God's Dice

In the article "The Game of Stock Market", we described the process of building a simplified stock market trading simulation system. In this simulation system:

1. Based on the behavioral characteristics of traders, we have added several types of investors, including: value investors, trend investors, up-and-down investors, random investors, never-stop-loss investors, bottom-picking investors, and news investors.
2. In terms of trading, we only used a call auction to simulate daily trading, generate price sequences and trading volume sequences, and observe market changes.
3. From the output of the simulation results, we can observe the fluctuations in stock prices and trading volumes, as well as the average changes in assets, cash, and holdings of each type of investor.
4. We have added the function of injecting or withdrawing funds into the market, and added the transaction fee information, so that we can observe the impact of overall market capital changes on transactions.

Next, we will continue this game, which will be more realistic and explore some issues that were not discussed in " The Game of Stock Market ".

I. Model Adjustment

Before starting a new topic, let's make some necessary adjustments to the model:

1. The value curve sequence square wave is changed to a pre-generated method, and the random number seed can be set to generate different value curves (to facilitate subsequent testing and analysis);
2. In order to make the trading behavior of value investors more consistent with the actual investment strategy, modify the operation method of value investors:
    a) They will adjust their holdings according to the degree of deviation between price and valuation. When the price is close to the valuation, the holding ratio is close to the target value (about 50%). When the price deviates significantly from the valuation, the holding ratio will be adjusted accordingly, and eventually the position will be full or empty. Different investors have different tolerances for price deviations, resulting in different maximum deviation ratios. Different investors also have different target holding ratios, reflecting different risk preferences.

b) When the value curve changes, value investors will not respond immediately to changes in stock value, butwill re-evaluate after a lag period of 1-20 days. The valuation deviation percentages of all investors generally follow a normal distribution with a mean of 0 and a standard deviation of 15% (settable).

3. Because random investors are easily affected by market sentiment, a market sentiment indicator is introduced, and the investment strategy of random investors will be affected by this indicator: their trading probability is affected by market sentiment, and the trading probability increases when the sentiment is high, and vice versa; and their trading ratio is also affected by market sentiment, and the trading ratio increases when the sentiment is high, and vice versa.
4. Introduce new insider traders: They are investors who can obtain public information in advance to learn about changes in stock value (equivalent to bad or good news). We assume that they have the following characteristics:
    a) Be able to know the direction of stock value changes 1-5 days in advance
    b) When they predict that the future value will rise, they buy; when they predict that the future value will fall, they sell;
    c) Set certain take-profit, stop-loss and holding period targets in the simulation.

The code main_OHLC_2.0.5.py first made the above modifications based on main_ca_3.2.1.1.py , the main purpose is to make it closer to the actual market situation. However, the biggest adjustments made to the code are as follows:

1. To be as close to the real market as possible, each trading day is divided into three stages: opening, intraday, and closing;
2. Opening call auction: 30%-50% of orders are randomly selected to participate in the opening call auction
3. Intraday trading: up to 100 rounds of iterations, 10%-30% of orders are randomly selected in each round to participate in this round of matching. Unfulfilled orders have a 40% probability of returning to the main order list, a 30% probability of entering the closing call auction, and a 30% probability of being cancelled.
4. Closing auction: All remaining orders participate in the closing auction
5. The price that can generate the largest transaction volume is selected as the transaction price. If there are multiple prices that generate the same maximum transaction volume, the price closest to the previous price is selected.

The detailed code can be found in main_OHLC_2.0.5.py . After running, the running results are as shown in the figure below:

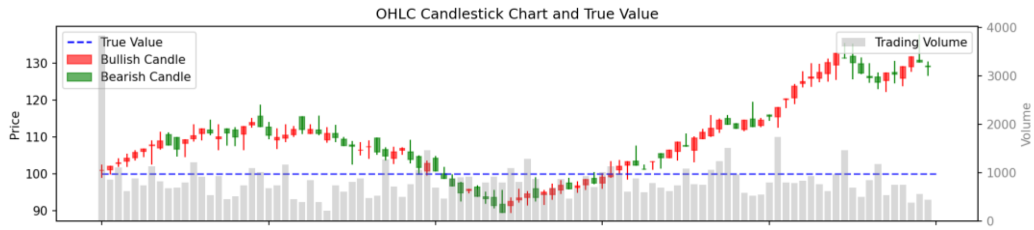


Figure 1

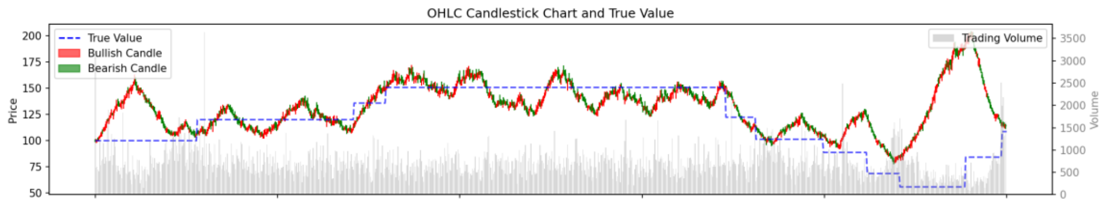


Figure 2

Figure 1 above is a 100-day operation simulation; Figure 2 above is a 1000-day operation simulation.

II. Random Walk

Einstein once said, " I am sure, at any rate, that God does not play dice. " But the opposite is true in many aspects of the real world. Almost everything is full of uncertainty, especially in the financial world.

There is an important theory in finance related to the randomness of the stock market called the Random Walk Theory . Its main points are as follows:

1. Price changes are random and unpredictable: The random walk theory believes that stock price changes are similar to " Brownian motion " , that is, each step of rise and fall is independent and there is no pattern to follow; since market information appears randomly (such as economic data, political events, etc.), price changes are also random, and future trends cannot be predicted through historical data.
2. The market is efficient and prices have reflected all information: This theory is based on the Efficient Market Hypothesis (EMH), which holds that market prices have fully digested all public information, including fundamentals, news, market sentiment, etc. Therefore, no technical analysis or fundamental analysis can continuously beat the market because prices are already at a " reasonable " level.
3. Active investing is unlikely to consistently outperform the market, so passive investing (such as index funds) is better: Due to random price fluctuations, excess

returns for fund managers or investors are mostly due to luck rather than skill; since the market is difficult to beat, the theory suggests that investors adopt a " buy and hold " strategy.

4. Oppose technical analysis and trend prediction: The random walk theory believes that technical analysis (such as K -line charts, moving averages, etc.) is invalid because price changes have no memory and past trends will not affect the future.
5. Extreme fluctuations are rare, and most stocks have limited fluctuations: the proportion of stocks that rise sharply (such as a 4-5 times increase) or plummet (such as a 99% drop) is very low, and the fluctuation range of most stocks is between ±10% and 30% , which conforms to the normal distribution.

In our project, as mentioned in the previous paragraph, main_OHLC_2.0.5.py adjusted the market trading method, and the adjusted running results showed random characteristics. The three figures below are three simulations of main_OHLC_2.0.5.py running for 1000 days without changing any other parameters , and the market price and trading volume changes are different.

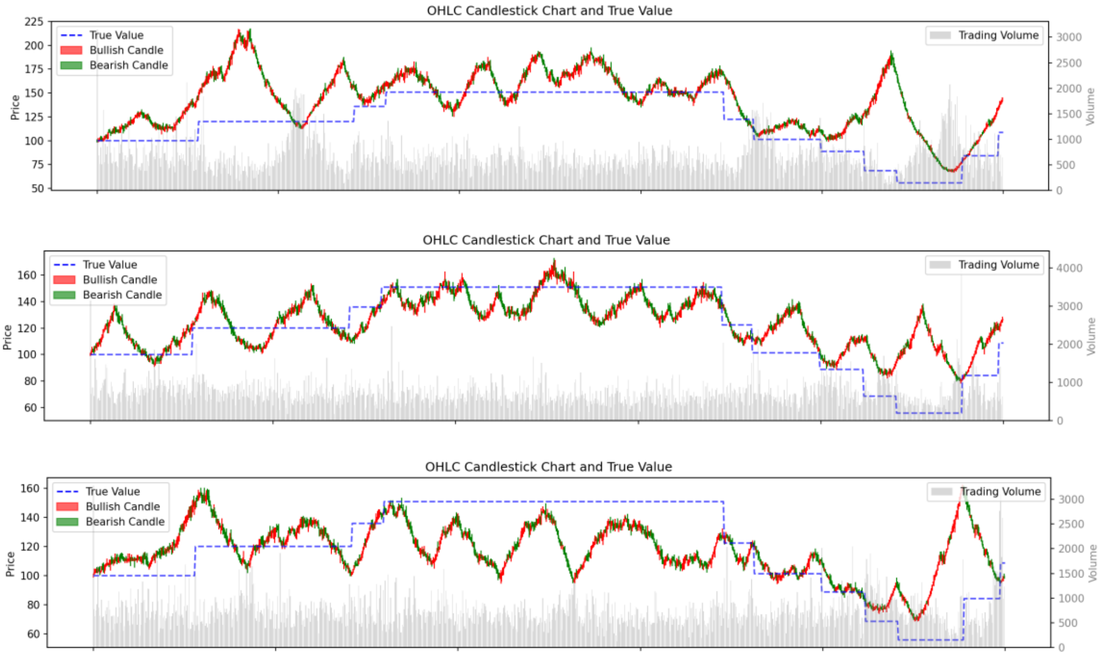


Figure 3

As mentioned above, the random walk theory believes that since market information appears randomly (such as economic data, political events, etc.), price changes are also random. However, from the results of program simulation, we cannot rule out the impact of the randomness of stock market participants' behavior on the market. The frequency of economic data and political events is much lower than the frequency of random behavior of stock market participants. The various behaviors of stock market participants occur all the time and will have an impact on the stock market all the time.

If the behavior of traders has random characteristics, it will inevitably lead to the randomness of stock prices. For example, a value investor made a buy decision at the close of the previous day, and he may buy at any time on the second day; a trend investor may also delay the time of the original transaction because of a phone call ... At this time, their counterparts will also be different. The occurrence of a series of random behaviors of traders will lead to intraday fluctuations, and finally lead to the randomness of the closing price, and the closing price will affect some investors who rely on the closing price sequence to make decisions, thereby changing their trading behavior and affecting the next day's trading. In this way, day after day, even without the influence of economic data and political events, random walks will still occur. Of course, sudden economic data, political events, and the random occurrence of negative and positive factors in a company itself will also affect investors' decisions, and ultimately, through changes in their behavior, will bring price fluctuations to the market.

The random walk theory is a theory that is summarized and analyzed by observing the real world market. There is a problem: due to the randomness of the price sequence, the price sequence we get is just one of countless possible price sequences, and this sequence is formed by countless coincidences. Various factors will have an impact on stock prices, but it is difficult for us to analyze the impact of each of these factors based on this existing sequence alone.

The program main_OHLC_2.0.5.py can simulate many random sequences of stock prices based on some assumptions, and then we can use the mathematical methods for processing random sequences to process them. We need to emphasize that this provides a systematic method of thinking, researching and analyzing the stock market (or other financial systems) based on behavioral finance. At this stage, don't pay too much attention to whether the assumptions of market participants and their data are absolutely correct: although the assumed participants in the program are based on reality, they are certainly very different from the real market. But I think that if we can get more information about investors' investment styles or habits from the big data of the stock market (for example: how much money, whether they are technical or fundamental, what time they like to buy or sell, etc.), we may be able to get a simulation that is closer to reality.

III. Brownian motion

In this section, we will discuss whether the price curve generated by our simulation program conforms to the geometric Brownian motion. We made a few changes to the main_OHLC_2.0.5.py program, with the aim of setting a random number seed for each pseudo-random number generated in order to achieve reproducibility. The generated program is main_OHLC_2.0.5.1.py . In addition, we wrote a Brownian motion detection program - brownian_motion_test_1.0.py . Here we simulate the data changes of stock prices for 2000 days, and the test report is as follows:

1. Normality test: passed all normality tests very well
    1. Shapiro-Wilk test: p value is 0.428901 > 0.05 , indicating that the return distribution cannot reject the normal distribution hypothesis
    2. Jarque-Bera test: p value is 0.291005 > 0.05 , which also supports that the rate of return follows a normal distribution
    3. Lilliefors test: p value is 0.515399 > 0.05 , further confirming that the rate of return follows a normal distribution
    4. Skewness: -0.0857 , close to 0 , indicating that the distribution is basically symmetrical and slightly biased to the left
    5. Excess Kurtosis: -0.0159 , very close to 0 , indicating that the tail of the distribution is very similar to the normal distribution

    Conclusion: All normality tests passed very well.

2. Autocorrelation test:
    1. Ljung-Box test: p -value is 0.230261 > 0.05 , indicating that there is no significant autocorrelation between the returns

    Conclusion: The autocorrelation test was passed, indicating that there is no significant correlation between the returns.

3. Variance - time relationship test:
    1. Slope (log - log coordinates): -0.0217 , the theoretical value should be 1.0
    2. R -square: 0.1012 , low fit
    3. Deviation from theoretical value: 1.0217 , large deviation

    Conclusion: Theoretically it should be 1.0 . This is the only test that does not conform to the characteristics of Brownian motion.

4. Random walk test:
    1. ADF test: p value is 0.981601 > 0.05

    Conclusion: It passed the random walk test and the random walk characteristics are very obvious.

5. Hurst Index:

    2. The value is 0.4892 , which is very close to 0.5 (the theoretical value of Brownian motion)

Conclusion: Very close to ideal Brownian motion, exhibiting slight anti-persistence.

Summary: The simulated stock price data also meets 4 of the 5 conditions , so the conclusion is that " the price series strongly resembles Brownian motion " . The generated price curves show very strong Brownian motion characteristics for longer time series. After increasing the sample size (from 500 to 2000), the Brownian motion characteristics of both data become more obvious, especially the random walk characteristics and the Hurst exponent. Despite the deviation from the variance - time relationship, the simulated stock price data still meets most of the key characteristics of Brownian motion, indicating that the model can be well used for financial market simulation. For the failure to pass the variance - time relationship test, this may be due to: there may be problems with our test method; the discrete simulation of Brownian motion itself may cause this deviation; a more complex model (such as fractional Brownian motion) may be needed to better capture this relationship.

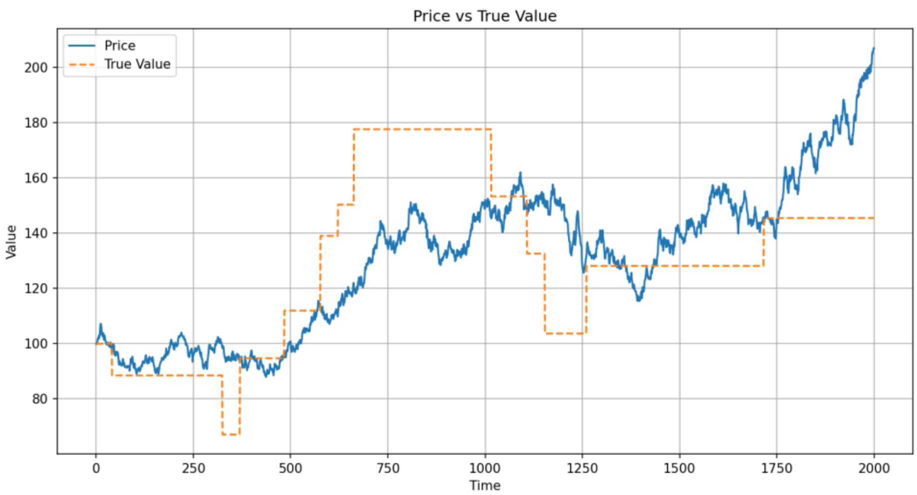


Figure 4

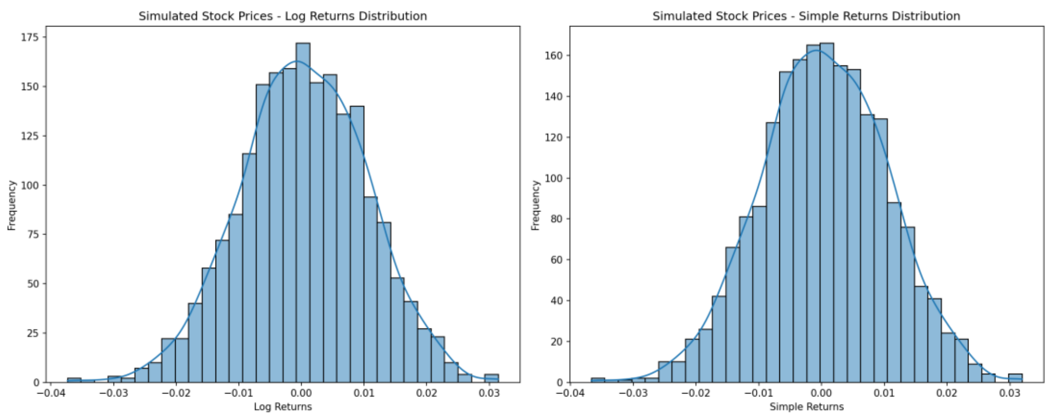


Figure 5

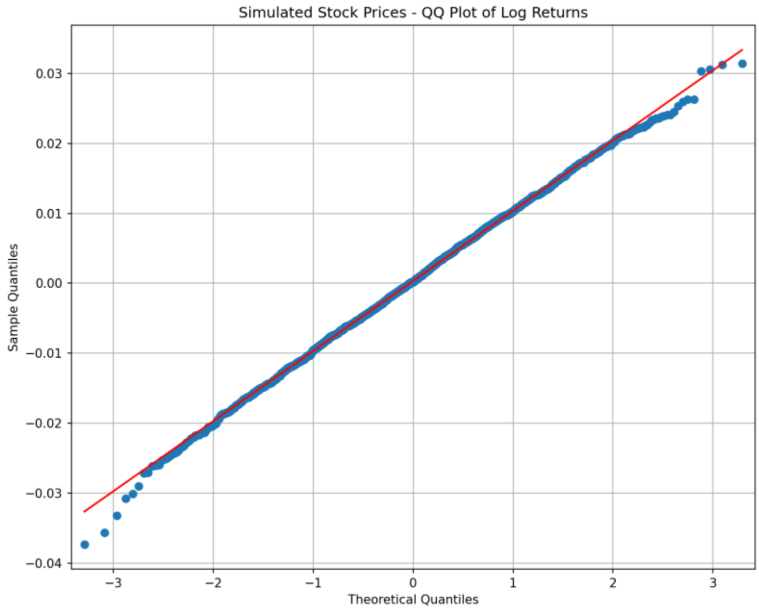


Figure 6

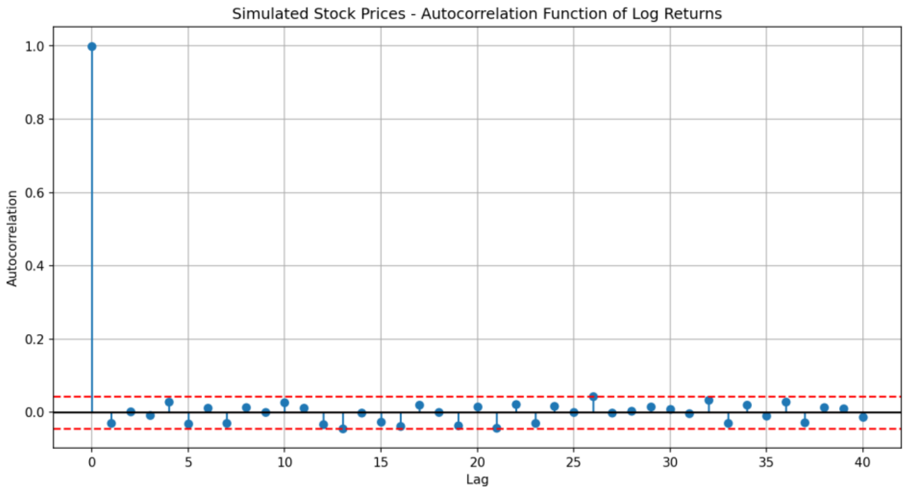


Figure 7

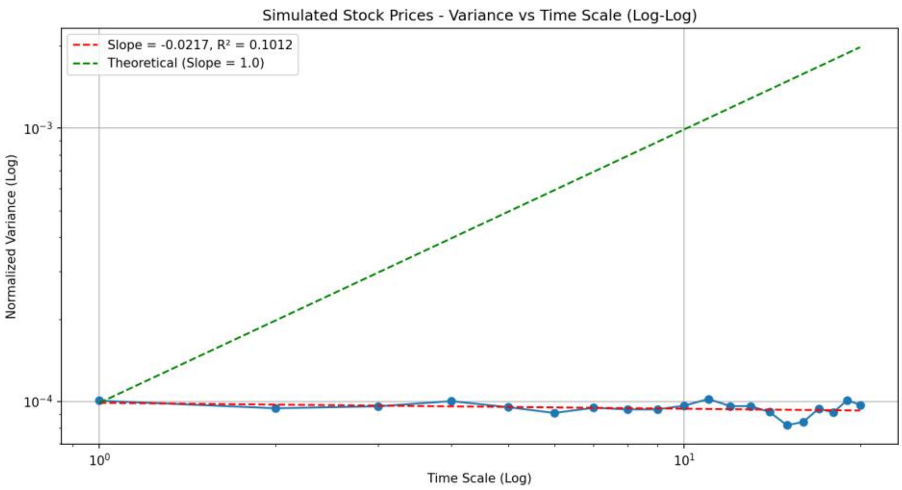


Figure 8

IV. The Butterfly Effect

The " butterfly effect " was first proposed by Lorenz in his research in 1963. It originated from his discovery of the extreme sensitivity of weather models to initial conditions. This discovery was later visualized as " a butterfly flapping its wings in Brazil may cause a typhoon in the Pacific " , emphasizing that small changes may lead to big results.

In financial systems such as the stock market, this theory is used to describe the market's amplification effect on small events. Studies have shown that the stock market is an open system that is affected by multiple factors, such as economic data, political events, and investor psychology. This system characteristic makes it susceptible to the butterfly effect. Behavioral finance research believes that investor psychology and bias will affect the market. The butterfly effect is reflected here in that small changes in investor sentiment may amplify market fluctuations. Below we simulate three situations:

1. Changes in closing price:

The program butterfly_effect_simulation_1.0.py in the project can simulate the butterfly effect. The program is based on the existing main_OHLC_2.0.5.1.py file. By modifying the closing price of a specified date (such as 300 days) (the change ratios are 0.5%, 1.5%, 4%, -0.5%, -1.5%, -4%), it simulates a sudden change in the closing market of a certain day for some reason, and then observes and compares the impact of this small change on the subsequent market. In the test, the random number seed is set to be completely consistent, and other parameters are completely unchanged. Only the impact of small fluctuations in the closing price on the subsequent closing price sequence is observed. The results are shown in the figure below:

Butterfly Effect Analysis Results:

Change %	Max Diff	Final Diff	Avg Diff	Amplification	Direction
0.5 %	23.28 %	3.74 %	5.11 %	46.56 x	Same
1.5 %	21.23 %	3.37 %	5.61 %	14.15 x	Same
4.0 %	21.48 %	13.03 %	4.84 %	5.37 x	Same
-0.5 %	29.43 %	0.87 %	6.63 %	58.87 x	Opposite
-1.5 %	26.02 %	10.12 %	5.65 %	17.35 x	Opposite
-4.0 %	26.37 %	15.18 %	6.08 %	6.59 x	Opposite

Figure 9

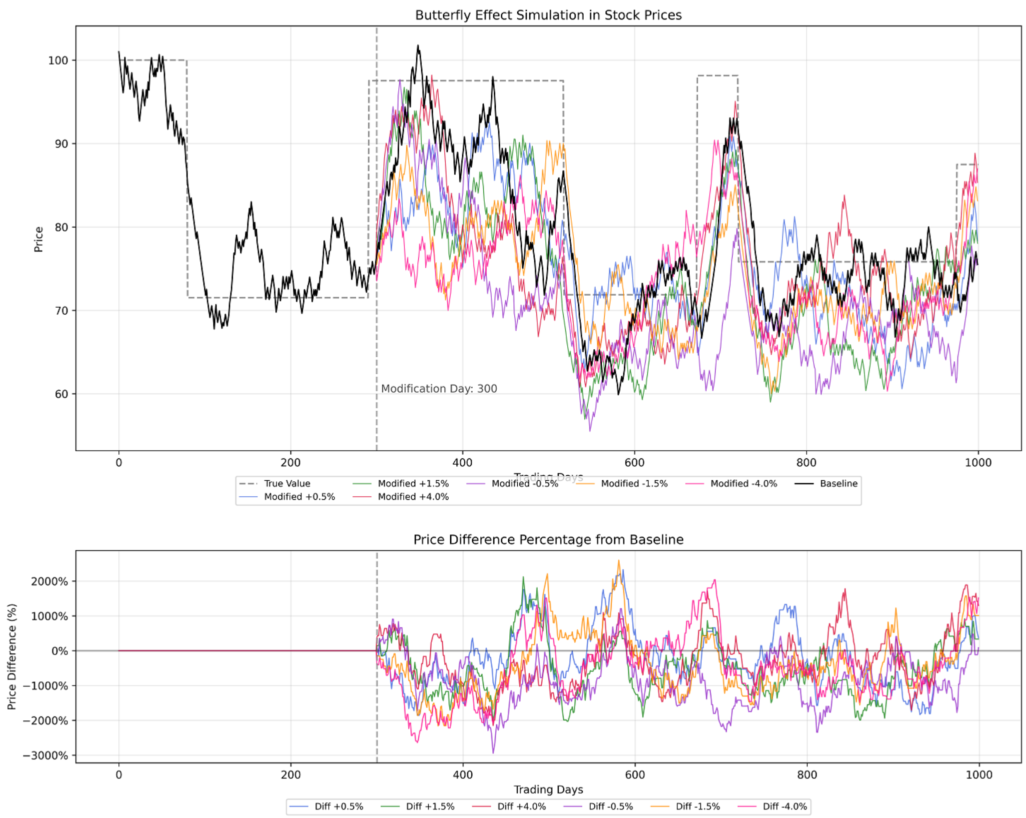


Figure 10

The statistical table contains the following information: percentage change of initial setting, maximum difference, final difference, average difference, magnification direction, etc.

Through the graphical display, we can observe the following phenomena:

A. Compared to the black baseline (the 300-day 0% deviation price curve), the other price curves are significantly different, even if the change is only 0.5%
B. The fluctuation range of the later price curve has little to do with the initial deviation
C. These price curves still have the trend of following the value curve (grey dotted

line)

The figure below shows a more extreme change, where the corrected price curves deviate significantly from the baseline after the value curve continues to fall.

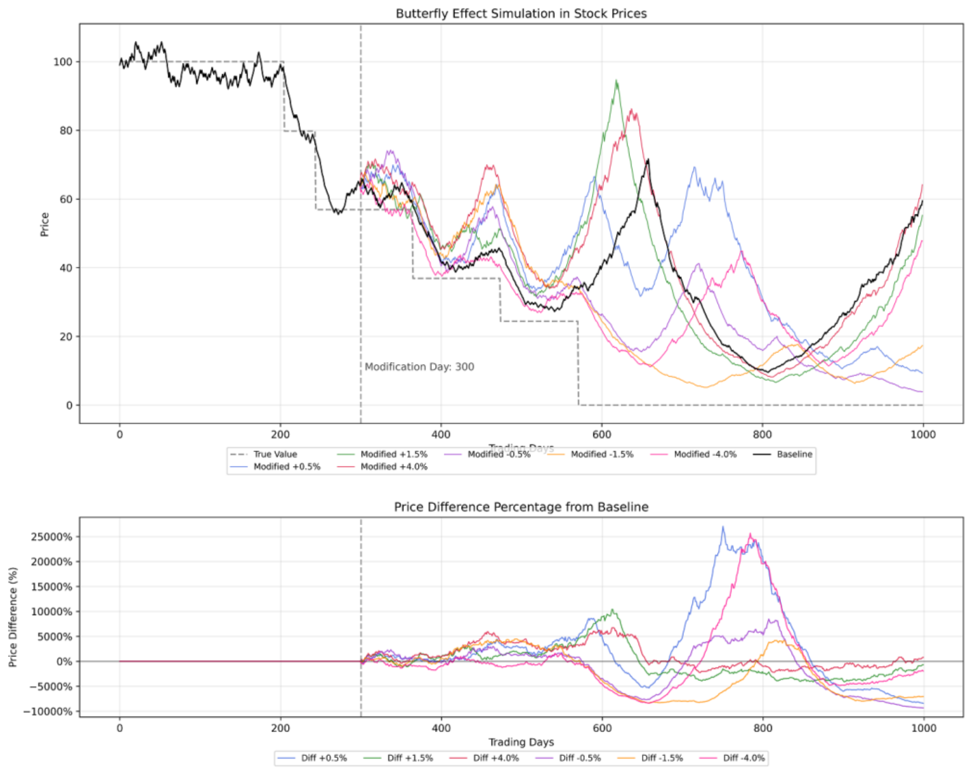


Figure 11

By modifying the program, we can also simulate the impact of other sudden changes in internal and external environments (even small changes) on long-term stock price fluctuations.

2. The influence of individual behavior - the first case

Here we simulate (program butterfly_effect_simulation_1.2.py) how the sudden participation of a single investor can have a long-term impact on the entire market. We design an investor who suddenly participates in the transaction (Sudden Investor), who buys stocks at a price slightly higher than the market price at that time (premium 5%) on a specified trading day (300th day) , and then observe the impact of this intervention on subsequent market price trends.

We conducted multiple sets of simulations, each with different initial capital of sudden investors (ranging from 300 yuan to 100,000 yuan), and compared them with the baseline simulation (without the participation of sudden investors) to analyze the impact of different sizes of funds on the market.

Investor funds	**Order quantity**	**Transaction Quantity**	**Transaction ratio**	**Remaining cash**	**Transaction status**
￥300	3 shares	3 shares	100%	￥74.55	All sold
￥1,000	13 shares	13 shares	100%	￥23.06	All sold
￥5,000	65 shares	65 shares	100%	￥115.31	All sold
￥10,000	131 shares	129 shares	98.50%	￥22.46	Partially sold
￥20,000	263 shares	155 shares	58.90%	￥8,011.48	Partially sold
￥50,000	658 shares	155 shares	23.60%	￥38,011.48	Partially sold
￥100,000	1,317 shares	155 shares	11.80%	88,011.48n	Partially sold

Since the number of participants in each category is relatively small (100 people), in the above table, small-amount orders (≤5,000 yuan) can be fully executed, while larger orders are only partially executed. The maximum tradable volume of the current-sized market is approximately 155 shares.

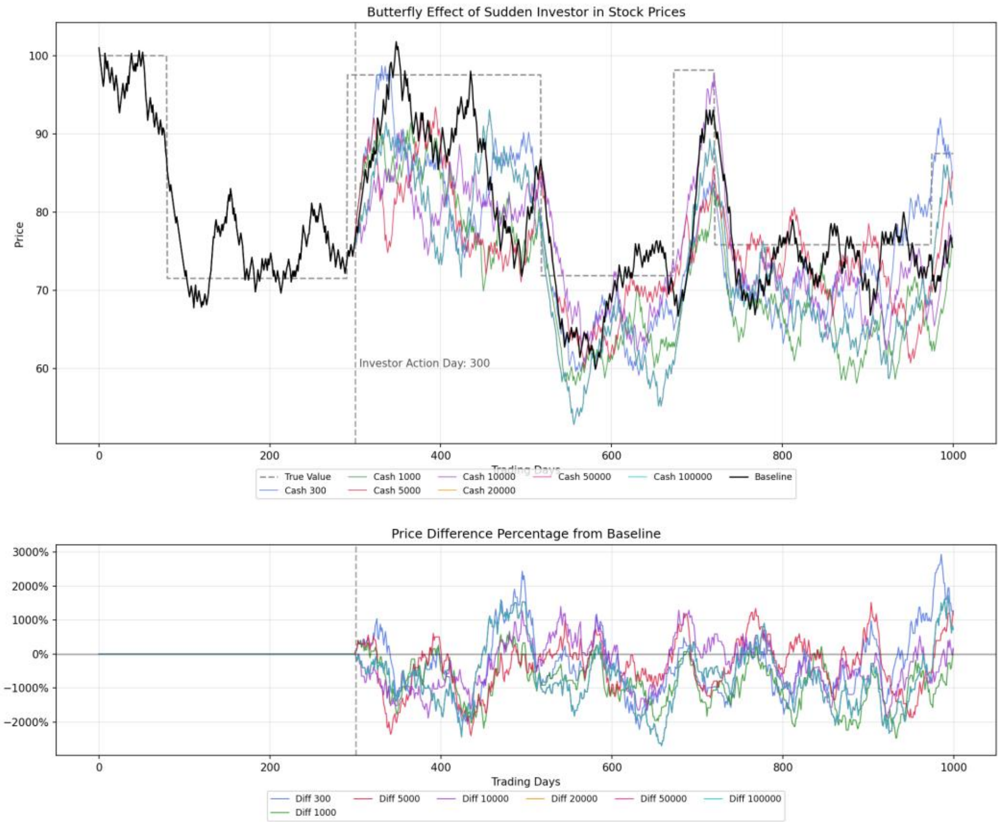


Figure 12

The figure below shows the operating results when setting a 2% premium to buy.

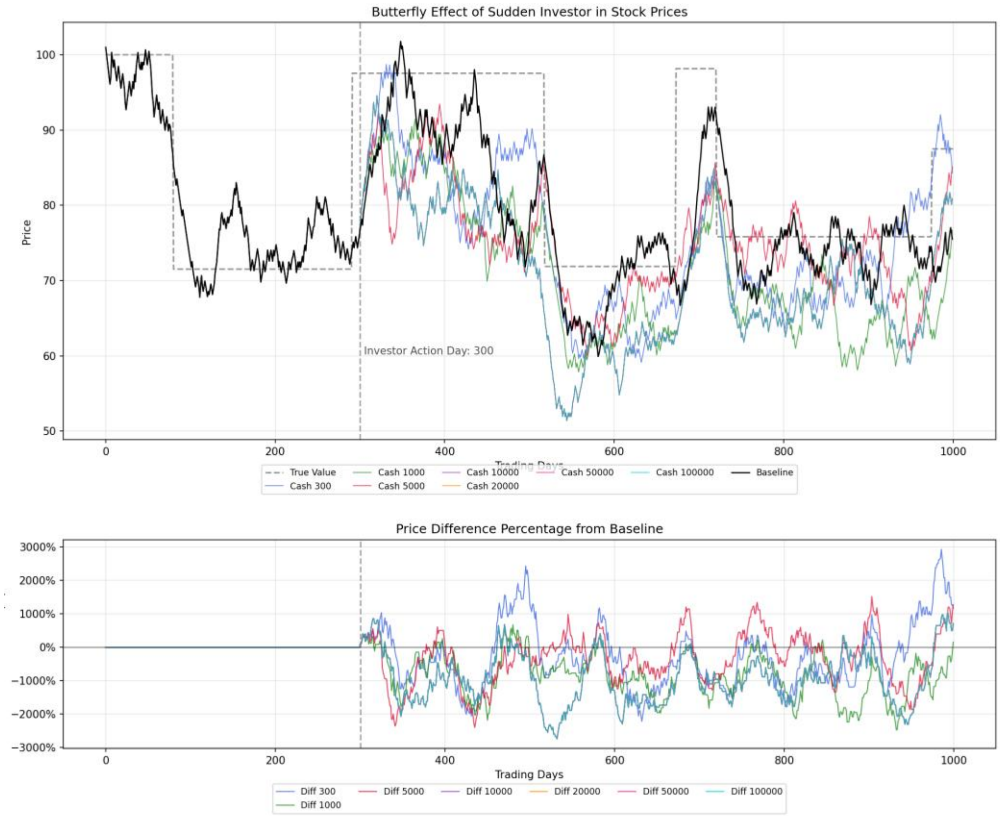


Figure 13

The following figure shows the result of setting a 1% premium to buy. The transaction record shows that all investors only bought 2 shares. This indicates that when the market depth is limited, there are limited sell orders in the market, or there is competition from buy orders from other investors, which means that even if more funds are provided, more stocks cannot be bought.

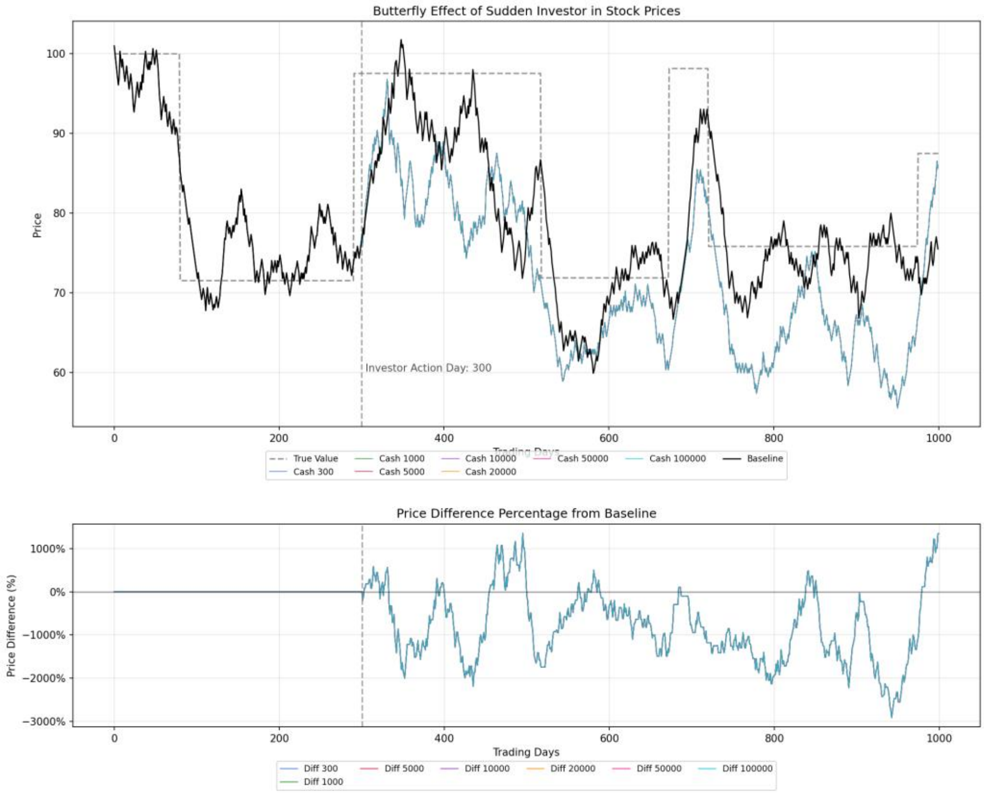


Figure 14

From the running results, we can find that: ① In all cases, the sudden participation of investors caused the market price to deviate from the benchmark simulation, indicating that buying behavior has an impact on the market price. ② Even small amounts of funds can have a significant impact on the market, and even if the trading volume is only two shares, it can have a significant impact on the market . ③ The price deviation caused by the initial intervention still exists at the end of the simulation, indicating that the market has not completely returned to the non-intervention state. ④ There is no obvious relationship between the intensity of the butterfly effect and the size of the sudden purchase amount.

Let's briefly analyze the possible causes or mechanisms of the butterfly effect:

A. Direct causes: ① Price discovery: Suddenly, investors placed orders at a premium of 5% above the market price , which directly increased the buying pressure in the market, leading to a higher transaction price in the auction. ② Liquidity absorption: Investors' buy orders absorbed some of the sell orders in the market, reducing the number of shares available for other buyers to purchase, further pushing up prices.
B. Indirect causes: ① Changes in investor behavior: Initial price changes may cause other investors (such as trend investors, investors who chase ups and downs) to change their trading decisions, forming a chain reaction. ② Changes in technical

indicators: Price changes affect technical indicators such as moving averages, further affecting the decisions of investors who rely on these indicators. ③ Transmission of market sentiment: Price increases may be interpreted as positive signals, triggering more buying behavior, forming a positive feedback loop. ④ Sustained long-term impact: Even long after sudden investor transactions, market prices still deviate from the benchmark, indicating that the impact of the initial intervention is amplified and continued through market mechanisms.

In butterfly_effect_simulation_1.3.py and butterfly_effect_simulation_1.4.py , the number of all other investors in the market except the sudden investor is enlarged by 10 and 50 times to study whether the sudden participation of a single investor can still produce a significant butterfly effect in a larger market. The experiment maintains the same random number seed and other parameter settings so that the results can be directly compared with the small-scale market. The following two figures are generated by version 1.3 and 1.4 of the program respectively:

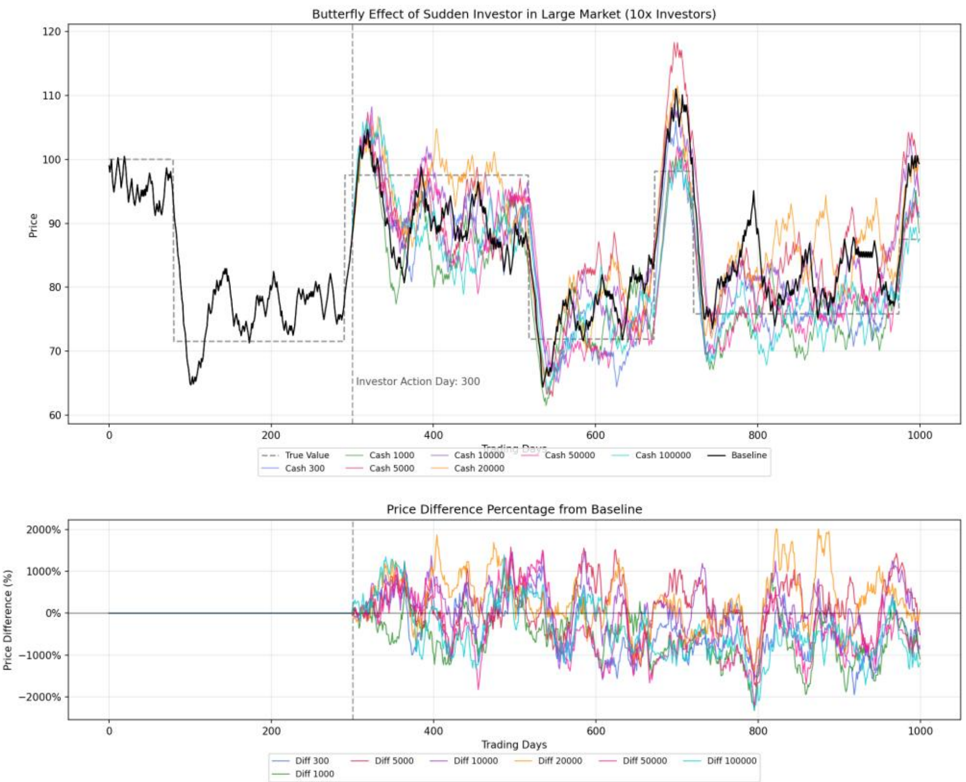


Figure 15

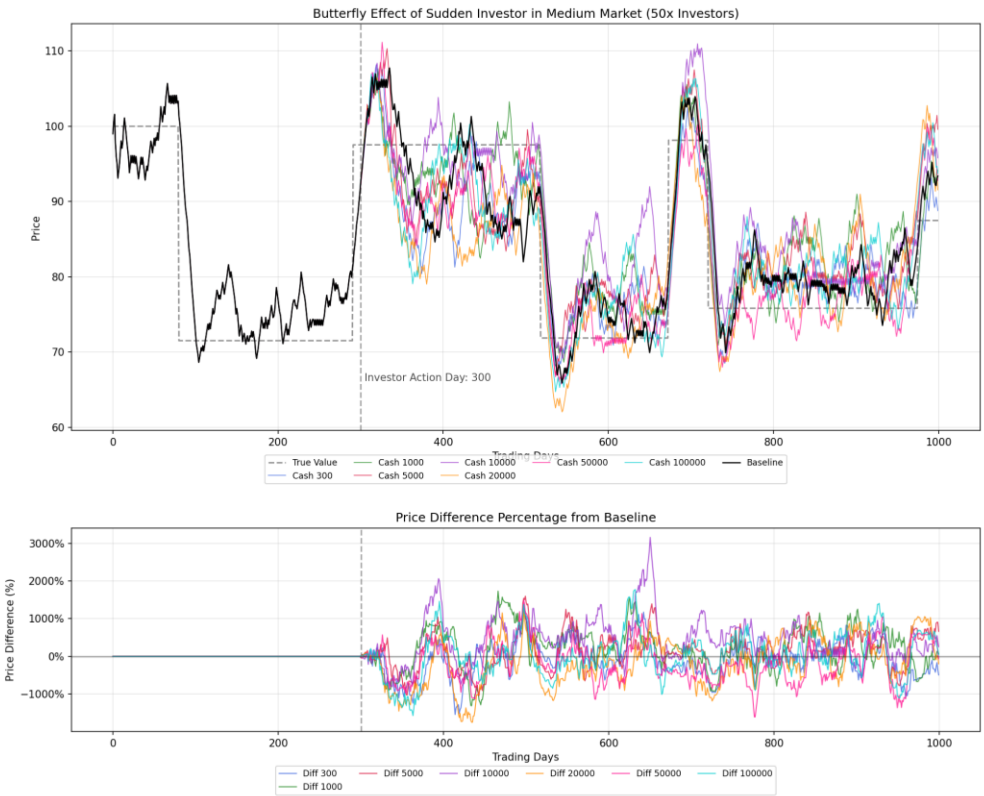


Figure 16

Compared with the small-scale market, the order transaction situation in the large-scale market has changed significantly - the transaction rate has increased, indicating that the liquidity of the large-scale market has increased significantly. The market can find some new rules: ① In the large-scale market, the maximum price deviation that investors can suddenly produce is generally smaller than that in the small-scale market, and the intensity of the butterfly effect is generally weakened, indicating that the market size is negatively correlated with the intensity of the butterfly effect. ② The impact ratio of the amount of funds (maximum price difference / 10,000 yuan of funds) has decreased in the large-scale market, indicating that the influence of unit funds has weakened after the market scale has expanded. ③ Small funds can still have an impact in the large-scale market and have a relatively higher impact ratio. ④ As the market size increases, the relative impact intensity of the butterfly effect generally shows a downward trend, but the rate of decline is not linear.

3. The influence of individual behavior - the second case

This is an unexpected discovery, but it is very necessary to list it separately. We set the buy premium parameter (price_premium) of butterfly_effect_simulation_1.2.py to 0. After running, all investor orders were not executed, but the result of the operation was: the market price was still affected, showing the butterfly effect.

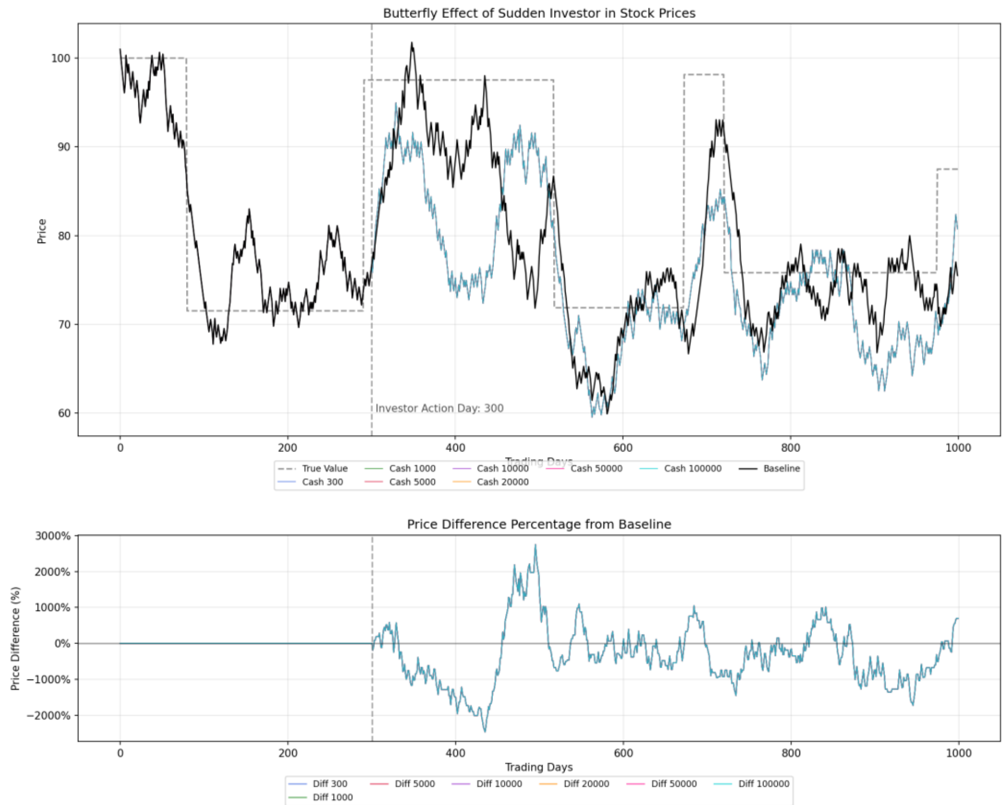


Figure 17

This simulation illustrates the complexity of the price formation mechanism in market microstructure and the potential impact of investor actions on the market even if these actions do not directly lead to the execution of trades: market prices are affected not only by actual trades but also by potential willingness to trade .

Possible reasons why unfilled orders affect the market include:

A. Order book impact: The existence of a buy order changes the supply and demand balance in the market and affects the decisions of other investors. In the bidding mechanism, even if an order fails to be executed, it participates in the price discovery process.

B. Changes in trading behavior: From the changes in trading volume, it can be seen that the participation of a single investor changes the trading behavior of other investors, even if the investor's own orders are not executed on that day.

In the real market, there are two other factors that may affect the market due to unfilled orders:

A. Information transmission: Orders convey information about investment intentions and influence other investors' expectations of the market. In particular, large orders may be regarded as market signals by other investors.
B. Market sentiment transmission: The behavior of a single investor may affect a small number of investors, which in turn affects more investors, forming a chain reaction. This may be another core mechanism of the butterfly effect.

The implication of this result for real markets is that even unfulfilled orders may indirectly affect market prices by influencing the behavior of other market participants. This " existential influence " is particularly important in modern markets dominated by high-frequency trading and algorithmic trading.

In summary, we have used simulation experiments to confirm the existence of the " butterfly effect " phenomenon in the stock market: the sudden participation of an investor, even if the amount of funds is small and even if there is no transaction, may have a long-term and significant impact on market prices. This impact is transmitted and amplified through direct price discovery mechanisms and indirect investor behavior change mechanisms, causing market prices to deviate from the trajectory without intervention for a long time. As mentioned before: a butterfly flapping its wings may cause a typhoon in the Pacific. People often say: "No snowflake is innocent in an avalanche." The same is true in the stock market.

V. Monte Carlo Method

Since stock prices are random sequences, we can use the same methods to process and analyze random sequences to process them. The Monte Carlo method is one of them. The Monte Carlo method is a numerical computing technique based on random sampling. It is widely used to simulate and analyze random sequences (such as financial time series, physical processes, engineering systems, etc.). Its core idea is to approximate the real distribution or calculate complex mathematical problems through a large number of random experiments:

1. Core steps
   a) Define the random process: clarify the random sequence model to be simulated.
   b) Generate random samples: Generate random pathsthrough a pseudo-random number generator (PRNG) or a quasi-Monte Carlo method (such as the Sobol sequence).

c) Calculate statistics: perform statistical analysis on the simulation results (such as mean, variance, quantile, etc.).

d) Convergence test: Increase the number of simulations to improve accuracy (the law of large numbers ensures convergence).

2. Mathematical foundation

a) Law of large numbers: When the number of simulations $N \to \infty$, the sample mean approaches the expected value:

$$\frac{1}{N}\sum_{i=1}^{N} f(X_i) \to \mathbb{E}[f(X)]$$

b) Central Limit Theorem: The estimated error follows a normal distribution and the confidence interval can be calculated.

So far, we have actually completed the first step of the core steps, defining the stochastic process using simplified assumptions about the behavior of market participants and market rules. Now we will implement steps 2-3 .

The following two figures are generated by the program MC_simulation_1.0.py (using main_OHLC_2.0.5.1.py as a module). They use the Monte Carlo method to simulate the closing price mean sequence obtained by generating 20 and 100 800 - day closing price curves respectively by changing the market random number seed while keeping other parameters unchanged. We can observe that the mean curve converges more with the increase in the number of simulations. We can also observe that many closing price curves simulated randomly have large fluctuations. In this case, the sample mean curve and the stock value curve show a strong correlation. Of course, we can calculate the expected value and perform various statistical analyses later, but this is not the focus of this chapter.

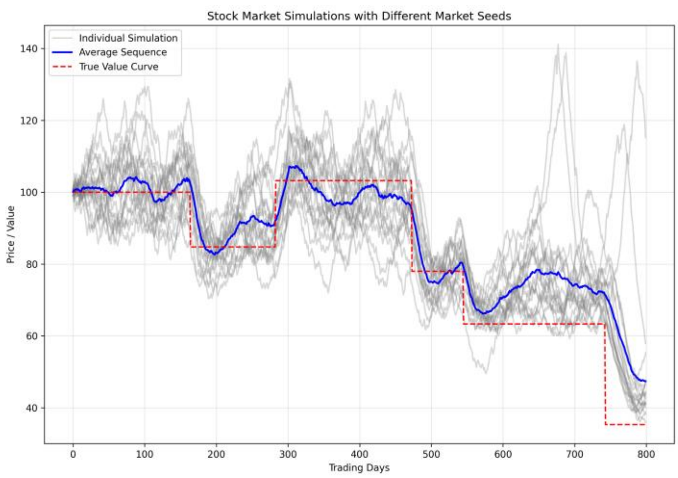


Figure 18

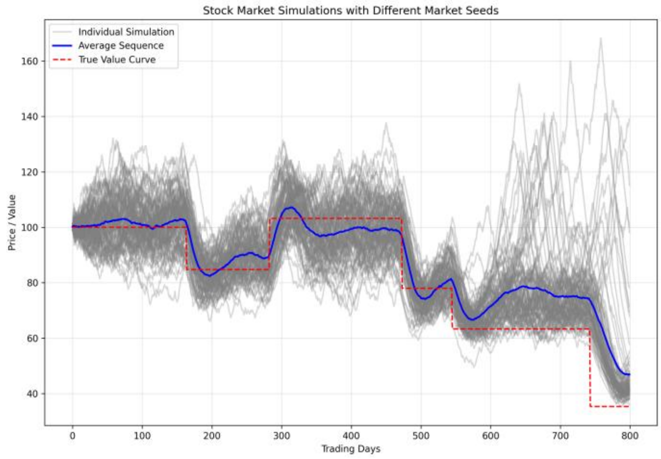


Figure 19

The following figure is generated by the program MC_simulation_1.1.py , which simulates the converged closing price mean sequence obtained by generating 100 800-day closing price curves with only the value curve unchanged and other random number seeds randomly changed . We can observe that this curve has slight changes compared with the curve generated by only changing the market random number above, but the overall difference is not big.

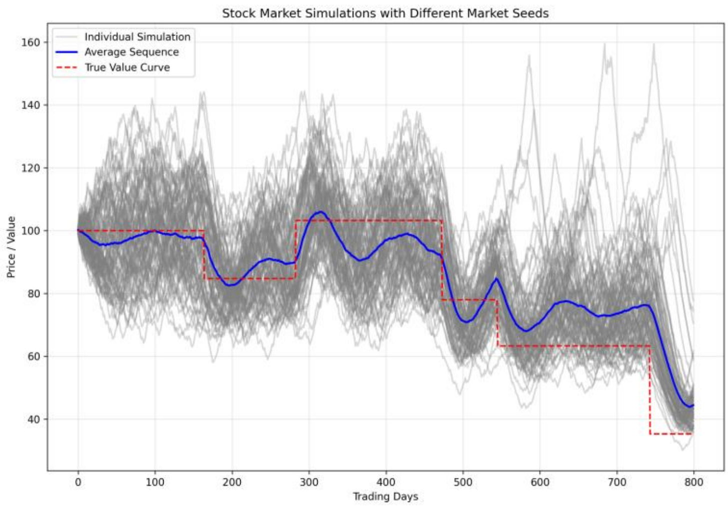


Figure 20

VI. Re-examination - the impact of capital

1. Capital injection and withdrawal

In MC_simulation_1.2.py , we added the function of injecting or withdrawing funds from the market, and implemented Monte Carlo simulation to analyze the impact of funds on the stock price average. The program compares the impact of different fund change strategies, supports parallel simulation of multiple fund change strategies, and returns the average closing price series and true value curve of each strategy. In the program, we define multiple fund change strategies, including:

- Baseline case (no funding changes)
- Single capital injection (10%)
- Single fund withdrawal (10%)
- Massive capital injection (50%)
- Massive capital withdrawal (50%)
- Fund injection in batches (4 times, 5% each time)
- Fund withdrawal in batches (4 times, 5% each time)
- Inject first and then withdraw (inject 20% first and then withdraw 20%)

This modified procedure can help analyze the impact of different fund flow scenarios on stock market prices, especially:

- Whether the capital injection will lead to a rise in the share price
- Whether the withdrawal of funds will cause the stock price to fall
- The impact of capital changes of different sizes and timing on the market varies
- Short-term and long-term impact of funding changes on market prices

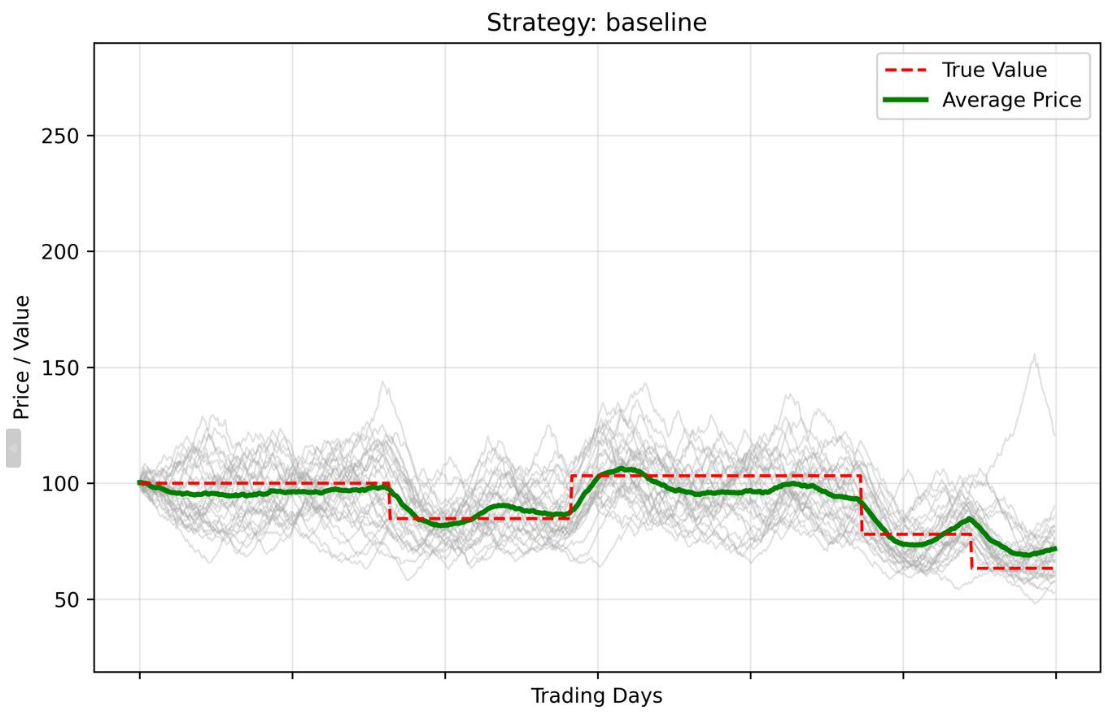


Figure 21

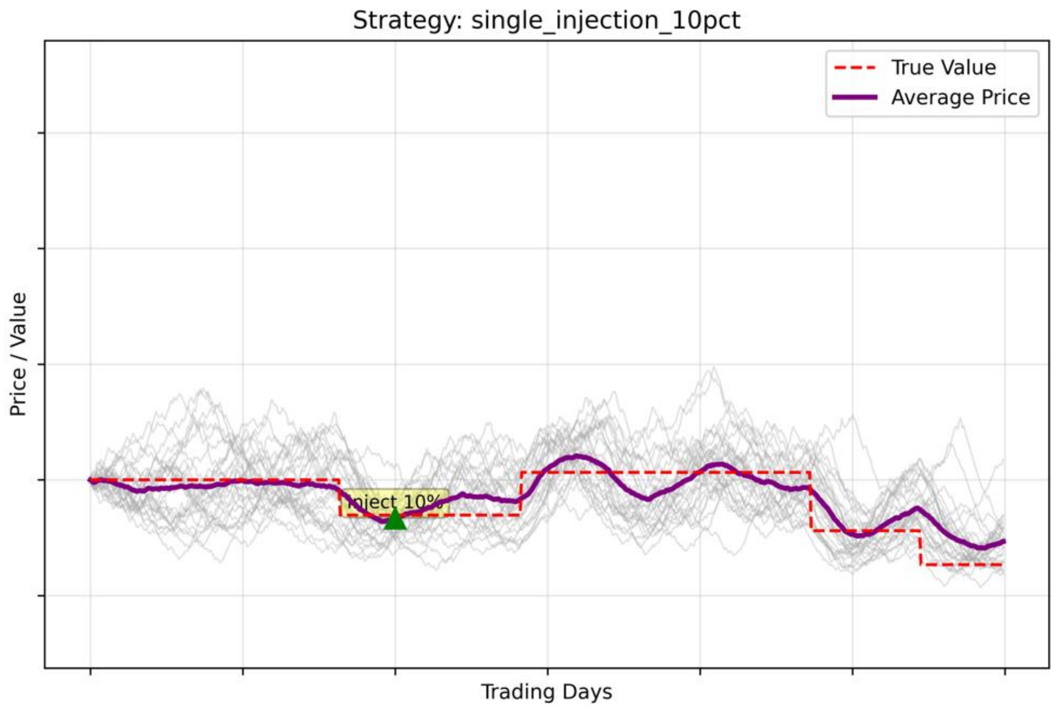


Figure 22

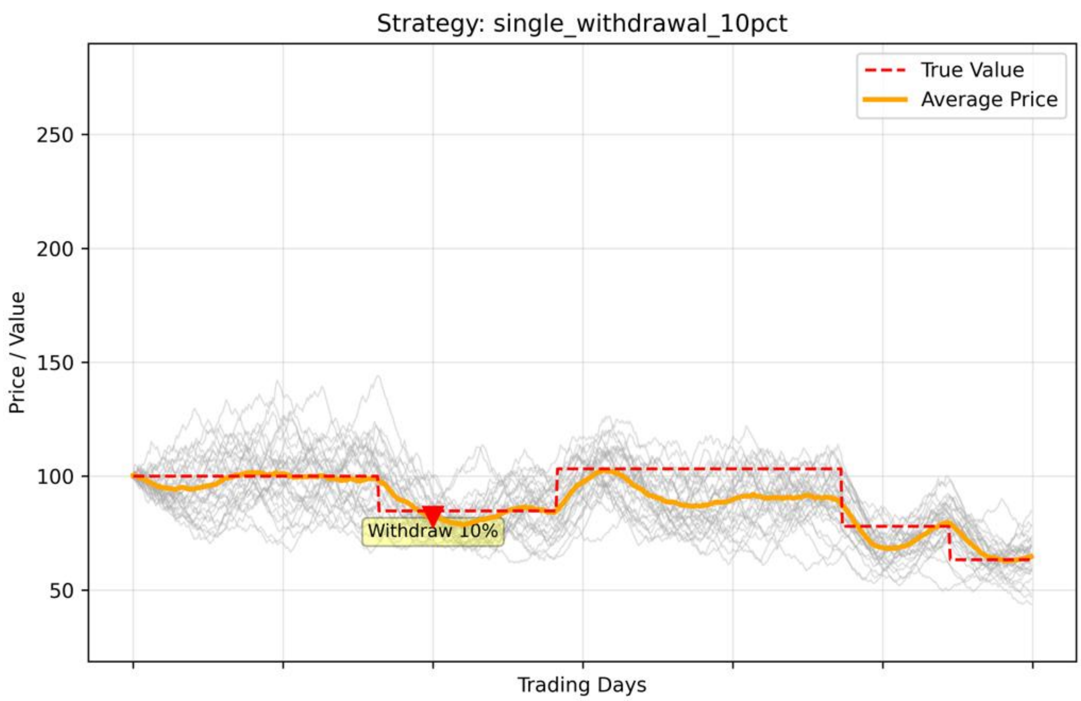


Figure 23

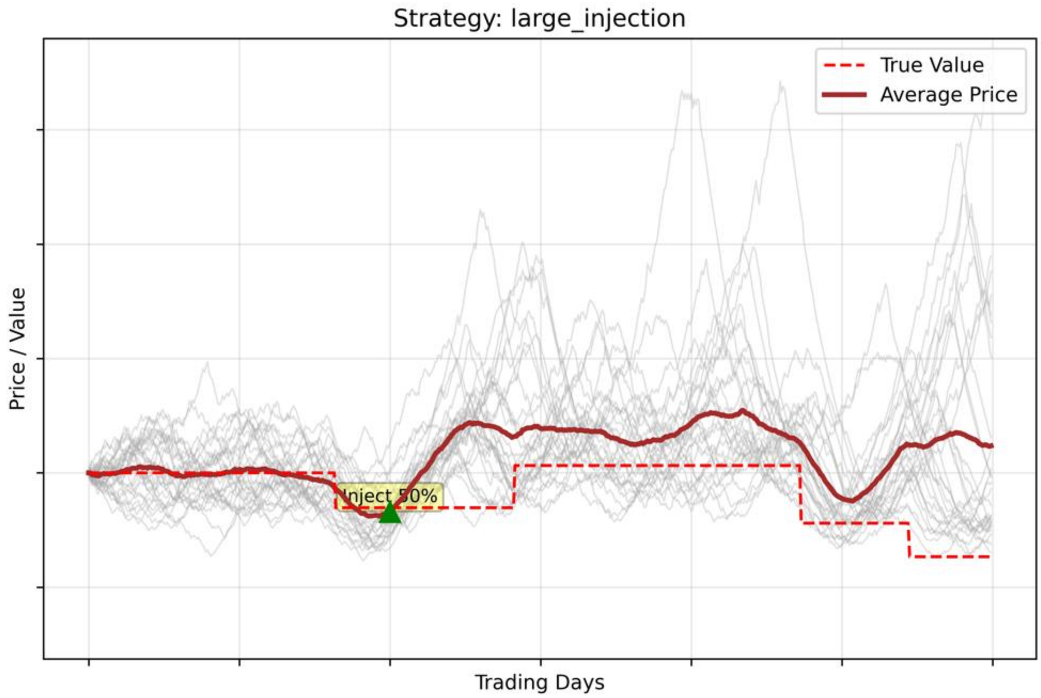


Figure 24

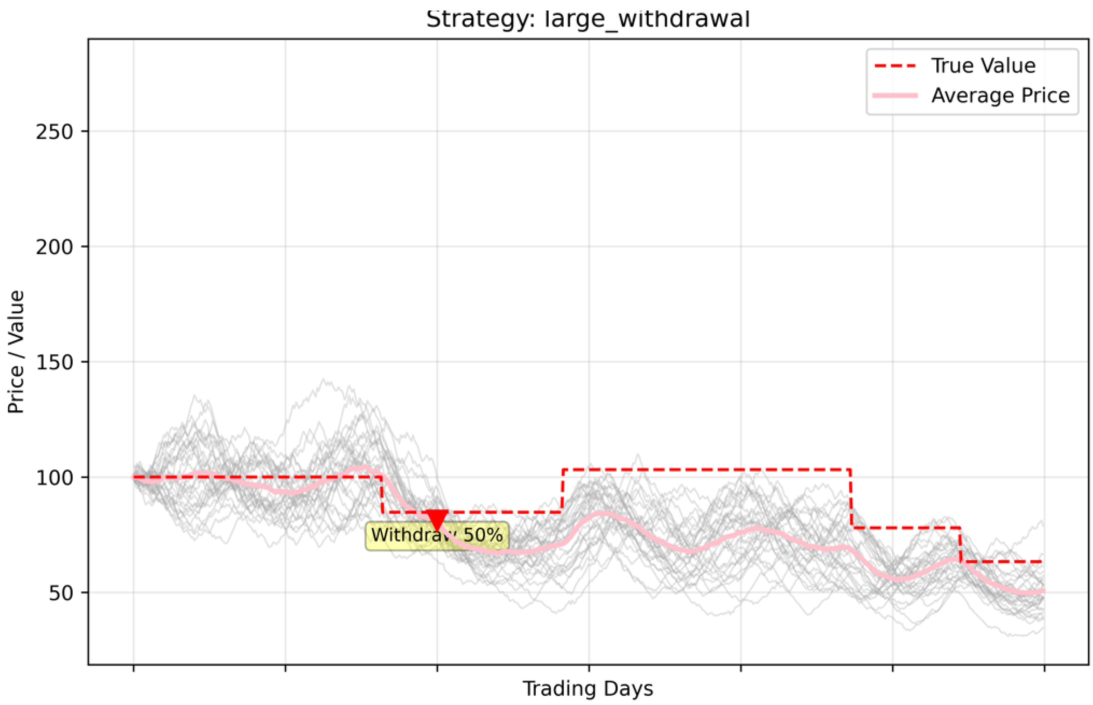


Figure 25

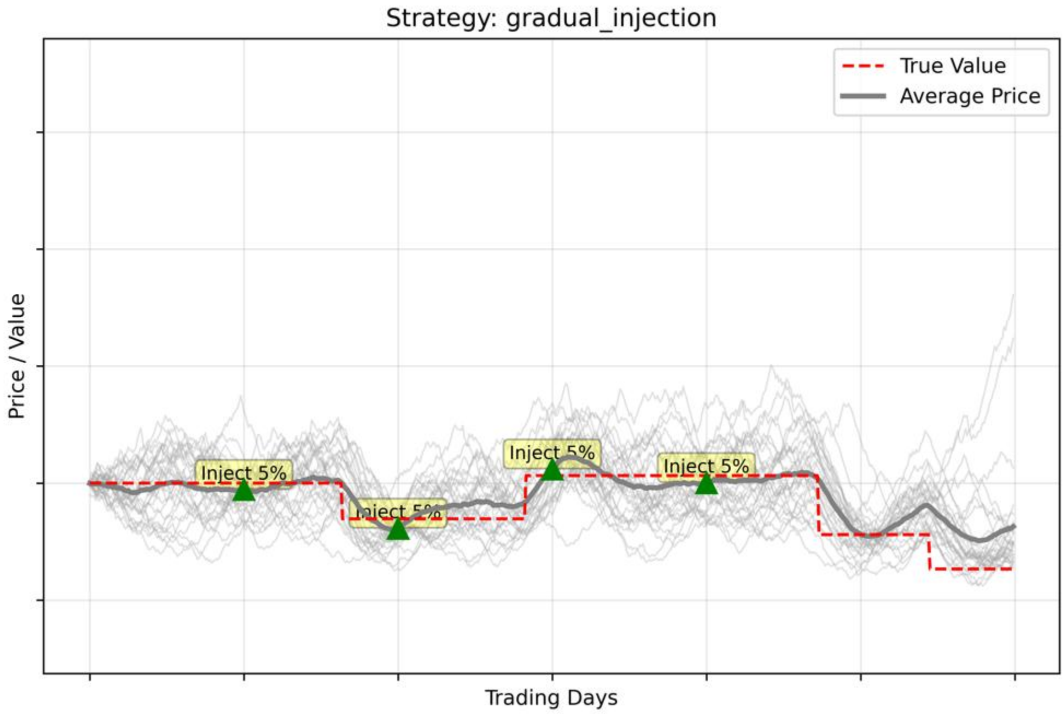


Figure 26

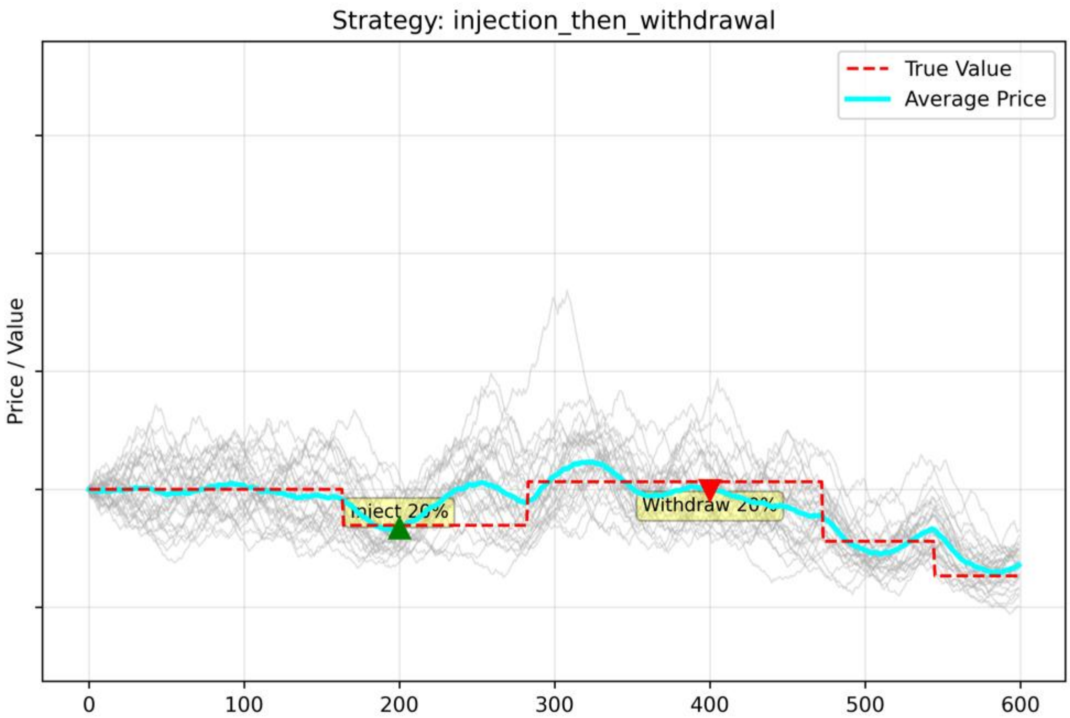


Figure 26

Through the above simulation results (30 simulations per round), we can observe that the injection and withdrawal of funds will indeed have a significant impact on the average market price, and the impact is clearly correlated with the amount of funds injected or withdrawn. The impact cycle is not limited to the short term, but will also have a long-term impact on the market. From the perspective of a single simulation event, due to the existence of the butterfly effect, it is even possible to set off a storm in the market after the injection of funds.

The following is a comparison of the difference between increasing funds gradually and suddenly. The same 50% increase in funds is done in one injection and in five injections (see MC_simulation_1.3.py for the code). From the results, both the one-time injection and the batch injection have a positive impact on the stock price, but the former may cause more drastic market fluctuations.

2. The impact of transaction costs on the market

The program MC_simulation_1.4.py simulates the impact of different transaction costs on the market. The following figure simulates four transaction cost situations from top to bottom:

- No transaction cost: buy_fee_rate = 0, sell_fee_rate = 0
- Low transaction costs: buy_fee_rate = 0.0003, sell_fee_rate = 0.0003 (0.03%)
- Transaction costs: buy_fee_rate = 0.001, sell_fee_rate = 0.001 (0.1%)
- High transaction costs: buy_fee_rate = 0.01, sell_fee_rate = 0.01 (1%)

From the figure, we can intuitively feel that the differences in the mean stock price curves of the four situations are very small.

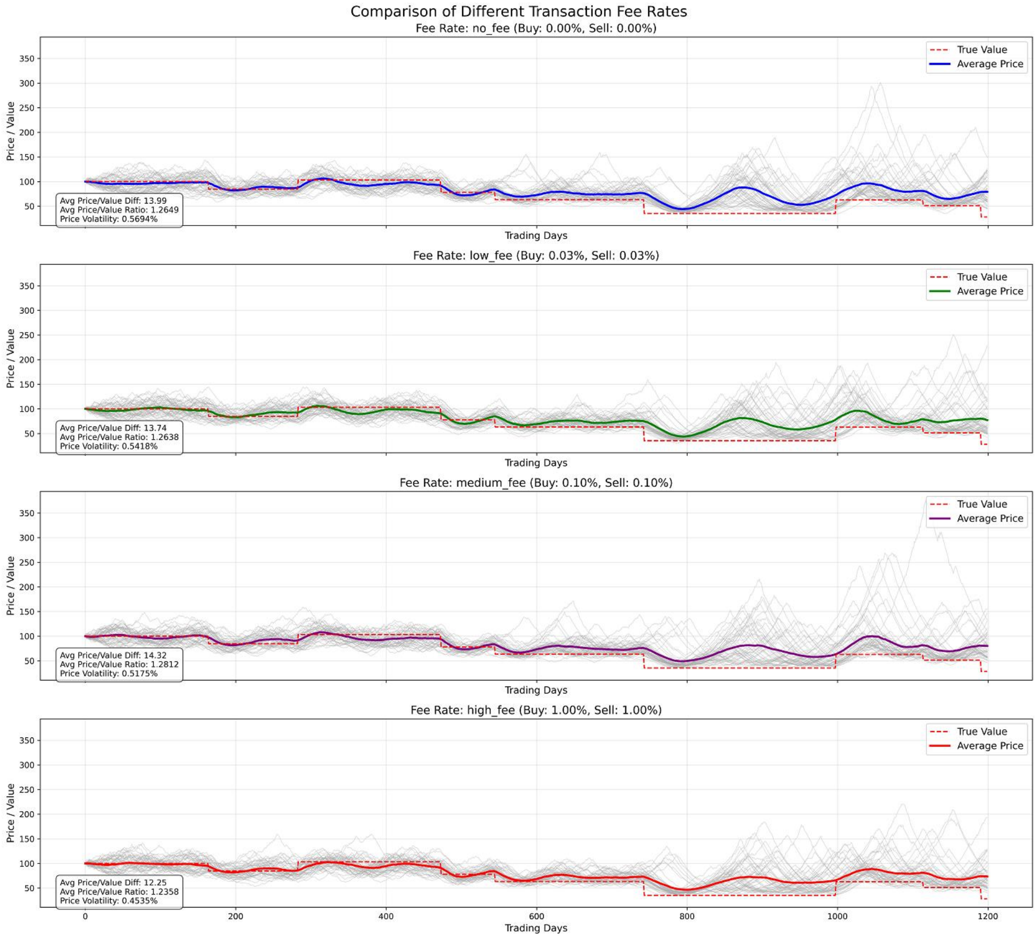


Figure 27

VII. Re-examination - the impact of investor behavior

1. Value Investors

MC_simulation_bias_std.py attempts to study the impact of the bias_percent_std parameter of value investors on the market. By running 20 Monte Carlo simulations, we compare three different bias_percent_std settings: 0.15 (low), 0.30 (medium), and 0.50 (high).

A. Overall volatility index

index	Low standard deviation (0.15)	Standard deviation of mean deviation (0.30)	High deviation standard deviation (0.50)
Average daily volatility (%)	1.3729	1.4467	1.5289
Volatility standard deviation (%)	0.0409	0.0263	0.0362
Upward volatility (%)	0.7386	0.7831	0.8215
Downside volatility (%)	0.7595	0.7914	0.8433

B. Maximum drawdown analysis

index	Low standard deviation (0.15)	Standard deviation of mean deviation (0.30)	High deviation standard deviation (0.50)
Average maximum drawdown (%)	64.9730	65.7613	66.2239
Maximum drawdown standard deviation (%)	5.5588	4.0447	4.5874

C. Analysis of the relationship between price and value

index	**Low standard deviation (0.15)**	**Standard deviation of mean deviation (0.30)**	**High deviation standard deviation (0.50)**
The correlation between price and value	0.9528	0.9323	0.8822
Average deviation between price and value (%)	10.8261	12.8510	15.4079

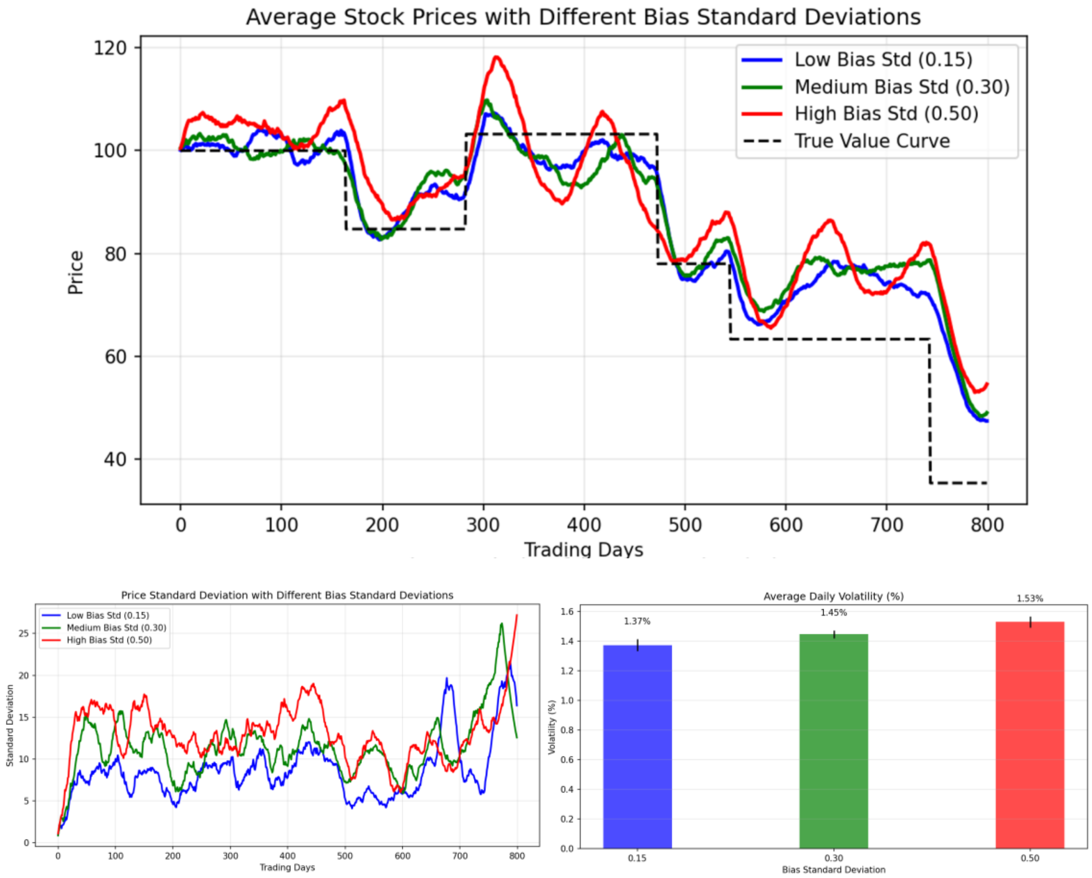


Figure 28

From the above running results we can see:

D. Volatility increases with the standard deviation of deviation: Data shows that as the standard deviation of value investors' deviation increases, the market's daily volatility increases significantly.

E. The market is more volatile when prices are falling than when prices are rising.

F. Maximum drawdown increases with the standard deviation of deviation: Data shows that as the standard deviation of value investors' deviation increases, the maximum drawdown of the market also increases.

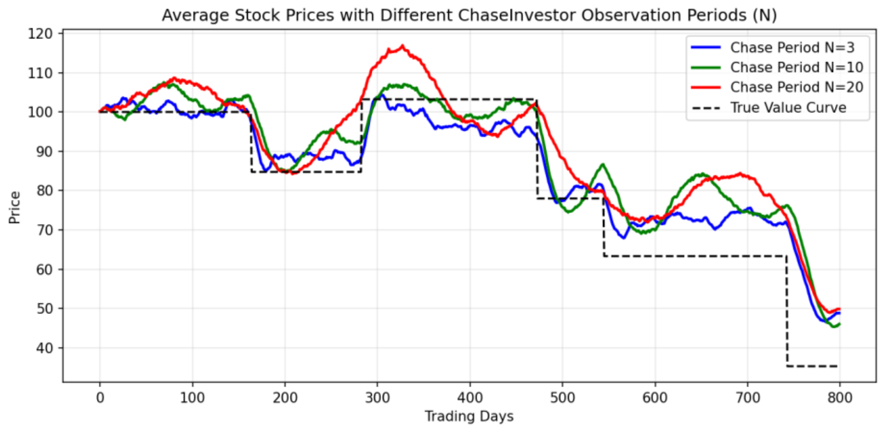
G. Price and value are positively correlated in all settings,

H. The average deviation between price and value is positively correlated with the standard deviation of the deviation, indicating that the larger the distribution of value investors' respective valuations, the greater the price volatility.

The above shows that the standard deviation parameter of value investors has a significant impact on market volatility. With the increase of bias_percent_std , market volatility, maximum drawdown, and the deviation between price and value have all changed significantly. Of course, the above volatility data is the volatility at the statistical level after 20 tests. For a single test, due to its random walk characteristics, its volatility may be more intense.

2. Investors who chase ups and downs

In our hypothesis, there is a parameter for investors who chase ups and downs , which is: the observation period N days, which represents the number of days of historical price data that this type of investor considers when calculating the speed of price changes. In this section, we will compare the different impacts of investors who chase ups and downs with different observation periods on the market. We set up three different observation periods: short-term (N=3) , medium-term (N=10) and long-term (N=20) , and run 20 simulations for each setting through the Monte Carlo simulation method to ensure the statistical reliability of the results.
(For detailed code, see MC_simulation_chase_period.py)



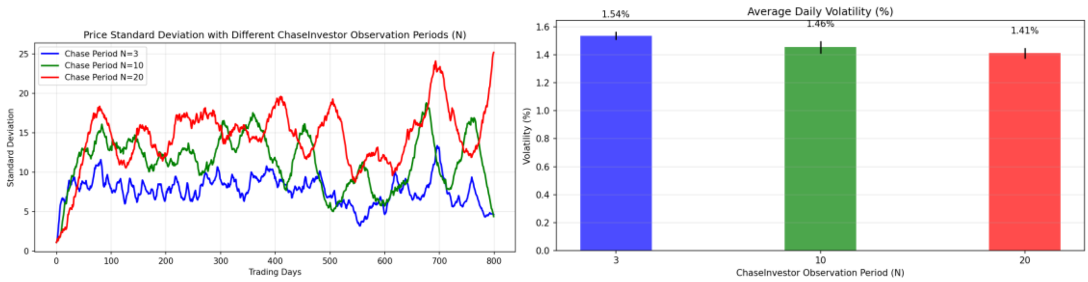


Figure 29

After running, the following phenomena can be found:

A. The relationship between market volatility and observation period:
As ChaseInvestor's observation period increases, the overall market volatility shows a downward trend.
- Short-term observation period (N=3) : average daily volatility is 1.5374%
- Medium-term observation period (N=10) : average daily volatility is 1.4555%
- Long-term observation period (N=20) : average daily volatility is 1.4121%

This suggests that when investors use a longer observation period to evaluate price trends, market price fluctuations become more stable. This may be because the long observation period makes investors less sensitive to short-term price fluctuations, thereby reducing overreaction and frequent trading.

B. Upward and downward volatility analysis: Under all three observation period settings, the downward volatility is slightly higher than the upward volatility, and this difference increases with the increase of the observation period:
- When N=3 , the upside / downside volatility ratio is 0.9993
- When N=10 , the upside / downside volatility ratio is 0.9667
- When N=20 , the upside / downside volatility ratio is 0.9592

This finding shows that regardless of the observation period, the market volatility is greater when prices fall than when they rise, which is consistent with the " panic selling " phenomenon commonly seen in real markets. This asymmetry becomes more obvious as the observation period increases.

C. Relationship between price and value: Under all observation period settings, there is a strong positive correlation between market price and underlying value, but this correlation weakens as the observation period increases.
- When N=3 , the correlation is 0.9670
- When N=10 , the correlation is 0.9358
- When N=20 , the correlation is 0.9261

At the same time, the average deviation between price and value increases as the observation period increases:

- When N=3 , the average deviation is 10.1180%
- When N=10 , the average deviation is 12.7666%
- When N=20 , the average deviation is 14.7752%

This suggests that when investors who chase gains and losses use a longer observation period, market prices are more likely to deviate from underlying values and market efficiency may decrease.

D. Maximum Drawdown Analysis: Maximum drawdown is an important indicator for measuring investment risk. Studies have found that as the observation period increases, the average maximum drawdown of the market increases significantly.
    - When N=3 , the average maximum drawdown is 63.0137%
    - When N=10 , the average maximum drawdown is 65.9761%
    - When N=20 , the average maximum drawdown is 67.8714%

    At the same time, the standard deviation of the maximum drawdown also increases with the increase of the observation period (from 2.6433% to 5.9085%), indicating that the long-term observation period not only increases the drawdown amplitude, but also increases the uncertainty of the drawdown.

Through the above phenomena, we can roughly summarize the following conclusions from a statistical sense:

A. Shorter observation periods lead to higher market volatility: When investors who chase ups and downs are more sensitive to short-term price changes, overall market volatility increases. This may be because they trade more frequently, amplifying price fluctuations.
B. Longer observation periods lead to larger maximum drawdowns: Although long observation periods reduce daily volatility, they increase the risk of extreme declines. This may be because long observation periods make investors react more slowly to market turns, causing downtrends to last longer and market reversals to be slower. Short observation periods may cause the market to recover from declines faster and trend reversals to be more frequent.
C. Longer observation periods reduce market efficiency: As the observation period increases, the deviation between price and underlying value increases, indicating that the ability of market prices to reflect underlying value decreases.
D. Under all observation period settings, the volatility is greater when the market is

falling than when it is rising: This asymmetry becomes more obvious as the observation period increases, reflecting the behavioral characteristics of investors who are more sensitive when facing losses than when facing gains.

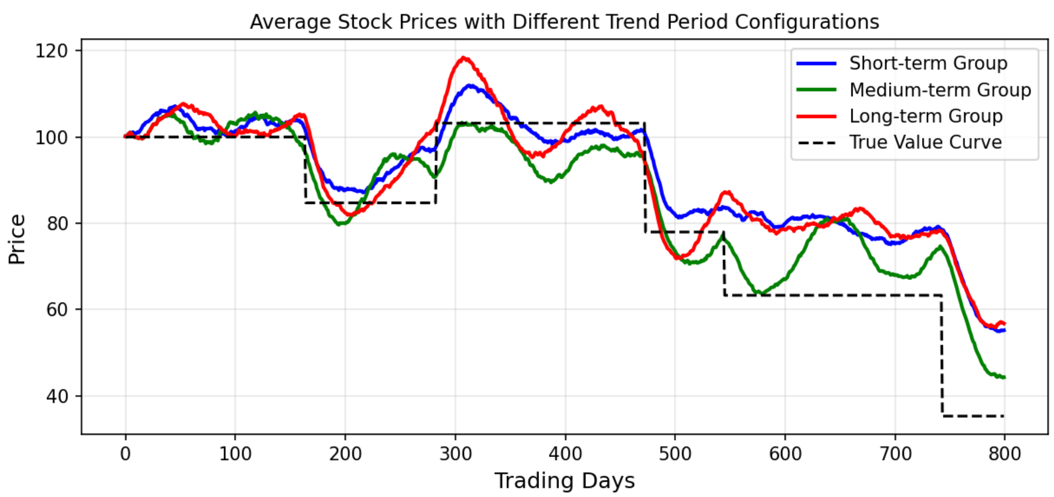
E. Short-term observation periods enable market prices to better follow changes in underlying values and form trends that are more consistent with underlying values. As the observation period increases, the correlation between price and value decreases and the deviation increases, indicating that long-term observation periods may cause market prices to form trends that are inconsistent with underlying values.

3. Trend Investors

In this section, we analyze the impact of the trend period configuration of TrendInvestor on the stock market simulation. By running 20 Monte Carlo simulations (MC_simulation_trend_period.py), we compared three different trend period group configurations:

- Short-term Group : Trend investors using 5-day, 7-day and 10-day moving averages
- Medium-term Group : Trend investors using 30 -day, 45- day and 60 -day moving averages
- Long-term Group : Trend investors using 120 -day, 160- day and 200- day moving averages

The observation period of ChaseInvestor is fixed to 10 in all simulations .



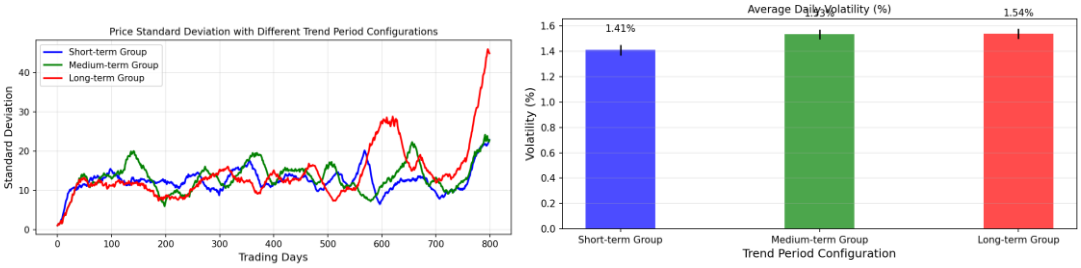


Figure 30

According to the operation result data, we can roughly analyze the following conclusions:

i. Volatility analysis: The market volatility generated by short-term trend investors is significantly lower than that of medium-term and long-term trend investors. There is a certain relationship between volatility and trend cycle, although it is not necessarily a simple linear relationship, but in general, short-term trend investors can generate lower market volatility.

ii. Drawdown analysis: The maximum drawdown generated by short-term trend investors is significantly smaller than that of medium-term and long-term trend investors; the maximum drawdown standard deviation generated by long-term trend investors is the smallest, indicating that their drawdown pattern is more stable and predictable . Medium-term trend investors tend to generate the largest drawdown and the highest drawdown standard deviation.

iii. Analysis of the relationship between price and value: In the market where only short-term trend investors participate, the correlation between price and true value is the highest, indicating that short-term trend tracking may more effectively reflect fundamental value; the average deviation between price and value generated by medium-term trend investors is the smallest, indicating that medium-term trends may be more efficient in price discovery; under long-term trend investors, the correlation between price and value is the lowest and the deviation is higher, indicating that long-term trend tracking may lead to a certain degree of disconnection between price and fundamental value.

iv. Market stability: Simulations with only short-term trend investors produced lower market volatility and maximum drawdowns, suggesting that short-term trend following may contribute to market stability. This finding is contrary to the conventional wisdom that short-term trading increases volatility and warrants further study. One possible explanation is that short-term trend investors are able to react more quickly to price deviations, thus reducing the likelihood of large fluctuations.

v. Market asymmetry: Under different simulation parameter settings, the market may show different volatility asymmetry. In some cases, the downward volatility may be greater than the upward volatility, while in other cases, the upward volatility may be greater than the downward volatility. This change in asymmetry indicates that the market volatility characteristics are sensitive to parameter settings and need to be further studied in different market environments.

vi. Investment strategy implications: Combining short-term and medium-term trend signals may be the optimal investment strategy. Short-term signals provide higher value relevance and lower volatility, while medium-term signals provide lower price deviation. In terms of risk management, strategies should be adjusted according to the dominant trend investors in the market, especially in markets dominated by medium-term trend investors, and it is necessary to be prepared to deal with higher volatility and greater drawdown risks.

These conclusions show that the moving average period used by trend investors has a significant impact on market behavior, and trend investors with different periods have their own advantages and disadvantages in terms of market stability, price discovery and risk characteristics.

VIII. Trader's Profit Expectation

In this section, we will observe the performance of various investments of market traders in the model. MC_simulation_asset_return_analysis_1.2.py This test conducted 400 Monte Carlo simulations for a period of 1200 days, and the transaction fee rate was set to 0.1% for both buying and selling . Each simulation used a different random seed to ensure the comprehensiveness and representativeness of the test. The investor configuration is shown in the following table:

Investor Type	quantity	Features
ValueInvestor	50	Trading based on value deviation, with a standard deviation of 0.30
ChaseInvestor	50	Buy high and sell low, observation period is random (5-20 days)
TrendInvestor	50	Based on moving average crossover signals, the period is distributed between 5-200 days

Investor Type	quantity	Features
RandomInvestor	50	Random trading decisions
NeverStopLossInvestor	10	Do not set a stop loss and continue to hold until the profit target is reached
BottomFishingInvestor	10	Bottom-picking strategy, buy after a continuous decline
InsiderInvestor	5	Insider traders can predict changes in value
MessageInvestor	5	News investors, delayed in learning about value changes

The upper graph below shows the average asset appreciation percentage change of various investors during the simulation period, with the horizontal axis being trading days and the vertical axis being asset appreciation percentage. The lower graph shows the total return and annualized return comparison of various investors, with the blue column being the total return (%) and the red column being the annualized return (%) [Note: the annualized return is calculated based on the assumption of 250 trading days / year].

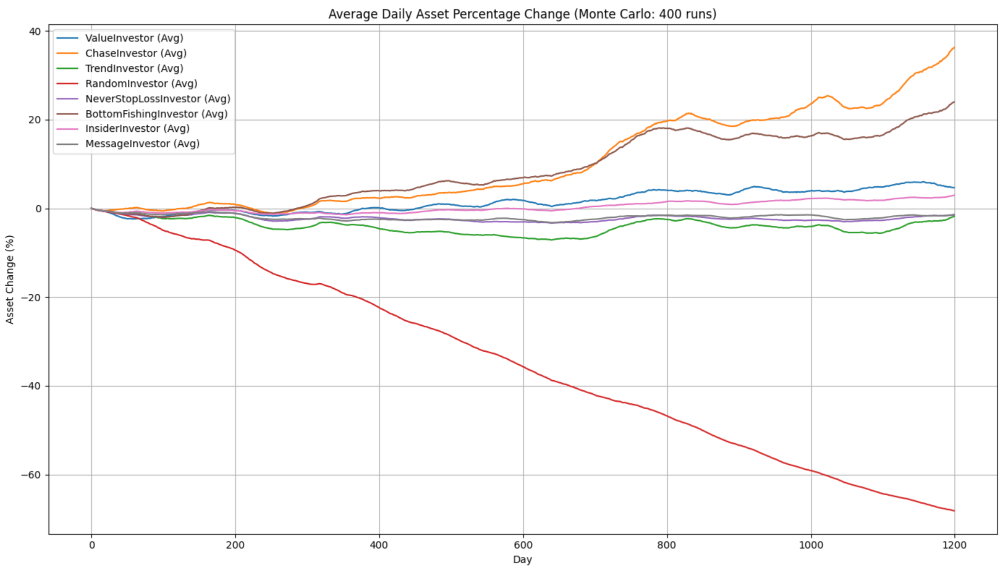


Figure 30

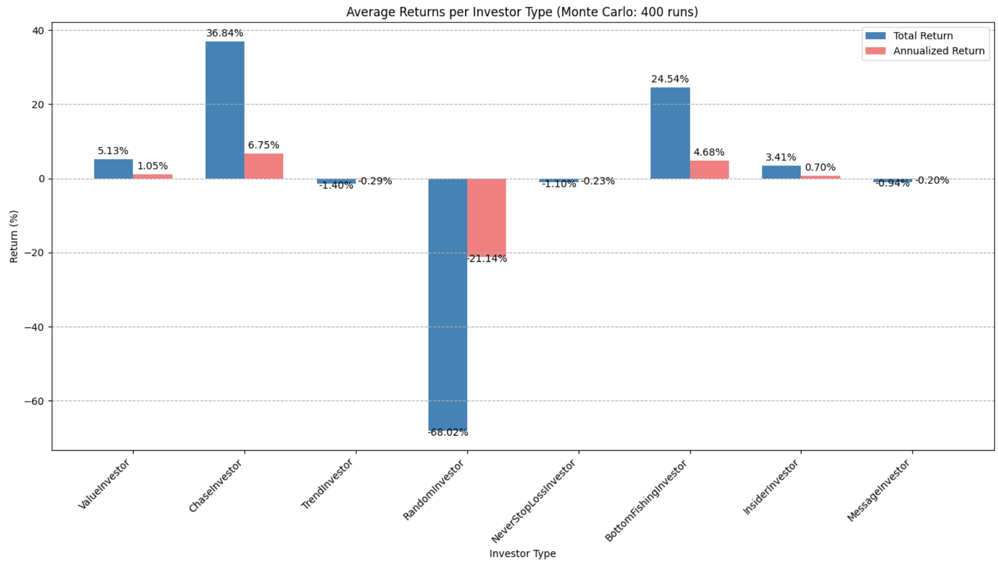


Figure 30

We rank the performance of the investors assumed in this model based on the size of their returns:

1. ChaseInvestor
2. Bottom Fishing Investor
3. Value Investor
4. InsiderInvestor
5. MessageInvestor
6. NeverStopLossInvestor
7. TrendInvestor
8. RandomInvestor follows market sentiment

This result is quite different from what we intuitively imagine or think, especially those who chase ups and downs are far ahead. This result is only the test performance of our model, which is not equivalent to the actual market situation. There are the following differences between the model and the actual market:

1. The model only simulates a limited number of representative investor types, and there may be countless types of investors in the actual market;
2. The number of investors in the model is small, and the proportion is arbitrarily set by us in the absence of data, and is not the same as the actual market.

Therefore, when we have more actual market data, we may be able to obtain test data that is closer to the actual market. The following two figures show the impact of transaction fees on market profitability. When we increase the buy and sell fees to 1% , although the impact on the average market volatility is not significant as shown above, the return rate for various market traders is greatly reduced, which is consistent with our intuitive feeling.

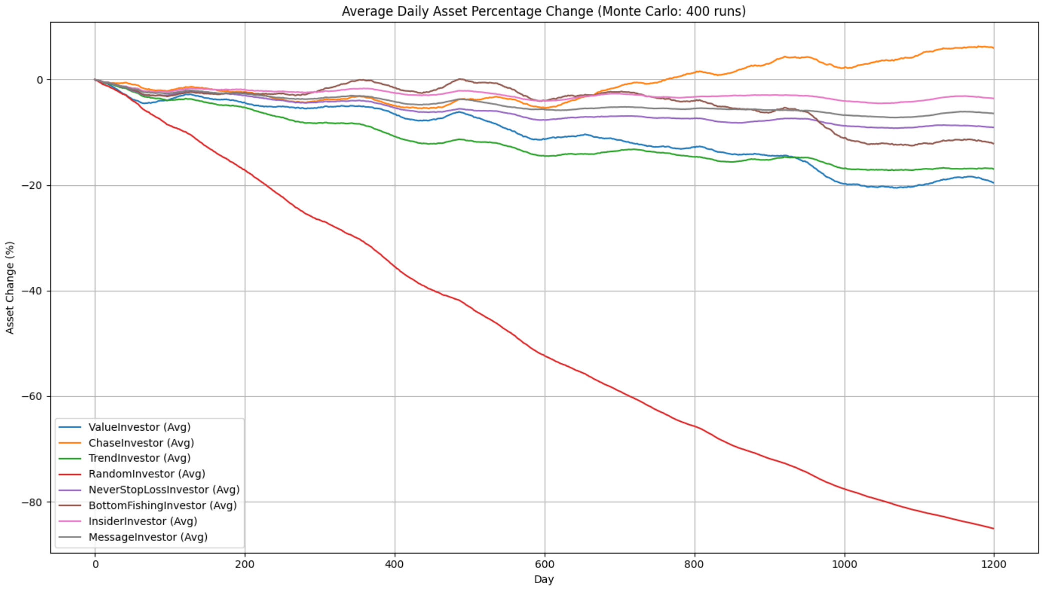


Figure 31

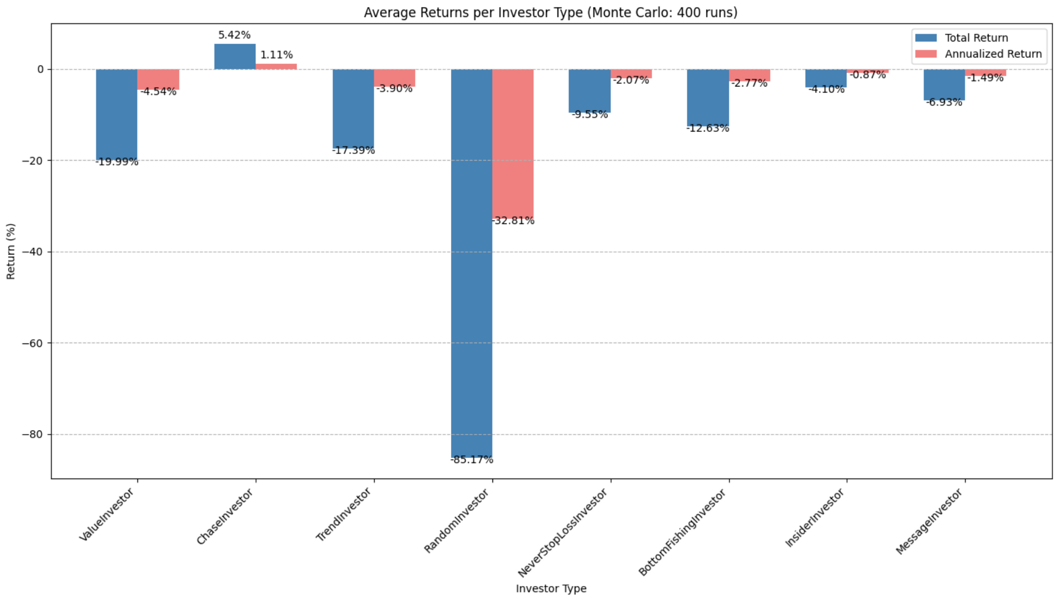


Figure 32

MC_simulation_asset_return_analysis_1.3.py is modified from MC_simulation_asset_return_analysis_1.2.py . The Monte Carlo method test method remains unchanged, all trader settings and parameters remain unchanged, and the transaction operation remains unchanged, but we only focus on the average asset curve, total return and annualized rate of return of investors with different cycle trends .

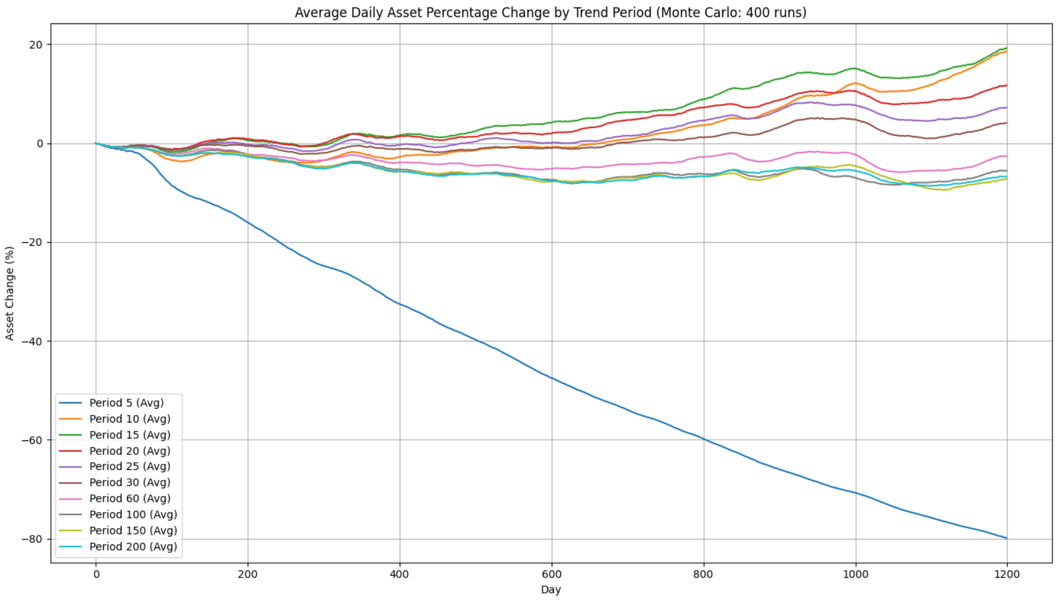


Figure 33

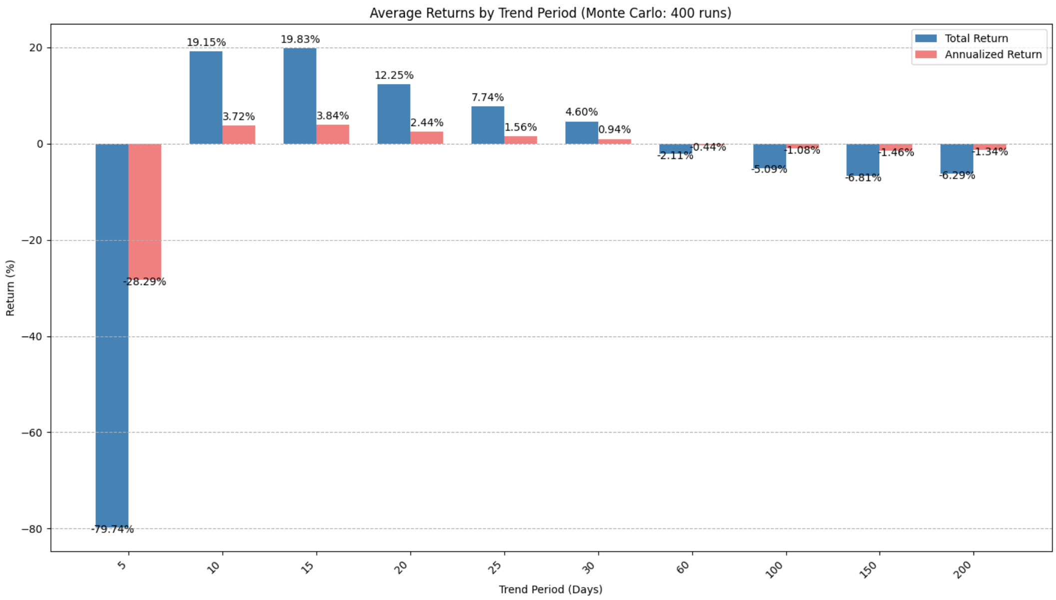


Figure 34

IX. Conclusion

When we observe the trend of individual stocks, due to the randomness of the participants' behavior and the various events and information that occur randomly and affect the valuation, individual stocks show the characteristics of random walks. The individual stock trend sequence we observe is just a random event (in the sense of probability theory), one of thousands of possibilities. Because we cannot go back to the past and do it again, we cannot travel through parallel universes to observe. In this world, we can only see a random sequence composed of various coincidences, which belongs to a sample in the infinite sample space.

Through behavioral-based models and analysis methods, we can discover the truth of the market to the greatest extent, because we can use probability theory and statistical tools to summarize and discover the essence of the problem. We do not need to pursue the ability to predict market trends, because we cannot do it, but we can discover statistical regularity and effective and lasting profit models. Many quantitative investors (including me in the past) fall into this misunderstanding, hoping to derive a profitable method from historical data, but often through a lot of calculations, what they get may only be a survivor bias based on a random event, lacking broad adaptability. We are fortunate to have found this lucky person who dodged countless bullets, but who can predict whether the next bullet will end everything.

Let's go back to the model in this article and review previous work:

1. We simulated a stock market price series based on the behavior of market participants, and this price series conforms to the characteristics of random walk. In this step, we put forward the most important point of this article: the various random behaviors of stock market participants are the main reason for the randomness of stock price trends, rather than being driven solely by unpredictable economic data, political events and other information as stated in the efficient market hypothesis and random walk theory.
2. In this model, we verified the existence of the butterfly effect. We also simulated the butterfly effect caused by changes in closing prices, participation in transactions, etc. In a series of simulations, we obtained some interesting findings, such as: " Even a small amount of capital access can cause the future trend of the stock market " , and the most interesting one is: " Regardless of whether the transaction is completed or not, as long as you participate in the market, it will affect the future price sequence ."
3. Due to the randomness of price series, we use Monte Carlo method for analysis.
4. We explored the impact of funding on the market.
5. We explored the impact on the market when the three main types of investors

in this model (value investors, rising and falling investors, and trend investors) adopt different operating parameters.

6. We simulated the changes in the asset curves of all investors in this model and understood their returns.

In the model of this article, although all of our market participants have a certain realistic basis, they are all imaginary. Their proportion in the market, the funds they hold, and all their behaviors are set arbitrarily, so the results and findings in the simulation are only for reference and may not necessarily reflect the real market. But in today's big data, each user's fund holding data and buying and selling behavior data are stored in the database. If we get such data, we can train a neural network model, the input is market environment and information data, and the output is the user's behavior probability (the probability of trading at a certain time under certain conditions). In this way, using the model of this article, we can get as close to the truth as possible, discover the rules, find profit opportunities, or conduct market regulation. However, due to the existence of the butterfly effect, we should not expect to accurately predict future stock prices or trends, because it is impossible to do so. I feel that for quantitative investors, similar models can also be combined with big data through reinforcement learning methods to train their own profit agents and truly defeat the market.

Finally, I still want to make a statement: the above model was independently established based on my hobby of exploring the laws of market operation and my superficial understanding of economic theory. It seems to be able to reflect the laws of the market to a certain extent. Some of them fit the market phenomena, while others do not (such as the relationship between quantity and price). It seems that some laws can be summarized, but they are a bit specious. In view of my limited academic ability and limited cognition, the model is too simplified and has too many assumptions based on daily experience. Therefore, the model can only be regarded as an interesting experimental game or a teaching tool. In addition, my program development ability is also relatively limited. Many codes are generated by AI . Perhaps a flaw in a code may overturn all the conclusions. The number of running tests of this model under various conditions is not enough, and there is not enough data to summarize. Some of the conclusions involved in the article can only be called conjectures, which may not be enough to fully explain and understand the market. Therefore, I open source the various evolutionary code versions here for like-minded people to play with and improve together.

Yichong

Completed on May 13 , 2025