JOURNAL OF SOCIAL COMPUTING
ISSN 2688-5255 07/07 pp382−397
Volume 4, Number 4, December 2023
DOI: 10.23919/JSC.2023.0027

# Bitcoin Price Manipulation Regulation from a Game Perspective

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**Abstract:** Frequent price manipulation in the Bitcoin market will lead to market risk and seriously disrupt the financial order, but there is less research on its regulation. We address the Bitcoin price manipulation problem by building a regulatory game model. First, we study the price manipulation mechanism of the Bitcoin market based on behavioral finance and clarify the boundary conditions. Second, we introduce regulator constraints and establish a game model between the manipulator and the regulator. Further, through variable deconstruction, parameter verification, and simulation analysis, we explore how to achieve effective regulation of Bitcoin price manipulation. We find that the effective regulation of Bitcoin price manipulation can be achieved in three ways: (1) Adjust the penalty coefficient with a certain lower threshold so that the manipulator's expected return is negative; (2) Set the lowest possible price fluctuation standard while ensuring that it does not interfere with market-based transactions; (3) The simulation of price manipulation regulation is optimized and most efficiently controlled when the probability of investigation is dynamically adjusted by a concave function on the price fluctuation standard.

**Key words:** Bitcoin; price manipulation; game model; behavioral finance; financial regulation

## 1 Introduction

As the most popular cryptocurrency, Bitcoin has continued to expand its user scale globally since its birth, the transaction amount and frequency have continued to remain at a high level. In addition, the transaction price has kept climbing in an oscillating manner[1]. Although Bitcoin transactions have achieved decentralized and low-cost value exchange to a certain extent, more and more people are taking advantage of its high price fluctuation to wildly engage in illegal and speculative activities[2, 3], such as price manipulation, transaction fraud, cross-border money laundering, insider trading, and shadow economy[4]. Taking Bitcoin price manipulation as a typical representative, the price of Bitcoin skyrocketed 10 times (from 116 US dollars to 1150 US dollars) within two months from 3 October to 30 November, 2013, and 20 times (from 1046 US dollars triggering a price high of over 20 000 US dollars) within nine months from 27 March to 17 December, 2017. There was price manipulation behind both of the above-mentioned skyrocketing[5]. Among them, the Bitcoin price manipulator in 2013 was "Mt. Gox" (the largest trading platform at the time), who pulled up the price of Bitcoin by inflating specific accounts and assets, and conducting frequent transactions between inflated accounts. Meanwhile, the Bitcoin price manipulator in 2017 was Tether, who issued USDT, a stable currency that was not backed by sufficient US dollars, and pulled up the price of Bitcoin through the Bitfinex. Both of the two issues led to price distortions and severe speculation throughout the Bitcoin market. In the face of frequent Bitcoin price manipulation problems, it is urgent that we clarify the price manipulation mechanism of Bitcoin, establish a regulatory game model, and find rules for its effective regulation.

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Manuscript received: 2023-06-30; revised: 2023-12-13; accepted: 2023-12-17

At this stage, most of the research on the price manipulation mechanism focuses on stock trading. There is a lack of research on the price manipulation mechanism in the Bitcoin market. Stock markets are protected from traditional manipulation strategies through regulation and structuring, however, this is in stark contrast to the Bitcoin market. In the Bitcoin market, the decentralized and less regulated setup breeds unique manipulation strategies. The US Securities and Exchange Commission (SEC) has also emphasized the need for a specialized research and regulatory framework tailored to the characteristics of price manipulation mechanisms in the Bitcoin market. Specifically, Kaiser and Stöckl[6] proposed that Bitcoin as a "transfer currency" has a herd effect, which inspires us to explore the price manipulation mechanism in the Bitcoin market from the perspective of behavioral finance. Further, the two cores of price manipulation include Bitcoin price and liquidity. From the perspective of manipulator, this virtual currency "game" is often based on the manipulator's Bitcoin buying and selling transactions, and the manipulation is achieved through the imbalance of market order[7]. Then, the Bitcoin chips held by the manipulator and their changes are particularly important in the research of the price manipulation mechanism.

While the price manipulation mechanism of Bitcoin is the basis for regulatory research, controlling the manipulator's manipulation return is the direct factor that determines the effectiveness of regulation. Previous research on the manipulation returns of price manipulation is scarce for the Bitcoin market, and more measured directly using manipulation returns minus manipulation costs, without considering the probability of investigation and the adjustment of returns after the imposition of penalties.

Moreover, from the perspective of the regulator, enforcing regulation can curb the incentives of the Bitcoin price manipulator, while consuming a certain amount of regulatory costs. However, regulating the safety and stability of financial markets is one of the functional objectives of government authorities, and the cost of regulation is not high compared to the social damage caused by Bitcoin price manipulation. Therefore, the regulator's policy enforcement is more significant compared to the financial market risks associated with Bitcoin price manipulation. Currently, regulatory authorities around the world pay high attention to the problem of price manipulation in the Bitcoin market, but lack control measures to effectively avoid this illegal behavior. Some countries represented by the UK, Singapore, and Canada have launched "Regulatory Sandbox" pilots, but the core trend is still penetrating regulation under the framework of mature technology; represented by the US, federal the regulator pay close attention to pump-and-dump measures in the cryptocurrency ecosystem. It is worth noting that whether penetrating regulation or pump-and-dump measures, it is necessary to raise red flags and trigger regulatory standards[8]. However, the regulatory constraints and triggering criteria for Bitcoin price manipulation are currently unclear. Finally, it is interesting to see how the regulator can achieve victory in this "game" with Bitcoin price manipulators.

Based on the above discussion, this research is well motivated to explore the following questions:

- Cutting from the perspective of behavioral finance, how price manipulation is achieved in the Bitcoin market? Are there equilibrium boundary conditions for manipulation? If based on equilibrium boundary conditions, what is the impact of enforcing regulatory penalties on the manipulator's price manipulation returns?
- What controllable variables should the regulator's binding rules and trigger criteria start from? How can these controllable variables be set to achieve effective regulation of Bitcoin price manipulation?

To answer the above questions, we research the price manipulation mechanism of the Bitcoin market by introducing behaviorally deviant users and perfectly rational users with behavioral finance as the theoretical support. Then, we establish a game model between the manipulator and the regulator based on the equilibrium conditions of the price manipulation mechanism. Considering the probability of investigation and penalty coefficient, we determine the adjusted manipulation returns through the game model. Further, we sort out the key controllable variables of the regulator (penalty coefficient, price fluctuation standard, and probability of investigation) by variable disassembly analysis and parameter verification with the expected returns of price manipulation as the core. Comparing three kinds of adjustment mechanisms about the probability of investigation, we try to research how the regulator can use controllable variables to achieve effective regulation of Bitcoin price manipulation.

From a game perspective, this paper summarizes the influence rules between the regulator's key controllable variables and the price manipulator's expected returns. The results of our research show that: firstly, when the regulator enforces the penalty, setting the penalty coefficient above a certain lower threshold can achieve the negative control of the manipulator's expected returns; secondly, without interfering with market-based trading, setting the price fluctuation standard as low as possible can effectively regulate the extreme value of the manipulator's expected returns and the declining inflection point; thirdly, through equilibrium analysis and experimental simulation, when the probability of investigation is dynamically adjusted with respect to the price fluctuation standard, the combined effect of the penalty coefficient and the price fluctuation standard on the manipulator's expected returns is optimal and the regulatory efficiency is the highest.

## 2 Literature Review

This research is closely related to the literature on price manipulation in financial markets. Starting from the securities stock market, the types of price manipulation discussed in previous studies are mainly as follows:

- Information-based manipulation, in which trading agents with information advantages conduct manipulation by issuing falsely oriented announcements;
- Behavioral manipulation, in which the manipulators manipulate prices by altering market fundamentals;
- Transaction-based manipulation, in which price movements are influenced solely through trading behavior and thus manipulated for profit.

The first two types of price manipulation is more applicable to the securities stock market, and Xiang[9] similarly developed a behavioral bias model for stock price manipulation in China. Nevertheless, the transaction-based manipulation as the most typical manipulation method, based on trading strategies and price mechanisms to execute manipulation, is most applicable to the analysis of price manipulation in the Bitcoin market[10, 11]. This is also the starting point of our research. Regarding price manipulation in the Bitcoin market, Gandal et al.[12] empirically demonstrated that suspicious trading activities in the Bitcoin market may lead to large fluctuations in Bitcoin prices. Although the price is related to its age and market value, large price fluctuations caused by Bitcoin's own age and market capitalization are infrequent in the long run, so this does not affect the short-term analysis of price manipulation mechanism in this study[13]. And Shi et al.[14] verified the existence of Bitcoin price manipulation by normalizing log price returns. Subsequently, Hu et al.[7] investigated the evidence of price manipulation during the 2017 Bitcoin price distortion, and Fratrič et al.[10] designed a proxy market model to simulate and reproduce the Bitcoin market price manipulation in 2017. However, our research differs from the above series of literature in that we introduce behavioral finance theory into the analysis of price manipulation in the Bitcoin market, investigate the price manipulation mechanism that is applicable to the Bitcoin market, and obtain the equilibrium boundary conditions for achieving price manipulation. Further, we build a game model between the manipulator and the regulator based on the equilibrium boundary conditions and finally clarify the expected returns function of the manipulator adjusted by the enforcement of regulatory penalties.

This research also involves the literature that studies regulatory countermeasures and regulatory games.

In terms of regulatory countermeasures, there are currently some regulatory countermeasures that are adapted to different national conditions internationally to maintain the stable development of fintech and reduce the uncertainty brought by potential risks, including three regulatory models: proactive regulation represented by the UK, restrictive regulation represented by the US, and passive regulation represented by China[15]. Among them, proactive regulation is mainly manifested in formulating corresponding regulatory approaches for different financial businesses, incorporating all emerging financial businesses into regulatory norms, and encouraging the development of regulatory technology as the key to overcome the problems of regulatory failure and over-regulation[16]. Among them, proactive regulation is gradually recognized by countries as one of the ways to achieve ex ante regulation. It brings all emerging financial businesses into the regulatory norms and develops corresponding regulatory methods for different financial businesses. Thus, targeted regulatory countermeasures are particularly crucial.

However, at present, scholars' research on the regulatory countermeasures of Bitcoin price manipulation usually focuses on the aspects of case evidence such as establishing regulatory regulations, adopting a licensing system to regulate the legal qualifications, and using regulatory technology[17, 18], or on the aspects of theoretical concepts such as improving the regulatory mechanism of financial technology, strengthening the construction of financial infrastructure, and attaching importance to the research and development of basic technologies[19], or on the aspects of government strategy such as strengthening governmental digital, establishing specialized functional departments, and promoting international cooperation[20]. Based on the above analysis, at this stage, there is a lack of regulation research on operational regulatory countermeasures that combine macro and micro aspects. This study, however, starts from the micro-foundations of behavioral finance and explores effective regulatory countermeasures in conjunction with existing macro-policy practices, which precisely bridges the gap above.

In terms of regulatory games, Liu et al.[21] compared the equilibrium differences between fixed and dynamic penalty mechanisms in the regulatory strategies of Internet platforms, based on evolutionary game theory. Wang et al.[22] investigated how parameters such as penalty intensity and platform size optimally affect government regulation of platform markets, based on a dynamic game model. Our research is closest to Wang et al.[22] as we both investigate how the regulatory parameters are set to make the regulation optimal. However, our research differs from Wang et al.[22] in several important aspects: first, the scenario of our research is the Bitcoin market, and the regulatory problem we research is the price manipulation, so the equilibrium bounds of the model are quite different. Second, in addition to penalty coefficients, we introduce parameters such as probability of investigation and price fluctuation standard in our research to explore how the regulator set these controllable variables to effectively achieve price manipulation regulation. Whereas, the research by Wang et al.[22] focuses more on the comparative static analysis of different regulatory models.

At present, these analyses of the intrinsic mechanism of price manipulation in the Bitcoin market more focus on exploring existential evidence, lacking micro-behavioral level analysis, while the regulatory game in the Bitcoin market scenario is less studied. At the same time, the regulatory settings about the price fluctuation standard and the probability of investigation are not considered. Therefore, in this paper, we analyze the mechanism of Bitcoin price manipulation based on behavioral finance theory from a micro-game perspective, introduce price fluctuation standard and probability of investigation, and establish a regulatory game model, hoping to obtain rules for effective regulation through model analysis and experimental simulation.

## 3 Analysis of Bitcoin Price Manipulation Mechanism

This section first discusses the model setup for price manipulation by the manipulator in the Bitcoin market. After that, we will give the phased price manipulation mechanism, and then analyze boundary conditions such as the volume of manipulated Bitcoin, the number of price manipulation periods, and the profit of price manipulation as a benchmark for further analysis later.

### 3.1 Model assumption

Based on the characteristics of the Bitcoin market, the following basic model settings are made:

- Miners are not involved in influencing the market, and the total market coin volume is stable;
- Manipulators are price determiners, using financial advantages to influence supply and demand;
- Manipulator is a pure manipulation strategist, does not have information advantage, and only manipulates price through trading behavior.

### 3.2 Market body division

Based on behavioral finance theory, we classify Bitcoin market subjects ($C$) into abnormal users ($C_u$) and normal users ($C_n$) according to whether they are normal or not, where abnormal users are regarded as manipulator accounts and normal users are further classified as behaviorally deviant users ($C_B$) and fully rational users ($C_r$), respectively, as shown in Fig. 1.

When behaviorally deviant users $C_B$ make Bitcoin

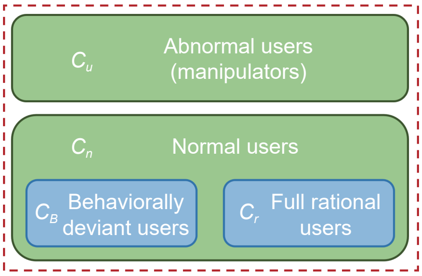


**Fig. 1 Bitcoin market body division.**

trading decisions, on one hand, they exhibit representative deviation (i.e., they blindly follow the trend of buying when the price rises); on the other hand, they exhibit the disposition effect (i.e., after the manipulation ended, in the face of the downward trend in the price of Bitcoin, they are reluctant to sell the Bitcoin that had lost money, expecting the price to recover). However, fully rational users' trading decisions are not affected by price fluctuations. Price manipulators exploit the representative deviation and the disposition effect of behaviorally deviant users to implement trading-based manipulation strategies to achieve manipulation returns.

## 3.3 Price manipulation mechanism

Bitcoin trading is carried out continuously 24 h a day, so we divide the number of trading periods by unit days and treat the whole process of Bitcoin price manipulation as a discrete time series from period 0 to $T$, and divide it into four phases, as shown in Fig. 2.

### 3.3.1 Phased state description

To simplify the interaction effects of the complex behavior of a large number of ordinary users at different periods in the study, it is assumed that users make only one sell (or buy) transaction during the entire period 0 to $T$ price manipulation.

- **First stage: $t=0$**

At the beginning of price manipulation when $t=0$, the market is in equilibrium and the Bitcoin price is equal to the intrinsic value. The amounts of coins held by manipulators, behaviorally deviant users, and perfectly rational users in the market are $Q_{C_{u,0}}, Q_{C_{B,0}}$, and $Q_{C_{r,0}}$, respectively. Assuming the total amount is 1, and there is always $Q_{C_{B,0}}=Q_{C_{r,0}}=(1-Q_{C_{u,0}})/2$. The manipulator has held a sufficient amount of Bitcoin chips to affect supply and demand at this point.

- **Second stage: $t=1$ to $N$**

The manipulator submits a buy order each period and the Bitcoin price shows a continuous upward trend. Assuming that the expected single-period pull-up spread is $\delta$ ($\delta=P_t-P_{t-1}$). Maximum price $P_{\max}$ and the maximum amount of coins held by manipulators $Q_{C_{u,N}}$ reached in period $N$.

Fully rational users submit sell trades per issue $D_{C_{r,t}}=\alpha\cdot\delta$, where $D_{C_{r,t}}$ is the total amount of bitcoins sold per unit period t by the full rational users, and $\alpha$ is the rational selloff coefficient. Sold completely in period $N$, $Q_{C_{r,0}}=\sum\limits_{t=1}^{N}D_{C_{r,t}}=\alpha\cdot(P_N-P_0)$.

Behaviorally deviant users are stimulated by the price increase and exhibit a representative deviation by being bullish on Bitcoin, then increase their purchases. Assuming their representative deviation coefficient is $\beta$, the buy and sell probabilities are $q_1$ and 1. In which, in order to ensure that the total amount of coins held by

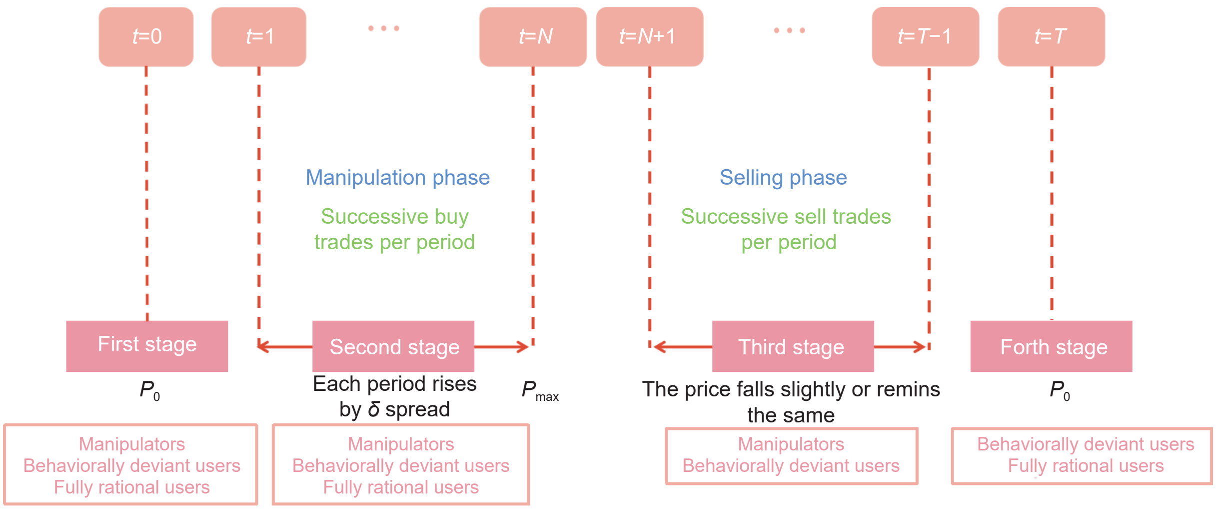


**Fig. 2 Four stages of price manipulation.**

market participants is constant, the manipulator's buying coins are treated as basic units and are obtained by behaviorally deviant users' sellings. And then the net buyings by behaviorally deviant users are equal to the amount of Bitcoin sold by fully rational users: $q_1 = Q_{C_{B,0}} = (1 - Q_{C_{u,0}})/2$.

- **Third stage: $t = N+1$ to $T-1$**

The manipulator submits a sell order for each of $M$ consecutive periods, sells completely, and exits the market in period $T-1$. At this stage, the Bitcoin price is higher than the intrinsic value, fully rational users do not enter the market, and only manipulators and behaviorally deviant users exist in the market.

Behaviorally deviant users, faced with a price that is no longer rising or even falling slightly, exhibit a disposition effect, assuming that the buy and sell probabilities are $q_2$ and $q_3$, which meet $q_3 \leqslant q_2 \leqslant q_1$.

- **Forth stage: $t = T$**

The manipulator completely exits, and the Bitcoin price returns to equilibrium.

### 3.3.2 Equilibrium analysis

- **Equilibrium analysis of 0−$N$ periods with the representative deviation**

Based on the above four-stage analysis, the sum of the net buying volume $Q_{C_{r,0}}$ of behaviorally deviant users and the net buying volume $\Delta Q_{C_B}$ of manipulators is equal to the net selling volume $\Delta Q_{C_u}$ of perfectly rational users in the period 0 to $N$. Based on this market clearing constant equation, we give Table 1.

According to the constant equation of market clearing, at period $N$, the manipulator's holdings $Q_{C_{u,N}} = \sum_{t=0}^{N} Q_{C_{u,t}} = Q_{C_{u,0}} + N \cdot \alpha\delta - (N-1)\beta$, the holdings $Q_{C_{B,N}} = \sum_{t=0}^{N} Q_{C_{B,t}} = Q_{C_{B,0}} + (N-1)\beta = (1 - Q_{C_{u,0}})/2 + (N-1)\beta$ is the behaviorally deviant user's, and the manipulator's holding cost TC is

$$
\begin{aligned}
\mathrm{TC} = {} & Q_{C_{u,0}} \times P_0 + \Delta Q_{C_{u,1}} \times P_1 + \cdots + \Delta Q_{C_{u,N}} \times P_N = \\
& Q_{C_{u,0}} \times P_0 + \alpha\delta \times (P_0 + \delta) + \\
& (\alpha\delta - \beta) \times [(N-1)P_0 + \frac{(N+2)(N-1)}{2}\delta]
\end{aligned} \tag{1}
$$

- **Equilibrium analysis of $N$+1 to $T$−1 periods with the disposition effect**

Using market clearing theory, the number of price pull-up periods $N$ can be solved, which is equal to $(1 - Q_{C_{u,0}})/2 + \alpha\beta = (1 - Q_{C_{u,0}})/2\alpha\delta$. And we give Table 2.

In the phase $t = N + 1$ to $T - 1$, the net buying volume of the behaviorally deviant users is equal to the net selling volume of the manipulator, then we get the manipulator's holdings $Q_{C_{u,N}}$ in period $N$ is equal to $\sum_{i=1}^{M} (1 - q_3)^{i-1} \cdot (q_2 - q_1 \cdot q_3)$. Further, the solution gives the manipulator's manipulation profit $\pi$ as

$$
\begin{aligned}
\pi = {} & Q_{C_{u,N}} \times (P_0 + N\delta) - \mathrm{TC} = \\
& \left[\frac{1 + Q_{C_{u,0}}}{2} - (N-1)\beta\right](P_0 + N\delta) - \mathrm{TC}
\end{aligned} \tag{2}
$$

Derivative of the above price manipulation profit to the manipulator's initial holdings, such that the derivative $\mathrm{d}\pi/\mathrm{d}Q_{C_{u,0}}$=0. Solve for the equilibrium boundary conditions, the price manipulator's initial holdings $Q_{C_{u,0}}$ and the number of periods $N$ in which the manipulator pulls up the price as

$$Q_{C_{u,0}} = \frac{\alpha^2\delta^2 + \alpha\delta + \alpha\beta\delta - 3\beta}{3\alpha\delta - 3\beta} \tag{3}$$

$$N = \frac{2 - \alpha\delta - \beta}{6(\alpha\delta - \beta)} \tag{4}$$

In order to maximize the expected returns of price manipulation, the manipulator should complete the price pull with an equilibrium initial holdings $Q_{C_{u,0}}$ in the equilibrium period $N$.

**Table 1 Equilibrium analysis of 0−$N$ periods with the representative deviation.**

| Period | Bitcoin price | Probability: Behaviorally deviate users: Buy | Sell | Net purchases | Manipulator net purchases |
|---|---|---|---|---|---|
| $t=1$ | $P_1 = P_0 + \delta$ | $q_1$ | 1 | 0 | $\alpha\delta$ |
| $t=2$ | $P_2 = P_0 + 2\delta$ | $q_1 + \beta$ | 1 | $\beta$ | $\alpha\delta - \beta$ |
| $t=3$ | $P_3 = P_0 + 3\delta$ | $q_1 + 2\beta$ | 1 | $\beta$ | $\alpha\delta - \beta$ |
| … | … | … | … | … | … |
| $t=i$ | $P_i = P_0 + i \cdot \delta$ | $q_1 + (i-1)\beta$ | 1 | $\beta$ | $\alpha\delta - \beta$ |
| … | … | … | … | … | … |
| $t=N$ | $P_N = P_0 + N \cdot \delta$ | $q_1 + (N-1)\beta$ | 1 | $\beta$ | $\alpha\delta - \beta$ |

**Table 2 Equilibrium analysis of *N*+1 to *T*−1 periods with the disposition effect.**

| Period | Probability | | |
|---|---|---|---|
| | Behaviorally deviate users | | Behaviorally deviate users net purchases = manipulator net purchases |
| | Buy | Sell | |
| $t=N+1$ | $q_2$ | $q_1\cdot q_3$ | $q_2-q_1\cdot q_3=h$ |
| $t=N+2$ | $q_2$ | $[q_1+h]\cdot q_3$ | $q_2-[q_1+h]\cdot q_3=(1-q_3)\cdot h$ |
| … | … | … | … |
| $t=N+i$ | $q_2$ | 1 | $(1-q_3)^{i-1}\cdot h$ |
| … | … | … | … |
| $t=T-1$ | $q_2$ | 1 | $(1-q_3)^{M-1}\cdot h$ |

## 4 Game Model Between the Manipulator and the Regulator

In this section, we build the game model between the manipulator and the regulator based on the equilibrium boundary conditions of price manipulation. Only considering the case of enforcing regulation, we give the expected returns function of the manipulator under theoretical conditions.

First, in the previous discussion of the price manipulation mechanism, we obtained the cost of manipulation without considering the regulatory penalty adjustment as TC and the manipulation profit $\pi$. Suppose the regulator is given the price fluctuation standard of $S\in[0,1]$. When the manipulator expects to increase the spread in a unit period $\delta$ more than $S$, the regulatory penalty is enforced, and vice versa. The penalty $M(S)$ depends on the deviation of $\delta$ from $S$ and is defined as $m\cdot\max(\delta-S,0)$, where $m$ is the penalty coefficient. Then, based on the assumption of the probability of investigation PG, the incremental manipulator cost $\Delta$TC is

$$\Delta\mathrm{TC}=\mathrm{PG}\cdot m\cdot\max(\delta-\alpha,0)+(1-\mathrm{PG})\cdot 0 \tag{5}$$

Further, we can build the payoff matrix of the game model between the manipulator and the regulator, as shown in Table 3.

This results in the manipulator's price manipulation expected returns function $E(\pi)$ as follows:

$$E(\pi)=\mathrm{PG}\cdot(\pi-\Delta\mathrm{TC})+(1-\mathrm{PG})\cdot\pi \tag{6}$$

## 5 Model Analysis

### 5.1 Parameter verification

Based on the model setup, this section will further analyze how to achieve effective regulation of Bitcoin price manipulation specifically. The ultimate goal of our research can be translated into making the expected returns of the manipulator meet $E(\pi)\leqslant 0$. Then, we combine the equilibrium conditions and the expected returns function (Eqs. (1) to (6)), decompose the key variables, and obtain Table 4.

Introducing some of the validated parameters from previous studies[9, 23], we make the following assumptions on some of the variables: (1) The number of representative deviation coefficient $\beta=0.001$; (2)

**Table 3 Payoff matrix of game model between the manipulator and the regulator.**

| Manipulator | High-cost "incumbents"-enforcing regulator | | Low-cost "incumbents" |
|---|---|---|---|
| | Investigated and punish manipulation | Not investigated | |
| Enter | $(\pi-\Delta\mathrm{TC},\Delta\mathrm{TC}-C(\mathrm{PG}))$ | $(\pi,-C(\mathrm{PG}))$ | — |
| No entry | $(0,-C(\mathrm{PG}))$ | $(0,-C(\mathrm{PG}))$ | — |

Note: (Number 1, Number 2), Number 1 denotes the manipulator's returns and Number 2 denotes the regulator's returns; $C(\mathrm{PG})$ is the cost of regulation.

**Table 4 Dissociation table of key variables.**

| Column 1 | Column 2 | Column 3 | Target parameter |
|---|---|---|---|
| **Equation (6)**<br>Expected return $E(\pi)$ | Probability of investigation of PG | Probability of investigation of PG | Probability of investigation of PG |
| | **Equation (1)**<br>Manipulation costs TC<br><br>**Equation (2)**<br>Manipulation returns $\pi$ | **Equation (3)**<br>Initial holdings of the manipulator $Q_{C_{u,0}}$<br><br>**Equation (4)**<br>Number of price pull-up periods $N$ | Rational selling factor $\alpha$<br>Representative deviation coefficient $\beta$<br>Expected single-period pull-up spread $\delta$ |
| | **Equation (5)**<br>Regulatory penalties $\Delta$TC | Bitcoin initial price $P_0$<br>Penalty coefficient $m$<br>Price fluctuation standard $S$ | Bitcoin initial price $P_0$<br>Penalty coefficient $m$<br>Price fluctuation standard $S$ |

Bitcoin initial price $P_0$=$P_{\max}/2=150$; (3) Initial holdings of the manipulator $Q_{C_{u,0}}$= 0.5. Firstly, we sort the rational selloff coefficient $\alpha$ as a function of the pull-up spread $\delta$ as $\alpha^2\delta^2+(\alpha+\alpha\beta-3\alpha Q_{C_{u,0}})\delta+3\beta Q_{C_{u,0}}-3\beta=0$, which is treated as a quadratic equation of $\delta$. Secondly, iterate over $\alpha$ and solve for the corresponding value of $\delta$. Finally, the equilibrium pull-up period (normalized) $N$ is calculated according to the equilibrium boundary conditions, as shown in Fig. 3. Interestingly, we find that the value of $N$ fluctuates in the range of 0.498 005–0.498 945, which is extremely close to 0.5 and thus has the following Lemma 1.

**Lemma 1:** $N$= 0.5, the rational selloff coefficient $\alpha$ takes a value that hardly affects the manipulator's price manipulation interval, so "the manipulator's price pull-up phase: market exit phase" is approximately 1:1.

Next, based on the fixed parameters $\beta$ = 0.001, $P_0$ = $P_{\max}/2=150$, $Q_{C_{u,0}}=0.5$, and $N=0.5$, then we can disassemble the manipulator's expected return function. Furthermore, we sort out the key controllable variables for the regulator, which are the penalty coefficient $m$, the price fluctuation standard $S$, and the probability of investigation PG.

## 5.2 Analysis of price manipulation returns without enforcement of regulatory penalties

Based on the parameter assumptions and simulation verification, we analyzed the price manipulation returns when no regulatory penalty is enforced. In the case where no regulatory penalty is enforced, it corresponds to a game without influence between the manipulator and the regulator, and thus the expected returns of Bitcoin price manipulation is equal to the manipulation profit $\pi$. The manipulation profit corresponding to different single-period pull-up spreads is obtained by the following calculation (Fig. 4).

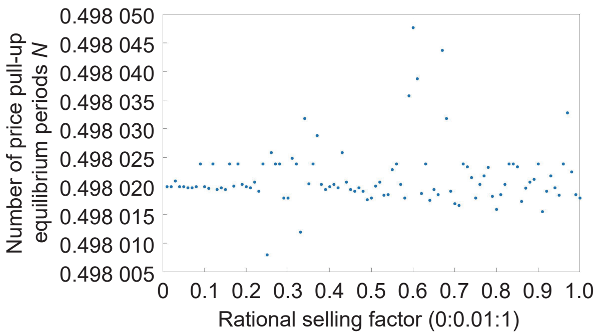


**Fig. 3 Number of price pull-up equilibrium periods $N$ (normalized) for different values of $\alpha$. Rational selling factor ranges from 0 to 1, and the step interval is 0.01.**

We find a positive correlation between the calculated pull-up spread for different single periods and the corresponding manipulated profit without the enforcement of regulatory penalties. Meanwhile the manipulated profit is always positive, i.e., Lemma 2.

**Lemma 2:** In the absence of regulatory penalties, once the manipulator chooses the price manipulation strategy, it can make positive returns from the manipulation by eliminating its cost. And the larger the single-period pull-up spread $\delta$, the higher the returns from the manipulation. Thus, the regulator must impose a penalty mechanism to make the manipulator's returns less than or equal to zero.

Therefore, our research introduces three controllable variables of the regulator (the probability of investigation, the penalty coefficient, and the price fluctuation standard) to explore the impact of the above controllable variables on the expected returns of manipulation when the manipulator performs different degrees of price manipulation (i.e., different values of $\delta$), to derive relevant propositions for achieving effective regulation, as shown in Fig. 5.

## 5.3 Analysis of price manipulation returns with enforcement of regulatory penalties

### 5.3.1 Analysis of expected returns under the fixed probability of investigation

Assuming the fixed probability of investigation PG = 0.5, with the price fluctuation standard $S$= 10, 20, 30, and 40, observing the penalty coefficient $m$=0 to 10, the regulator adjusts the manipulator's expected returns by enforcing the regulatory penalty, as shown in Fig. 6.

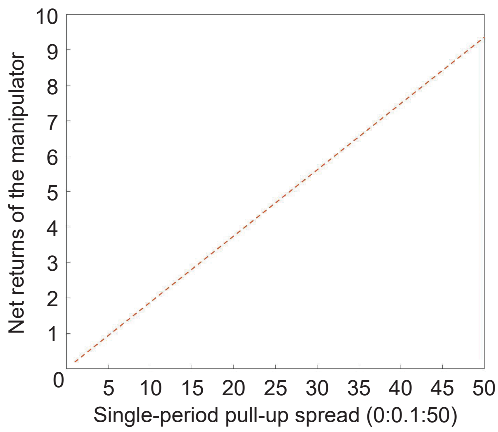


**Fig. 4 Influence of single-period pull-up spread on the net returns of the manipulator.**

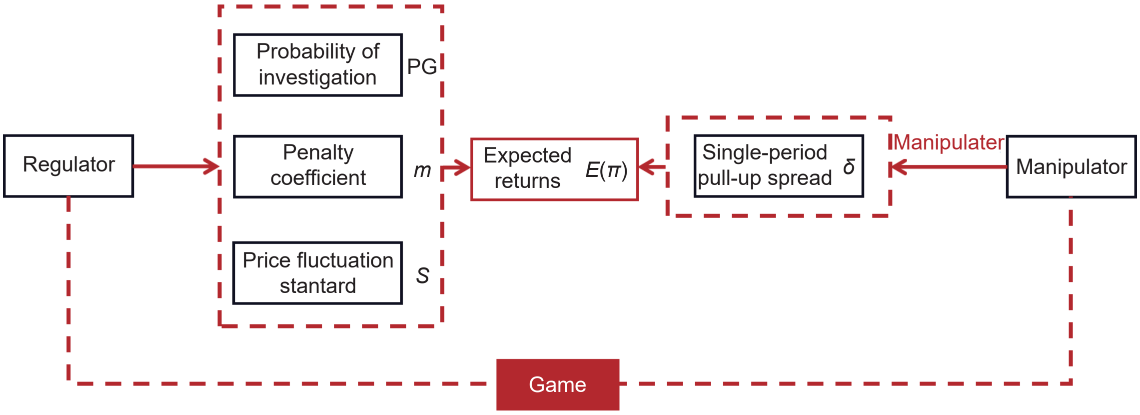


**Fig. 5 Regulatory analysis framework.**

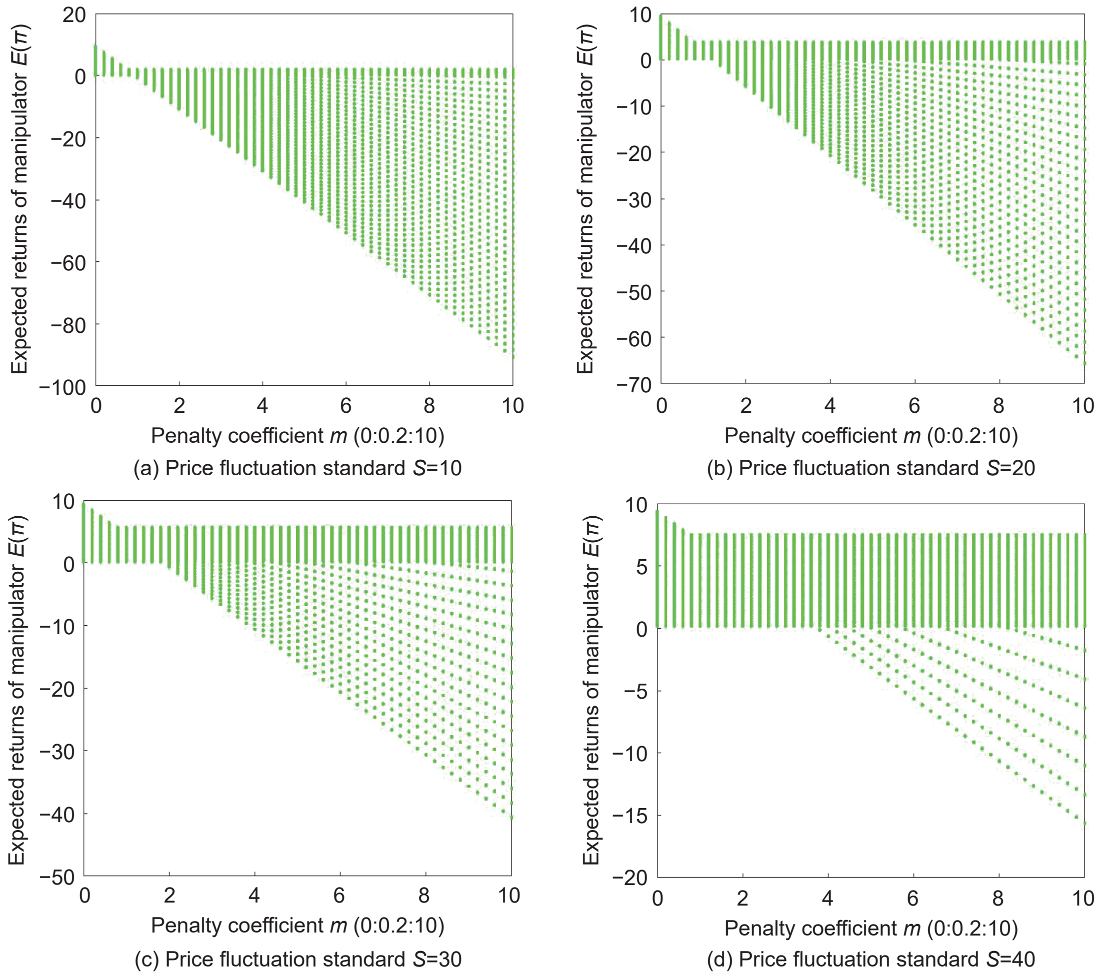


**Fig. 6 Fixed probability of investigation mechanism. The impact of penalty coefficient on the expected returns of manipulator under the fixed probability of investigation mechanism (single-period pull-up spread from 0 to 50).**

Under the fixed probability of investigation mechanism, when the manipulator implements different single-period pull-up spreads $\delta$, the combined effect of the regulator's control penalty coefficient $m$ and the price fluctuation standard $S$ on the expected returns of the manipulator $E(\pi)$, is reflected in Fig. 7.

### 5.3.2 Analysis of expected returns under the dynamic probability of investigation

Under the dynamic probability of investigation mechanism, the probability of investigation adjusts dynamically with the setting of the price fluctuation standard. We discuss the effect of different penalty

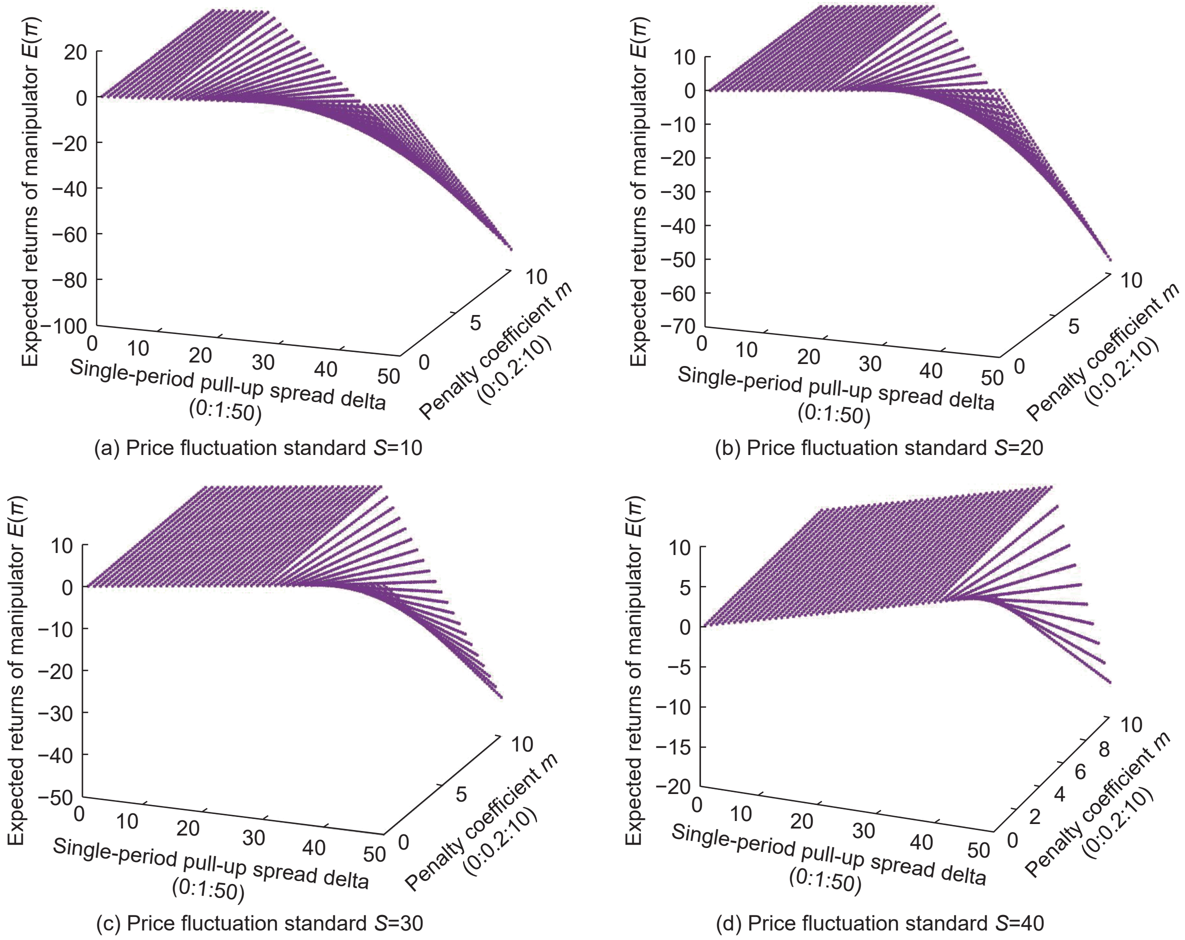


**Fig. 7 Fixed probability of investigation mechanism. The combined effect of single-period pull-up spread and penalty coefficient on the expected returns of the manipulator under the fixed probability of investigation mechanism (penalty coefficient from 0 to 10).**

coefficients and price fluctuation standard settings on the manipulator's expected returns under the two dynamic adjustment mechanisms, in terms of the concavity of the probability of investigation adjustment function, as well as the combined effect when the manipulator implements different single-period pull-up spreads.

- **Probability of investigation is a convex function with respect to the price fluctuation standard**

Assume that the convex function of the dynamic probability of investigation with respect to the price fluctuation standard is

$$\mathrm{PG}(S) = \cos\left(\frac{\pi}{100}(S+50)\right)+1 \tag{7}$$

With the price fluctuation standard $S$= 10, 20, 30, and 40, observing the penalty coefficient $m$=0 to 10, the regulator adjusts the manipulator's expected returns by enforcing the regulatory penalty, as shown in Fig. 8.

Under the dynamic convex function probability of detection mechanism, when the manipulator implements different single-period spreads $\delta$, the combined effect of the regulator's control penalty coefficient $m$ and the price fluctuation standard $S$ on the expected returns of the manipulator $E(\pi)$, is reflected in Fig. 9.

- **Probability of investigation is a concave function with respect to the price fluctuation standard**

Assume that the concave function of the dynamic probability of investigation with respect to the price fluctuation standard is

$$\mathrm{PG}(S) = \cos\left(\frac{\pi}{100}S\right) \tag{8}$$

With the price fluctuation standard $S$= 10, 20, 30, and 40, observing the penalty coefficient $m$=0 to 10, the regulator adjusts the manipulator's expected returns by enforcing the regulatory penalty, as shown in Fig. 10.

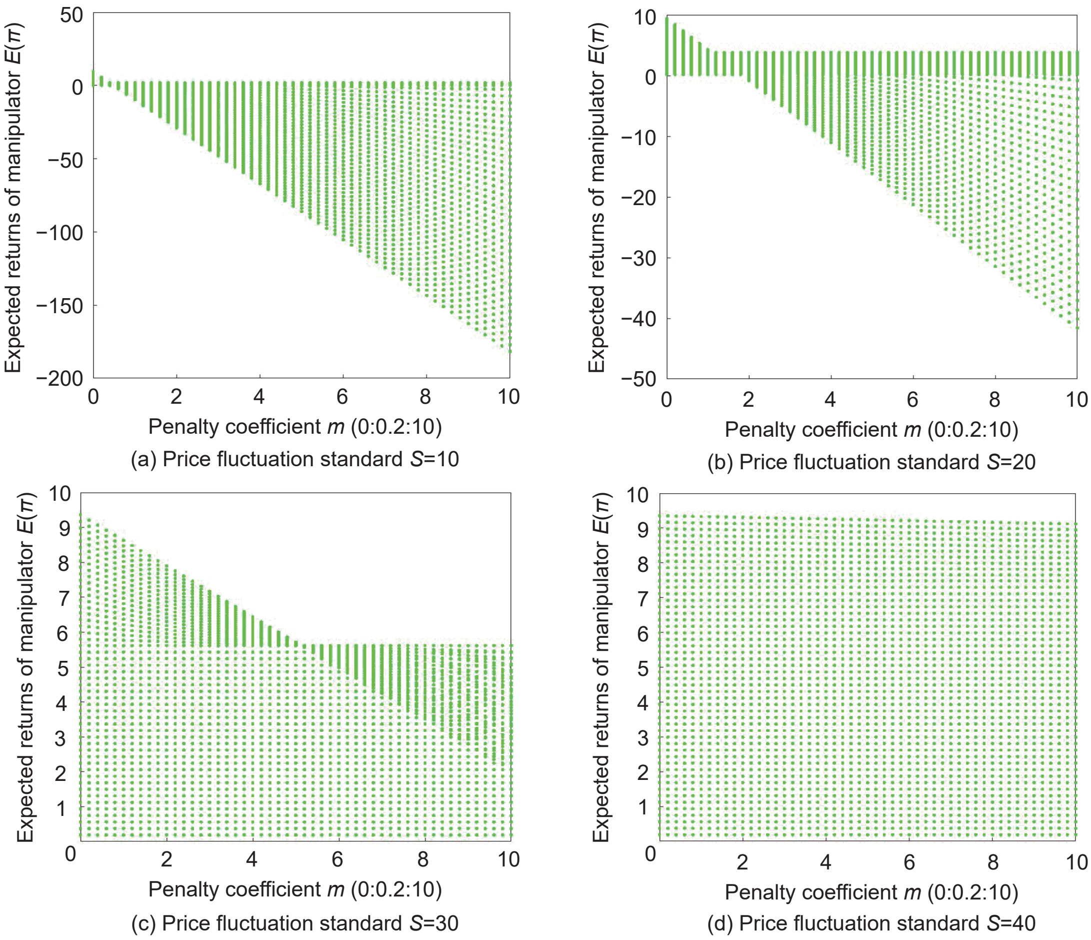


**Fig. 8 Dynamic probability of investigation mechanism—Convex function. The impact of penalty coefficient on the expected returns of manipulator under the dynamic convex function probability of investigation mechanism (single-period pull-up spread from 0 to 50).**

Under the dynamic concave function probability of detection mechanism, when the manipulator implements different single-period spreads $\delta$, the combined effect of the regulator's control penalty coefficient $m$ and the price fluctuation standard $S$ on the expected returns of the manipulator $E(\pi)$, is reflected in Fig. 11.

Based on the initial regulatory judgments of the fixed probability of investigation mechanism, we make a comparative analysis of the impact of the penalty coefficient on the expected returns from manipulation and the combined effect of different regulatory controls on the expected returns from manipulation under three regulatory mechanisms: fixed probability of investigation, dynamic convex function probability of investigation, and dynamic concave function probability of investigation. In the end, we conclude three core propositions of effective regulation controllable by the regulator as follows:

**Proposition 1: About the penalty coefficient**

The regulator needs to exceed a certain lower threshold when setting the penalty coefficient in order to achieve a negative bound on the expected returns, and thus effectively regulate price manipulation in the Bitcoin market.

After the inflection point of the expected returns maximum, along with the rise of the penalty coefficient $m$, the expected returns $E(\pi)$ will fall. While its critical single-period pull-up spread $\delta$ from positive to negative will also fall, i.e., the manipulator must achieve positive returns within a smaller controllable range of single-period pull-up spread after reaching the expected returns maximum, which will eventually make price manipulation more difficult. In addition, the penalty coefficient affects the maximum value of the expected returns, and the larger the penalty coefficient $m$ is, the smaller the maximum value of the expected returns is, which in turn will lead to a weaker incentive to

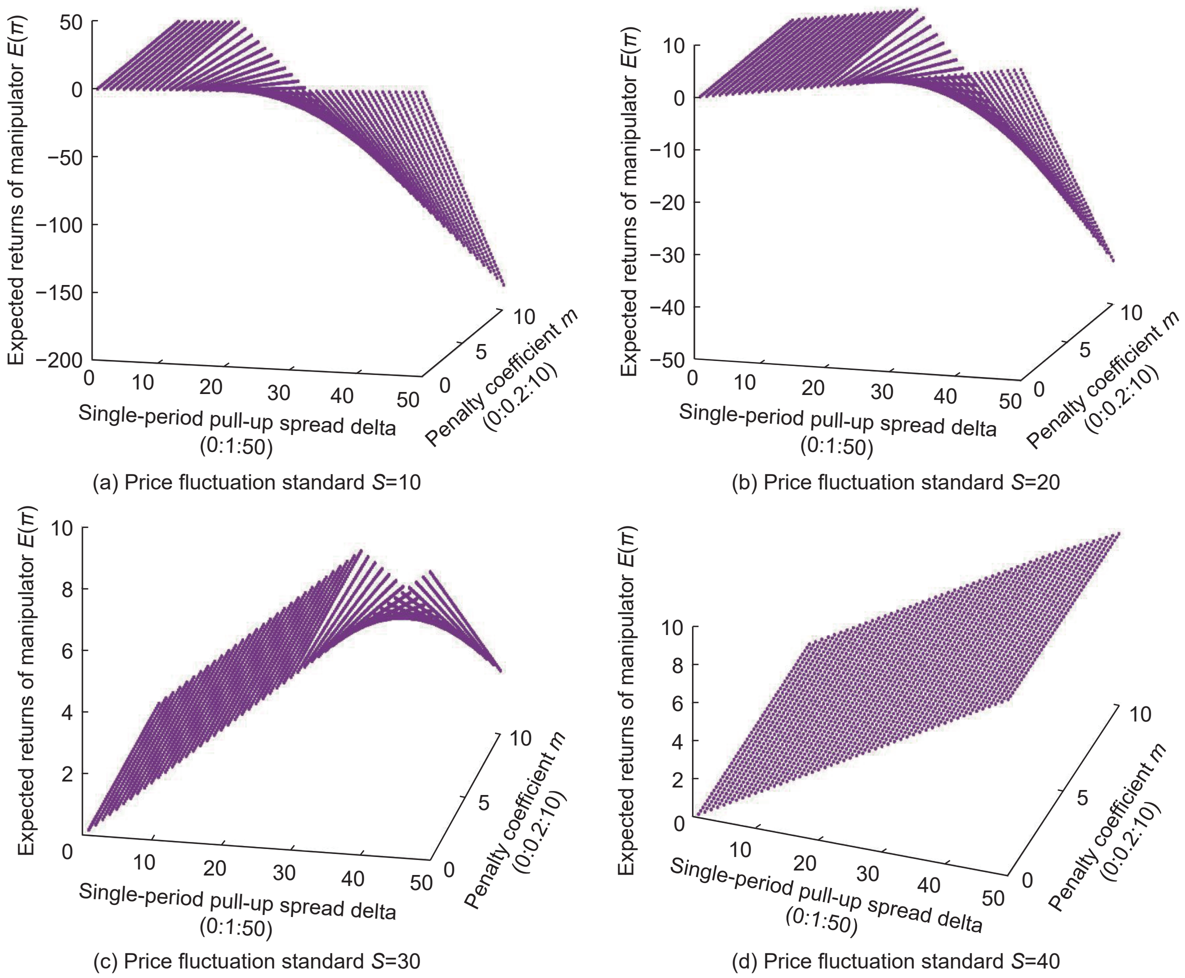


**Fig. 9 Dynamic probability of investigation mechanism—Convex function. The combined effect of single-period pull-up spread and penalty coefficient on the expected returns of the manipulator under the dynamic convex function probability of investigation mechanism (penalty coefficient from 0 to 10).**

manipulate the price. In contrast, when the penalty coefficient is lower, the manipulator's expected returns are always positive so that effective regulation cannot be achieved.

**Proposition 2: About the price fluctuation standard**

The regulator should set price fluctuation standard $S$ as low as possible while ensuring that they do not interfere with the market-based trading of Bitcoin.

On one hand, the price fluctuation standard determines the inflection point at which the manipulator's expected returns decline as the single-period pull-up spread $\delta$ rises, i.e., the single-period pull-up spread $\delta$ required for the manipulator to maximize its expected returns. On the other hand, by affecting the amount of the penalty, the price fluctuation standard determines the rate at which the manipulator's expected returns decline later as the single-period pull-up spread rises, i.e., the higher the price fluctuation standard is set, the greater the impact of the amount of change per unit of $\delta$ on the expected returns will be. Therefore, a lower price fluctuation standard will make the manipulator need to maximize the expected returns within a smaller manipulation space, effectively discouraging the behavior of the manipulator in terms of price manipulation difficulty.

**Proposition 3: On the probability of investigation**

When the regulator dynamically adjusts the probability of investigation by a concave function with respect to the price fluctuation standard, the simulation result is optimal and the control of price manipulation regulation is most efficient.

In the cross-sectional analysis based on the same penalty coefficient and price fluctuation standard, there is no difference in the inflection point of the manipulator's expected returns with the single-period pull-up spread. However, after the expected returns

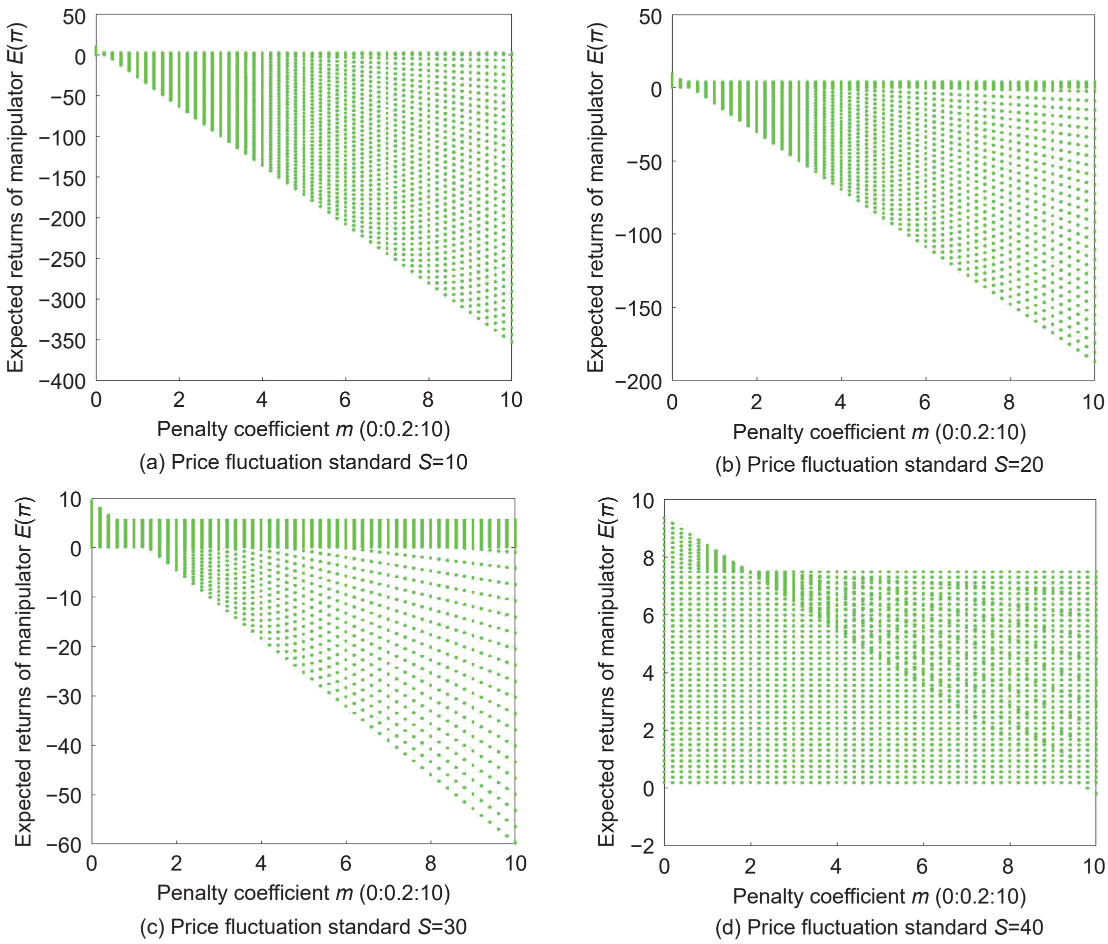


**Fig. 10 Dynamic probability of investigation mechanism—Concave function. The impact of penalty coefficient on the expected returns of manipulator under the dynamic concave function probability of investigation mechanism (single-period pull-up spread from 0 to 50).**

reaches its maximum, the expected returns decreases significantly faster under the dynamic concave function probability of investigation mechanism than under the fixed probability of investigation mechanism and the dynamic convex function probability of investigation mechanism. This makes the manipulator's attempt to increase one unit of the manipulated spread in the price manipulation process, which will cause a sharp decline in its expected returns, and the manipulation motive is inhibited. Thus the dynamic concave function detection probability mechanism is beneficial for the regulator to try to regulate effectively.

## 6 Conclusion

The scale of Bitcoin trading is expanding and the associated fields are deepening, so exploring effective regulatory rules for price manipulation in the Bitcoin market is conducive to maintaining international financial security. Introducing behavioral finance theory, we analyze the price manipulation mechanism of the Bitcoin market through the microscopic research perspective and establish a game model between the manipulator and the regulator. Finally, focusing on three controllable variables of the regulator, a comparative analysis of the combined effects and changes in the impact of manipulation expected returns under different regulatory variables' settings is conducted. The results show that the regulator can effectively control the extreme values of fluctuations and declining inflection points of expected returns by setting penalty coefficient above a certain lower bound threshold and the lowest possible price fluctuation standard. In addition, among the three mechanisms for the probability of investigation discussed, it is found that the simulation results for price manipulation regulation are optimal and most efficient when the probability of investigation is dynamically adjusted by a concave function about the price fluctuation standard.

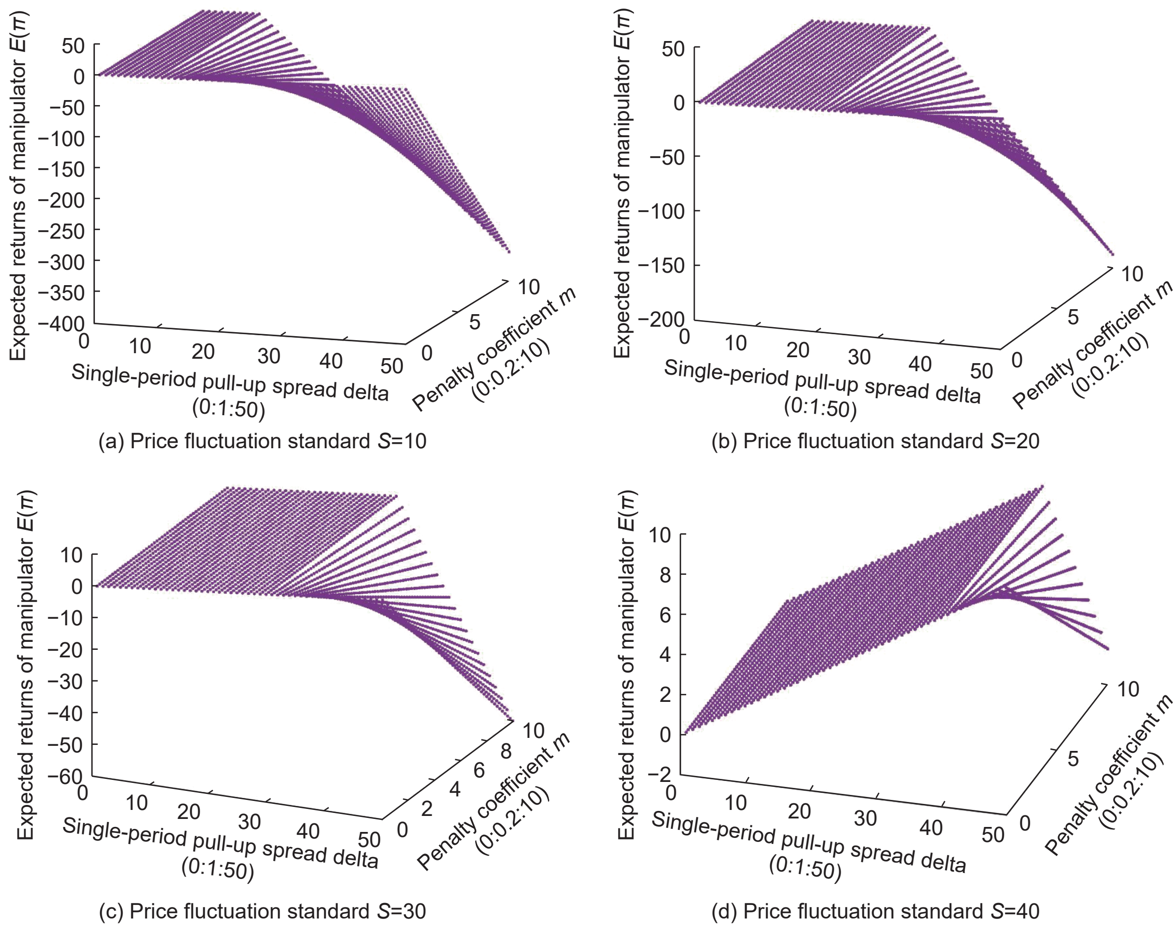


**Fig. 11 Dynamic probability of investigation mechanism—Concave function. The combined effect of single-period pull-up spread and penalty coefficient on the expected returns of the manipulator under the dynamic concave function probability of investigation mechanism (penalty coefficient from 0 to 10).**

Meanwhile, we identify several research limitations. First, the complexity of market dynamics, such as behavioral biases and liquidity issues[24], may challenge the effectiveness of these regulatory models. Second, the model assumptions in this article may oversimplify the actual complexities of the Bitcoin market, particularly in predicting rational and irrational user behaviors. The data and model validation used might limit the universality of the conclusions[25]. Furthermore, the article exposes shortcomings in the existing regulatory frameworks, especially the lack of clear guidance in implementing fines and controlling market manipulation.

Future research should develop more refined behavioral models to accurately capture the behavioral diversity of participants in the Bitcoin market. It is crucial to explore the development of a global regulatory framework that adapts to the decentralized nature of the Bitcoin market, along with empirical analyses of specific cases[14]. As blockchain and cryptocurrency technologies evolve, future studies should adjust to new manipulation strategies and develop more advanced countermeasures. A multidisciplinary approach, integrating knowledge from finance, computer science[26], and law, can provide a more comprehensive perspective. For future research, we will include all these issues in our future research program.

## Acknowledgment

This work was supported by the National Science Foundation of China (No. 61602536), Emerging Interdisciplinary Project of Central University of Finance and Economics (CUFE), and Financial Sustainable Development Research Team.

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