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SUBSIDY AND PRICING STRATEGIES OF AN AGRI-FOOD SUPPLY CHAIN CONSIDERING THE APPLICATION OF BIG DATA AND BLOCKCHAIN

Pan Liu*, Ziran Zhang and Fen-Yi Dong

Abstract. Based on the advantages of Big Data and blockchain in food traceability area and information sharing area, it has attracted widespread attentions. However, it is not so popular in agricultural field, a vital reason is the scarcity of effective incentives. Government incentive as an important incentive measure is thought to be useful. To study the subsidy rules in the new background, we chose an agri-food supply chain with one producer and one retailer as research object and divided government incentive into direct incentive and indirect incentive. Then, considering the changes of consumer perceived safety on agri-food in the new environment, the demand function was revised. Furthermore, we proposed and analyzed three subsidy models and their benefit functions considering the information service inputs based on Big Data and blockchain (BBIS). Findings: (1) The subsidy models will not change the variation tendency of prices and benefits with the BBIS optimization coefficient, the BBIS investment costs from the producer and the retailer, the ascension of the unreliability coefficient of quality safety and the agri-food quality level. (2) When the subsidy coefficients about direct and indirect subsidies can meet a relationship, benefits of chain members in the indirect subsidy model are higher than them in the direct subsidy model. Findings offer a theoretical guidance for government departments to make and implement the subsidy strategies. In addition, for company, it can provide a theoretical guidance on setting pricing strategies in the new technology background.

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1. Introduction

In China, following the enhancement of consumer living standard, their consumption demands are also changing. Fresh, green and safe agricultural products were becoming more and more popular [5, 25]. However, over the past 10 years, a series of agricultural product quality and safety incidents deeply hurt consumers' confidence [26]. Especially in the period of COVID-19 prevention and control, food safety incidents from cold chain occurred frequently in China. To enhance consumers' confidence and purchase intention, information traceability and supervision based on the product life cycle was thought to be critical [6, 16, 37]. In addition, about 94% of participants would buy products with transparent sourcing information [64]. Although, many technologies (Internet of Things, Radio Frequency Identification, Near Field Communication, etc.) had been used to monitor and track food quality, traceability system based on these technologies was a centralized server-client

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Information & Management College, Henan Agricultural University, NongYe Road 63, Zhengzhou, Henan, P.R. China.
*Corresponding author: hnycliupan@163.com

mechanism [33, 45]. The data managers in the centralized server-client mechanism are also the supply chain members, when they found these data are adverse, these data may be modified. So, the credibility of the traditional traceability service is not high. Therefore, for consumers and chain partners, gaining the full information about the product life cycle and tracking the agri-food origins were very difficult [20, 56]. Blockchain technology as a shared database is thought to be useful in solving the trust issues, but its statistical analysis ability for data is weak, and the storage and statistical analysis of data are the strengths of Big Data. Thus, integrating Big Data technology into blockchain could greatly explore the data value and usage potential in blockchain [62].

The fusion usage of big data and blockchain was a management revolution and can improve enterprises' competitive advantage [32]. In fact, many enterprises had implement their Big Data and blockchain plan when they realized that its application could help reduce operation costs [58], for instance, Zhongnan Group and HeiLongJiang Agriculture Company Limited worked together to build an agri-food traceability platform based on Big Data and blockchain [51]. JD (the second largest online retailer in China) and Ali Cloud have launched their traceability service and retail service based on blockchain and Big Data. In fact, in other countries, some information technology providers (ripe.io, IBM, etc.), producers and retailers (Tyson food, Walmart, etc.) have themselves traceability plans.

Although the fusion application of Big Data and blockchain has huge advantages, in the past days, it is not so popular in agri-food supply chain area because of the contradiction between investment and income. Currently, in China, with more and more frozen products were detected with COVID-19 Virus in their outer packaging [9, 47], blockchain-based traceability has attracted the attention and concern of enterprises and governments again. However, facing big inputs in these technology, companies need government incentives. In addition, for traditional agricultural producers or retailers, the integrated R&D of blockchain and big data is very challenging. Therefore, many enterprises choose to purchase information services based on big data and blockchain (hereafter, BBIS) from specialized information technology companies. For government, implementing this incentive can also help them better supervise product. In these conditions, chain members should think over and focus on the following questions.

(1) How many subsidy models? Which one is the best?
(2) In different subsidy models, how to price can gain more benefits?

The core of these questions is to discuss subsidy and pricing strategies of an agir-food supply chain considering the BBIS application.

Although, applications of Big Data and blochchain in agri-food supply chain had attracted many researchers' attention, most of them focused on technical integration and breakthrough, conceptual definition and division, etc. [45, 68]. Based on game theory and considering the changes of demand function and quality in the new environment, discussing subsidy and pricing strategies of an agri-food supply chain is few.

Therefore, the goal of our study is to research subsidy and pricing rules of an agir-food supply chain considering the changes of consumers' perceived product quality safety and the demand equation in the new background. To gain these rules, we focused on government incentive and divided it into direct subsidy and indirect subsidy based on previous efforts [52]. In addition, the perceived safety about agri-food was adopted to reflect the effects of traceability on agri-food safety in the new environment. Then, considering the changes of demand function because of using BBIS, an agri-food supply chain with one prouder and one retailer was chosen as the research object, and then three game models were built. For government departments, results can offer theory bracings and help them make and implement the subsidy strategies.

There are two innovations: (1) the perceived safety of agri-food was adopted to reflect the effects of traceability on agri-food safety in the new environment, based on this, we revised the demand function. (2) Dividing government incentives into direct subsidy and indirect subsidy, then, building three benefit models considering BBIS and quality R&D inputs.

This study is organized as follows. Section 1 explains the study background. Section 2 is literature review. Section 3 introduces parameter and model descriptions. Section 4 presents subsidy and pricing strategies in different subsidy models. Section 5 shows a numerical simulation. Section 6 is conclusions and significances. Section 6.3 is limitations and future researches.

2. Literature review

Researches related to this paper can divided three aspects. The first is agri-food supply chain management, and the second is the fusion applications of Blockchain and Big Data, and the third is subsidy strategies in agri-food supply chain.

2.1. Agri-food supply chain management

The concepts of agri-food supply chain management are from supply chain management. In the 21st century, if an enterprise wants to gain more competitive advantage, paying attention to the effective management of supply chain may help them [31]. In recent years, regarding the discussions of supply chain management are very rich in agricultural product area. For instance, Ali and Gölgeci [1] discussed the effects of consortia and social capital on mitigating climate risks in an agri-food supply chain. Stranieri *et al.* [48] studied the impact of blockchain technology on supply chain profits by through semi-structured interviews to collect data. Rajagopal *et al.* [42] offered a new method to predict the retailing resilience based on grey theory and Markov models. Pérez-Mesa *et al.* [40] put forward a strategic analysis framework of agri-food supply chain. Hu *et al.* [18] introduced management strategies of an online green agri-food supply chain.

There are many researches about the agri-food supply chain management. These researches offered us a big and wide perspective to study this question. However, efforts closely related to this research also have the fusion applications of Blockchain and Big Data, and subsidy strategies in an agri-food supply chain. Therefore, in the next section, we will analyze and discuss the relevant literatures.

2.2. Fusion applications of Blockchain and Big Data

In the past ten years, Big Data have attracted widespread attention from scientific and engineering areas because of its huge potential values. However, Big Data have also many challenges needing to solve for better service, and privacy and security are thought to be important issues. For instance, Big Data saving in Cloud will achieve effective management, but facing the risk of being distorted, and the data integrity cannot be guaranteed. These would damage the value of data [34, 44]. Blockchain as a sharing database has appeared as an attractive approach for solving the privacy and security problem of big data. In fact, many researches have also brief mentioned the fusion application of blockchain and big data [12, 35, 36]. Recently, Deepa *et al.* [13] deeply introduced opportunities about blockchain for big data (*e.g.*, improving data security and integrity, fraud prevention, enhancing data sharing and quality, etc.). Based on blockchain technology, Li and Zhao [25] built a new public auditing model to verify data integrity in Cloud.

Based on the aforementioned advantages, in supply chain management area, the fusion application of big data and blockchain also caused widespread concern. For instance, Tian [53] analyzed the superiorities and deficiencies of adopting big data and blockchain in building traceability system of an agri-food supply chain. Rubio *et al.* [43] proposed a decentralized supply chain model in the fusion application environment of big data and blockchain. Based on lightweight blockchain, Jangirala *et al.* [21] proposed an authentication system for supply chain in the background of 5G mobile edge computing. In practice, Thomas Bocek used blockchain to ensure the public availability and immutability of product temperature data in a drag supply chain [11]. IBM worked with Walmart to construct a platform based on blockchain, Cloud technology and big data. This traceability platform could greatly shorten the agri-food traceability time and improve the transparency of supply chain information [4]. A blockchain-based platform for supply chain management could help to collect product information and share it credibly and securely [24]. Research showed that the fusion application of Big Data and blockchain could help to enhance the sustainability of supply chain [66]. "Blockchain + Big Data" can rely on its above advantages to solve many challenges faced by the supply chain [54]. Sundarakani *et al.* [49] proposed big data-driven blockchain implementation measures in supply chain management. Unal *et al.*

[57] proposed a practical method that integrates blockchain and FL-based big data analysis to provide privacy protection and secure big data analysis services.

In the agri-food supply chain area, the related researches are not so rich, especially, from the aspect of game theory, studies are rarely. In 2018, Rabah [41] introduced the application of big data and blockchain in agriculture area. Facing the problems of data collection and analysis in the process of agri-food production and currency, a new model was developed based on big data and blockchain [59]. Kamble *et al.* [23] thought if decision makers wanted to build a data-driven green supply chain, Big Data and blockchain would help them. However, the aforementioned efforts did not consider how to encourage chain members to use the new technology. In the combination application of big data and blockchain, Liu [26] explored the investment and coordination strategies considering the changes of agri-food freshness and greenness. Wu *et al.* [61] studied the optimal decisions of supply chain members when the blockchain-based traceability was constructed in different modes, and found that whether adopting blockchain technology was the optimal decision was related to factors such as consumers' acceptance of products without blockchain. Collart and Canales [10] discussed whether blockchain can improve the operation of the fresh agricultural product supply chain and the limitations and challenges of future development. However, they did not consider the changes of agri-food quality in the new environment.

In summary, existing researches believe that the fusion application of blockchain and big data has great value in enhancing the information value. The related tractability system can improve consumers' perceived value about product quality. However, studying the subsidy and pricing things is failing considering the changes of agri-food quality in the new environment. Therefore, in this study, we will discuss this problem. Before that, we should know government subsidy strategies in agriculture field.

2.3. Subsidy Strategies in agri-food supply chain

Although, about the effects of agricultural subsidies, there is controversy, many studies thought that appropriate subsidy policies could increase farmers' incomes and added the agricultural yield [46, 67]. To encourage grow crops, many countries had implemented agricultural subsidy policies. In China, over the past 40 years, there was a dramatic shift in agricultural policy, which now involved a wide range of policy tools (including output policy, input policy, public infrastructure, etc.) [30]. According to the objects of government subsidies, it can be divided into the following two aspects [68]. Firstly, the government subsidizes the supply side of produce. Secondly, the government subsidizes the demand side of agricultural products. From the view of supply chain management, researches about government subsidy polices are relatively abundant. For instance, based on a three-stage contract-farming supply chainf and considering chain members' risk preference characteristics, Peng and Pang [39] analyzed the optimal benefits strategies and the effects of the subsidy on chain partners' profits. Considering the budgetary constraints of subsidies, the environmental benefits of bioenergy usage, farmers' risk aversion and the output uncertainty of raw material, Ye *et al.* [63] studied the optimal government subsidy plan for chain members. Zhang *et al.* [66] and Chen *et al.* [7] studied the impact of quantitative subsidies and emission reduction innovation subsidies on agricultural pollution. Zhang *et al.* [66] thought that neither environmental innovation subsidy nor production subsidy could solve the dilemma of increasing production and environmental protection, and only a mixed subsidy scheme was the most effective. A survey from Wang *et al.* [60] indicated that input subsidies (*i.e.*, the direct grain subsidy, the machinery subsidy, etc.) could add the incomes of Chinese farmers. In addition, there are many efforts focusing on subsidy rules of fresh-keeping effort. For instance, Liu and Wang [27] constructed an evolutionary game model of logistics outsourcing considering fresh-keeping subsidies, and analyzed the realization path that fresh companies and third-party logistics were willing to invest in fresh-keeping effort. The subsidy about BBIS belongs to the input subsidy strategy. However, from a supply chain perspective, discussing the subsidy policies about BBIS and pricing rules of an agri-food supply chain is few.

Our research are closely related with government subsidies on agri-food traceability. In fact, using blockchain technology was a promising method to encourage agri-food traceability system application and applying subsidy strategy [16,55]. Meanwhile, to better monitor the quality and safety of products and realize the rapid traceability about the safety incident reasons, government subsidy for agri-food traceability system or application were implemented in many countries [2,3]. In China, although government subsidy for agri-food traceability system could reduce firms' extra costs, the company could not continue to receive government subsidies [8]. It received government support in the initial stage of the traceability system establishment. However, a survey from China indicated that 76% consumers did not know the traceability system [8]. Based on the incomplete information game, Fu *et al.* [15] discussed the optimal subsidy polices about IoT investment and investment decision issues. Hou *et al.* [17] investigated consumers' preferences for traceable pork with different safety levels and found that consumers were willing to pay extra to obtain traceability information, and the government should increase subsidies for the construction of the traceability system. Hu *et al.* [18] researched dynamic strategy of food supply chain partners considering government subsidy for green innovation and traceability technology. However, the traditional traceability systems usually did not cover the entire supply chain, nor could they ensure the openness and transparency of data [50], while "Blockchain + Big Data" could realize information sharing across the entire chain. However, they did not analyzed the effects of blockchain and big data application on agri-food traceability.

In summary, based on the aforementioned analyses, we can find the following shortages: (1) government subsidy for agri-food traceability can motivate participants to adopt traceability systems or services. However, existing researches about the subsidy polices do not fully consider the effects of traceability system or service (*e.g.*, BBIS) on the quality and safety of agricultural products and operating costs. (2) Pricing rules considering government subsidy strategies are not discussed in different subsidy models. Therefore, in this paper, we will further enrich these studies.

3. Parameter and model descriptions

3.1. Parameter description

μ is the retail price discount coefficient.

p^i indicates the retail price in different subsidy models, here, $i = \{\mathrm{NI}, \mathrm{WID}, \mathrm{WII}\}$. The NI model demonstrates that agri-food chain members will invest in BBIS and government will not provide any subsidy policy. The WID model indicates that agri-food chain members will invest in BBIS and government will provide direct subsidy policy. The WII model shows that agri-food chain members will invest in BBIS and government will provide indirect subsidy policy.

λ^i is the unreliability coefficient of quality safety in different subsidy models.

q shows the product quality safety.

$C(q)$ is the unit cost of product quality, here, $C(q) = zq^2/2$, and $z > 0$.

w^i expresses the wholesale price in different models.

c_p is the production cost of producer.

c_r is the sale cost of retailer.

ϑ is the cost optimization coefficient because of using BBIS. According to the research Liu [26], the fusion application of BBIS and firms' internal information can help to optimize production and sale costs. Therefore, we make ϑ as the cost optimization coefficient.

γ is the undertaken cost coefficient of chain members and we can call it cost discount coefficient

c_{op} and c_{or} expresses the BBIS costs from the producer and the retailer, respectively.

3.2. Model description

The demand forecasting based on Big Data and Blockchain will be more precise. In this paper, we assume that the total demand in the market is 1. In addition, the market demand will be affected by the retail price and the product quality. In the traditional environment, the market demand has a negative relationship with the retail price and has a positive relationship with the product quality. However, in the fusion application environment about Big Data and blockchain, the unreliability of quality information can be better to express the relationship between the market demand and the product quality. In fact, it is similar with previous researches [28,29]. Based on the study of Liu [26], we get formula (3.1).

$$D^i = 1 - \mu^x p^i - \lambda^i q. \tag{3.1}$$

In this formula, D^i indicates the market demand in different subsidy models. Here, $i = \{\mathrm{NI}, \mathrm{WID}, \mathrm{WII}\}$. When $i = \{\mathrm{NI}, \mathrm{WID}\}$, $x = 0$, otherwise, $x = 1$.

3.3. Assumptions

(a) The producer provides only an agri-food and sells these product monopoly. In addition, it has enough production capacity. Chain members are risk neutral and completely rational.
(b) Target consumers are very concerned about the product quality. In other words, buyers are very like the product with high quality and low price.
(c) To better meet the market demand and add the reliability of product quality, producer should know the demand information timely, correctly and accurately, thus, the producer will adopt BBIS. To better implement ordering decisions and add the reliability of product quality, the retailer should also grasp the demand information, thus, the retailer will adopt BBIS.

4. Subsidy and pricing strategies in different subsidy models

4.1. NI model

Before discussing the subsidy rules and pricing policies of the proposed three subsidy models, we should know the investment threshold value. Therefore, benefits of chain members in the no subsidy condition should be explored, in this paper, we call it NN model.

In the NN model, agri-food chain members will not invest in BBIS. The producer as the decision leader will set the agri-food wholesale price. Based on the wholesale price, the retailer will set the agri-food retail price. Revenue functions of the retailer and the agri-food producer see formulas (4.1) and (4.2), respectively.

$$\pi_p^{\mathrm{NN}} = \left(w^{\mathrm{NN}} - c_p\right) D^{\mathrm{NN}} \tag{4.1}$$
$$\pi_r^{\mathrm{NN}} = \left(p^{\mathrm{NN}} - w^{\mathrm{NN}} - c_r\right) D^{\mathrm{NN}}. \tag{4.2}$$

Based on the backward induction method and formula (4.2), we get $p^{\mathrm{NN}}(w^{\mathrm{NN}})$. Then we put $p^{\mathrm{NN}}(w^{\mathrm{NN}})$ into formula (4.1) and get the optimal wholesale price w^{NN^*}. According to w^{NN^*}, we get the optimal retail price p^{NN^*}. Putting w^{NN^*} and p^{NN^*} into formulas (4.1) and (4.2), we get the optimal revenues of chain members and Inference 4.1.

Inference 4.1. The optimal prices and revenues of chain members are expressed as ($\pi_p^{\mathrm{NN}^*}$, $\pi_r^{\mathrm{NN}^*}$, w^{NN^*}, p^{NN^*}), here, $\left(\pi_p^{\mathrm{NN}^*}, \pi_r^{\mathrm{NN}^*}, w^{\mathrm{NN}^*}, p^{\mathrm{NN}^*}\right) = \{(1 - \lambda^{\mathrm{NN}} q - c_r - c_p)^2/8 - zq^2/2,\ \left(1 - \lambda^{\mathrm{NN}} q - c_r - c_p\right)^2/16,$ $\left(1 + c_p - c_r - \lambda^{\mathrm{NN}} q\right)/2,\ \left(3 + c_p + c_r - 3\lambda^{\mathrm{NN}} q\right)/4\}$.

In the NI model, agri-food chain members will invest in BBIS, however, government will not provide any subsidy policy to encourage chain member to adopt these new technologies. In this condition, the producer as the decision leader will set the agri-food wholesale price. Based on this wholesale price, the retailer will set the agri-food retail price. Revenue functions of the retailer and the agri-food producer see formulas (4.3) and (4.4), respectively.

$$\pi_p^{\mathrm{NI}} = \left(w^{\mathrm{NI}} - \vartheta c_p - c_{op}\right) D^{\mathrm{NI}} - zq^2/2 \tag{4.3}$$
$$\pi_r^{\mathrm{NI}} = \left(p^{\mathrm{NI}} - w^{\mathrm{NI}} - \vartheta c_r - c_{or}\right) D^{\mathrm{NI}}. \tag{4.4}$$

Based on the backward induction method and formula (4.4), we get $p^{\mathrm{NI}}(w^{\mathrm{NI}})$. Then we put $p^{\mathrm{NI}}(w^{\mathrm{NI}})$ into formula (4.3) and get the optimal wholesale price w^{NI^*}. According to w^{NI^*}, we get the optimal retail price p^{NI^*}. Putting w^{NI^*} and p^{NI^*} into formulas (4.3) and (4.4), we get the optimal revenues of chain members and Inference 4.2.

Inference 4.2. The optimal prices and revenues of chain members are expressed as $(\pi_p^{\mathrm{NI}^*}, \pi_r^{\mathrm{NI}^*}, w^{\mathrm{NI}^*}, p^{\mathrm{NI}^*})$, here, $(\pi_p^{\mathrm{NI}^*}, \pi_r^{\mathrm{NI}^*}, w^{\mathrm{NI}^*}, p^{\mathrm{NI}^*}) = \{(1-\lambda^{\mathrm{NI}}q - \vartheta c_r - \vartheta c_p - c_{or} - c_{op})^2/8 - zq^2/2,\ (1-\lambda^{\mathrm{NI}} q - \vartheta c_r - \vartheta c_p - c_{or} - c_{op})^2/16,\ (1+\vartheta c_p - \vartheta c_r - \lambda^{\mathrm{NI}}q + c_{op} - c_{or})/2,\ (3+\vartheta c_p + \vartheta c_r + c_{op} + c_{or} - 3\lambda^{\mathrm{NI}}q)/4\}$.

Through comparing Inferences 4.1 and 4.2, we can get that if chain members want to gain more benefits after using Big Data and blockchain, $\pi_p^{\mathrm{NI}^*} \geq \pi_p^{\mathrm{NN}^*}$ and $\pi_r^{\mathrm{NI}^*} \geq \pi_r^{\mathrm{NN}^*}$ should be satisfied. Namely, $\pi_p^{\mathrm{NI}^*} - \pi_p^{\mathrm{NN}^*} \geq 0$ and $\pi_r^{\mathrm{NI}^*} - \pi_r^{\mathrm{NN}^*} \geq 0$, based on these, we get formula (4.5).

$$c_{op} + c_{or} \leq (1-\vartheta)(c_r + c_p) + (\lambda^{\mathrm{NN}} - \lambda^{\mathrm{NI}})q. \tag{4.5}$$

It tells us that the investment costs about BBIS have a negative relationship with the industry cost optimization coefficient ϑ and a positive relationship with the perceived safety failure rate $\lambda^{\mathrm{NN}} - \lambda^{\mathrm{NI}}$. In other words, if chain members want to gain a big investment threshold about Big Data and blockchain, they should reduce the industry cost optimization coefficient ϑ and the perceived safety failure rate λ^{NI}. An effective way is to excavate the information value from Big Data and blockchain and produce agri-food needed by consumers.

4.2. WID model

In the WID model, agri-food chain members will invest in BBIS. Meanwhile, government will provide direct subsidy policy to encourage the producer and the retailer to adopt these new technologies. In this paper, we assume that after direct subsidy, the BBIS costs of the retailer and the producer change into γc_{or} and γc_{op}, respectively. Here, γ is the undertaken cost coefficient of chain members and we can call it cost discount coefficient, and the direct subsidy rate $\gamma' = 1-\gamma$. The producer as the decision leader will set the agri-food wholesale price. Based on this wholesale price, the retailer will set the agri-food retail price. Revenue functions of the retailer and the agri-food producer see formulas (4.6) and (4.7), respectively.

$$\pi_p^{\mathrm{WID}} = (w^{\mathrm{WID}} - \vartheta c_p - \gamma c_{op})D^{\mathrm{WID}} - zq^2/2 \tag{4.6}$$

$$\pi_r^{\mathrm{WID}} = (p^{\mathrm{WID}} - w^{\mathrm{WID}} - \vartheta c_r - \gamma c_{or})D^{\mathrm{WID}}. \tag{4.7}$$

Based on the backward induction method and formula (4.7), we get $p^{\mathrm{WID}}(w^{\mathrm{WID}})$. Then we put $p^{\mathrm{WID}}(w^{\mathrm{WID}})$ into formula (4.6) and get the optimal wholesale price w^{WID^*}. According to w^{WID^*}, we get the optimal retail price p^{WID^*}. Putting w^{WID^*} and p^{WID^*} into formulas (4.6) and (4.7), we get the optimal revenues of chain members and Inference 4.3.

Inference 4.3. The optimal prices and revenues of chain members are expressed as $(\pi_p^{\mathrm{WID}^*}, \pi_r^{\mathrm{WID}^*}, w^{\mathrm{WID}^*}, p^{\mathrm{WID}^*})$, here, $(\pi_p^{\mathrm{WID}^*}, \pi_r^{\mathrm{WID}^*}, w^{\mathrm{WID}^*}, p^{\mathrm{WID}^*}) = \{(1-\lambda^{\mathrm{WID}}q - \vartheta c_r - \vartheta c_p - \gamma c_{or} - \gamma c_{op})^2/8 - zq^2/2,\ (1-\lambda^{\mathrm{WID}}q - \vartheta c_r - \vartheta c_p - \gamma c_{or} - \gamma c_{op})^2/16,\ (1+\vartheta c_p - \vartheta c_r - \lambda^{\mathrm{WID}}q + \gamma c_{op} - \gamma c_{or})/2,\ (3+\vartheta c_p + \vartheta c_r + \gamma c_{op} + \gamma c_{or} - 3\lambda^{\mathrm{WID}}q)/4\}$.

Based on Inference 4.3, by finding the first partial derivative of dependent variable $(w^{\mathrm{WID}^*}, \partial p^{\mathrm{WID}^*}, \pi_r^{\mathrm{WID}^*}$ and $\pi_p^{\mathrm{WID}^*})$ about independent variable $(\vartheta, c_{or}, c_{op}, \lambda^{\mathrm{WID}}, q, \mu)$, we get Property 4.4.

Property 4.4.

① $\dfrac{\partial \pi_r^{\mathrm{WID}}}{\partial \vartheta} = \dfrac{(c_p + c_r)M}{8} < 0; \dfrac{\partial \pi_p^{\mathrm{WID}}}{\partial \vartheta} = \dfrac{(c_p + c_r)M}{4} < 0; \dfrac{\partial p^{\mathrm{WID}}}{\partial \vartheta} = \dfrac{c_p + c_r}{4} > 0; \dfrac{\partial w^{\mathrm{WID}}}{\partial \vartheta} = \dfrac{c_p - c_r}{2};$

② $\dfrac{\partial \pi_r^{\mathrm{WID}}}{\partial c_{or}} = \dfrac{\gamma M}{8} < 0$; $\dfrac{\partial \pi_p^{\mathrm{WID}}}{\partial c_{or}} = \dfrac{\gamma M}{4} < 0$; $\dfrac{\partial p^{\mathrm{WID}}}{\partial c_{or}} = \dfrac{\gamma}{4} > 0$; $\dfrac{\partial w^{\mathrm{WID}}}{\partial c_{or}} = -\dfrac{\gamma}{2} < 0$;

③ $\dfrac{\partial \pi_r^{\mathrm{WID}}}{\partial c_{op}} = \dfrac{\gamma M}{4} < 0$; $\dfrac{\partial \pi_p^{\mathrm{WID}}}{\partial c_{op}} = \dfrac{\gamma M}{4} < 0$; $\dfrac{\partial p^{\mathrm{WID}}}{\partial c_{op}} = \dfrac{\gamma}{4} > 0$; $\dfrac{\partial w^{\mathrm{WID}}}{\partial c_{op}} = \dfrac{\gamma}{2} > 0$;

④ $\dfrac{\partial \pi_r^{\mathrm{WID}}}{\partial \lambda^{\mathrm{WID}}} = \dfrac{qM}{8} < 0$; $\dfrac{\partial \pi_p^{\mathrm{WID}}}{\partial \lambda^{\mathrm{WID}}} = \dfrac{qM}{4} < 0$; $\dfrac{\partial p^{\mathrm{WID}}}{\partial \lambda^{\mathrm{WID}}} = -\dfrac{3q}{4} < 0$; $\dfrac{\partial w^{\mathrm{WID}}}{\partial \lambda^{\mathrm{WID}}} = -\dfrac{q}{2} < 0$;

⑤ $\dfrac{\partial \pi_r^{\mathrm{WID}}}{\partial q} = \dfrac{\lambda^{\mathrm{WID}} M}{8} < 0$; $\dfrac{\partial \pi_p^{\mathrm{WID}}}{\partial q} = \dfrac{\lambda^{\mathrm{WID}} M}{4} < 0$; $\dfrac{\partial p^{\mathrm{WID}}}{\partial q} = -\dfrac{3\lambda^{\mathrm{WID}}}{4} < 0$; $\dfrac{\partial w^{\mathrm{WID}}}{\partial q} = -\dfrac{\lambda^{\mathrm{WID}}}{2} < 0$;

⑥ $\dfrac{\partial \pi_r^{\mathrm{WID}}}{\partial \gamma} = \dfrac{(c_{op}+c_{or})M}{8} < 0$; $\dfrac{\partial \pi_p^{\mathrm{WID}}}{\partial \gamma} = \dfrac{(c_{op}+c_{or})M}{4} < 0$; $\dfrac{\partial p^{\mathrm{WID}}}{\partial \gamma} = \dfrac{c_{op}+c_{or}}{4} > 0$; $\dfrac{\partial w^{\mathrm{WID}}}{\partial \gamma} = \dfrac{c_{op}-c_{or}}{2}$.

Here, $M = \vartheta c_p + \vartheta c_r + \lambda^{\mathrm{WID}} q + \gamma c_{op} + \gamma c_{or} - 1 < 0$.

According to ① in Property 4.4, we can get that with the ascension of BBIS optimization coefficient, the optimal retail price will add, and the diversification trend of the optimal wholesale price is related to the value of $c_p - c_r$. Namely, when $c_p > c_r$, with the ascension of BBIS optimization coefficient, the optimal wholesale price will increase, conversely, it will reduce. However, following the growth of BBIS optimization coefficient ϑ, benefits of agri-food the producer and the retailer will decrease. Perhaps it is because the retail price growth will reduce the market demand, and then the optimal revenues of chain members will go down. Meanwhile, about the change of BBIS optimization coefficient ϑ, the producer's benefit is more sensitive than the retailer's revenue.

According to ② and ③ in Property 4.4, we can get that with the ascension of BBIS investment costs from the producer and the retailer, the optimal retail price will add, benefits of agri-food the producer and the retailer will decrease. Perhaps it is because the retail price growth will reduce the market demand, and then the optimal revenues of chain members will go down. Meanwhile, about the changes of BBIS investment costs from the producer and the retailer, the producer's benefit is more sensitive than the retailer's revenue. However, with the ascension of BBIS investment costs from the producer and the retailer, the optimal wholesale price will add and reduce, respectively.

According to ④ and ⑤ in Property 4.4, we can get that with the ascension of the unreliability coefficient of quality safety and the agri-food quality, the optimal retail price and the optimal wholesale price will reduce, and benefits of agri-food the producer and the retailer will decrease. Perhaps it is because the retail price growth will reduce the market demand, and then the optimal revenues of chain members will go down. Meanwhile, about the changes of BBIS investment costs from the producer and the retailer, the producer's benefit is more sensitive than the retailer's revenue. These tell us that chain members should try their best to extract the value from BBIS and reduce the unreliability coefficient of quality safety to gain more revenues.

According to ⑥ in Property 4.4, we can get that with the undertaken cost coefficient of chain members, the optimal retail price will add, and the diversification trend of the optimal wholesale price is related to the value of $c_p - c_r$. Namely, when $c_p > c_r$, with the ascension of the undertaken cost coefficient of chain members, the optimal wholesale price will increase, conversely, it will reduce. However, following the growth of the undertaken cost coefficient of chain members, benefits of agri-food the producer and the retailer will decrease. Perhaps it is because the retail price growth will reduce the market demand, and then the optimal revenues of chain members will go down. Meanwhile, about the change of the undertaken cost coefficient of chain members, the producer's benefit is more sensitive than the retailer's revenue. These tell us that government subsidy strategy will help reduce the retail price and gain more benefits.

4.3. WII model

In the WII model, agri-food chain members will invest in BBIS. Meanwhile, government will provide indirect subsidy policy to encourage the producer and the retailer to adopt these new technologies. In the indirect subsidy strategy, the subsidy model of government is retail price subsidy. In this paper, we assume that after indirect subsidy, the retail price changes into μp. Here, μ is the retail price discount coefficient, and the indirect subsidy rate $\mu' = 1 - \mu$. The producer as the decision leader will set the agri-food wholesale price. Based on this wholesale price, the retailer will set the agri-food retail price. Revenue functions of the retailer and the agri-food producer see formulas (4.8) and (4.9), respectively.

$$\pi_p^{\mathrm{WII}} = \left(w^{\mathrm{WII}} - \vartheta c_p - c_{op}\right)\left(1 - \mu p^{\mathrm{WII}} - \lambda^{\mathrm{WII}} q\right) - zq^2/2 \tag{4.8}$$
$$\pi_r^{\mathrm{WII}} = \left(p^{\mathrm{WII}} - w^{\mathrm{WII}} - \vartheta c_r - c_{or}\right)\left(1 - \mu p^{\mathrm{WII}} - \lambda^{\mathrm{WII}} q\right). \tag{4.9}$$

Based on the backward induction method and formula (4.9), we get $p^{\mathrm{WII}}\left(w^{\mathrm{WII}}\right)$. Then we put $p^{\mathrm{WII}}\left(w^{\mathrm{WII}}\right)$ into formula (4.8) and get the optimal wholesale price w^{WII^*}. According to w^{WII^*}, we get the optimal retail price p^{WII^*}. Putting w^{WII^*} and p^{WII^*} into formulas (4.8) and (4.9), we get the optimal revenues of chain members and Inference 4.5.

Inference 4.5. The optimal prices and revenues of chain members are expressed as ($\pi_p^{\mathrm{WII}^*}$, $\pi_r^{\mathrm{WII}^*}$, $w^{\mathrm{WII}^*}, p^{\mathrm{WII}^*}$), here, $(\pi_p^{\mathrm{WII}^*}, \pi_r^{\mathrm{WII}^*}, w^{\mathrm{WII}^*}, p^{\mathrm{WII}^*}) = \Big\{[1 - \lambda^{\mathrm{WII}} q - \mu(\vartheta c_r + \vartheta c_p + c_{or} + c_{op})]^2/8\mu - zg^2/2,\ \left[1 - \lambda^{\mathrm{WII}} q - \mu(\vartheta c_r + \vartheta c_p + c_{or} + c_{op})\right]^2/16\mu,\ \left[1 + \mu(\vartheta c_p - \vartheta c_r + c_{op} - c_{or}) - \lambda^{\mathrm{WII}} q\right]/2\mu,\ \left[3 + \mu(\vartheta c_p + \vartheta c_r + c_{op} + c_{or}) - 3\lambda^{\mathrm{WII}} q\right]/4\mu\Big\}$.

Based on Inference 4.5, by finding the first partial derivative of dependent variable $\left(w^{\mathrm{WII}^*}, \partial p^{\mathrm{WII}^*}, \pi_r^{\mathrm{WII}^*} \text{ and } \pi_p^{\mathrm{WII}^*}\right)$ about independent variable $\left(\vartheta, c_{or}, c_{op}, \lambda^{\mathrm{WII}}, q, \mu\right)$, we can Property 4.6.

Property 4.6.

① $\dfrac{\partial w^{\mathrm{WII}^*}}{\partial \vartheta} = \dfrac{c_p - c_r}{2\mu}; \dfrac{\partial p^{\mathrm{WII}^*}}{\partial \vartheta} = \dfrac{c_p + c_r}{4\mu} > 0; \dfrac{\partial \pi_p^{\mathrm{WII}^*}}{\partial \vartheta} = -\dfrac{(c_p + c_r)B}{4} < 0; \dfrac{\partial \pi_r^{\mathrm{WII}^*}}{\partial \vartheta} = -\dfrac{(c_p + c_r)B}{8} < 0;$

② $\dfrac{\partial w^{\mathrm{WII}^*}}{\partial c_{or}} = -\dfrac{1}{2} < 0; \dfrac{\partial p^{\mathrm{WII}^*}}{\partial c_{or}} = \dfrac{1}{4} > 0; \dfrac{\partial \pi_p^{\mathrm{WII}^*}}{\partial c_{or}} = -\dfrac{B}{4} < 0; \dfrac{\partial \pi_r^{\mathrm{WII}^*}}{\partial c_{or}} = -\dfrac{B}{8} < 0;$

③ $\dfrac{\partial w^{\mathrm{WII}^*}}{\partial c_{op}} = \dfrac{1}{2} > 0; \dfrac{\partial p^{\mathrm{WII}^*}}{\partial c_{op}} = \dfrac{1}{4} > 0; \dfrac{\partial \pi_p^{\mathrm{WII}^*}}{\partial c_{op}} = -\dfrac{B}{4} < 0; \dfrac{\partial \pi_r^{\mathrm{WII}^*}}{\partial c_{op}} = -\dfrac{B}{8} < 0;$

④ $\dfrac{\partial w^{\mathrm{WII}^*}}{\partial \lambda^{\mathrm{WII}}} = -\dfrac{q}{2\mu} < 0; \dfrac{\partial p^{\mathrm{WII}^*}}{\partial \lambda^{\mathrm{WII}}} = -\dfrac{3q}{4\mu} < 0; \dfrac{\partial \pi_p^{\mathrm{WII}^*}}{\partial \lambda^{\mathrm{WII}}} = -\dfrac{qB}{4} < 0; \dfrac{\partial \pi_r^{\mathrm{WII}^*}}{\partial \lambda^{\mathrm{WII}}} = -\dfrac{qB}{8} < 0;$

⑤ $\dfrac{\partial w^{\mathrm{WII}^*}}{\partial q} = -\dfrac{\lambda^{\mathrm{WII}}}{2\mu} < 0; \dfrac{\partial p^{\mathrm{WII}^*}}{\partial q} = -\dfrac{3\lambda^{\mathrm{WII}}}{4\mu} < 0; \dfrac{\partial \pi_p^{\mathrm{WII}^*}}{\partial q} = \dfrac{-\lambda^{\mathrm{WII}} B - 4gz}{4\mu} < 0; \dfrac{\partial \pi_r^{\mathrm{WII}^*}}{\partial q} = -\dfrac{\lambda^{\mathrm{WII}} B}{8\mu} < 0;$

⑥ $\dfrac{\partial w^{\mathrm{WII}^*}}{\partial \mu} = \dfrac{\lambda^{\mathrm{WII}} g - 1}{2\mu^2} < 0; \dfrac{\partial p^{\mathrm{WII}^*}}{\partial \mu} = -\dfrac{3(1 - \lambda^{\mathrm{WII}} g)}{4\mu^2} < 0; \dfrac{\partial \pi_p^{\mathrm{WII}^*}}{\partial \mu} = A < 0; \dfrac{\partial \pi_r^{\mathrm{WII}^*}}{\partial \mu} = \dfrac{A}{2} < 0.$

Here, $B = 1 - \lambda^{\mathrm{WII}} q - \mu(c_{op} + c_{or} + \vartheta c_p + \vartheta c_r)$ and $A = \frac{\left[1 - \lambda^{\mathrm{WII}} q + \sqrt{\mu}(c_{op} + c_{or} + \vartheta c_p + \vartheta c_r)\right]}{8\mu} \times \frac{\left[\sqrt{\mu}(c_{op} + c_{or} + \vartheta c_p + \vartheta c_r) - 1 + \lambda^{\mathrm{WII}} q\right]}{8}$.

According to ① in Properties 4.4 and 4.6, we can get that in the models of WII and WID, with the ascension of the BBIS optimization coefficient, the change trends about the optimal prices and revenues do not alter. Namely, following the growth of BBIS optimization coefficient ϑ, benefits of agri-food the producer and the retailer will decrease, and the optimal retail price will add, and the diversification trend of the optimal wholesale price is related to the value of $c_p - c_r$. These tell us that the subsidy models will not change the variation tendency of prices and benefits with the BBIS optimization coefficient.

According to ② and ③ in Properties 4.4 and 4.6, we can get that in the models of WII and WID, with the ascension of the BBIS investment costs from the producer and the retailer, the change trends about the optimal prices and revenues do not alter. Namely, following the growth of the BBIS investment costs from the producer and the retailer, the optimal retail price will add, benefits of agri-food the producer and the retailer will decrease. Meanwhile, about the changes of BBIS investment costs from the producer and the retailer, the producer's benefit is more sensitive than the retailer's revenue. These tell us that the subsidy models will not change the variation tendency of prices and benefits with the BBIS investment costs from the producer and the retailer.

According to ④ and ⑤ in Properties 4.4 and 4.6, we can get that in the models of WII and WID, with the ascension of the unreliability coefficient of quality safety and the agri-food quality, the change trends about the optimal prices and revenues do not alter. In other words, the optimal retail price and the optimal wholesale price will reduce, and benefits of agri-food the producer and the retailer will decrease. Meanwhile, about the changes of BBIS investment costs from the producer and the retailer, the producer's benefit is more sensitive than the retailer's revenue. These tell us that the subsidy models will not change the variation tendency of prices and benefits with the ascension of the unreliability coefficient of quality safety and the agri-food quality.

According to ⑥ in Property 4.6, we can get that with the retail price discount coefficient, the optimal retail price and the optimal wholesale price will go down, however, benefits will also decrease. These tell us that government indirect subsidy strategy will help reduce the retail price.

4.4. Subsidy strategy analyses

Implementing the subsidy strategy about BBIS will encourage the producer and the retailer research and adopt blockchain and Big Data technologies. Therefore, after implementing the subsidy strategy, benefits of chain members should be higher than it before implementing the subsidy strategy. Namely, in the direct subsidy condition, $\pi_p^{\mathrm{WID}^*} \geq \pi_p^{\mathrm{NI}^*}$ and $\pi_r^{\mathrm{WID}^*} \geq \pi_r^{\mathrm{NI}^*}$. Meanwhile, $\pi_p^{\mathrm{NI}^*} \geq \pi_p^{\mathrm{NN}^*}$ and $\pi_r^{\mathrm{NI}^*} \geq \pi_r^{\mathrm{NN}^*}$ should also be met, namely, without subsidy strategy, benefits of chain members in the NI model should be higher than it in the NN model. Therefore, we get if chain members want to adopt BBIS, its investment costs $c_{op} + c_{or}$ should be lower than $(1-\vartheta)(c_p + c_r) + q(\lambda^{\mathrm{NN}} - \lambda^{\mathrm{NI}})$. Namely,

$$c_{op} + c_{or} \leq (1-\vartheta)(c_p + c_r) + q\big(\lambda^{\mathrm{NN}} - \lambda^{\mathrm{NI}}\big). \tag{4.10}$$

Based on formula (4.10), we can get Inference 4.7.

Inference 4.7. When $c_{op} + c_{or} \leq (1-\vartheta)(c_p + c_r) + q\big(\lambda^{\mathrm{NN}} - \lambda^{\mathrm{NI}}\big)$ and $0 < \gamma \leq 1$, implementing the direct subsidy strategy will help chain members gain more benefits. In addition, when $c_{op} + c_{or} \leq (1-\vartheta)(c_p + c_r) + q\big(\lambda^{\mathrm{NN}} - \lambda^{\mathrm{NI}}\big)$, implementing the indirect subsidy strategy will help chain members gain more benefits.

Proof. In the direct subsidy condition, $\pi_p^{\mathrm{WID}^*} \geq \pi_p^{\mathrm{NI}^*}$ and $\pi_r^{\mathrm{WID}^*} \geq \pi_r^{\mathrm{NI}^*}$ should be met. Then, we get $\big(1 - \lambda^{\mathrm{WID}} q - \vartheta c_r - \vartheta c_p - \gamma c_{or} - \gamma c_{op}\big)^2/8 - zq^2/2 \geq \big(1 - \lambda^{\mathrm{NI}} q - \vartheta c_r - \vartheta c_p - c_{or} - c_{op}\big)^2/8 - zq^2/2$ and $\big(1 - \lambda^{\mathrm{WID}} q - \vartheta c_r - \vartheta c_p - \gamma c_{or} - \gamma c_{op}\big)^2/16 \geq \big(1 - \lambda^{\mathrm{NI}} q - \vartheta c_r - \vartheta c_p - c_{or} - c_{op}\big)^2/16$. We get $0 < \gamma \leq 1$ because of the hypothesis in Section 3 (namely, $\lambda^{\mathrm{NI}} = \lambda^{\mathrm{WID}}$), and it indicates that in the WID model, chain members will gain more benefits than them in the WII model.

In indirect and direct subsidy conditions, $\pi_p^{\mathrm{WII}^*} \geq \pi_p^{\mathrm{NI}^*}$, $\pi_r^{\mathrm{WII}^*} \geq \pi_r^{\mathrm{NI}^*}$, $\pi_p^{\mathrm{WID}^*} \geq \pi_p^{\mathrm{NI}^*}$ and $\pi_r^{\mathrm{WID}^*} \geq \pi_r^{\mathrm{NI}^*}$ should be met. Then, we get $\big[1 - \lambda^{\mathrm{WII}} q - \mu(\vartheta c_r + \vartheta c_p + c_{or} + c_{op})\big]^2/8\mu - zq^2/2 \geq (1 - \lambda^{\mathrm{NI}} q - \vartheta c_r - \vartheta c_p - c_{or} - c_{op})^2/8 - zq^2/2$ and $\big[1 - \lambda^{\mathrm{WII}} q - \mu(\vartheta c_r + \vartheta c_p + c_{or} + c_{op})\big]^2/16\mu \geq (1 - \lambda^{\mathrm{NI}} q - \vartheta c_r - \vartheta c_p - c_{or} - c_{op})^2/16$. Due to the hypothesis in Section 3 (namely, $\lambda^{\mathrm{NI}} = \lambda^{\mathrm{WII}}$), we get $\pi_p^{\mathrm{WII}^*} > \pi_p^{\mathrm{NI}^*}$ and $\pi_r^{\mathrm{WII}^*} > \pi_r^{\mathrm{NI}^*}$. Based on formula (4.9), Inference 4.7 was confirmed. □

According to Inference 4.7, we can get that the sum of the BBIS costs from the producer and the retailer has a negative relationship with the cost optimization coefficient because of using BBIS, and it also has an positive relationship with the unreliability coefficient of quality safety in the NN model and has an negative relationship with the unreliability coefficient of quality safety in the NI model. Namely, if chain members want to obtain more benefits after using the BBIS, they should try their best to discovery and apply the BBIS value, and then reduce the cost optimization coefficient because of using BBIS ϑ. In addition, they can make every effort to promote the reliability coefficient of quality safety after using the BBIS λ.

However, for the government, how to choose the subsidy models is also an important issue. Through comparing the revenues of chain members in the models of WID and WII, we get Inference 4.8.

Inference 4.8. When $\gamma \leq \frac{(\sqrt{\mu}-1)(1-\lambda^{\mathrm{WID}}q)+(\mu+\sqrt{\mu})(\vartheta c_r+\vartheta c_p)+\mu(c_{op}+c_{or})}{\sqrt{\mu}(c_{op}+c_{or})}$, benefits of chain members in the indirect subsidy models are higher than them in the direct subsidy model. Otherwise, implementing the direct subsidy strategy will be better for chain members.

Proof. To gain the optimal subsidy strategy, we should compare the revenues of chain members in the models of WID and WII. If $\pi_p^{\mathrm{WII}^*} \geq \pi_p^{\mathrm{WID}^*}$ and $\pi_r^{\mathrm{WII}^*} \geq \pi_r^{\mathrm{WID}^*}$, namely, benefits of chain members in the indirect subsidy models are higher than them in the direct subsidy model. Therefore, $\left(1-\lambda^{\mathrm{WII}}q-\mu\vartheta c_r-\mu\vartheta c_p-\mu c_{or}-\mu c_{op}\right)^2/8\mu - zq^2/2 \geq \left(1-\lambda^{\mathrm{WID}}q-\vartheta c_r-\vartheta c_p-\gamma c_{or}-\gamma c_{op}\right)^2/8 - zq^2/2$ and $\left(1-\lambda^{\mathrm{WII}}q-\mu\vartheta c_r-\mu\vartheta c_p-\mu c_{or}-\mu c_{op}\right)^2/16\mu \geq \left(1-\lambda^{\mathrm{WID}}q-\vartheta c_r-\vartheta c_p-\gamma c_{or}-\gamma c_{op}\right)^2/16$. Then, we get $\gamma \leq \frac{\left(\sqrt{\mu}-1\right)\left(1-\lambda^{\mathrm{WID}}q\right)+\left(\mu+\sqrt{\mu}\right)(\vartheta c_r+\vartheta c_p)+\mu(c_{op}+c_{or})}{\sqrt{\mu}(c_{op}+c_{or})}$. Thus, Inference 4.8 was confirmed. □

According to Inference 4.8, we can discovery that the undertaken cost coefficient of chain members has a negative relationship with the unreliability coefficient of quality safety, and has a positive relationship with t he cost optimization coefficient because of using BBIS ϑ. That is to say, the subsidy coefficient of government has a negative relationship with the reliability coefficient of quality safety after using BBIS λ, and has a negative relationship with the cost optimization coefficient because of using BBIS. Therefore, for government, if the perceived reliability of consumers on quality safety can be improved, he/she can set a low subsidy coefficient. In addition, if the cost optimization coefficient because of using BBIS is higher, the government can set a low subsidy coefficient. Thus, for governments, they should encourage chain members to try their best to discovery and apply the BBIS value, and then reduce the cost optimization coefficient because of using BBIS and the unreliability coefficient of quality safety.

5. Mathematical simulation

Based on the advantages in food traceability area and demand forecasting area, the fusion application of Big Data and blockchain has attracted widespread attentions. Many information service providers have launched information service business based on Big Data and blockchain. However, it is not so popular in agricultural field. A vital reason is the lack of effective incentives. Therefore, in this paper, we focused on government incentives and divided it into direct incentives and indirect incentives. In addition, the perceived safety of agri-food was adopted to reflect the effects of traceability on agri-food safety in the new environment. Then, considering the changes of demand function because of using Big Data and blockchain, we chose an agri-food supply chain with one prouder and one retailer as research object and built three game models. Finally, we gain some meaningful inferences and properties.

To verify the proposed inferences and properties, we adopt Matlab to implement a numerical case study. According to the market demand should be bigger than zero and formulas (4.5) and (4.10), we set $q = 0.5$, $c_r = 0.15$, $c_p = 0.1$, $c_{op} = 0.05$, $c_{or} = 0.06$, $u = 0.8$, $z = 0.1$, $\lambda^i = 0.8$ and $\vartheta = 0.65$. Based on the proposed inferences, we get the following figures (*i.e.*, from Figs. 1 to 4). From Figure 1, we can get the change trends of the optimal prices following the variation of ϑ, c_{or}, c_{op} and λ^i. In the NN model, the variations of ϑ, c_{or} and c_{op} will not affect the change tendencies of the optimal prices. However, in the models of NI, WID and WII, the retail price has a positive relationship with the BBIS optimization coefficient and the BBIS investment costs from the producer and the retailer, and it also has a negative relationship with the unreliability coefficient

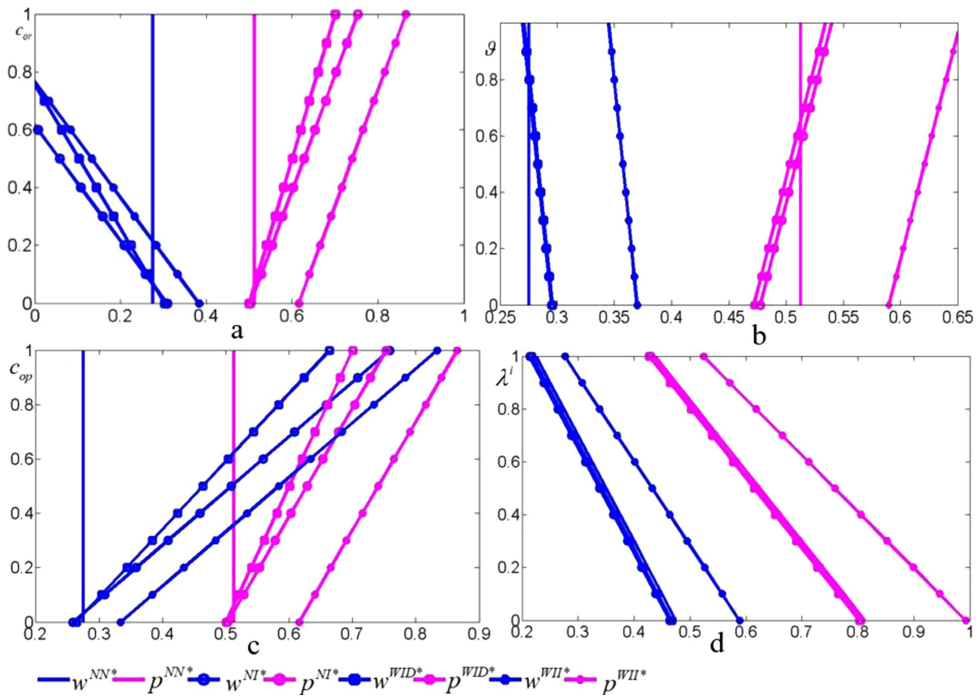

FIGURE 1. Change trend of prices with the variation of ϑ, c_{or}, c_{op} and λ^i.

of quality safety. In the models of NI, WID and WII, the wholesale price has a negative relationship with the BBIS optimization coefficient, the BBIS investment costs from the retailer and the unreliability coefficient of quality safety. These tell us that the retailer adopted BBIS will help her/him get a low wholesale price. This perhaps that using the BBIS can help improving the unreliability coefficient of quality safety, and then promote the sales volume. The growth of the sales volume will help the retailer get a low wholesale price. Moreover, the wholesale price has a negative relationship with the BBIS investment costs from the producer. The aforementioned analyses tell us that if chain members want to gain bigger profit margins, they can achieve it through improving the unreliability coefficient about product security, and reducing the BBIS investment costs and the BBIS optimization coefficient.

From Figure 2, we can get the change trends of the optimal prices following the variation of γ, μ and q. Based on the Figure 2c, we find that in the proposed four models, with the ascension of the agri-food quality, the optimal prices will reduce. This perhaps that the enhancement of the ascension of the agri-food quality will lead to an increase in sales volume, therefore, chain members can set low prices. Due to $c_p = 0.1 < c_r = 0.15$, therefore, Based on the Figure 2a, we find that with the undertaken cost coefficient of chain members, the optimal retail price will add. This also demonstrates that with the growth of the direct subsidy rate, the optimal retail price will reduce (based on $\gamma' = 1 - \gamma$). The diversification trend of the optimal wholesale price is related to the value of $c_p - c_r$. Namely, when $c_p < c_r$, with the undertaken cost coefficient of chain members, the wholesale price will reduce, otherwise, it will add. From the Figure 2b, we find that with growth of the retail price discount coefficient, the optimal retail price and the optimal wholesale price will go down. This indicates that with the growth of the indirect subsidy rate, the optimal retail price and the optimal wholesale price will add (based on $\mu' = 1 - \mu$). Therefore, we can find the indirect subsidy strategies will not bring the decline of the retail price and the wholesale price.

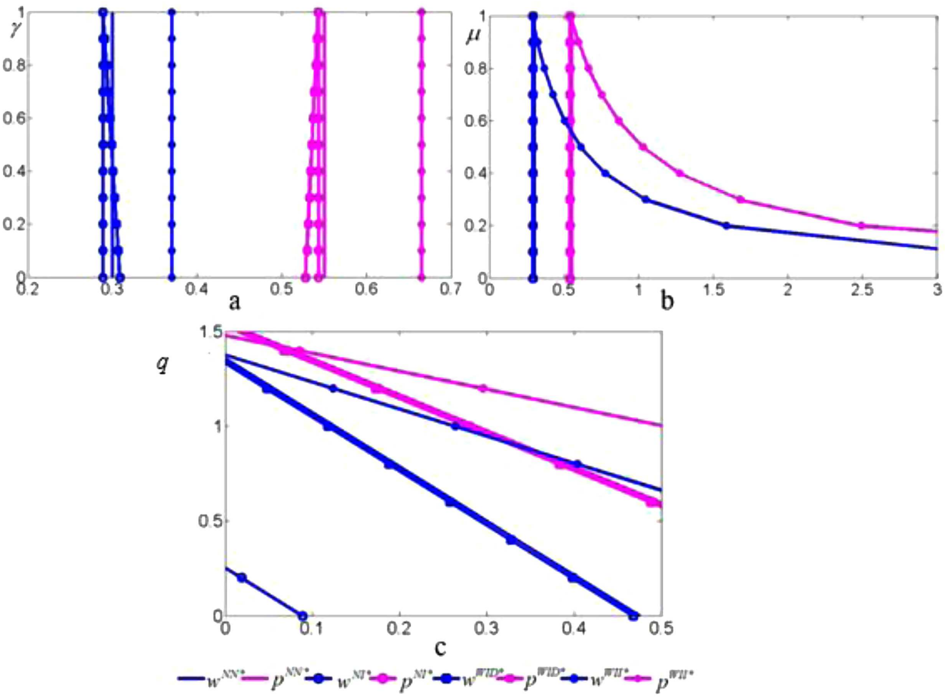

FIGURE 2. Change trend of prices with the variation of γ, μ and q.

From Figure 3, we can get the change trends of revenues following the variation of ϑ, c_{or}, c_{op} and λ^i. In the NN model, the variation of ϑ, c_{or} and c_{op} will not affect the change tendency of the optimal benefits. According to Figures 3a–3d, we can understand that in the models of NI, WID and WII, when the BBIS investment costs from the producer and the retailer met a certain value, the producer benefits and the retailer revenues have a negative relationship with the BBIS optimization coefficient, the BBIS investment costs from the producer and the retailer, and the unreliability coefficient of quality safety. The aforementioned analyses tell us that if chain members want to gain bigger profit margins, they can achieve it through improving the unreliability coefficient about product security and the BBIS optimization coefficient. That is to say, chain members should try their best to discovery and apply the BBIS value, and then promote the reliability coefficient of quality safety after using the BBIS and reduce the BBIS optimization coefficient. Furthermore, they can also gain more benefits by reducing the BBIS investment costs, and this depends on the bargaining power of supply chain members in purchase BBIS.

From Figure 4, we can get the change trends of the optimal benefits following the variation of γ, μ and q. In the proposed four models, with the ascension of the undertaken cost coefficient of chain members, and the retail price discount coefficient, the optimal revenues will reduce. These demonstrate that in the WID model, with the growth of the direct subsidy rate, the optimal revenues will add (based on $\gamma' = 1 - \gamma$). That is to say, the direct subsidy strategies will help chain members obtain more revenues. Furthermore, in the WID model, with the growth of the indirect subsidy rate, the optimal revenues will add (based on $\mu' = 1 - \mu$). That is to say, the indirect subsidy strategies will also help chain members obtain more revenues. Based on the Figure 4c, we find that in the proposed four models, with the ascension of the agri-food quality, the optimal earnings of chain members will reduce. This perhaps that the enhancement of the ascension of the agri-food quality may lead to the increase of the retail price and the wholesale price, and then bring the decease of the sales volume, therefore, chain members may gain low incomes. In summary, Properties 4.4 and 4.6 were confirmed.

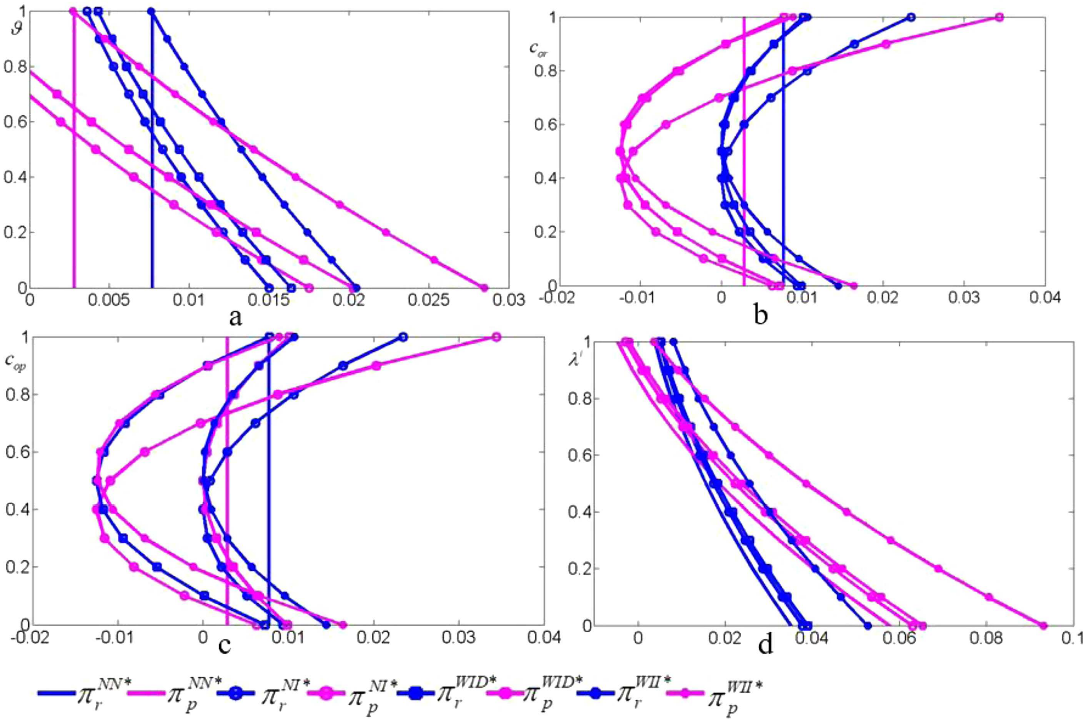

FIGURE 3. Change trend of benefits with the variation of ϑ, c_{or}, c_{op} and λ^i.

From Figure 5, we can get that when the BBIS investment costs are lower than R, implementing the direct and indirect subsidy strategies will help chain members gain more benefits. From Figure 6, we can know that when γ and μ can met a relationship ($i.e.$, $\gamma \leq \frac{(\sqrt{\mu}-1)(1-\lambda^{\mathrm{WID}}q)+(\mu+\sqrt{\mu})(\vartheta c_r+\vartheta c_p)+\mu(c_{op}+c_{or})}{\sqrt{\mu}(c_{op}+c_{or})}$) benefits of chain members in the indirect subsidy models are higher than them in the direct subsidy model. Otherwise, implementing the direct subsidy strategy will be better for chain members. In summary, Inferences 4.7 and 4.8 were proved.

6. Conclusions and significances

6.1. Conclusions

The advantages of Blockchains in preventing data from being tampered, copied and plagiarized can increase the trust levels among supply chain members [14, 38]. But its statistical analysis ability for data is weak, and the storage and statistical analysis of data are the strengths of Big Data. Thus, integrating Big Data technology into blockchain could greatly explore the data value and usage potential in blockchain [62]. The fusion usage of big data and blockchain was a management revolution and can improve enterprises' competitive advantage [32]. Although the fusion usage of big data and blockchain has huge merits, its applications are not so popular. A vital reason is the shortage of effective incentive mechanism. Government incentives as important incentive measures were thought to be useful. However, how many subsidy models? Which one is the best? In different subsidy models, how to price can gain more benefits? All of these are vital for agents.

To explore the aforementioned issues, we focused on government incentives and divided it into direct subsidy and indirect subsidy. In addition, the perceived safety of agri-food was adopted to reflect the effects of traceability on agri-food safety in the new environment. Then, considering the changes of demand function because of using

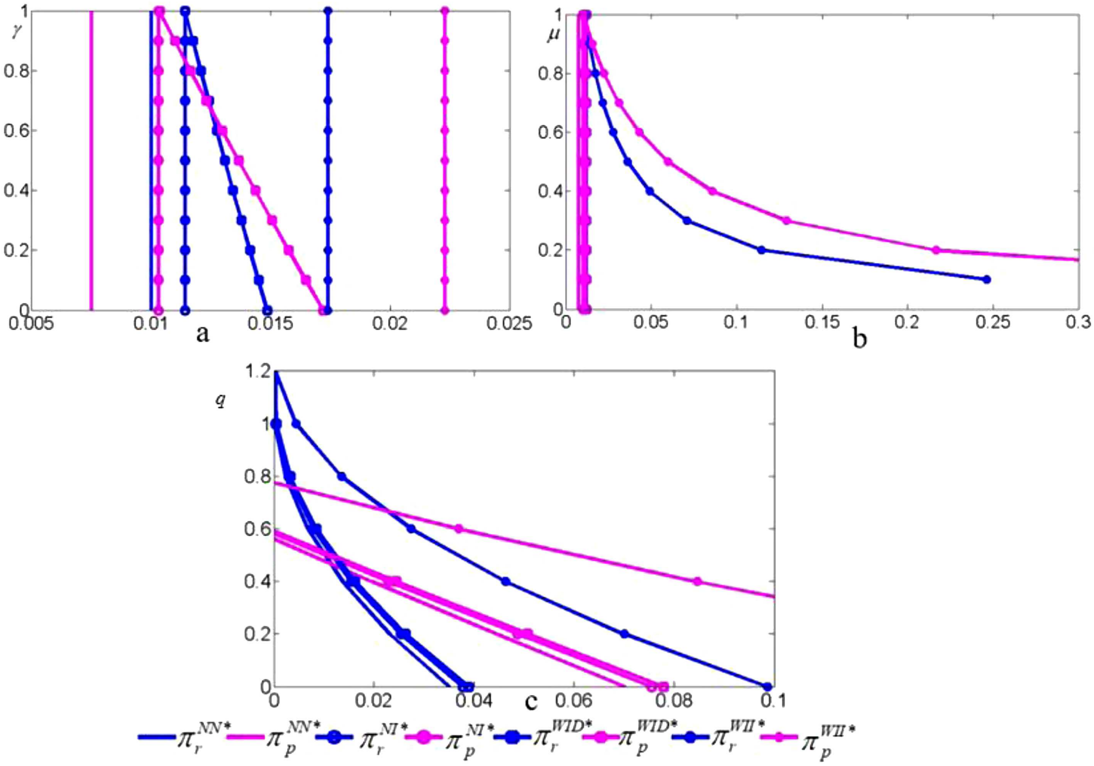

FIGURE 4. Change trend of revenues with the variation of γ, μ and q.

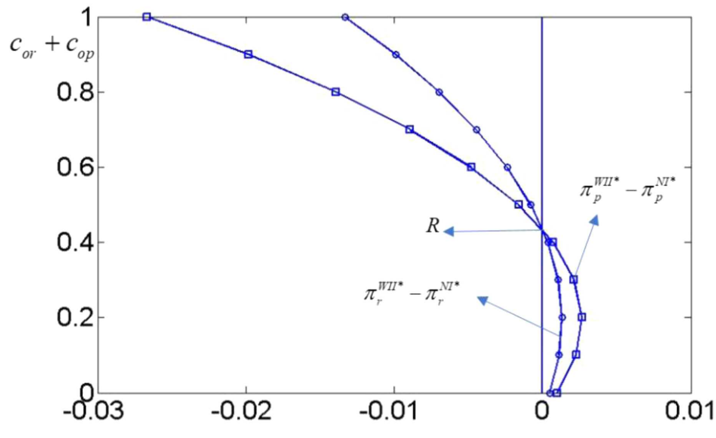

FIGURE 5. Relationships between investment costs and benefits of chain members after implementing subsidy strategies.

implementing subsidy strategies.

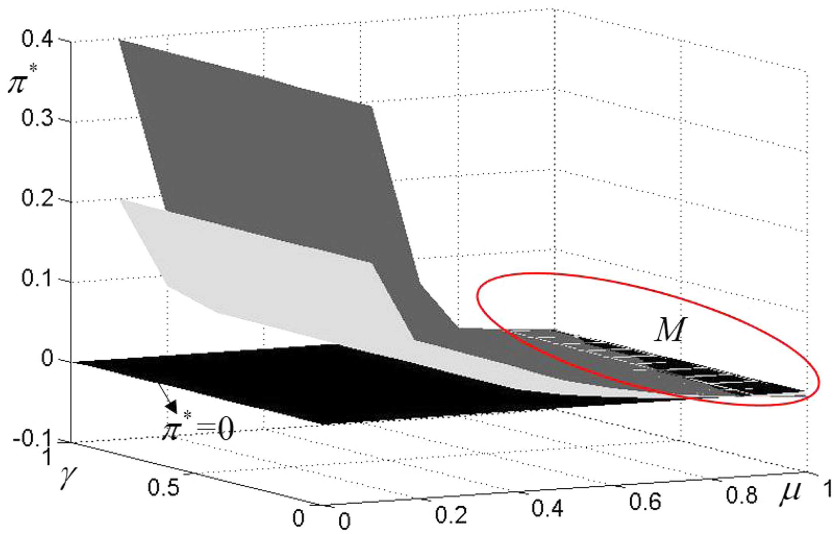

FIGURE 6. Subsidy model selection.

Big Data and blockchain, we chose an agri-food supply chain with one prouder and one retailer as research object and built four game models. Findings:

(1) When the BBIS investment costs from the producer and the retailer can meet a certain value, the producer benefits and the retailer revenues have a negative relationship with the BBIS optimization coefficient, the BBIS investment costs from the producer and the retailer, the unreliability coefficient of quality safety, the agri-food quality, the undertaken cost coefficient of chain members, and the retail price discount coefficient.
(2) In the three investment models, the retail price has a positive relationship with the BBIS optimization coefficient and the BBIS investment costs from the producer and the retailer, and has a negative relationship with the unreliability coefficient of quality safety. The wholesale price has a negative relationship with the BBIS optimization coefficient, the BBIS investment costs from the retailer and the unreliability coefficient of quality safety, a negative relationship with the BBIS investment costs from the producer.

Namely, if chain members want to gain bigger profit margins, they should try their best to adjust related parameters, for instance, reducing the BBIS investment costs and the BBIS optimization coefficient.

(3) The subsidy models will not change the variation tendency of prices and benefits with the BBIS optimization coefficient, the BBIS investment costs from the producer and the retailer, the ascension of the unreliability coefficient of quality safety and the agri-food quality.
(4) When the BBIS investment costs can meet a certain value, implementing the subsidy strategies will help chain members gain more benefits. In addition, when subsidy coefficients about Direct and indirect subsidies can meet a relationship, benefits of chain members in the indirect subsidy models are higher than them in the direct subsidy model. Otherwise, implementing the direct subsidy strategy will be better for chain members.

6.2. Significances

The significances of our research are as following. Academically, (1) the market demand was improved considering the product quality change in the new environment. It enriched the demand management theory. (2) Three subsidy models were proposed considering BBIS inputs and the product quality change in the new environment, and the subsidy rules and pricing policies were gained. It was a new development of subsidy theory and pricing theory in the fusion application environment of Big Data and blockchain.

In practice, (1) the proposed market demand provided a tool reference for forecast market demand and demand management, meanwhile, our research method in discussing the market demand is a reference for future research about the market demand. (2) The subsidy rules and pricing strategies will offer theory bracings for government departments to make and implement the subsidy strategies, in addition, for company, it can provide a theoretical guidance to make price strategies in the subsidy strategy environment and the new technology background.

6.3. Limitations and future research

In this research, we only discussed the subsidy rules and the pricing policies of a two-stage agri-food supply chain with one retailer and one producer. In fact, agri-food supply chain is a very complicated network. There are multi-stage and multi-channel supply chain. In the future, we will focus on the dual-channel agri-food supply chain to discuss the subsidy strategies. Furthermore, our research focused on the changes of the reliability of quality safety and the effects of BBIS application on the cost optimization. In reality, after using BBIS, other factors (such as, fraud behaviors of chain members and shopping time.) may change, too. In the next step, we can also focus on the situations about fraud behaviors of chain members or the changes about shopping time. In addition, in this paper, we did not discussed the coordination issues in the subsidy strategy environment and the new technology background. Therefore, we will also consider to make a contract to achieve the supply chain coordination in the subsidy strategy environment and the new technology background. In this paper, we assume that the chain members are risk-neutral and completely rational. In reality, decision maker is risk appetite. Therefore, in the future research, we should further liberalize the restrictions.

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References

[1] I. Ali and I. Gölgeci, Managing climate risks through social capital in agrifood supply chains. *Supply Chain Manage. Int. J.* **25** (2020) 1–16.

[2] APHIS, USDA, Animal disease traceability: summary of program reviews and proposed directions from state-federal working group. https://www.aphis.usda.gov/publications/animal_health/adt-summary-program-review.pdf (2018).

[3] APHIS, USDA, Sheep and goat identification. Available at https://www.aphis.usda.gov/aphis/ourfocus/animalhealth/animal-disease-information/sheep-and-goat-health/scrapie-tags (2020).

[4] J.F. Arvis, Germany tops 2016 logistics performance index. Web page The World Bank, from http://www.worldbank.org (2016).

[5] N. Bumbudsanpharoke and S. Ko, Nano-food packaging: an overview of market, migration research, and safety regulations. *J. Food Sci.* **80** (2015) R910–R923.

[6] M.P. Caro, M.S. Ali and M.E.A. Vecchio, Blockchain-based traceability in Agri-Food supply chain management: a practical implementation. In: 2018 IoT Vertical and Topical Summit on Agriculture-Tuscany (IOT Tuscany) (2018) 1–44.

[7] Y.H. Chen, X.W. Wen, B. Wang and P.Y. Nie, Agricultural pollution and regulation: how to subsidize agriculture? *J. Cleaner Prod.* **164** (2017) 258–264.

[8] H. Chen, Z. Tian and F. Xu, What are cost changes for produce implementing traceability systems in China? Evidence from enterprise A. *Appl. Econ.* **51** (2019) 687–697.

[9] C. CN, Two places have detected the new coronavirus in the outer packaging of imported seafood. https://baijiahao.baidu.com/s?id=1672329966417563915&wfr=spider&for=pc (2020).

[10] A.J. Collart and E. Canales, How might broad adoption of blockchain-based traceability impact the U.S. fresh produce supply chain? *Appl. Econ. Perspect. Policy* **44** (2022) 219–236.

[11] C.B.B. Comunicación, De Alan Turing al "ciberpunk": la historia de"blockchain". https://www.bbva.com/es/historia-origen-blockchain-bitcoin/ (2017).

[12] H.N. Dai, Z. Zheng and Y. Zhang, Blockchain for Internet of things: a survey. *IEEE Int. Things J.* **6** (2019) 8076–8094.

[13] N. Deepa, Q.V. Pham, D.C. Nguyen, S. Bhattacharya, B. Prabadevi, T.R. Gadekallu, P.K.R. Maddikunta, F. Fang and P.N. Pathirana, A survey on blockchain for big data: approaches, opportunities, and future directions. *Future Gener. Comput. Syst.* **131** (2022) 209–226.

[14] W. Du, S.L. Pan, D.E. Leidner and W. Ying, Affordances, experimentation and actualization of FinTech: a blockchain implementation study. *J. Strategic Inf. Syst.* **28** (2019) 50–65.

[15] N. Fu, X. Zhang and Z. Jia, Game analysis on government subsidy for agricultural enterprise' IoT investment. *IOP Conf. Ser. Mater. Sci. Eng.* **688** (2019) 55040.

[16] J.F. Galvez, J.C. Mejuto and J. Simal-Gandara, Future challenges on the use of blockchain for food traceability analysis. *TrAC Trends Anal. Chem.* **107** (2018) 222–232.

[17] B. Hou, L. Wu and X. Chen, Market simulation of traceable food in China based on conjoint-value analysis: a traceable case of pork. *Int. Food Agribusiness Manage. Rev.* **23** (2020) 735–746.

[18] Q. Hu, Q. Xu and B. Xu, Introducing of online channel and management strategy for green agri-food supply chain based on pick-your-own operations. *Int. J. Environ. Res. Public Health* **16** (2019) 1990.

[19] J. Hu, Y. Liu and D. Ma, Dynamic strategy of food supply chain considering greenness and traceable goodwill under technological innovation. *Soft Sci.* (2020) 1–10.

[20] A. Imeri and D. Khadraoui, The security and traceability of shared information in the process of transportation of dangerous goods. Paper presented at the IFIP International Conference on New Technologies (2018).

[21] S. Jangirala, A.K. Das and A.V. Vasilakos, Designing secure lightweight blockchain-enabled RFID-based authentication protocol for supply chains in 5G mobile edge computing environment. *IEEE Trans. Ind. Inf.* **16** (2019) 7081–7093.

[22] L. Jiaxing, W. Jigang and J. Guiyuan, Blockchain-based public auditing for big data in cloud storage. *Inf. Process. Manage.* **57** (2020) 1–17.

[23] S.S. Kamble, A. Gunasekaran and S.A. Gawankar, Achieving sustainable performance in a data-driven agriculture supply chain: a review for research and applications. *Int. J. Prod. Econ.* **219** (2020) 179–194.

[24] H.M. Kim and M. Laskowski, Toward an ontology-driven blockchain design for supply-chain provenance. *Int. J. Intell. Syst. Accounting Finance Manage.* **25** (2018) 18–27.

[25] W. Li and S. Zhao, Research on decision-making model of high-quality fresh agricultural products dual-channel supply chain considering the application of traceability system. *Oper. Res. Manage. Sci.* **28** (2019) 98–109.

[26] P. Liu, Investment decision and coordination of green agri-food supply chain considering information service based on blockchain and big data. *J. Cleaner Prod.* **277** (2020) 123646.

[27] P. Liu and S. Wang, Logistics outsourcing of fresh enterprises considering fresh-keeping efforts based on evolutionary game analysis. *IEEE Access* **9** (2021) 25659–25670.

[28] P. Liu and S.P. Yi, A study on supply chain investment decision-making and coordination in the Big Data environment. *Ann. Oper. Res.* **270** (2018) 235–253.

[29] P. Liu and S.P. Yi, Investment decision-making and coordination of a three-stage supply chain considering data company in the big data era. *Ann. Oper. Res.* **78** (2018) 1–17.

[30] R.A. Lopez, X. He and E. De Falcis, What drives China's new agricultural subsidies? *World Dev.* **93** (2017) 279–292.

[31] C. Martin, Logistics & Supply Chain Management: Financial Times Prentice Hall. Harlow, England (1992).

[32] A. McAfee, E. Brynjolfsson, T.H. Davenport, D.J. Patil and D. Barton, Big data: the management revolution. *Harvard Bus. Rev.* **90** (2012) 60–68.

[33] B.K. Mohanta, S.S. Panda and D. Jena, An overview of smart contract and use cases in blockchain technology. Paper presented at the 2018 9th International Conference on Computing, Communication and Networking Technologies (ICCCNT) (2018).

[34] B. Nelson and T. Olovsson, Security and privacy for big data: a systematic literature review. Paper presented at the IEEE International Conference on Big Data (2017).

[35] D.C. Nguyen, P.N. Pathirana, M. Ding and A. Seneviratne, Blockchain for 5G and beyond networks: a state of the art survey. *J. Network Comput. App.* **166** (2020) 102693.

[36] D.C. Nguyen, P.N. Pathirana, M. Ding and A. Seneviratne, Integration of blockchain and cloud of things: architecture, applications and challenges. *IEEE Commun. Surv. Tutorials* **22** (2020) 2521–2549.

[37] P. Olsen and M. Borit, The components of a food traceability system. *Trends Food Sci. Technol.* **77** (2018) 143–149.

[38] L. Pawczuk, R. Massey and D. Schatsky, Breaking Blockchain Open: Deloitte's 2018 Global Blockchain Survey. Accessed 2020. https://www2.deloitte.com/content/dam/Deloitte/cz/Documents/financial-services/cz-2018-deloitte-globalblockchain-survey.pdf:Deloitte (2018).

[39] H. Peng and T. Pang, Optimal strategies for a three-level contract-farming supply chain with subsidy. *Int. J. Prod. Econ.* **216** (2019) 1–36.

[40] J.C. Pérez-Mesa, L. Piedra-Muoz, E. Galdeano-Gómez and C. Giagnocavo, Management strategies and collaborative relationships for sustainability in the agrifood supply chain. *Sustainability* **13** (2021) 749.

[41] K. Rabah, Convergence of AI, IoT, big data and blockchain: a review. *Lake Inst. J.* **1** (2018) 1–18.

[42] R. Rajagopal, A.K. Agariya and C. Rajendran, Predicting resilience in retailing using grey theory and moving probability based Markov models. *J. Retail. Consumer Serv.* **62** (2021) 102599.

[43] M.A. Rubio, G.M. Tarazona and L. Contreras, Big Data and Blockchain Basis for Operating a New Archetype of Supply Chain. Springer, Cham (2018).

[44] M.K. Saggi and S. Jain, A survey towards an integration of big data analytics to big insights for value-creation. *Inf. Process. Manage.* **54** (2018) 758–790.

[45] K. Salah and M.A. Khan, IoT security: review, blockchain solutions, and open challenges. *Future Gener. Comput. Syst.* **82** (2018) 395–411.

[46] P. Sckokai and D. Moro, Modeling the reforms of the common agricultural policy for Arable crops under uncertainty. *Soc. Sci. Electron. Publ.* **88** (2010) 43–56.

[47] Sohu, New coronavirus has been detected in the outer packaging of frozen seafood 20201217. https://www.sohu.com/a/413025856_100000405 (2020).

[48] S. Stranieri, F. Riccardi, M. Meuwissen and C. Soregaroli, Exploring the impact of blockchain on the performance of agri-food supply chains. *Food Control* **119** (2021) 107495.

[49] B. Sundarakani, A. Ajaykumar and A. Gunasekaran, Big data driven supply chain design and applications for blockchain: an action research using case study approach. *Omega* **102** (2021) 102452.

[50] A.C. Tagarakis, L. Benos, D. Kateris, N. Tsotsolas and D. Bochtis, Bridging the gaps in traceability systems for fresh produce supply chains: overview and development of an integrated IoT-based system. *Appl. Sci.* **11** (2021) 7596.

[51] S.L. Taste, The world's first blockchain farm-rice bags for good food, 2020/05/16. http://www.agrichains.cn/ (2020).

[52] N. Tengfei, Y.U. Haisuo and D.U. Shaofu, Agriculture supply chain optimization based on supply and demand uncertainty with government subsidy policies. *J. Univ. Sci. Technol. Chin.* **47** (2017) 267–273.

[53] F. Tian, An agri-food supply chain traceability system for China based on RFID & blockchain technology. Paper presented at the 2016 13th international conference on service systems and service management (ICSSSM). IEEE (2016).

[54] K. Tian, X. Zhuang and B. Yu, The incentive and supervision mechanism of banks on third-party B2B platforms in online supply chain finance using big data. *Mobile Inf. Syst.* **2021** (2021) 1–16.

[55] M.S.J. Tripoli, Emerging Opportunities for the Application of Blockchain in the Agri-food Industry: FAO and ICTSD: Rome and Geneva. Licence: CC BY-NC-SA 3 (2018).

[56] M. Ul Hassan, M.H. Rehmani and J. Chen, Privacy preservation in blockchain based IoT systems: integration issues, prospects, challenges, and future research directions. *Future Gener. Comput. Syst.* **97** (2019) 512–529.

[57] D. Unal, M. Hammoudeh, M.A. Khan, A. Abuarqoub and R. Hamila, Integration of federated machine learning and blockchain for the provision of secure big data analytics for internet of things. *Comput. Secur.* **109** (2021) 102393.

[58] V.G. Venkatesh, K. Kang and B. Wang, System architecture for blockchain based transparency of supply chain social sustainability. *Rob. Comput.-Integr. Manuf.* **63** (2020) 101896.

[59] K. Wang, Design of agricultural product quality and safety big data fusion model based on blockchain technology. Paper presented at the International Conference on Advanced Hybrid Information Processing (2019).

[60] C. Wang, M. Deng and J. Deng, Factor reallocation and structural transformation implications of grain subsidies in China. *J. Asian Econ.* **71** (2020) 101248.

[61] X.Y. Wu, Z.P. Fan and B.B. Cao, An analysis of strategies for adopting blockchain technology in the fresh product supply chain. *Int. J. Prod. Res.* (2021) 1–18. DOI: 10.1080/00207543.2021.1894497.

[62] Y. Yang, Z. Cai and Y. Liu, Blockchain + Big Data: Break Through the Bottleneck and Open a New Era of Intelligence. China Machine Press, Beijing (2019).

[63] F. Ye, Z. Cai, Y.U. Chen, Y. Li and G. Hou, Subsidize farmers or bioenergy producer? The design of a government subsidy program for a bioenergy supply chain. *Nav. Res. Logistics* **68** (2021) 1082–1097.

[64] F. Zhang, N.V.R. Masna, S. Bhunia, C. Chen and S. Mandal, Authentication and traceability of food products through the supply chain using NQR spectroscopy. Paper presented at the 2017 IEEE Biomedical Circuits and Systems Conference (BioCAS) (2017).

[65] A. Zhang, R.Y. Zhong and M.E.A. Farooque, Blockchain-based life cycle assessment: an implementation framework and system architecture. *Resour. Conserv. Recycling* **152** (2020) 104512.

[66] R. Zhang, W. Ma and J. Liu, Impact of government subsidy on agricultural production and pollution: a game-theoretic approach. *J. Cleaner Prod.* **285** (2021) 124806.

[67] S. Zheng, D., Lambert, S. Wang and Z. Wang, Effects of agricultural subsidy policies on comparative advantage and production protection in China. *Chin. Econ.* **46** (2013) 20–37.

[68] Z. Zheng, S. Xie, H. Dai, X. Chen and H. Wang, An overview of blockchain technology: architecture, consensus, and future trends. Paper presented at the 6th IEEE International Congress on Big Data (2017).