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Bidirectional Control of Collusion in Chinese Herbal Medicines on the Platform Powered by Data Factors

Abstract. *Quality is essential for the global trade of Chinese herbal medicines(CHMs), but quality collusion has damaged their reputation. Under digital intelligence, data factors in the traceability platform are the key to controlling collusion. From the empowerment of data factors, this paper focuses on controlling collusion and designs a bidirectional control system on the platform. The results show that the bidirectional control system controls collusion by increasing costs and reducing motivation, which can improve pricing strategies. The platform enhances consumer recognition to encourage product premiums, but price sensitivity diminishes the premium effect. The bullwhip effect mitigates the impact of price sensitivity on the pricing strategies of upstream enterprises. The collusion governance mechanism transforms from parallel to serial during data factor empowerment. The serial mode depends on data centres to reduce the pressure of regulation and traceability, coordinates information through data networks, and establishes accountability mechanisms to control collusion. Our results provide strategies to prevent CHMs collusion and support the high-quality development of the CHMSC.*

Keywords: *bidirectional control, Chinese herbal medicines, collusion, biform game, data factors.*

JEL Classification: C72, C71, L11.

Received: 21 October 2025	**Revised: 10 March 2026**	**Accepted: 12 March 2026**

1. Introduction

Chinese herbal medicines (CHMs) have gained international prominence through the Belt and Road Initiative (BRI), spreading to 196 countries and regions (Fu et al., 2024). This vigorous development has promoted the popularisation of CHMs, but it

DOI: 10.24818/18423264/60.1.26.15

also challenges the market order. Adulteration with inferior products continues to emerge(Zhang et al., 2021). Therefore, the governance of cheating behaviours is urgent to improve the quality of CHMs and stabilise the market order.

In the era of digital intelligence, a regulation and traceability system using information technology is necessary to ensure the quality of CHMs (Li et al., 2017). The difficulties of data traceability in CHMSC are data accuracy and recognised trust consensus. Each participant has the motivation to tamper with data for profit (Qin et al., 2021). Improving the transparency and accuracy of the data is essential. Technologies such as blockchain and QR codes provide technical support for CHMs quality traceability system (Zhang et al., 2021). Artificial intelligence digs the value of data, transforms data factors into assets, and presents the platformisation and digitalisation of CHMSC (Wu et al., 2024). Therefore, how data factors empower the CHMs quality traceability platform is the key to improving the quality of CHMs.

Collusion among multiple entities affects supervision and traceability. This paper applies the concept of collusion from principal-agent theory. Agents privately agree to benefit themselves at the expense of the principal, leading to collusive behaviour (Zhao et al., 1998). Therefore, two or more entities collude to deceive the government and consumers through implicit agreements in CHMSC (Colombo, 2013), which is termed quality collusive cheating in CHMs (abbreviated as collusion). Compared to traditional cheating behaviours, collusion seriously disrupts the CHMs market order and threatens consumers’ health due to its complexity and concealment (Cardinaels et al., 2008). Collusion hinders the construction of the CHMs quality traceability platform and the high-quality development of CHMs.

In conclusion, facing the expansion of the market and the challenges of quality regulation, the empowerment of data factors on the CHMs quality traceability platform can control cheating behaviours. Then, the constraints between the platform and collusion impede the enhancement of CHMs quality. Existing research lacks understanding and control of collusion in CHMs. How data factors empower the platform to govern collusion deserves research.

This study has three marginal contributions. First, compared with single-subject behaviours such as quality adulteration, this study focused on the quality collusion of CHMs involving multiple subjects. Second, we considered different stages of data factors to empower the CHMs quality traceability platform, and proposed a bidirectional control system. Finally, our paper used the biform game to study the competitive and cooperative relationship among the government, CMPEs, and CHMPFs, investigating the influencing factors of the bidirectional control system and collusion, and providing suggestions for improving the quality of CHMs.

The remainder of this paper is organised as follows: Section 2 provided a literature review. Section 3 detailed the model design. Section 4 analysed the non-cooperative game model with the regulatory function. In Section 5, we examined the noncooperative-cooperative biform game model with regulatory and traceable functions, focusing on the stages of empowerment by data factors. Section 6 compared the single-function and dual-function models and presented numerical simulation analysis. Section 7 concluded the study.

2. Literature review

2.1 Quality of Chinese herbal medicines

The quality of CHMs is essential for CHMSC's sustainable growth. The encyclopedia of CHMs summarises the quality control standards and offers a pathway for data organisation and management (Xu et al., 2019). Current research on CHM quality management mainly centres on two areas: quality standards and quality cheating behaviours.

Regarding quality standards, discrepancies exist between the Chinese Pharmacopoeia and those of other countries. The quality markers in these standards are relatively limited, lacking efficient, unified quality control technologies and international standards (Wang et al., 2022). To promote international trade development in CHMSC, the ISO/TC 249 platform refines the quality assurance system to establish the international CHMs pharmacopoeia (Huang et al., 2020). Therefore, improving the standards and quality testing methods promotes the CHMSC's sustainable development (Gao et al., 2020) amid global trade growth (Ye et al., 2020).

Current attention to quality cheating behaviours remains inadequate. Hu et al. (2023) pioneered a four-dimensional evolutionary game model analysing quality cheating between CMPEs and CHMPFs, demonstrating optimised government incentive-penalty mechanisms. Xie et al. (2022) examined pesticide contamination in medicinal-food homologous herbs, emphasising urgent soil remediation protocols and precision pesticide application systems. Cheng et al. (2019) offered seedling management methods to control the quality of CHMs from their origins. Existing research focuses on technical quality issues rather than proactive quality management, revealing gaps in systemic prevention against collusion.

In summary, existing research focuses on CHMs quality standards and quality control processes, with limited attention to CHMs quality cheating behaviours. This paper primarily examines collusion aimed at deceiving consumers and the government to secure excessive profits between CMPEs and CHMPFs. Our study bridges the gap in combating CHMs collusion.

2.2 Collusion

Collusion was first introduced by Tirole (1986) in the principal-agent model. Existing research classifies collusion patterns into three types based on participating entities: government-enterprise collusion, intra-enterprise collusion, and inter-enterprise collusion.

To control government-enterprise collusion, common strategies include implementing third-party monitoring systems (Jiang et al., 2019) and strengthening regulatory policies (Hu and Shi, 2021). Intra-enterprise collusion involves internal administrators' collusion (Shen et al., 2020) and shareholder-executive collusion (Rehman et al., 2021). Inter-enterprise collusion mainly occurs within principal-agent frameworks and can be categorised as horizontal collusion (among peer entities) or vertical collusion (across supply chain levels) based on organisational hierarchy. Vertical collusion manifests itself through transfer payments and coordinated pricing strategies between upstream suppliers and downstream distributors. Gilo et al. (2020) developed a repeated game model showing that vertical collusion is easier to sustain than horizontal collusion.

To summarise, collusion is widespread and challenging to regulate. Our study examines vertical collusion between CMPEs and CHMPFs in CHMSC and uses the biform game to analyse pricing strategies and coordination mechanisms, which enriches the research on vertical collusion and its control ways.

2.3 Biform game

Brandenburger and Stuart (2007) first introduced the biform game and divided it into two phases: the non-cooperative game and the cooperative game and proposed three conditions: additivity, non-externality, and non-coordination. Feess and Thun (2014) explored surplus allocation and investment incentives in supply chains by incorporating the Shapley allocation value as part of the payoff function in the non-cooperative stage of the biform game. Mahjoub and Hennet (2014) integrated the cooperative game and the Stackelberg game for supply chain network design, noting that the Shapley value allocation may not be reasonable for non-convex games.

In recent years, Li Dengfeng's team has applied the Minimax Theorem to the characteristic function in the cooperative stage, satisfying the conditions of a convex game, where the Shapley value is used as the payoff function in the non-cooperative stage (Zheng and Li, 2023). The team proposed research paradigms by integrating the Shapley value (Yang et al., 2023), interval values (Liang et al., 2023), and Banzhaf values (Liang and Li, 2020) for solving cooperative games, combined with Stackelberg games (Zheng and Li, 2023) and Nash games (Liang et al., 2023) for solving non-cooperative games. Additionally, Nguyen (2024) highlighted the ATM biform game method for achieving maximum utility in ATM networks. The innovations in these biform game paradigms break previous research limitations and expand the applications of biform games.

The biform game framework has been widely used across various research fields. Costa and Zemsky (2021) explored strategies for allocating innovation efforts to improve corporate bargaining power during technology licensing negotiations. Gonzalez et al. (2022) assessed the systemic effects of community energy projects on power grid resilience using the biform game.

The biform game can analyse competitive and cooperative strategies among enterprises. Following established methods, our paper applies a noncooperative-cooperative biform game to solve continuous decision-variable optimisation problems. We use the Shapley value to set the payoff functions for the noncooperative phase and obtain characteristic functions from the Minimax Theorem in the cooperative phase. Then, a Stackelberg game model is developed in the non-cooperative phase and solved through backward induction. We first apply a biform game to control collusion in CHMSC and confirm the operational feasibility of the biform game in digital platform networks.

In conclusion, the following are the novelties of this paper: (1) This paper first focuses on collusion control between CHMPFs and CMPEs. (2) A bidirectional control system is established to balance regulation and traceability based on the CHMs quality traceability platform with data factors. (3) This paper examines the mechanism of the bidirectional control system in the DFT stage and the DFF stage and proposes dynamic strategies to control collusion.

3. Model Setup

We consider a two-tier supply chain comprising a CHMPF (S) and a CMPE (R), with a government (G) executing regulatory and traceable functions through the platform. S produces CHMs at a unit technical cost c_0 and a unit inherent cost c_1, then sells them to R at a wholesale price ω. R sells to consumers at a unit selling price p. The demand function is expressed as:

$$q_0 = v - \mu p \tag{1}$$

We refer to v as the inherent market demand, and μ as the price sensitivity coefficient of consumers for CHMs. The implementation of the platform elevates consumer quality consciousness regarding CHMs, with preference premium for platform-certified products compared to non-certified alternatives. The Cobb-Douglas production function reflects the interdependence and nonlinearity between cost inputs and outputs. Therefore, to quantify the platform's impact on market dynamics, we extend the demand function under the platform as follows.

$$q = v + \delta_1 {\delta_2}^{f_1} {\delta_5}^{f_2} - \mu p \tag{2}$$

In the demand function, we refer to δ_1 as the conversion rate of social welfare enhancement into market demand, δ_2 and δ_5 represent the cost coefficients for R and G's platform participation, respectively. We use f_1 and f_2 to describe the proportions of efforts by R and G in the conversion of positive social effects into market demand. Since not all efforts will be converted into market demand, we set $0 < f_1 + f_2 < 1$ to represent diseconomies of scale.

Considering collusion leads to less quality, we define $k = k_0 + \delta_3 \alpha$ as the non-conformance rate. Among these, k_0 represents the CHMs initial non-conformance rate, α denotes the collusion speculation coefficient and δ_3 is the unit technical loss coefficient caused by collusion ($\delta_3 \in (0,1)$).

R needs to join the platform as regulation, incurring associated costs $t_2 = \delta_2 \gamma^2 / 2$(D'Aspremont and Jacquemin, 1988), and gains reward b from G. γ is the effort level of R in joining the platform. Following the extant literature (Gilo and Yehezkel, 2020), S must invest in collusion costs to induce collusion with R. We set the collusion cost is $t_1 = \delta_4 \omega^2$ (Liu et al., 2023) and δ_4 represents the collusion cost coefficient.

The supply chain cooperation mechanism is as follows: S bears a proportion η of the costs for the R to join the platform. Both parties share the CHMs accidents' responsibility, represented by the S's undertaken punishment proportion β for R in case of collusion being detected or substandard products causing accidents.

G imposes a tax d on CHMs product and invests$h$ in constructing platform to perform regulatory and traceable functions. We set the traceability effort coefficient as i and the regulatory effort coefficient as j, where $0 \leq i + j \leq 1$. After the CHMs product safety accident, G fines R m_1 and loses public support m_3. If collusion is detected, G fines R m_2. When G, R, and S construct the platform together, they gain social co-governance benefits f, where $f > m_3 > m_2 > m_1$.

In Model N under a non-platform scenario, G only regulates CHMs without detecting collusion. A Stackelberg game is between R (leader) and S (follower). Model N only considers non-cooperative interactions. The decision-making sequence is: S determines the wholesale price, and R establishes the retail price. Both parties pursue profit maximisation.

In Model M under the platform scenario with regulatory and traceable functions, we establish a noncooperative-cooperative biform game among G, R, and S. In the non-cooperative segment, R and S determine the retail price and the wholesale price, forming a competitive equilibrium. In the cooperative segment, G decides i and j, R decides γ, and S decides α, β, and η. We employ the Minimax Theorem to derive the different coalitions' characteristic functions, and the Shapley value to allocate the payoffs in coalitions. Finally, we use the Shapley values as the payoff functions to solve the Stackelberg game between R and S, determining the optimal retail price and wholesale price.

4. Model Setup

In this section, we examine a two-tier supply chain consisting of R (leader) and S (follower). A Stackelberg game is employed to solve the optimal retail and wholesale prices. Based on Section 3, the profit function of R is as follows:

$$\pi_{RN}(p,\omega) = (p-\omega)q_0 - (1-\beta)kjm_1 + \alpha t_1 \tag{3}$$

For Equation (3), the first term represents the sales profit of CHM products. The second term denotes the expected penalty when G detects substandard CHMs products. The third term represents S's cost to induce collusion.

The profit function of S is as follows:

$$\pi_{SN}(p,\omega) = (\omega - (1-\alpha)c_0 - c_1)q_0 - \beta kjm_1 - \alpha t_1 \tag{4}$$

For Equation (4), the first term represents the sales profit of CHMs. The second term denotes S's undertaken punishment for R's substandard CHMs products. The third term represents S's cost to induce collusion.

We set $c_1 = 0$ to simplify the process. Model N is solved using backward induction. The results are presented in Corollary 1.

Corollary 1. Using backward induction, it is found that Model N has a unique Nash equilibrium with the optimal retail price and wholesale price given by: $p^* = \frac{v(2\alpha\delta_4+\mu)}{\mu(4\alpha\delta_4+\mu)}$, $\omega^* = \frac{v}{\mu+4\alpha\delta_4}$.

Substituting p^* and ω^* into Equations (3) and (4), we obtain the optimal profits: $\pi_{RN}(p^*,\omega^*) = (p^* - \omega^*)(v - \mu p^*) - (1-\beta)(k_0 + \delta_3\alpha)jm_1 + \alpha\delta_4{\omega^*}^2 = \frac{jkm_1(\beta-1)\mu^2 + 4jkm_1\alpha\delta_4(\beta-1)\mu + \alpha\delta_4 v^2}{\mu(4\delta_4\alpha+\mu)}$, $\pi_{SN}(p^*,\omega^*) = (\omega^* - (1-\alpha)c_0 - c_1)(v - \mu p^*) - \beta(k_0 + \delta_3\alpha)jm_1 - \alpha\delta_4{\omega^*}^2 = \frac{8\alpha^3 c_0{\delta_4}^2 v - \delta_4((8(c_0+c_1)v + 16jkm_1\beta)\delta_4 - 2vc_0\mu)\alpha^2}{(4\delta_4\alpha+\mu)^2} - \frac{(2\mu(c_0+c_1)v + 8jkm_1\mu\beta - v^2)\delta_4 + \beta jkm_1\mu^2}{(4\delta_4\alpha+\mu)^2}$.

Figure 1 shows the governance mechanism of the single-function model. The government needs to balance the supervision of enterprises and the protection of consumers' rights, but fails to achieve the traceability of responsibility for CHMs accidents.

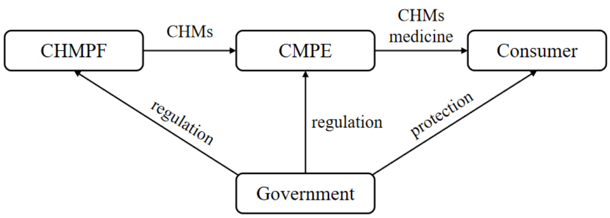


Figure 1. The governance mechanism in the Single-function model
Source: Authors' own creation.

5. Dual-function model

5.1 Model formulation

The government requires R to join the platform and S to standardise production. Through information technologies, the platform converts data into data factors by processing data onboarding and on-chain traceability certification, which empowers the bidirectional control system to realise forward regulation and reverse traceability. The government implements forward regulatory controls across upstream-downstream supply chains and reverse traceability for pharmaceutical incident accountability, as shown in Figure 2.

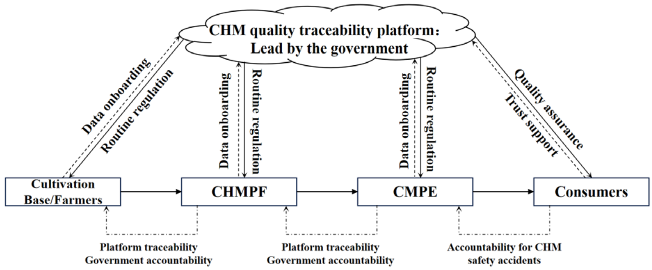


Figure 2. The workflow of the bidirectional control system
Source: Authors' own creation.

We set the objective functions of the dual-function model as follows. R's objective function consists of five parts, namely the sales profit of CHMs products, government subsidies or rewards, the cost of joining the platform, the benefits from collusion, and the punishment from the government for violations, which can be expressed as:

$$\pi_{RM}(p,\omega,i,j,\gamma,\alpha,\beta,\eta) = (p-\omega)q + b - (1-\eta)t_2 + \alpha t_1 - (1-\beta)(kjm_1 + \alpha im_2) \quad (5)$$

The objective function of S consists of four components: the profit from the sale of CHMs, the punishment shared for R, the cost of collusion, and the cost shared for R to join the platform, which can be expressed as:

$$\pi_{SM}(p,\omega,i,j,\gamma,\alpha,\beta,\eta) = (\omega-(1-\alpha)c_0)q - \beta(kjm_1+\alpha im_2) - \alpha t_1 - \eta t_2 \quad (6)$$

As the regulator of CHMSC, G only participates in the cooperative game, pursuing the maximisation of social welfare. G's objective function comprises four components: tax revenue and budget surplus, losses from accidents, the sum of rewards and penalties, and consumer surplus. This can be represented as:

$$\pi_{GM}(p,\omega,i,j,\gamma,\alpha,\beta,\eta) = dq + t_2 + (1-i-j)h - (1-i-j)km_3 + kjm_1 + \alpha im_2 - b + \tfrac{1}{2}q^2 + y(n)f \quad (7)$$

Where n denotes the number of participants in the coalition, $y(n)$ is given by: $y(n) = \begin{cases} 0, n = 0,1,2 \\ 1, n = 3 \end{cases}$. In the non-cooperative game segment, a Stackelberg game is established with R as the leader and S as the follower. In the cooperative game segment, three players can form $2^3 = 8$ possible coalitions, denoted as $\{\phi\}$, $\{G\}$, $\{R\}$, $\{S\}$, $\{N_1\} = \{G,R\}$, $\{N_2\} = \{G,S\}$, $\{N_3\} = \{R,S\}$ and $\{N_4\} = \{G,R,S\}$. All possible coalitions can be represented by the set Q.

R procures S's CHMs to manufacture products and sells to consumers. The retail price $p$set by R and the wholesale price ω set by S are strategies in the non-cooperative game segment, forming the competitive equilibrium.

In any competitive equilibrium, R determines the effort level γ to join the platform, S decides the cost-sharing proportion η, the punishment-sharing proportion β, and the collusion speculation coefficient α, and G decides the traceability effort coefficient i and the regulatory effort coefficient j.

Using the Minimax Theorem, we calculate the minimum expected profit for each coalition, serving as the characteristic function. Then, we prove the coalition's superadditivity and convexity. The Shapley value is used to allocate the profits of the grand coalition. Among these, we use the profits allocated to R and S as the pay-off functions in the non-cooperative game segment.

Finally, we establish a Stackelberg game to solve the price strategy, deriving the optimal competitive equilibrium. Then, we incorporate it into the cooperative game segment, allowing the determination of optimal solutions and profits in the cooperative game.

Theorem 1. In the cooperative game $v(p,\omega)$, the game is convex if $v(p,\omega)(\{A\}) + v(p,\omega)(\{T\}) \leq v(p,\omega)(\{A \cup T\}) + v(p,\omega)(\{A \cap T\})$ for $\forall\{A\} \subseteq \{N_4\}$ and $\forall\{A\} \subseteq \{N_4\}$.

Satisfying Theorem 1 indicates that the cooperative game is superadditive and convex. Every convex game has a non-empty core, where the Shapley value lies

(Nan et al., 2021). Allocating the payoffs in cooperative games by the Shapley value ensures stability.

Proposition 1. The Shapley value (Casajus and Huettner, 2014) calculation formula is given by:

$$\varphi_r(v(p,\omega)) = \sum_{r\in A\subseteq N_4} \frac{(|A|-1)!(n-|A|)!}{n!}(v(p,\omega)(A) - v(p,\omega)(A\backslash r)), r \in (N_4) \quad (8)$$

The specific process is illustrated in Figure 3. Under the background of digital intelligence, AI promotes data factors to facilitate the platform and combat collusion. The empowerment of data factors is a gradual process, which conforms to the investment patterns. Therefore, we divide the Model M into the data factors transformation (DFT) stage (Model M_I, where $h > m_3 + m_2 + m_1$) and the data factors facilitation (DFF) stage (Model M_O, where $h = 0$).

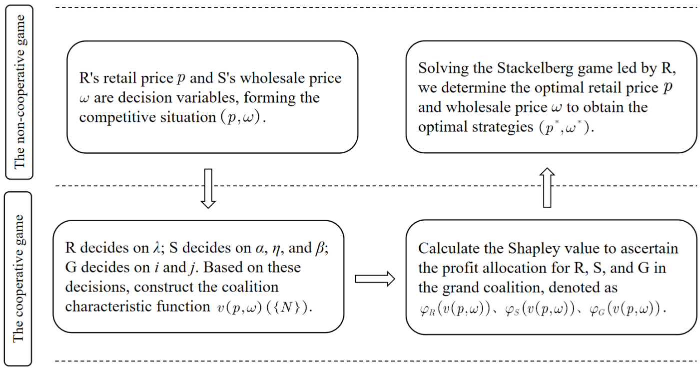


Figure 3. Process of the biform game

Source: Authors' own creation.

5.2 Data factors transformation stage

In the DFT stage, G allocates the substantial budget for platform construction, leveraging financial advantages to compensate for resource integration's deficiencies, with the budget denoted as $h > m_3 + m_2 + m_1$. The DFT stage in the Model M is denoted as Model M_I. The solution process is as follows.

We calculate the characteristic functions of the cooperative game segment, as shown in Corollary 2. Under any competitive equilibrium, all players aim to maximise their own benefits.

Corollary 2. *In the Model* M_I *, we can obtain:* $v_I(p,\omega)(\{\phi\}) = 0$, $v_I(p,\omega)(\{G\}) = dq - b + \frac{1}{2}q^2$, $v_I(p,\omega)(\{R\}) = (p-\omega)q + b + t_1 - m_2$, $v_I(p,\omega)(\{S\}) = \omega q - t_1$, $v_I(p,\omega)(\{N_1\}) = (p - \omega + d)q + t_1 + \frac{1}{2}q^2 + h - \delta_3 m_3$, $v_I(p,\omega)(\{N_2\}) = (\omega + d - c_0)q - b + \frac{1}{2}q^2 + h$, $v_I(p,\omega)(\{N_3\}) = (p - c_0)q + b$, $v_I(p,\omega)(\{N_4\}) = (p - c_0 + d)q + h + \frac{1}{2}q^2 + f$.

Based on Proposition 1, the Shapley values in the $v(p,\omega)$ are shown in Corollary 3, which verifies that the characteristic functions of all coalitions satisfy Theorem 1. Thus, the Shapley values can be the solution in the cooperative game.

Corollary 3. The Shapley values are: $\varphi_{RI}(v(p,\omega)) = (p-\omega)q + b + \frac{2t_1-m_2+f}{3} + \frac{h-\delta_3 m_3 - c_0 q}{6}$; $\varphi_{SI}(v(p,\omega)) = \omega q + \frac{\delta_3 m_3 - 2c_0 q + f}{3} + \frac{m_2+h-5t_1}{6}$; $\varphi_{GI}(v(p,\omega)) = dq + \frac{q^2}{2} - b + \frac{2h+f}{3} + \frac{t_1+m_2-\delta_3 m_3 - c_0 q}{6}$.

By using the backward induction method, the optimal solution is shown in Corollary 4.

Corollary 4. $p_I{}^* = \frac{150A\delta_4 + 108A\mu + 25c_0\delta_4\mu}{108\mu^2 + 300\delta_4\mu}$, $\omega_I{}^* = \frac{30A\delta_4 - 5c_0\delta_4\mu}{\delta_4(36\mu + 100\delta_4)}$, $q_I = A - \frac{150A\delta_4 + 108A\mu + 25c_0\delta_4\mu}{108\mu + 300\delta_4}$.

We set $F_I = 150A\delta_4 + 108A\mu + 25c_0\delta_4\mu$, $G_I = 108\mu^2 + 300\delta_4\mu$, $q_I = A - \mu p_I{}^*$,$p_I{}^* = F_I/G_I$. Substituting I_{N_4} and the optimal strategy profile$(p_I{}^*, \omega_I{}^*)$ into the payoff functions for R and S. We obtain: $f_{RI}(p_I{}^*, \omega_I{}^*) = b + \frac{f-m_2}{3} + \frac{h-\delta_3 m_3 - c_0 q_I}{6} - \frac{9q_I{}^2}{25\delta_4} + q_I p_I{}^*$; $f_{SI}(p_I{}^*, \omega_I{}^*) = \frac{\delta_3 m_3 - 2c_0 q_I + f}{3} + \frac{m_2+h}{6} - \frac{3q_I{}^2}{10\delta_4}$.

Substituting the optimal decisions I_{N_4} of the grand coalition and the optimal strategy profile$(p_I{}^*, \omega_I{}^*)$ into R's objective function$\pi_{RM}(p,\omega,i,j,\gamma,\alpha,\beta,\eta)$ and S's objective function$\pi_{SM}(p,\omega,i,j,\gamma,\alpha,\beta,\eta)$, we obtain: $\pi_{RMI}(\gamma,\beta,\eta) = \frac{\delta_2(\eta-1)\gamma^2}{2} + b - (A-\mu p_I{}^*)(\frac{AG_I - \mu F_I}{5\delta_4 G_I} - p_I{}^*)$; $\pi_{SMI}(\gamma,\beta,\eta) = (A-\mu p_I{}^*)(\frac{3AG_I - 3\mu F_I}{5\delta_4 G_I} - c_0) - \frac{\delta_2\gamma^2\eta}{2}$.

By solving equations $f_{RI}(p_I{}^*, \omega_I{}^*)$ and $\pi_{RMI}(\gamma,\beta,\eta)$, $f_{SI}(p_I{}^*, \omega_I{}^*)$ and $\pi_{SMI}(\gamma,\beta,\eta)$ simultaneously, we obtain: $\eta_I{}^* = \frac{2f+h+m_2+2\delta_3 m_3 + 2c_0 q_I - \frac{9q_I{}^2}{5\delta_4}}{4f+2h-m_2+\delta_3 m_3 + c_0 q_I - \frac{9q_I{}^2}{25\delta_4}}$.

Proposition 2. $\frac{\partial\eta_I{}^*}{\partial\delta_3} > 0$ if $f > \frac{25\delta_4 m_2 - 9q_I{}^2 - 25\delta_4 h}{50\delta_4}$, and $\frac{\partial\eta_I{}^*}{\partial m_2} > 0$ if $f > \frac{18q_I{}^2 - 25\delta_4 h - 25\delta_4\delta_3 m_3 - 25\delta_4 c_0 q_I}{50\delta_4}$.

Proposition 2 demonstrates that when social co-governance benefits generated by the bidirectional control system reach a critical threshold, S's share proportion of R's cost of joining the platform ($\eta_I{}^*$) is directly proportional to the punishment of G to R (m_2) and the unit technical loss coefficient caused by collusion (δ_3). Meanwhile, the increase of the unit technical loss coefficient caused by collusion (δ_3) and the government's penalty intensity (m_2) raises the probability of detecting non-conforming CHMs products. To stabilise collaborative relationships with R, S must assume higher platform adoption costs, thereby establishing closer partnerships to access shared platform benefits. Thus, during the DFT stage, intensified governmental regulatory penalties not only deter collusion but also promote close cooperation between R and S.

5.3 Data factors facilitation stage

After the initial transformation, the bidirectional control system was built. In the DFF stage, G can diminish the budget input and we set $h = 0$. The DFF stage in Model M is denoted as Model M_O.

In Model M_O, the characteristic functions of the coalitions $\{\phi\}$, $\{G\}$, $\{R\}$, $\{S\}$ and $\{N_3\}$are consistent with the Model M_I. The solution to the cooperative game segment of Model M_O is presented in Corollary 5.

Corollary 5. In the DFF stage, apart from the same ones in the DFT stage, the characteristic functions of the remaining three coalitions are: $v_O(p,\omega)(\{N_1\}) = (p-\omega+d)q+\frac{q^2}{2}$, $v_O(p,\omega)(\{N_2\}) = (\omega+d)q+m_2+\frac{q^2}{2}-t_1-b$, $v_O(p,\omega)(\{N_4\}) = (p+d)q+\frac{q^2}{2}+f$.

The subsequent solution process is the same as Section 5.2. We obtain Corollary 6 and Corollary 7.

Corollary 6. In the DFF stage, the Shapley values in the cooperative game are: $\varphi_{RO}(v(p,\omega)) = (p-\omega)q+b+\frac{f-2m_2}{3}+\frac{5t_1-c_0q}{6}$, $\varphi_{SO}(v(p,\omega)) = \omega q+\frac{f+m_2-2t_1}{3}-\frac{c_0q}{6}$, $\varphi_{GO}(v(p,\omega)) = dq-b+\frac{q^2}{2}+\frac{c_0q+f+m_2}{3}-\frac{t_1}{6}$.

Corollary 7. $p_O{}^* = \frac{48A\delta_4+27A\mu+8c_0\mu\delta_4}{27\mu^2+96\delta_4\mu}$ 、 $\omega_O{}^* = \frac{12A-2c_0\mu}{32\delta_4+9\mu}$ 、 $q_O{}^* = \frac{\delta_4(48A-8c_0\mu)}{27\mu+96\delta_4}$.

We also obtain $\gamma_O{}^2 = \frac{\delta_4\omega_O{}^{*2}+4m_2+c_0q_O{}^*-2f-6(1-\beta)(\delta_3jm_1+im_2)}{3\delta_2(1-\eta)}$, if $0 \le \delta_4\omega_O{}^{*2}+(6\beta-2)m_2-2f+c_0q_O \le 3\delta_2(1-\eta)$.

Proposition 3. In the Model M_O, we obtain $\frac{\partial\gamma_O{}^2}{\partial\eta} > 0$ and $\frac{\partial\gamma_O{}^2}{\partial\beta} > 0$.

Proposition 3 states that in Model M_O, R's effort level in joining the platform(γ_O) is positively correlated with S's share proportion of R's cost of joining the platform(η) and S's share proportion of R's punishment(β). Specifically, in the grand coalition, increasing the platform effort coefficient of R, the cost-sharing proportion borne by S for R, and the penalty-sharing proportion borne by S for R will increase. This is because in the DFF stage, the higher the cost incurred by R for joining the platform, the more preferred the platform-certified products are by consumers. Under the risk reduction, S proactively transfers risk by increasing the sharing proportion of cost and punishment to share the platform's benefits. Combined with the decrease in expected punishment, S incurs no losses, but gains the trust and orders from downstream enterprises such as R.

6. Comparisons and analysis

6.1 Two-stage comparison in the dual-function model

Table 1 compares the solution sets of decision variables for coalitions between Model M_I and Model M_O in the cooperative game.

Table 1. The comparison of coalition solution sets

Coalition	DFT stage (ModelM_I)	DFF stage (Model M_O)
$\{N_1\}$	$i = 0, j = 0, \alpha = 1$	$i = 1, j = 0, \alpha = 0$
$\{N_2\}$	$i = 0, j = 0, \alpha = 0$	$i = 1, j = 0, \alpha = 1$
$\{N_4\}$	$i = 0, j = 0, \alpha = 0, \eta_I{}^*$	$i + j = 1, \alpha = 1, \eta_O{}^*$

Source: Authors' processing.

In the coalition$\{N_1\}$, G and R ally to reduce S's motives for collusion. But during the DFT stage, driven by collusive profits, S still persuades R to collude, so $\alpha = 1$. In the DFF stage, data factors facilitate the platform to control collusion. High risk weakens S's collusive motivation, so $\alpha = 0$.

In coalitions $\{N_2\}$ and $\{N_4\}$, G encourages upstream companies to join the platform and downstream companies to cooperate. In the DFT stage, the collusion speculation coefficients are zero. S reduces collusion motives with a lower cost in the platform. In the DFF stage, the collusion speculation coefficients of both coalitions are one. This is because S adapts the mechanisms and upgrades collusive abilities. The overconfidence and benefits worsen collusion. Therefore, the platform should continuously upgrade to face new cheating challenges.

6.2 Two-stage comparison in the dual-function model

We obtain the following results from Corollary 1, Corollary 4, and Corollary 7.

Proposition 4. We take partial derivatives of the optimal prices and obtain the following conclusions: (i) $\frac{\partial p_i{}^*}{\partial \delta_4} < 0$; (ii) $\frac{\partial \omega_i{}^*}{\partial \delta_4} < 0$; (iii) $\frac{\partial p_j{}^*}{\partial A} > 0, \frac{\partial \omega_j{}^*}{\partial A} > 0, \frac{\partial p_0{}^*}{\partial v} > 0, \frac{\partial \omega_0{}^*}{\partial v} > 0$, where $i = 0,1,2$ and $j = 1,2$, and 0, 1, 2 denote Model N, Model M_I, and Model M_O.

Proposition 4(i) presents that as the collusion cost coefficient increases, the optimal retail price decreases. This is because products through collusion have quality gaps compared to normal products. A low retail price can decrease the risk of product incidents. Proposition 4(ii) indicates that an increase in the collusion cost coefficient will lead S to lower the optimal wholesale price under G's heightened supervision and penalties. To maintain collusion, S chooses to concede profits to R by reducing the wholesale price. S will abandon collusion when the burden becomes unbearable. Proposition 4(iii) reveals that if the total market demand increases, the optimal wholesale price and the optimal retail price will increase. When market demand is high and supply is less than demand, we find that R and S tend to raise prices to obtain higher profits, which aligns with economic intuition.

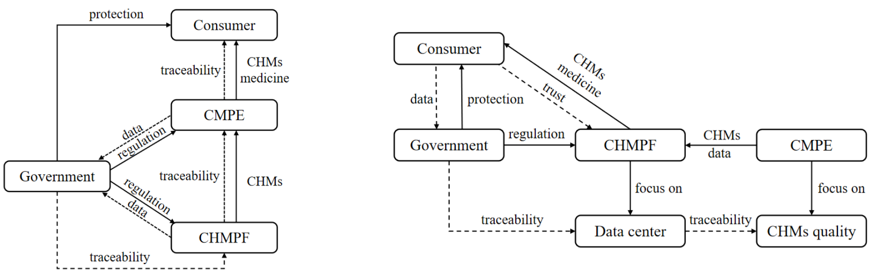
Proposition 5. We compare the demand in Model M and obtain the following conclusions: (i) $q_I < q_O$; (ii) $q_0 < q_I < q_O$, *if* $A > l_1$, *where* $l_1 = \frac{100\alpha c_0\delta_4\mu+600v\alpha\delta_4+216v\alpha\mu+25c_0\mu^2}{150(4\alpha\delta_4+\mu)}$.

Proposition 5(i) states that actual market demand increases from the DFT stage to the DFF stage. This indicates that the bidirectional control system promotes market expansion and consumer trust with data factors. Proposition 5(ii) clarifies that when market demand exceeds the threshold l_1, the demand in Model N is lower than that of Model M. This shows that the system improves consumers' trust in platform-certified products and benefits the healthy growth of the CHMs industry.

Proposition 6. The optimal prices satisfy the following: (i) $p_O{}^* < p_I{}^*$; (ii) If the actual market demand is high ($A > 2v$), then $p_0{}^* < p_O{}^* < p_I{}^*$; (iii) $\omega_I{}^* < \omega_O{}^*$; (iv) If the actual market demand is high ($A > l_2$), then $\omega_0{}^* < \omega_I{}^* < \omega_O{}^*$, where $l_2 = \frac{20\alpha\delta_4c_0+5c_0\mu^2+100v\delta_4+36\mu v}{30(4\alpha\delta_4+\mu)}$.

Proposition 6(i) and (iii) demonstrate that in Model M, the optimal retail price in the DFT stage is higher than that in the DFF stage, while the optimal wholesale price is lower. R should pay the costs to join the platform in the DFT stage, so it increases the retail price to secure cash flow. In the DFF stage, R decreases the retail price to capture more market demand, enhance brand recognition, and expand revenues. Consumer awareness of high-quality CHMs products increases S's cost. Then, S raises the wholesale price to maintain profits.

Proposition 6(ii) and (iv) show that when $A > max\{2v, l_1\}$, in Model N, the optimal retail price and the optimal wholesale price are both lower than those in Model M. Besides, with the CHMs market demand expanding, consumers prefer CHMs products with quality assurance and are willing to pay a premium. Consequently, implementing regulatory and traceable functions enhances the platform's effectiveness in improving the quality of CHMs and fostering sustainable market development. This validates the theoretical robustness of our models.



(a)The mechanism in the DFT stage (b)The mechanism in the DFF stage

Figure 4. The mechanism transformation in the dual-function model

Source: Authors' own creation.

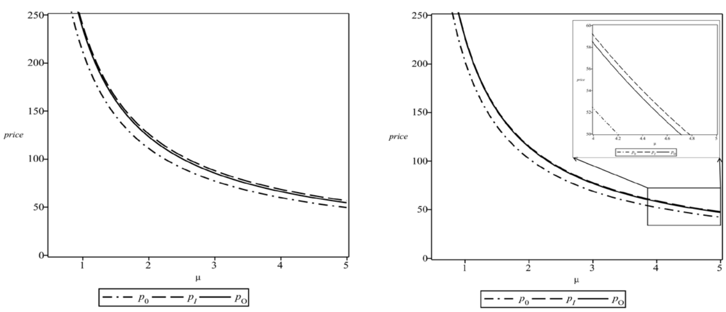
In conclusion, Figure 4 demonstrates the transformation of the governance mechanism under the dual-function model. Compared to Figure 3, the platform combines regulatory and traceability functions, alleviating the uneven distribution of government resources in Model N. In the DFT stage, the bidirectional control system simultaneously manages the data of CHMPF and CMPE, initially achieving the full-process data on the chain, establishing a traceability system, and controlling collusion. But the government lacks connections with consumers and should invest more resources to achieve comprehensive regulation and traceability of the CHMs market. In the DFF stage, a mature bidirectional control system consolidates CHMs data by establishing a data centre in CMPE, simplifying data processing, and creating a network among the government, consumers, and enterprises. This stage realises information exchange and resource sharing, providing a channel foundation for governance collaboration and improving the quality of CHMs.

The transformation from parallel management to series management is the key for the government to coordinate regulatory and traceability functions. Data factors empowerment in the bidirectional control system is significant to cooperative governance, maintaining market order, protecting consumer rights, and promoting the high-quality development of CHMs.

6.3 Parameters sensitivity analysis

The CHMs products have unique pharmacological properties and significant environmental sensitivity. Under normal circumstances, the demand is stable because of the similar efficacy of products and no monopolistic market dominance. However, public demand for specific CHMs products fluctuates dramatically in emergencies such as pandemics. For example, during the COVID-19 pandemic, the demand for Isatis root and Lianhua Qingwen surged sharply, contributing to the high demand and quickly selling out despite a significant price increase. This phenomenon indicates that consumers decrease the price sensitivity coefficient in some situations and are willing to pay a premium.

We analyse the impact of the price sensitivity coefficient on the retail price, the wholesale price, and the supply chain profits in Models N, M_I, and M_O, which ranges from 0.5 to 5. Based on the magnitude of the collusion cost coefficient, Figure 5, Figure 6, and Figure 7 illustrate the simulations for two scenarios, which are $\delta_4 = 5$ and $\delta_4 = 25$.



(a)$\delta_4 = 5$ (b)$\delta_4 = 25$

Figure 5. The impact of μ on the R's optimal retail price

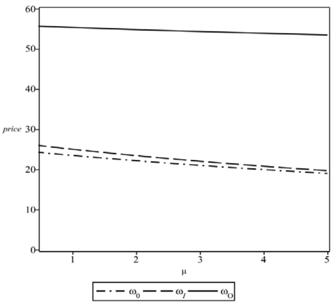
Source: Authors' own creation.

Figure 5 indicates that if the price sensitivity coefficient increases, the optimal retail price will diminish. It is evident that the optimal retail price in the DFF stage is higher than that in the DFT stage, and in Model N, it is lower than that in both stages of Model M under certain conditions, which matches with Proposition 6(i) and 6(ii). Comparing Figure 5(a) and Figure 5(b), regardless of the collusion cost coefficient, the optimal retail price in Model M is higher than that in Model N. When the collusion cost coefficient is low, the price gap between Model M_I and Model M_O is larger than when it is high. This indicates R's prices in different stages are affected by the higher collusion cost coefficient, decreasing as it increases.

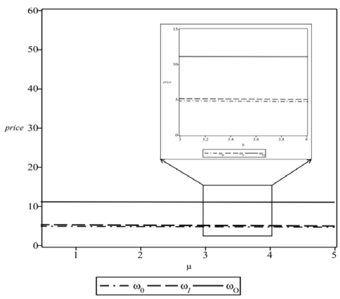
On the one hand, in the DFF stage, collusion motives occur again. Low price mitigates quality risks, so the price is lower in the DFF stage. On the other hand, Collusion motives decrease with the increasing collusion cost coefficient. High prices maintain profits, resulting in a smaller price gap compared to the DFT stage.

Figure 6 shows that the optimal wholesale price in the DFF stage is higher than that in the DFT stage. Satisfying certain conditions, the price in Model N is lower than other models. The optimal wholesale price decreases if the price sensitivity coefficient becomes larger. Compared with Figure 5, the fluctuation amplitude of the wholesale price is much less than that of the optimal retail price. This is because R exhibits vulnerability to consumer demand fluctuations due to direct market interfaces. But S accesses consumer insights through R, with fewer price sensitivity effects. Therefore, the bullwhip effect can alleviate the impact of consumer price sensitivity on the pricing strategies of upstream enterprises in the supply chain.

Compare Figure 6(a) and Figure 6(b), the optimal wholesale price in Model M_O is higher than those in Model N and M_I. When the collusion cost coefficient is low, the wholesale price is more influenced by the price sensitivity coefficient, with a more pronounced downward trend. Besides, the price gap between Model M_I and Model N in a high collusion cost coefficient (Fig.6(a)) is smaller than that in a low (Fig.6(b)). In the DFT stage, S should take some costs of the platform. However, in the DFF stage, S focuses on product quality and submits data from R to the platform. Thus, S can increase price under the dual guarantee of credibility and quality.



(a)$\delta_4 = 5$

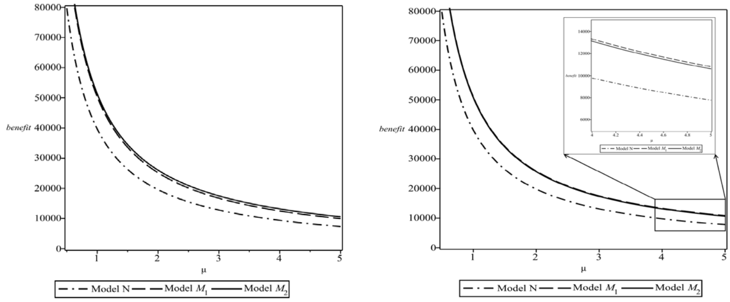


(b)$\delta_4 = 25$

Figure 6. The impact of μ on the S's optimal wholesale price

Source: Authors' own creation.

Due to the complexity of the CHMSC profits, this section employs a numerical simulation for comparison. Figure 7 clearly illustrates that, regardless of the collusion cost coefficient, the supply chain profit in Model N is smaller than that in Model M when the price sensitivity coefficient changes. This shows that the bidirectional control system effectively curbs collusion while enhancing supply chain profits. Our study has practical implications and promotes the high-quality development of CHMs.



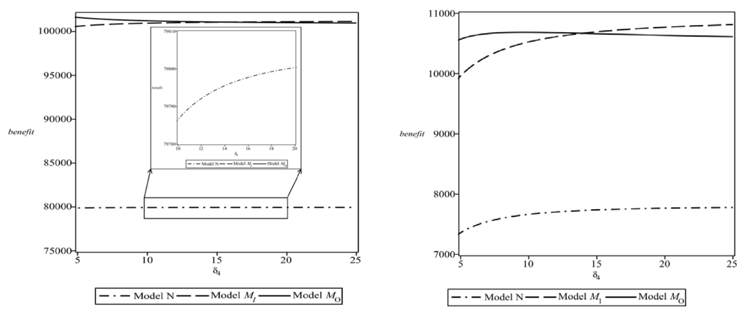
(a)$\delta_4 = 5$ (b)$\delta_4 = 25$

Figure 7. The impact of μ on the CHMSC profits

Source: Authors' own creation.

Then, we obtain that if the price sensitivity coefficient increases, the supply chain profit will decline. This shows the supply chain profit will be compromised if the CHMs products are price-sensitive, or increased if the products are less price-sensitive. The government should enhance regulatory measures to prevent sales panic driven by public sentiment. The bidirectional control system reduces the price sensitivity of CHMs products and promotes the stable development of the CHMSC.

Next, we analyse the impact of the collusion cost coefficient on the supply chain profit in Models N, M_I, and M_O, which ranges from 1 to 24. Based on the magnitude of the price sensitivity coefficient, Fig. 8 illustrates the simulations for two scenarios, which are $\mu = 0.5$ and $\mu = 5$.



(a)$\mu = 0.5$ (b)$\mu = 5$

Figure 8. The impact of δ_4 on the CHMSC profits

Source: Authors' own creation.

Figure 8 implies that in Model N and Model M_I, the supply chain profit has a positive correlation with the collusion cost coefficient, and a negative one in Model M_O. This is because the high cost weakens collusive motives, reducing the negative impact of collusion. But in the DFF stage, enterprises may collude again and weaken supply chain profits. Consequently, the bidirectional control system should be upgraded in the DFF stage to eliminate collusive opportunities. Compared Figure 10(a) and Figure 10(b), the impact of the collusion cost coefficient on supply chain profit is weak when the price sensitivity coefficient is low. Consumers' rationality decreases in emergencies, reducing the effectiveness of platform governance. It is essential to establish emergency mechanisms to avoid this phenomenon.

Additionally, we calculate the threshold of the collusion cost coefficient$\delta_{4i}(i = 1,2)$. It shows that when it is below the threshold, the supply chain profit in the DFT stage is lower than that in the DFF stage. Conversely, when it is above the threshold, the supply chain profit in the DFF stage is lower than that in the DFT stage. The calculation is $\delta_{41} \approx 15.72(\mu = 0.5) > \delta_{42} \approx 13.93(\mu = 5)$, which indicates that the threshold under the low price sensitivity coefficient is greater than the high one.

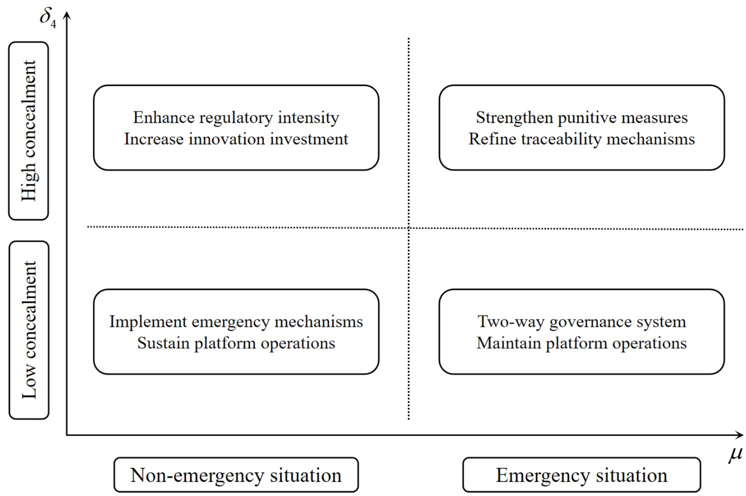


Figure 9. Matrix of governance policies

Source: Authors' own creation.

In summary, we divide scenarios based on the level of price sensitivity coefficient into emergency and non-emergency situations, and the level of collusion cost coefficient into high- and low-collusion concealment scenarios. To maximise supply chain profits, the government should adopt different governance approaches based on varying contexts and collusive technologies, as depicted in Fig. 9. Especially, in non-emergency situations with low collusion concealment, the existing platform can maximise the effectiveness of the bidirectional control system. In emergencies with high collusion concealment, the government should increase investment and innovate again to control collusion.

7. Comparisons and analysis

In this paper, we propose a bidirectional control system empowered by data factors under the CHMs quality traceability platform, providing theoretical guidance for controlling collusion. Comparing Model N with Model M, our study shows how data factors empower the bidirectional control system and control collusion. The conclusions are as follows.

(1) The bidirectional control system can enhance pricing strategies and control collusion by increasing costs and reducing motivation. The optimal retail price, wholesale price, and supply chain profits in the dual-function model are higher than those in the single-function model.

(2) The bidirectional control system empowered by data factors has phased characteristics. In the DFT stage, increasing rewards and punishments can control collusion and promote cooperation among enterprises. In the DFF stage, CMPEs prefer to join the platform, and CHMPFs share the platform's benefits by transferring costs and risks.

(3) Collusive costs and consumers' price sensitivity directly affect pricing strategies and supply chain profits. Collusion costs are negatively correlated with product pricing and supply chain benefits, while price sensitivity is negatively correlated with pricing and positively correlated with supply chain benefits.

(4) The bidirectional control system enhances consumers' recognition of the platform-certified CHMs products, increasing market demand. Data factors strengthen this effect. Therefore, platform certification encourages product premiums, but high price sensitivity will reduce the premium effect. The bullwhip effect can alleviate the impact of price sensitivity on the pricing strategies of upstream enterprises in the supply chain.

Fifth, the empowerment of data factors in the bidirectional control system indicates the transformation of the governance mechanism from a parallel model to a series model. Establishing data centres can alleviate the pressure on resource allocation and data management, achieving information intercommunication and resource sharing. The government can coordinate supervision and traceability for governance, clarify the responsible entities, implement dynamic rewards and punishments, and improve the quality of CHMs.

Our study provides managerial insights for CHMSC.

(1) The CHMs market is vulnerable to public sentiment and consumer attitudes. The government should dynamically adjust investments in platform construction. For example, investing more in controlling collusion is necessary in emergencies with high collusive concealment.

(2) Data factors are crucial for the construction of the CHMs quality traceability platform. The government should pay more attention to the application of technologies such as artificial intelligence or blockchain, accelerate the transformation of data resources into data factors, and thereby support the sustainable development of the CHMSC.

(3) Governance collusion is a long-term strategy, and governance measures must continually evolve. High profits will encourage cheating motivation and diverse forms. To ensure the quality of CHMs, the bidirectional control system should continuously upgrade and iterate to enhance the resilience of the CHMSC and crack down on all kinds of quality cheating behaviours.

Our current model can be extended in a few ways. First, this paper proposes a government-led platform, while some firms have independently built traceability systems in practice. Integrating these systems with our platform to combat CHMs quality cheating behaviours may offer additional insights into the CHMs industry. Second, our study distinguishes CHMPFs and CMPEs as separate entities, yet vertically integrated enterprises exist, which cover the entire value chain from cultivation to manufacturing. Whether such integrated firms engage in internal quality cheating remains unclear. Third, we focus exclusively on the governance of quality cheating behaviours, without considering the disposal of substandard CHMs, which could be another direction for future research.

Acknowledgements: *This study is supported by the Hebei Natural Science Foundation (No. G2024203023); Yanzhao Golden Terrace Talent Attraction Program - Backbone Talent Project (Overseas Returnee Platform) of Hebei Province (No. A20240027); 2024 Hebei Provincial Social Science Development Research Project (No. 202401045); Funding Support from the Collaborative Innovation Center for Port Industry Development in Coastal Areas of Hebei Province (No. lgzx202411).*

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