

# **Influence of Fear-of-Missing-Out on Market Volatility: Networked Minority Game Approach**

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## **Highlights**

- We extend the networked evolutionary minority game model by incorporating asymmetric price-to-fine ratios and the fear of missing out (FOMO).
- The asymmetric reward structure significantly improves the stability of the system, while investors' fear of missing out (FOMO) significantly reduces market efficiency.
- As agents become more interconnected and actively adapt their strategies, the adverse effects of FOMO on the system diminish.

## **Abstract**

This study investigates the influence of the fear of missing out (FOMO), which spreads through social networks, on financial market volatility. We extend the networked evolutionary minority game (NEMG) model by incorporating asymmetric price-to-fine ratios and FOMO. The agent-based simulation results reveal that the asymmetric reward structure significantly improves the stability of the system. In contrast, investors' FOMO significantly reduces market efficiency. FOMO-induced irrational behavior disrupts the market's normal functioning, leading to increased volatility and decreased efficiency. However, as agents become more interconnected and actively adapt their strategies, the adverse effects of FOMO on the system diminish.

**Keywords:** Agent-based simulation; Evolutionary game; Fear-of-missing-out (FOMO); Minority game; Network structure

**JEL Classification:** C63; D85; G41

C63: Computational Techniques • Simulation Modeling

D85: Network Formation and Analysis: Theory

G41: Role and Effects of Psychological, Emotional, Social, and Cognitive Factors on Decision Making in Financial Markets

## 1. Introduction

Many financial market pundits frequently attribute large or seemingly inexplicable moves in financial market prices to investor sentiment and psychology (Lu, Liu, and Chen, 2021). When faced with the need to make quick investment decisions or an overwhelming amount of information, investors may exhibit cognitive biases, such as making intuitive judgments or accepting only familiar information (Hirshleifer, 2001). If these behaviors are common among most investors, they can lead to abnormal market volatility (Xu, Wang, Jiang, and Zhang, 2019). This study investigates the psychological factors that contribute to abnormal market volatility, focusing on the fear of missing out (FOMO). FOMO is characterized by the apprehensiveness that individuals experience when they believe they may miss crucial information or opportunities (Przybylski, Murayama, DeHaan, and Gladwell, 2013). The widespread availability of smartphones and access to social media platforms have increased the accessibility of information. Paradoxically, greater access to information renders individuals more susceptible to FOMO (Buglass, Binder, Betts, and Underwood, 2017). In the context of investment activities, investors are vulnerable to FOMO and fear exclusion from critical investment information. Shiva, Narula, and Shahi (2020) note that such concerns can lead to overzealous trading by individual investors. Gupta and Shrivastava (2021) argue that in the context of investment opportunities, FOMO amplifies loss aversion and herding behavior.

In this study, we use a minority game (MG) model to simulate financial market dynamics. Challet and Zhang (1997) develop the MG model to describe competitive situations in which individuals strive to belong to the minority group rather than the majority. The game progresses based on the participants' choices, which collectively influence the overall outcome of the system. Each participant's objective is to choose differently from the other participants and become part of the minority. The participants belonging to the least frequently chosen group are the winners. MGs are well suited for modeling financial asset trading dynamics. In financial asset trading, prices tend to increase when the total volume of buy orders exceeds the total volume of sell orders. This situation favors sellers and may be disadvantageous for buyers. In other words, the minority group, which consists of sellers, emerges as the winning group. Conversely, when the total volume of sell orders exceeds the total volume of buy

orders, prices decline, and the buyers are the winning group. The dynamics of financial asset trading, in which the minority group wins, align well with the properties of the MG model.

Johnson, Hui, Jonson, and Lo (1999) propose an evolutionary MG (EMG) model by introducing evolutionary elements into the MG model. In this model, the participants adapt their strategies based on past information. An EMG is an adaptive belief system, meaning that it incorporates feedback such that past data influence future decision-making processes (Brock and Hommes, 1997). An adaptive belief system is particularly suitable for modeling financial asset investment behavior, as investors consider past price dynamics when making decisions (Bianconi, De Martino, Ferreira, and Marsili, 2008; Brock and Hommes, 1998; Challet, Chessa, Marsili, and Zhang, 2001; LeBaron, Arthur, and Palmer, 1999). Chen (2020) proposes a new financial market model based on an MG. Since the development of the EMG model, researchers have extended it in different directions. For example, several studies propose extensions of the EMG model that incorporate local information sharing and imitation through networks (Kirley, 2006; Metzler and Horn, 2003). The network structure is widely adopted when modeling spatial or social interactions among agents (Zhang and Zhang, 2022). These previous studies consistently demonstrate that information sharing and imitation among agents play crucial roles in improving system performance.

Quan and Deng (2007) show that a system with imitation involves a phase transition depending on the prize-to-fine ratio. This extension of the EMG model highlights the potential influence of asymmetric rewards on a system. Financial asset trading involves asymmetric rewards. When the total volume of buy orders is high relative to that of sellers, sellers tend to earn greater profits, and vice versa. Importantly, when the minority group's profits become substantial, individuals are more likely to experience FOMO, exacerbating its influence on the market. Thus, this setup is suitable for analyzing the impacts of FOMO on a market system. In this study, we assume that the prize-to-fine ratio is determined by the relative numbers of participants in the minority and majority groups. This assumption extends the work of Quan and Deng (2007), who explore the effects of a constant prize-to-fine ratio under specific conditions. Furthermore, we incorporate into the model the notion that high prizes in individuals' surroundings can induce FOMO. Individuals who observe excessive and high prizes may experience FOMO, increasing the likelihood that they engage in irrational behavior.

In a networked EMG (NEMG) model, the network's underlying structure critically affects the system dynamics (Fagiolo and Valente, 2005; Shang and Wang, 2007). Chen and Quan (2009) show that imitation among agents in small-world networks improves system efficiency. Building on their research, we incorporate imitation among agents within the network in our model. However, we modify the manner in which some agents imitate others. We define two types of imitation. The first is *strategy imitation*, in which agents consider how the target agent makes decisions and they autonomously make decisions by imitating the target agent's strategy. The second is *behavioral imitation*, in which agents simply mimic the target agent's actions without considering the decision-making process underpinning

those actions. Strategy imitation is based on rational thinking, whereas behavioral imitation is irrational. We observe that when individuals experiencing FOMO imitate behaviors, the system becomes less efficient.

In an MG, the system dynamics are determined by the complex interactions of multiple agents. Owing to the complexity of MG systems, obtaining analytical solutions is difficult. Thus, research on MGs is primarily conducted by analyzing data generated through agent-based simulations. Agent-based modeling is a suitable approach for studying the complex dynamics that emerge from interactions between individual agents (Lux, 2002; Park and Ryu, 2022). In this study, we design the NEMG model that reflects an asymmetric reward structure and FOMO and analyze it using a simulation. Our simulation results show that an asymmetric reward structure improves the system's stability by promoting the self-segregation of agents. However, the existence of FOMO undermines this effect, meaning that irrational FOMO-driven behavior has negative impacts on the market. As the agents become more interconnected and adapt their strategies, the detrimental effects of FOMO diminish. Our findings highlight that investors' FOMO exacerbates market volatility and reduces efficiency, disrupting the market's normal functioning. These findings shed light on the role of psychological factors in financial markets and provide implications for stakeholders interested in managing and improving market dynamics. Understanding FOMO enables informed decision-making to create more efficient and stable markets.

The remainder of this paper is organized as follows. In Section 2, we extend the NEMG model by introducing an asymmetric reward structure and FOMO. In Section 3, we conduct simulations based on our model and present the results. In Section 4, we summarize the findings and present conclusions.

## 2. Model

This study incorporates an asymmetric reward ( $R_t$ ) and FOMO into the NEMG model. In the MG model, an odd number of agents  $N$  with memory size  $m$  compete iteratively using a set of  $S$  strategies to belong to the minority group and gain access to limited resources. The participants predict and determine their future actions based on their previous experiences and choices. In each iteration, each agent selects the strategy with the highest score among the  $S$  strategies. These strategies shape the market's dynamic behavior. Both numerical simulations and analytical studies demonstrate that the distributions of strategies and histories among agents crucially determine system performance. Interestingly, studies show that unintended cooperation among inherently self-interested agents reduces resource waste. This finding highlights the importance of strategy selection and unintended cooperation in determining system efficiency (Challet and Zhang, 1998).

In the EMG proposed by Johnson, Hui, Jonson, and Lo (1999), at any given moment, each agent possesses a dynamic strategy and a  $p$ -value, also called a gene value, which indicates the probability that the agents follow the strategy's prediction. At the end of each turn, the agents belonging

to the minority (majority) group win (lose) the round and earn (lose) one point. Agents with scores below a threshold value  $d_c < 0$  can modify their  $p$ -values by introducing new values within the interval  $[p - dp, p + dp]$ . When an agent modifies the strategy, that agent's score is reset to zero. At this point, the agent can imitate the strategies of neighboring agents. Agents are aware of their closest neighbors' scores and  $p$ -values. Thus, if an agent's score falls below  $d_c$  and is lower than the best score among the closest neighbors, the agent randomly selects a new  $p$ -value within a range of  $2dp$  centered on the  $p$ -value of the highest-scoring neighbor. Conversely, if the agent's score does not satisfy these conditions, the agent randomly selects a new  $p$ -value within a range of  $2dp$  centered on the previous  $p$ -value and uses this new  $p$ -value. We impose a reflective boundary condition on the  $p$ -space to ensure that  $0 \leq p \leq 1$ . Specifically, if a newly selected  $p_{candidate}$  is less than zero, then  $p_{new} = |p_{candidate}|$ . If a new  $p_{candidate}$  is greater than one, then  $p_{new} = 1 - (p_{candidate} - 1)$ .

When agents lose, their scores decrease by one ( $S_l = -1$ ). However, when they win, their scores depend on the relative sizes of the minority and majority groups. We denote the number of agents in the minority group as  $N_n$  and the number of agents in the majority group as  $N_j$ , and we calculate the score earned by the winning group ( $S_w$ ) as follows:

$$S_w = \frac{N_j}{N_n} \quad (1)$$

The agents are connected through a network and can obtain information about the agents to which they are connected. This information includes the scores of the neighboring agents and other relevant data. In addition, agents can utilize globally available information, including the winning group in the previous round, the winning group's score, and the average and variance of the cumulative scores of all investors. We consider two factors that can induce a sense of anxiety in agents by indicating that they are falling behind. The first is that the winners of each round obtain significant gains. The second is that agents may be close to other agents who have achieved unusually high performances. The first factor creates the perception of falling behind globally, whereas the second creates the perception of falling behind within one's own community. By combining these two factors, we model a situation in which agents experience FOMO. When agents with scores below a threshold value  $d_c < 0$  need to modify their strategies, they observe the cumulative performances of the agents to whom they are connected in the network. If the observed performance of an agent's neighbors exceeds the sum of the average cumulative performance and its variance, the agent will become susceptible to FOMO. In this situation, we assume that the likelihood of an agent experiencing FOMO increases proportionally with the winning group's score. We set the probability that an agent experiences FOMO as  $P_{FOMO} = S_w - 1$  when an agent with high cumulative performance is in the agent's vicinity.

We assume that individuals experiencing FOMO engage in non-rational decision-making by imitating other agents' actions rather than making strategically rational judgments. Specifically, when agents enter a state of FOMO, they adopt their best neighbor as a role model and mimic that neighbor's choices from the previous round in the current round. As with other strategies, agents evaluate their imitation actions based on the resulting score. Agents whose performances fall below the threshold value  $d_c$  exit the FOMO state and modify their strategies again. In our model, agents are connected through a small-world network generated following the Watts-Strogatz model (Watts, 1998). In a small-world network, most nodes are located close to each other, allowing for efficient communication between any two nodes. Social networks commonly form this type of network. The network transitions from a regular network (with a rewiring probability of  $P_s = 0$ ) to a small-world network or random network (with a rewiring probability of  $P_s = 1$ ) based on the rewiring probability ( $P_s$ ).

The simulation process in our study is as follows. First, we set up the system, which involves initializing the history and recording it using random binary arrays. We then construct a small-world network in which the nodes are closely connected using the Watts-Strogatz model. We assign a random  $p$ -value to each node. During the iterations, the agents' scores are updated based on their group membership (minority or majority). If an agent belongs to a minority group, that agent's score increases; otherwise, it decreases. The score reflects the difference between the numbers of nodes in the majority and minority groups relative to the total number of nodes. The agents update their strategies based on their scores and those of their neighbors. If an agent's score is above a certain threshold and the best neighbor's score is below another threshold, then that agent's  $p$ -value remains unchanged. If the agent's score is below the threshold and the best neighbor's score falls within a specific range, then the agent's  $p$ -value is randomly adjusted to a value within that range. If the agent's score is below the threshold and the best neighbor's score is also below that threshold, then the agent's  $p$ -value is randomly adjusted within the agent's own range. Furthermore, if the best neighbor's score exceeds a certain value, then the agent enters a state of FOMO and imitates the best neighbor's previous action. When choosing actions, agents who are not experiencing FOMO consider their history and records to determine whether to repeat or modify their previous actions based on their  $p$ -value. However, agents experiencing FOMO disregard their history and records and simply mimic the previous action of their best neighbor.

A notable characteristic of the EMG model is that agents exhibiting extreme behaviors (i.e., agents using  $p \approx 0$  or  $1$ , never following the strategy's prediction, or always following it) outperform cautious agents (i.e., agents using  $p \approx 1/2$ ). This characteristic leads to the population to self-segregate, with the  $p$ -value distribution tending to peak around  $p \approx 0$  and  $1$ . When self-segregation occurs, the market tends to form two distinct clusters of similar size, leading to the stable maintenance of a minority group. This state indicates a relatively stable system with high overall efficiency. Thus, two main methods are commonly used to evaluate a system's performance using an EMG. The first method involves observing whether self-segregation occurs through a histogram analysis. By examining the

distribution of the  $p$ -values chosen by individuals ( $P(p)$ ), we can determine whether a clear division toward the extremes arises, which indicates whether self-segregation is present. The second method involves checking whether the variance has fallen. Specifically, we examine the number of agents choosing group 1 at time  $t$ , denoted as  $A(t)$ .

$$A(t) = \sum_{i=1}^N x_i(t) \quad (2)$$

The variance of  $A(t)$  over the period  $T$  can be expressed as follows:

$$\sigma^2 = \frac{1}{T} \sum_{t=1}^T (A(t) - \bar{A})^2 \quad (3)$$

where  $\bar{A} = \frac{1}{T} \sum_{t=1}^T A(t)$  represents the average number of agents that choose group 1. It is evident that a smaller  $\sigma^2$  corresponds to greater system profits. We calculate the variance by dividing  $\sigma^2$  by the total number of agents (i.e.,  $\sigma^2/N$ ). By analyzing the relationship between the variance and the parameters, we can examine the impacts of changes in the variations on the system's efficiency, as evidenced by a reduced variance.

### 3. Results

In this section, we analyze the impact of the asymmetric reward structure and irrational decisions to imitate others' actions in an MG in which neighbors in the network can exchange information. We investigate the effects of these factors on the stability of the system through simulations. We compare the performance of the three models under the same parameter settings. The first model is the NEMG model proposed in the literature, which serves as the baseline model for our analysis. In this model, the prize and the fine are symmetric, and individuals imitate the strategies of their well-performing neighbors in the network. The second model is an asymmetric reward model in which the prize varies in each round based on the relative sizes of the minority and majority groups. The third model is an expanded version that incorporates the possibility of individuals experiencing FOMO based on time-varying rewards. In this model, when an agent's neighbors perform substantially better than the agent does, that agent may enter a state of FOMO and choose an irrational strategy.

The detailed parameter settings for our simulations are primarily based on Shang and Wang (2007) and Chen and Quan (2009) and are as follows. We conduct ten runs and average the results obtained from each run. Each run consists of 50,000 iterations. The memory size is set to six, meaning that the agents can remember six previous actions or outcomes. The score threshold for strategy modification is set to -4, indicating that agents will consider modifying their strategies if their scores fall below this threshold. To evaluate the system's performance, we observe histograms and measure

the reduced variance. The histograms illustrate the distribution of the  $p$ -values chosen by the agents after the completion of the simulation. If the  $p$ -values are clustered around the extremes of the distribution, then self-segregation has occurred.

The reduced variance is calculated by examining the variance in the number of agents choosing group 1, which is the minority group, over the last 30,000 iterations of the simulation. We discard the initial 20,000 iterations and analyze the system only after it reaches a steady state. A lower reduced variance indicates greater system efficiency. In our analysis, we vary two parameters:  $dp$  and  $P_s$ . The mutation parameter ( $dp$ ) represents the range of randomness in the selection of new strategies during the modification process. A larger mutation parameter means that agents' new strategies are less correlated with their old strategies. We set  $dp$  equal to  $10^{-a}$ , where  $a$  ranges from zero to three. When  $dp$  is greater, the agents have a wider range of  $p$ -values from which to choose, resulting in more random strategy modifications. In contrast, a lower  $dp$  value limits the  $p$ -value range, leading to fewer modifications to strategies. The parameter  $P_s$  represents the rewiring probability in the Watts-Strogatz small-world network model. We set  $P_s$  equal to  $10^{-b}$ , where  $b$  ranges from zero to three. A higher  $P_s$  value indicates a higher probability of rewiring, resulting in a network structure that is closer to a random network. Conversely, a lower  $P_s$  value leads to a network structure that is closer to a regular network. When the network structure is closer to a random network, agents are more connected. Figure 1 shows the histograms of  $P(p)$  at  $T = 50,000$  for the three models.

[Figure 1 about here]

Consistent with previous studies, all three models exhibit self-segregation. In other words, individual agents' strategies tend to polarize toward the extremes as the simulation progresses and approaches a steady state. The asymmetric reward model exhibits the most extreme self-segregation. In the FOMO model, the degree of self-segregation is lower than in the asymmetric reward model, and the baseline model exhibits the lowest level of self-segregation. These results suggest that asymmetric rewards accelerate agents' adaptive beliefs, leading to greater system stability compared with the baseline model. However, the inclusion of FOMO in the model diminishes system stability because agents with FOMO tend to deviate from their adaptive beliefs by mimicking the actions of neighboring agents. This observation suggests that FOMO hinders improvements in system efficiency.

Figures 2 and 3 present log-log plots illustrating the impacts of  $dp$  and  $P_s$  on  $\sigma^2/N$  for each model. Similar to Figure 1, the asymmetric reward model exhibits the greatest stability, followed by the baseline and FOMO models. This relationship holds regardless of the parameter values.

[Figure 2 about here]



[Figure 3 about here]

In Figure 2, the mutation level has little impact on the system dynamics when it is less than 0.1. However, when the mutation level is between 0.1 and 1, we observe significant variations, although the direction of the impact is not consistent. When the mutation level is below 0.1, the magnitude of the variation is small, suggesting that it has minimal influence on the system. However, when the mutation level is above 0.1, the magnitude of the variation is significant, meaning that the parameter exerts a meaningful impact. In particular, when  $dp = 1$ , that is, when mutations occur completely randomly, a sufficient number of iterations is necessary for reliable interpretation, owing to the substantial magnitude of the variations. Figure 3 demonstrates that  $P_s$  has a decreasing impact on  $\sigma^2/N$ , and the impact is relatively stable compared to that of  $dp$ . As  $P_s$  increases, the individuals become more randomly connected, and the network resembles a random network. These additional connections increase the efficiency of information exchange, leading to faster self-segregation and greater efficiency improvements.

We find that FOMO has an adverse impact on the system. We explore ways to offset FOMO's negative impact by analyzing the impacts of the two parameters on the FOMO model. Figures 4 and 5 illustrate the influence of these two parameters on  $P(p)$  in the FOMO model.

[Figure 4 about here]

[Figure 5 about here]

In Figure 4, we represent strong, moderate, and weak mutation levels by  $dp = 1, 0.1, \text{ and } 0.01$ , respectively. Figure 4 shows that stronger mutations lead to more pronounced self-segregation. In Figure 5, the network structure is determined based on the rewiring probability. We generate random, small-world, and regular networks with  $P_s = 1, 0.1, \text{ and } 0.01$ , respectively. Figure 5 demonstrates that as the network transitions from regular to random, the distribution of  $p$ -values becomes more polarized toward the extremes.

Figures 6 and 7 show similar results. Figure 6 shows the relationship between the rewiring probability and reduced variance according to the mutation level in the FOMO model. Figure 7 shows the relationship between the mutation level and the reduced variance by the network structure.

[Figure 6 about here]

[Figure 7 about here]

Figure 6 shows that a strong mutation level is also the most inefficient and that a moderate mutation level is the most efficient. This result suggests that there are limits to improving the efficiency of the system if agents modify their strategies too liberally or too conservatively. In addition, Figure 6 shows that the reduced variance tends to decrease as the rewiring probability increases, suggesting that the system efficiency improves as the network structure approaches a random network. Figure 7 also illustrates this trend.

In summary, the simulation results indicate that an asymmetric reward enhances the stability of the system by promoting agent self-segregation through faster feedback. However, FOMO disrupts this phenomenon, offsetting the overall improvement in system stability. These findings suggest that the irrational behavior driven by FOMO can have detrimental effects on the market. Nevertheless, the simulation results suggest that as agents become more interconnected and actively adjust their strategies, FOMO's negative impacts on the system diminish.

#### **4. Conclusion**

This study investigates the influence of the spread of FOMO through social networks on financial market volatility. FOMO, which is characterized by feelings of social exclusion and disconnection, has become prevalent in contemporary society. The widespread use of social media and mobile devices has facilitated greater levels of interpersonal connection, increasing individuals' susceptibility to FOMO. In the context of financial markets, surges in specific assets' prices and success stories have generated widespread interest, even among previously disinterested individuals. Utilizing the NEMG model and incorporating an asymmetric reward structure and FOMO, this study analyzes and simulates the effects of FOMO on financial markets.

The simulation results suggest that an asymmetric reward structure improves system stability by encouraging agents to self-segregate, but FOMO counteracts this effect, highlighting the negative impacts of irrational, FOMO-driven behavior on markets. However, as agents become more interconnected and adapt their strategies, the detrimental effects of FOMO decrease. Our results reveal that investors' FOMO significantly exacerbates market volatility and reduces efficiency. FOMO-induced irrational behavior disrupts the normal functioning of the market, increasing volatility and reducing market efficiency. These findings shed light on psychological factors in the financial market and have implications not only for investors but also for policymakers and regulators interested in managing and improving market dynamics. By understanding FOMO's impact, stakeholders can make informed decisions to promote efficient and stable market environments.

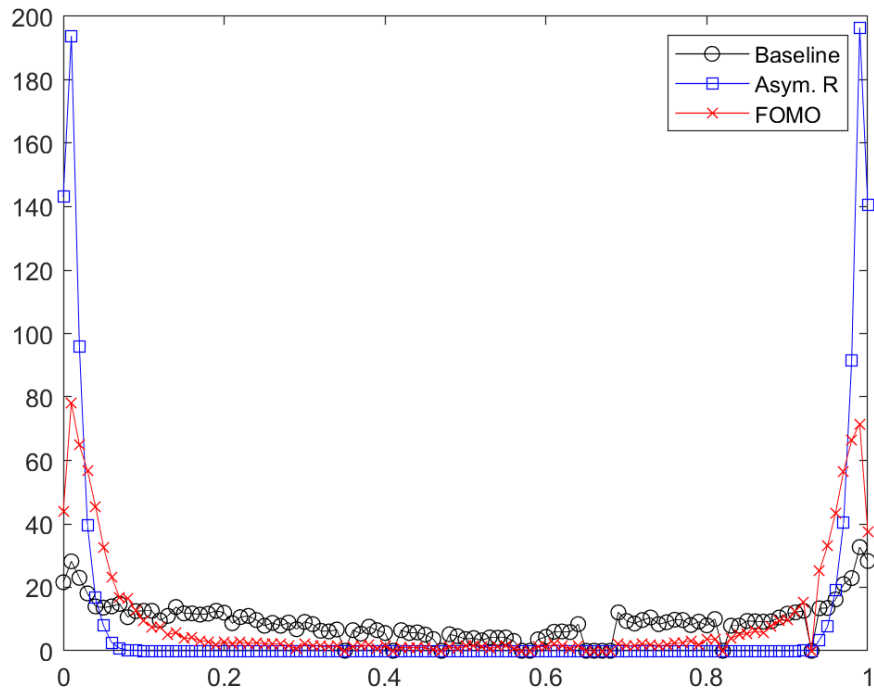
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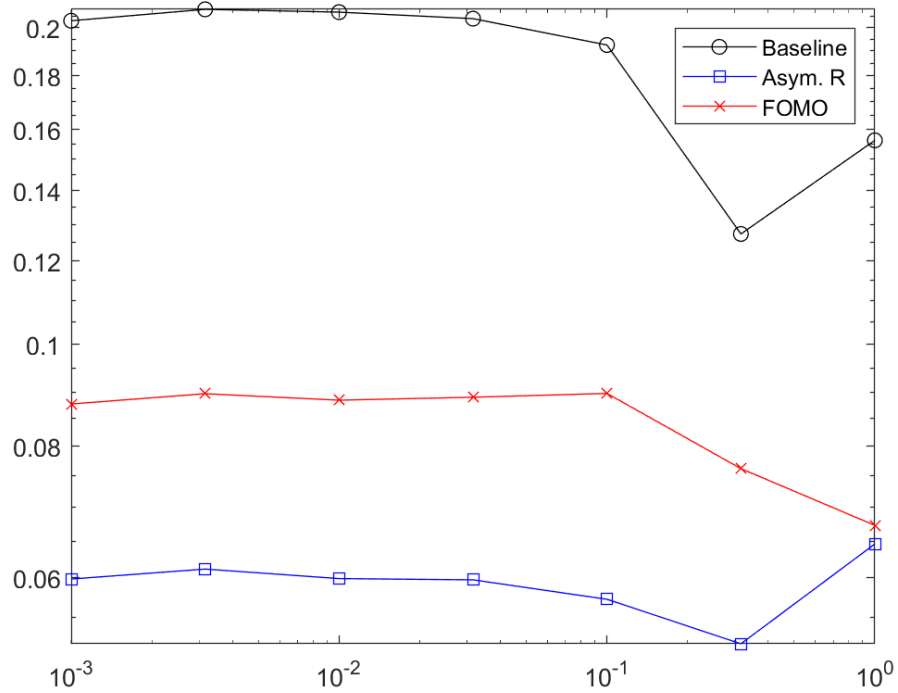
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**Figure 1.** Histogram of  $p$ -values by model



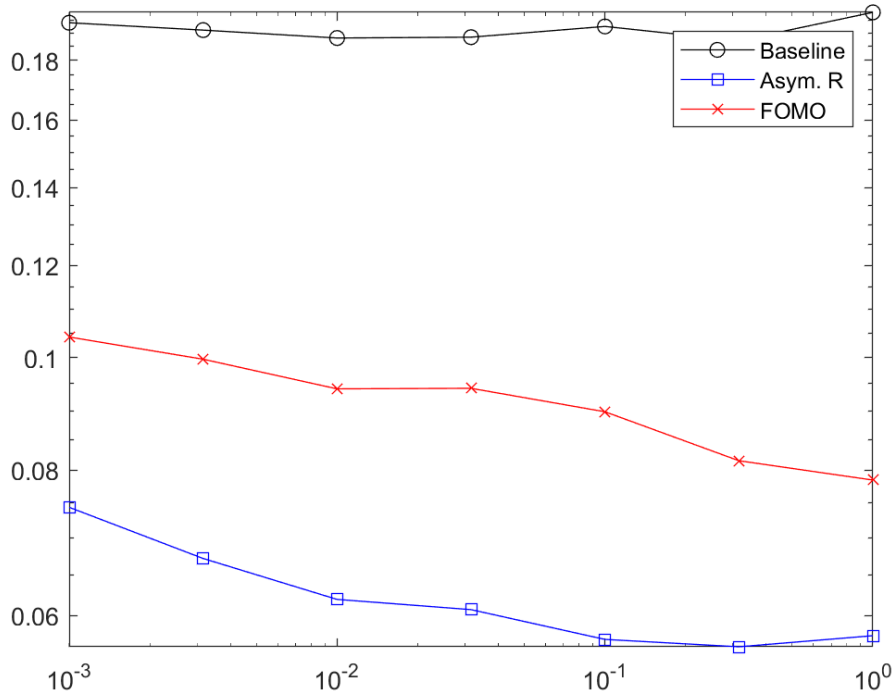
*Note:* This histogram illustrates the distributions of the  $p$ -values for each model.  $P(p)$  is plotted on the vertical axis, and the  $p$ -values are plotted on the horizontal axis. Each point is an average value over 10 runs, with each run consisting of 50,000 iterations. The lines marked with circles, squares, and x-markers represent the baseline, asymmetric reward, and FOMO models, respectively.

**Figure 2.** Relationships between the mutation level and the reduced variance by models



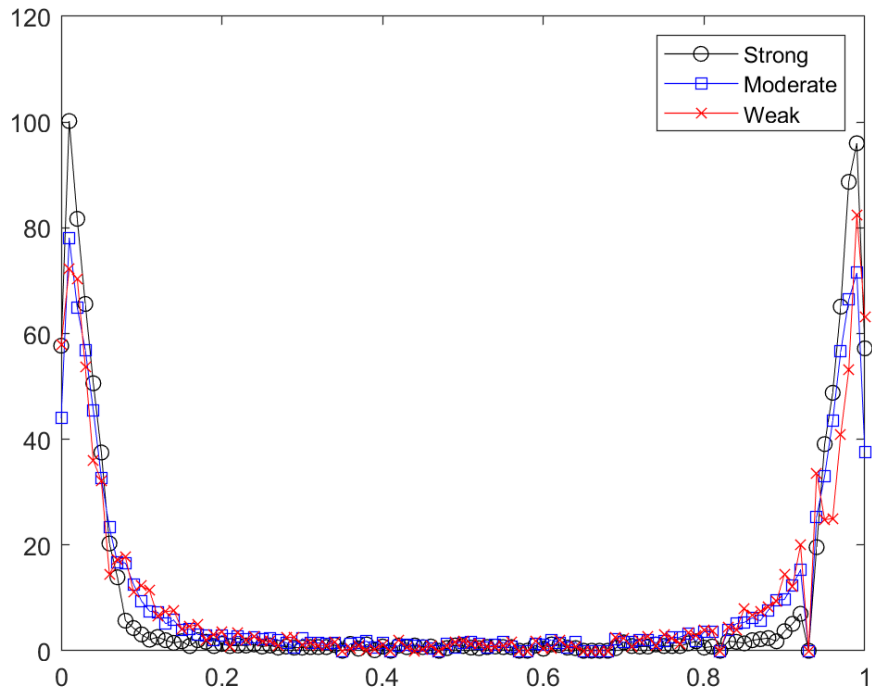
*Note:* This figure shows the relationship between the mutation level and the reduced variance for each model. The reduced variance is plotted on the vertical axis, and the mutation level is plotted on the horizontal axis. Each point is an average value over 10 runs, with each run consisting of 50,000 iterations. The lines marked with circles, squares, and x-markers represent the baseline, asymmetric reward, and FOMO models, respectively.

**Figure 3.** Relationships between the rewiring probability and the reduced variance by models



*Note:* This figure shows the relationship between the rewiring probability and the reduced variance for each model. The reduced variance is plotted on the vertical axis, and the rewiring probability is plotted on the horizontal axis. Each point is an average value over 10 runs, with each run consisting of 50,000 iterations. The lines marked with circles, squares, and x-markers represent the baseline, asymmetric reward, and FOMO models, respectively.

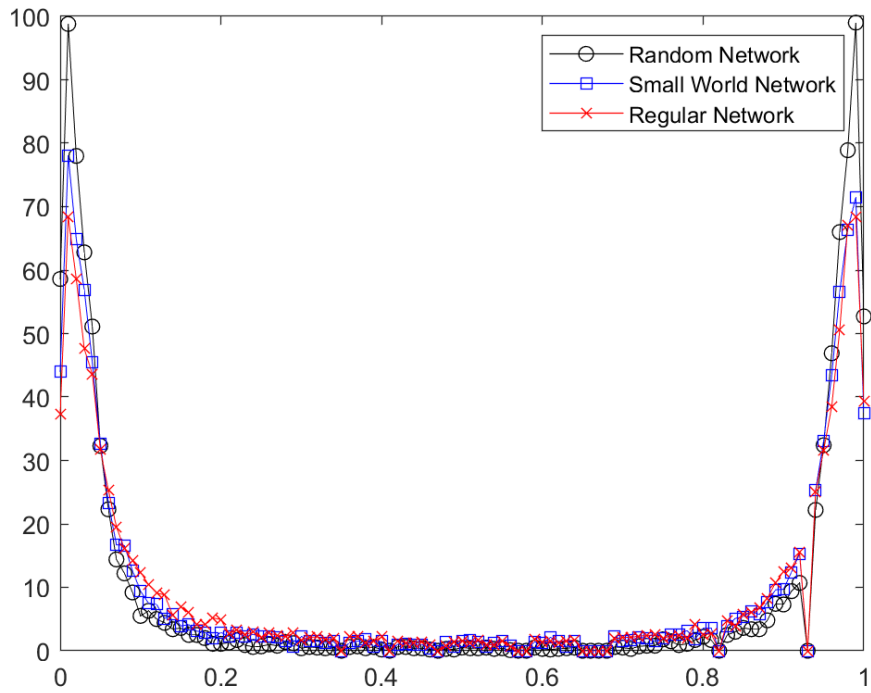
**Figure 4.** Histogram of  $p$ -values by mutation level



*Note:* This histogram illustrates the distribution of  $p$ -values by mutation level.  $P(p)$  is plotted on the vertical axis, and the  $p$ -values are plotted on the horizontal axis. Each point is an average value over 10 runs, with each run consisting of 50,000 iterations. The lines marked with circles, squares, and x-markers represent the strong, moderate, and weak mutation levels, respectively.

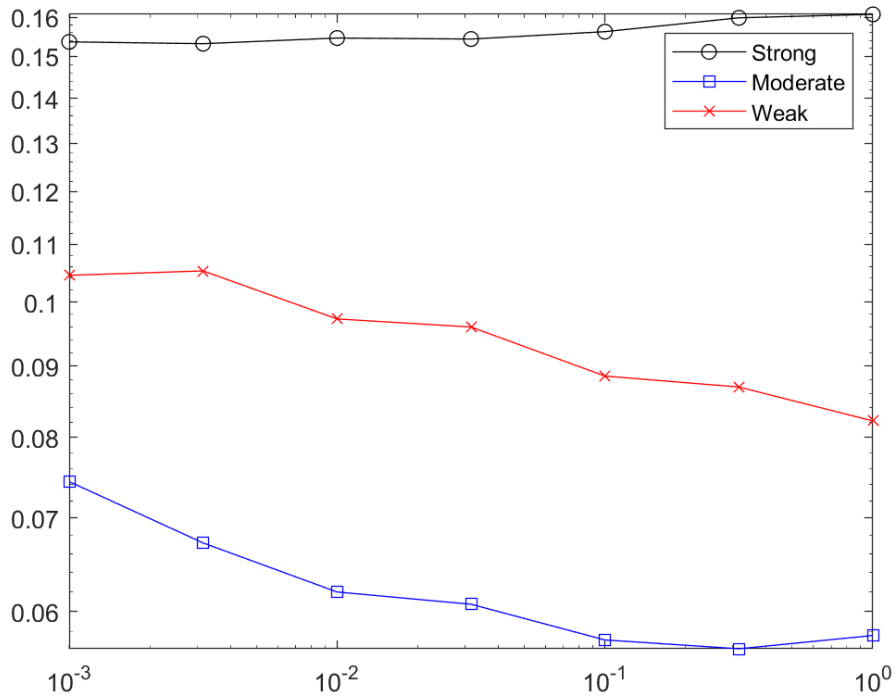


**Figure 5.** Histogram of  $p$ -values by network structure



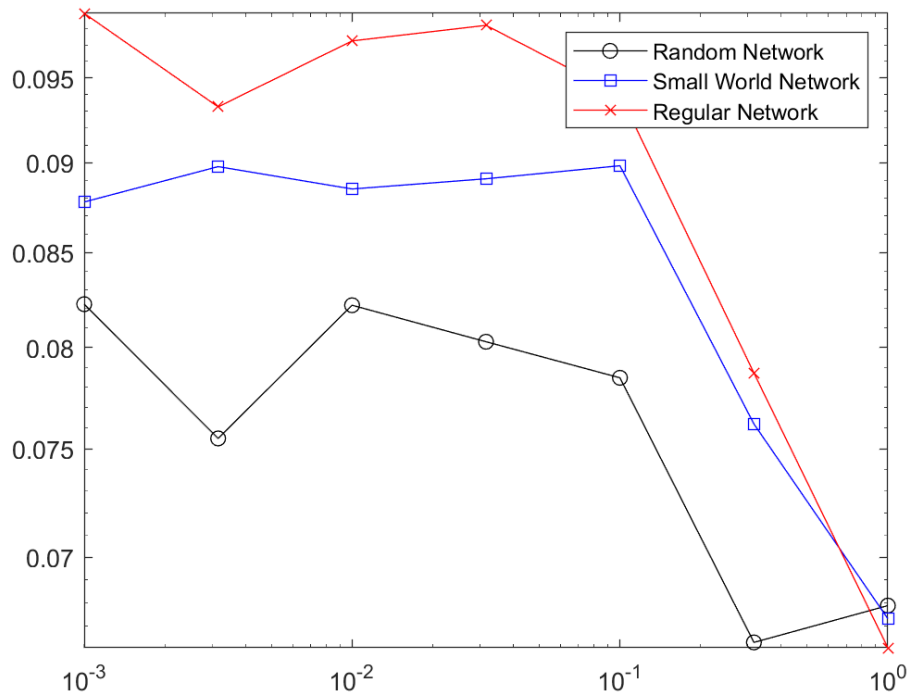
*Note:* This histogram illustrates the distribution of  $p$ -values by network structure.  $P(p)$  is plotted on the vertical axis, and the  $p$ -values are plotted on the horizontal axis. Each point is an average value over 10 runs, with each run consisting of 50,000 iterations. The lines marked with circles, squares, and x-markers represent the random, small world, and regular networks, respectively.

**Figure 6.** Relationships between the rewiring probability and the reduced variance in the FOMO model



*Note:* This figure shows the relationship between the rewiring probability and the reduced variance in the FOMO model. The reduced variance is plotted on the vertical axis, and the mutation level is plotted on the horizontal axis. Each point is an average value over 10 runs, with each run consisting of 50,000 iterations. The lines marked with circles, squares, and x-markers represent the strong, moderate, and weak mutation levels, respectively.

**Figure 7.** Relationships between the mutation level and the reduced variance in the FOMO model



*Note:* This figure shows the relationship between the mutation level and the reduced variance in the FOMO model. The reduced variance is plotted on the vertical axis, and the rewiring probability is plotted on the horizontal axis. Each point is an average value over 10 runs, with each run consisting of 50,000 iterations. The lines marked with circles, squares, and x-markers represent the random, small world, and regular networks, respectively.