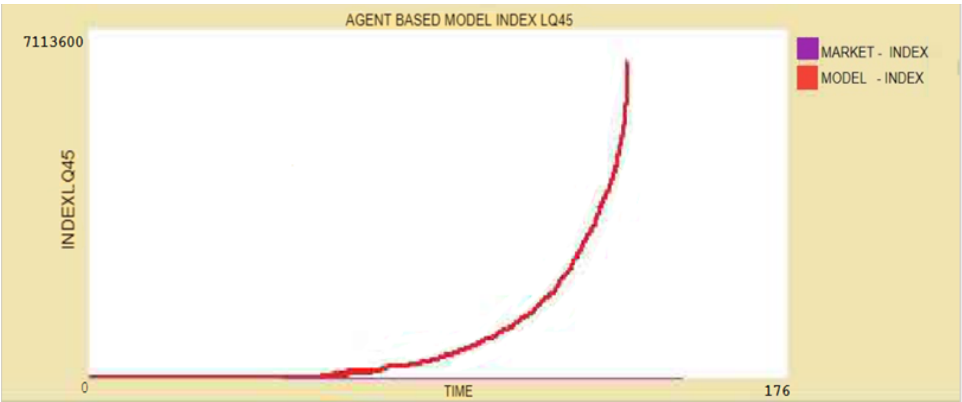

Figure 10: Graph Pattern of Scenario IX Simulation Model LQ45 Index for 2016-2022.

Just as the graphical output of the previous scenario, the extreme composition of investors and changes in the number of shares produce a new, reactionary graphical output both on the red and purple lines. The model index value scale far exceeds the LQ–45 index scale, which is 7.113.600 for the model index scale and 1.203 for the LQ–45 index scale. The iteration procedure is stopped on the 176th transaction day observation. The tenth scenario is a manual iteration with a scenario of changing the extreme composition of investors, namely 15 – 10 – 75 with the number of shares being 5, the impact coefficient is 0 and the risk expectation coefficient is 10. The construction of this change produces a graphical visual output as follows:

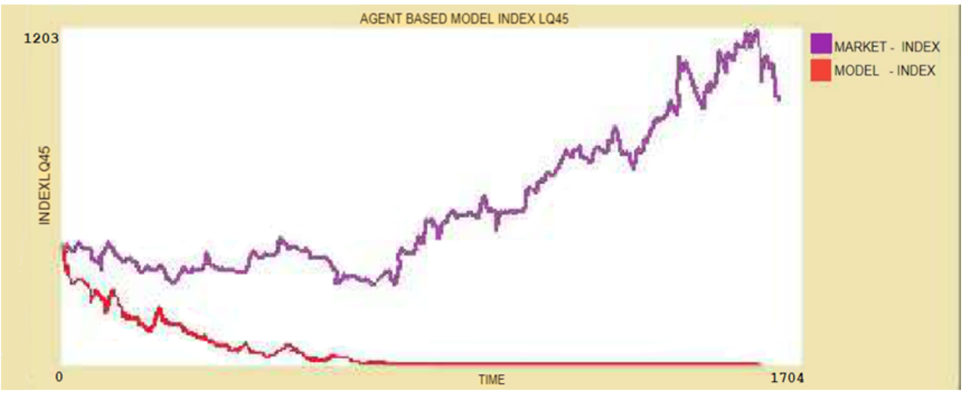

Figure 11: Graph Pattern of Scenario IX Simulation Model LQ45 Index for 2016-2022.

The eleventh scenario is carried out by changing the risk expectation coefficient to 5 and the investor composition is 35 – 34 – 35 , the impact coefficient and the number of shares are still the same as the tenth scenario. This variation of the eleventh scenario produces the graphical visual output as follows:

Figure 12: Graph Pattern of Scenario X Simulation Model LQ45 Index for 2016-2022.

The figure above shows the graphical visual patterns that are getting closer or “similar” to the model index scale chart and the LQ–45 index scale. Scenario changes are made repeatedly and are trial and error in nature. This is a consequence which can be said to be one of the weaknesses of the model. The goal is to produce a visual pattern that reflects the movement trend or index change that is closer to or more similar to the pattern of change in the real data of the LQ–45 index. Thus in the 12th scenario, namely the composition of investors 35 – 30 – 35, the number of shares is 25, the impact coefficient is 0,3 and the risk expectation coefficient is 5, a visual graph is found that is getting closer as follows:

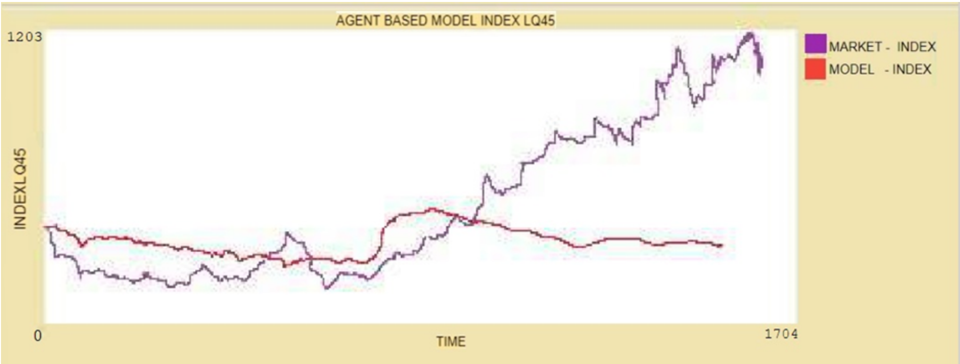

Figure 13: Graph Pattern of Scenario XI Simulation Model LQ45 Index for 2016-2022.

Small iteration process has been described above, especially in scenarios that produce graphical visual images that are closer or similar between the model index scale and the LQ–45 index scale. The results of the analysis can be summarized as follows:

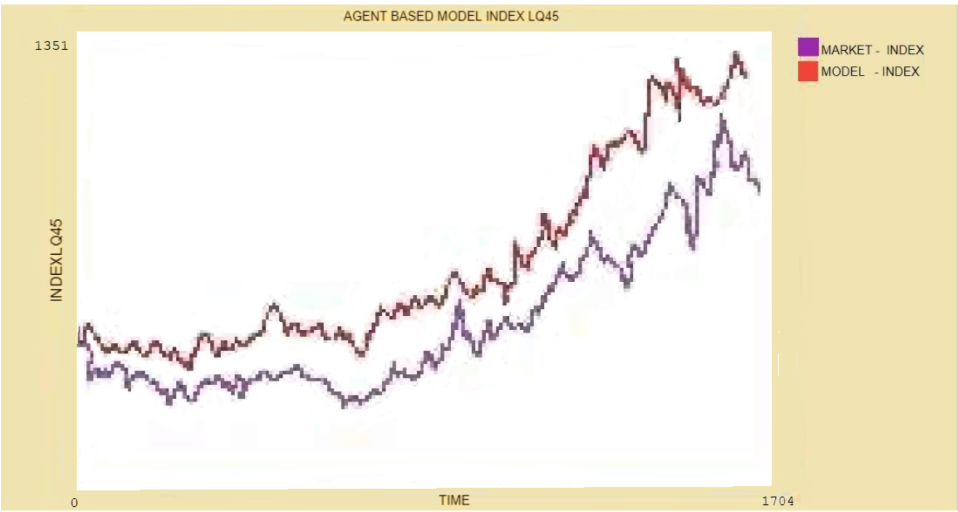

Figure 14: Graph Pattern of Scenario XII Simulation Model LQ45 Index for 2016-2022.

Based on the iteration process which is partly disclosed in the visual output of graph 4.2 to graph 4.15, it can be summarized the results of the analysis of the various model variants starting from variant I (one) to model variant 12 (twelve), namely as follows:

The thirteenth formulation scenario, namely the composition of investors as agents as follows: 1) the composition of fundamental investors is 35, having made 575.405 buying transactions and 95.920 selling transactions; 2) the composition of chartist investors is 30 buying transactions totaling 90.394 times and selling transactions totaling 542.766

times; 3) The composition of noisy investors is 35 investors with a total of 314.156 selling transactions and 280.615 buying transactions.

During the observation period there has been an accumulation of 952.842 selling transactions where most of the transaction activities were carried out by chartist investors. Meanwhile, the accumulation of buying transactions during the observation period was 944.852, which were dominated by fundamental investors.

The impact coefficient is how other agents' decisions impact other agents. The impact coefficient value of 0,5 means that the impact of other agents' decisions in selling, buying and being inactive has a very strong impact on other agents in making the same decision.

The risk expectation coefficient reflects an investor's out of the money situation where the investor does not have enough money to execute his trade. The value of 10 means that from the total weight of the investor's decision, the investor's hope for a negative difference situation between the contract index and the real index (market price) is 10.

The type of shares owned and the number of shares of 25 means that the condition of investor ownership of both the type and the number of shares is worth 25, which can be interpreted that the condition of ownership is relatively smaller when compared to the spectrum of the total value of ownership and the number of LQ45 shares is 45.

The research results show that the Basic Strategy, Impact Coefficient and Strength of Influence between agents are able to reconstruct the Agent-Based Model. Investors in making investment decisions are influenced by some of the elements above indicating that there are patterns of rational and irrational behavior. In the basic strategy elements, investors can choose as fundamental, chartist or noisy. Fundamental investors emphasize fundamental analysis such as economic, political, environmental and other relevant aspects. Financial statement analysis is an instrument for fundamentalists to make investment decisions. Meanwhile, chartist investors place more emphasis on analysis techniques for patterns or stock price trends that have a recurring nature. Utilization of stock price indices, market statistical tools, historical price and volume charts are important instruments for chartist investors. Furthermore, noisy is the decline in stock prices caused by rumors that have an impact on investor psychology. Changes in stock prices themselves are a reflection of investor behavior, so that investors who follow noise have a large risk even though on the other hand rumors also promise high returns. This basic strategy is proven to occur in ABM construction.

5. Conclusion

ABM is an approach that synergizes computing and social science to develop models of collective behavior from a group of interacting individuals or agents. This study produces an analysis of investor behavior, especially how investor character influences the market. Trading patterns have been successfully formed and reflect how investor behavior with fundamentalist, chartist, and noisy characteristics influences the market. The results of the analysis are able to reveal patterns of buying and selling of shares, trading frequency, stock prices and trading volume according to the character of the investor. This study was also successful in the reconstruction of the ABM computational program by two factors developed by Surya & Situngkir (2004), namely the interaction attributes between agents and the attributes of wealth [29]. ABM is able to develop investor behavior according to character in making investment decisions.

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