Customer Knowledge Sharing Incentive Mechanism in Agricultural Products Supply Chain in Big Data Context

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Abstract

Big data-driven supply chain has become a value co-creation network for knowledge sharing and collaboration. The customer knowledge sharing between the producers in the upstream of the agricultural product supply chain and the downstream distribution system enables producers to more accurately predict consumer demand, even ahead of time, thereby regulating production to better meet individualized and diverse consumers. However, in the process of customer big data knowledge sharing, due to the coexistence of big data and small data, different data causes different cost in acquiring and sharing knowledge, generating different benefits, which leads to different internal mechanisms of customer knowledge sharing between producers and distributors in different contexts. Based on this, starting from the perspective of agricultural producers, based on differentiation of two different knowledge sharing of customer big data knowledge and small data knowledge, this paper establishes customer knowledge sharing incentive model of producers and distributors using principal-agent theory to study its internal incentive mechanism, and analyzes the relationship between the variables of the incentive contract using numerical simulation. Research shows that: when designing big data customer knowledge sharing incentive contracts, producers tend to have preconceptions, always giving priority to incentives of first-observed customer data knowledge transformation ability, which leads to distributors’ lower income distribution ratio of customer big data knowledge than retailers’ income distribution ratio of customer small data knowledge when transformation ability equals for customer big data knowledge and customer small data knowledge; producers are more dependent on customer big data knowledge when greatly depending on distributors’ customer small data knowledge. Also, the relationship between incentive contract and its variables is further analyzed by numerical simulation.

Key words: Agricultural Products, Big Data, Customer Knowledge Sharing, Principal-Agent; Supply Chain

1. Introduction

Compared with industrial products, agricultural products are easily prone to factors such as climate, land, water and energy input. Production shows strong seasonal and regional characteristics. Consumption has dispersity in time and space. There is a big time-space gap between production and consumption, which leads to more complex and variable agricultural product supply chains than industrial product supply chains [1]. The complexity and variability of agricultural product supply chain makes knowledge sharing, especially customer knowledge sharing, more important for agricultural supply chain members to improve products and service quality, regulate production quantity, formulate pricing and marketing strategy, and transform management models.

Agricultural producers in the upstream of the supply chain are far away from end consumers, often slow to obtain and use customer information, thus a large number of products can be unsalable and even eventually wasted [2]. Meanwhile, massive distributors and retailers acquire extensive customer data, information and knowledge through establishment of online and offline omni-channel marketing and sales, and have the right to dispose and decide on these data resources and the embedded customer knowledge [3], which allows them to quickly have access to accurate customer demands and preferences, thereby achieving direct control of the market. It can be seen that in the big data environment, agricultural producers rely more on customer knowledge of the distribution system than in the past, resulting in sharply increased pressure to acquire customer knowledge on the market side, which means that agricultural producers need re-examine the relationship with distributors, and re-design customer knowledge sharing incentive mechanism for distributors.
At present, literature research on knowledge sharing between agricultural producers and distributors proves that customer knowledge sharing brings great value to the supply chain and its node enterprises [4]. Scholars' research shows that synergistic acquisition, sharing and utilization of customer information and knowledge, as well as customer knowledge sharing by agricultural producers and distributors play an important role in improving agricultural product supply chain efficiency and corporate profits [5]. Some scholars have studied customer knowledge sharing decision-making of producers and distributors in agriculture, agricultural products or agricultural food supply chains, and pointed out that customer knowledge sharing can help agricultural supply chain to build traceable quality management system for agricultural products [6], design multi-agent intelligent decision-making mechanism [7], realize accurate supply and demand matching [8], thereby promoting sales, improving profits and innovating product and marketing approach [9]. Obviously, customer knowledge sharing brings great value to agricultural product supply chain and its node enterprises. However, differences exist in customer data, information and knowledge owned by different node enterprises in the agricultural product supply chain. The complementarity of such difference promotes customer knowledge sharing and collaborative operation among agricultural supply chain enterprises, and also leads to information asymmetry between organizations. As rational economic men, producers and distributors often pursue maximal interests by utilizing information asymmetry, which damages partners' interests (Patrick et al., 2004) [10], resulting in difficulty to achieve the expected results through customer knowledge sharing. To solve this problem, some scholars have studied the issue of customer knowledge sharing incentives between agricultural producers and distributors Hine (2002) pointed out that instructing small farmers to promote collaborative production through customer knowledge sharing can increase supply elasticity of vegetable supply chain [11]. Ferguson (2004) studied market information sharing of Canadian corn producers and proposed to promote customer information sharing in the corn supply chain by designing incentive mechanisms[12]. Ho believed that market information sharing has an important impact on the selection of cooperative contracts for fresh milk producers [13]. Kurtz (2012) argued that the flow of knowledge in the agricultural supply chain, including customer knowledge, can drive cooperation between supply chain nodes, thus facilitating coordinated operations [14]. Xia (2015) pointed out that agricultural producers and retailers can better match supply and demand through customer knowledge sharing to avoid supply failure, and proposed a compensation mechanism based on knowledge sharing contribution [15]. The above literatures mainly consider customer knowledge sharing incentives in the traditional context, without considering that in the big data environment, producers in the agricultural product supply chain are more dependent on customer knowledge sharing with distributors than in the past to accurately predict market demand and adjust production. It also fails to consider heterogeneity of data and its knowledge in customer knowledge sharing as well as its derived impact on cooperation of agricultural supply chain nodes. Obviously, in the era of digital economy, big data and small data coexist. Faced with different data, knowledge acquisition and sharing bring different cost, and produce different benefits. The internal operating mechanism also differs. Then, seen from the perspective of agricultural producers, what different incentives should be implemented for distributors' big data customer knowledge and small data customer knowledge sharing behavior? How can incentives make producers gain the best returns? These issues are currently unclear. Based on this, this paper intends to study customer knowledge sharing incentive mechanism between producers and distributors on the basis of distinguishing customer knowledge differences in traditional scenarios and big data context.

2. Differences between Big Data Customer Knowledge and Small Data Customer Knowledge

Significant differences exist in the sources, nature, and access channels of customer knowledge in traditional small data context and big data context, which leads to differences in internal mechanisms of customer knowledge sharing between producers and distributors in different contexts. In the traditional scenario, the data mining customer knowledge mainly derives from transaction data and report data as well as some meetings exchange data generated by internal and inter-enterprise docking information systems such as ERP, CRM, etc.,. These data are referred to as “small data” (relative to big data), which is mainly structured business data. The traditional mining method can enable acquisition of relevant customer knowledge therefrom, and its value has been verified. However, in the big data context, more than 80% of the customer knowledge source data derives from different industries, fields or cross-sectors outside the enterprise[16]. With diverse content forms and access channels, the data is mostly semi-structured, unstructured data, which is consumer-driven data with great and confirmed value, but its value has yet to be verified by theory and practice. These characteristics of big data customer knowledge have an important impact on customer knowledge sharing game and incentive behavior of agricultural producers and distributors. Therefore, this paper attempts to explore the incentive process of customer knowledge sharing between agricultural producers and distributors in the big data environment from the
perspective of producers, and design incentive contract on effort level, cost and income distribution of the two sides in the process.

3. Customer Data Sharing Benefit Function under Big Data

In the agricultural product supply chain, producers focus on producing agricultural products and mastering a wealth of agricultural knowledge. Distributors are closely connected to the market and customers, who have grasped market information and massive customer data, and have rich customer knowledge. Obviously, knowledge of the two sides is very complementary. The sharing of customer knowledge between the two parties helps producers adjust production variety, quantity and quality, while distributors can use customer knowledge to provide better service to customers. However, agricultural producers and distributors, as two independent entities, have difficulty in observing the actual level of knowledge sharing efforts of each other in the process of knowledge sharing, which leads to information asymmetry between them. Meanwhile, this paper assumes that: agricultural producers and distributors are risk-neutral; agricultural producers and distributors are rational economic men who will pursue maximization of respective interests; distributors are agents in superior position, while agricultural producers are principals in a disadvantaged position; acquisition and sharing of customer big data knowledge and customer small data knowledge is subject to impact of external uncertainties.

Big data knowledge refers to the knowledge generated by large-scale data collections that greatly exceed the capabilities of traditional database software tools in terms of acquisition, storage, management and analysis. Its value needs to be verified. Small data knowledge is knowledge gained by data collection using traditional database software, and its value has been verified in practice. When agricultural producers and distributors are in a multi-stage game, because the value of customer big data knowledge needs to be verified, producers need to consider whether the discounted income produced by distributor's customer big data knowledge in the future multiple games is higher than the benefit of the first and only one game between producers and distributors, and then decide whether to collaborate with distributors in the future to acquire and share big data knowledge about customer. For customer small data knowledge, because its value can be verified, producers do not need to consider the future discounted income in cooperation with the distributor. Therefore, when setting up the incentive contract, producers will adopt different income distribution ratios for distributor's two-side knowledge about the customer.

When agricultural producers and distributors collaborate to acquire and share customer big data knowledge and small data knowledge, this is a process of new knowledge acceptance or innovation, and they need to invest resources or pay efforts. Therefore, assume that level of producers’ effort in knowledge acquisition and sharing is \( e_1 (e_1 > 0) \), level of distributors’ effort in customer big data knowledge acquisition and sharing is \( e_2 (e_2 > 0) \), level of distributors’ effort in customer small data knowledge acquisition and sharing is \( e_3 (e_3 > 0) \). Based on Cobb-Douglas cooperative production function model [17], the output yield function is assumed to be \( \pi(e_1, e_2, e_3, \theta) = e_1^\gamma e_2^\theta e_3^\eta + \theta \), where \( 0 \leq \gamma, \lambda, \eta \leq 1 \) are respectively producer effort level elastic coefficient, distributor effort level elastic coefficient in big data knowledge sharing, distributor effort level elastic coefficient in small data knowledge sharing, which indicate producers and distributors’ strength in knowledge transformation, and also suggest the ratio of changes in knowledge output during the entire knowledge acquisition and sharing process when producers or distributors increase their efforts. For bigger \( \gamma, \lambda, \eta \), the cooperative output between them is larger. \( k \) means the marginal benefit when customer knowledge is ultimately transformed into corporate income; \( \theta \) means exogenous random variable that affects knowledge of cooperative production, which obeys a normal distribution with a mean of 0 and a variance of \( \sigma^2 \), that is, \( \theta \sim N(0, \sigma^2) \).

Agricultural producers and distributors have to pay for cost in the process of customer knowledge acquisition and sharing. For the convenience of discussion, this paper ignores the impact of random factors on cost. It can be assumed that producers’ effort cost is \( c(e_1) = \frac{b_1}{2} e_1^2 \), distributors’ effort cost in customer big data knowledge sharing is \( c(e_2) = \frac{b_2}{2} e_2^2 \), distributors’ effort cost in customer small data
knowledge sharing is \( c(e_i) = \frac{b_i}{2} e_i^2 \). Where, \( b_i (i = 1, 2, 3) \) is the cost coefficient of their respective efforts, \( b_i > 0 \).

In customer knowledge acquisition and sharing under big data environment, producers and distributors in the agricultural product supply chain have a principal-agent relationship. The former is the principal, and the latter is the agent. To motivate distributors to acquire and share customer knowledge, producers need to provide a certain incentive reward contract. Form of linear contract is applied here, \( s(\pi) = \alpha + \beta \pi \). Where, \( \alpha = \alpha_1 + \alpha_2, \beta = \beta_1 + \beta_2 (0 < \beta < 1) \). \( \alpha_1 \) and \( \alpha_2 \) respectively represent producers’ fixed payment for distributor big data knowledge sharing and small data knowledge sharing; \( \beta_1 \) and \( \beta_2 \) respectively represent distributors’ income distribution ratio in big data knowledge sharing and small data knowledge sharing. Therefore, in this knowledge acquisition and sharing, distributors’ expected revenue function can be obtained:

\[
E_\text{w} = \alpha + \beta E \pi - \frac{b_2}{2} e_2^2 - \frac{b_3}{2} e_3^2
\]

Producers’ expected revenue function:

\[
E_\text{v} = (1 - \beta) E \pi - \alpha - \frac{b_1}{2} e_1^2
\]

Where, distributors’ reservation utility is \( w_0 \), that is, the maximum benefit under the same time and energy conditions when the distributor does not cooperate with the producer is \( w_0 \), \( Ew \geq w_0 \geq 0 \). Similarly, producers need also guarantee non-negative income. Otherwise, producers will not participate in knowledge sharing. Thus, \( E_\text{v} \geq 0 \), and contract \( s(\pi) = \alpha + \beta \pi \) satisfies:

\[
\frac{b_2}{2} e_2^2 + \frac{b_3}{2} e_3^2 \leq \alpha + \beta E \pi \leq E\pi - \frac{b_1}{2} e_1^2
\]

(3)

The function (3) indicates that producer’s incentive contract for the distributor is not lower than the distributor’s cost in efforts to share customer big data knowledge and small data knowledge. Otherwise, the distributor will consider not participating in the cooperation to share customer knowledge; likewise, (3) also indicates that as a principal, the producer needs to consider that the difference between cooperative income and cost in effort is not lower than the incentive contract. Otherwise, producers will lose money in the cooperation and consider not participating in the cooperation. It can be further derived from (3) that:

\[
\frac{b_2}{2} e_2^2 + \frac{b_3}{2} e_3^2 - \beta E \pi \leq \alpha \leq (1 - \beta) E \pi - \frac{b_1}{2} e_1^2
\]

(4)

This indicates that \( \alpha \) and \( \beta \) are interrelated and \( \alpha \) changes with \( \beta \) variation in the interval \([0,1]\).

Next, we discuss credibility of the informal incentive contract promised by the producer who is risk neutral. Informal contracts are often based on “relationships”, which is a kind of “self-executing” contract with long-term and dynamic nature. Because the value of customer big data knowledge is to be assessed, the producer may refuse to pay for this cost \( \beta \pi \), and only pay the fixed payment \( \alpha \) in this respect, then the expected income increment obtained by the producer through default is \( \beta E \pi \). Once the producer defaults, considering the multi-stage cooperation between the producer and the distributor, it is assumed that the distributor does not cooperate with the producer to share customer knowledge from the second stage;

The above equation (2) represents the producer’s expected return when fulfilling the promise, so the expected loss of future cooperation caused by producer’s default is \((1 - \beta) E \pi - \alpha - \frac{b_1}{2} e_1^2 \). Assume that the producer’s future income discount coefficient is \( \delta \), then from the second stage, the producer’s future discounted income is:

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\[
\lim_{n \to \infty} \sum_{i=1}^{n} \delta^i [(1 - \beta) E \pi - \alpha - \frac{b_1}{2} e_i^2] = \frac{\delta}{1 - \delta} [(1 - \beta) E \pi - \alpha - \frac{b_1}{2} e_i^2]
\]  
(5)

When the producer's expected income increment \( \beta_1 \pi \) by default is smaller than the future expected discounted income by default, the producer will not default. That is, the producer will not default if:

\[
\beta_1 \pi \leq \frac{\delta}{1 - \delta} [(1 - \beta) E \pi - \alpha - \frac{b_1}{2} e_i^2]
\]  
(6)

4. Model Construction and Solution

In this section, an incentive model for producers and distributors to collaborate in customer knowledge sharing in big data environment will be established, and corresponding incentive mechanism will be developed to maximize the benefits of both sides of the supply chain. Meanwhile, this contract satisfies other constraints besides equation (6): both producers and distributors need to meet respective incentive compatibility constraints in customer knowledge acquisition and sharing. Of course, distributors need to meet the incentive compatibility constraint in both customer big data knowledge acquisition and sharing and customer small data knowledge acquisition and sharing, which is to reduce or prevent moral hazard of both parties. It guarantees that the agent (distributor) benefit from accepting the contract and participating in cooperation is no less than the maximum expected return when the agent (distributor) does not accept the contract under the same time and effort.

Based on the above constraints, we can build customer knowledge incentive contract model under big data:

\[
\max_{\beta_1, \beta_2, \alpha} E v = (1 - \beta) E \pi - \alpha - \frac{b_1}{2} e_i^2
\]  
(7)

s.t.

\[
e_i^* \in \arg \max E w = \alpha + \beta E \pi - \frac{b_2}{2} e_2^2 - \frac{b_3}{2} e_3^2, i = 2, 3
\]  
(8)

\[
e_i^* \in \arg \max E v = (1 - \beta) E \pi - \alpha - \frac{b_1}{2} e_i^2
\]  
(9)

\[
\alpha + \beta E \pi - \frac{b_2}{2} e_2^2 - \frac{b_3}{2} e_3^2 \geq w_0
\]  
(10)

\[
\frac{\delta}{1 - \delta} [(1 - \beta) E \pi - \alpha - \frac{b_1}{2} e_i^2] \geq \beta_i E \pi
\]  
(11)

Where, (8) and (9) are incentive compatibility constraints for distributors and producers respectively, (10) is the participation constraint for distributors and (11) is the condition for producers to abide by the contract.

In the face of moral hazard, producers need maximize their expected returns when putting in efforts. It can be obtained from the first-order optimal condition of (9) that:

\[
(1 - \beta) k \gamma e_i^{-1} e_i^* - b_i e_i = 0
\]  
(12)

It can be obtained that the optimal solution of \( e_i \) is \( e_i^*(e_2, e_3, \beta) \).

If a distributor wants to maximize his expected return, he needs to decide how much effort should be put into customer big data knowledge sharing and small data knowledge sharing. Therefore, the first-order optimal condition of \( e_2, e_3 \) can be obtained from equation (8):

\[
\beta k \lambda e_2^{-1} e_2^* - b_2 e_2 = 0
\]  
(13)

\[
\beta k \eta e_3^{-1} e_3^* - b_3 e_3 = 0
\]  
(14)

According to the equations (13) , (14) , the respective optimal solutions \( e_i^*(e_1, e_i, \beta) \), \( e_i^*(e_1, e_2, \beta) \) can be obtained;

Based on (12)-(14) and simultaneous equations (7), (10)-(11), the above model can be solved by Lagrangian function:
\[
\beta^* = \frac{(\gamma - 2)(\lambda + \eta) + \sqrt{(\gamma^2 - 2\gamma)[(\lambda + \eta)^2 - 2(\lambda + \eta)]}}{2\gamma - 2(\lambda + \eta)}
\]  
(15)

\[
e_1^* = e^{\frac{1}{4(y + \eta + \lambda - 2)}((\lambda - 2)(\gamma + \lambda - 2)ln\frac{\beta k}{b_2} - (\gamma - 2)(\lambda + \eta)ln\frac{b_2}{b_2} - \lambda(\gamma + \lambda - 2)ln\frac{\beta k}{b_2} + 2(\lambda + \eta - 2)ln\frac{\gamma(\beta^* - 1)}{h_1})}
\]  
(16)

\[
e_2^* = e^{\frac{1}{4(y + \eta + \lambda - 2)}((\lambda - 2)(\gamma - 2)ln\frac{\beta k}{b_2} - ((\lambda - 2)(\gamma - 2) - 2\eta)ln\frac{b_2}{b_2} - \lambda(\gamma - 2)ln(\beta k) + 2ln\frac{\gamma(\beta^* - 1)}{h_1})}
\]  
(17)

\[
e_3^* = e^{\frac{(\lambda - 2)(\gamma - 2)ln(\beta k) - \lambda\gamma ln\frac{b_2}{b_2} - \lambda(\gamma - 2)ln(\beta k) + 2\gamma ln(-\frac{k_y(\beta^* - 1)}{h_1})}{4(y + \eta + \lambda - 2)}}
\]  
(18)

\[
\alpha^* = w_0 + \frac{\lambda + \eta - 2}{2} \beta^* k e_1^* e_2^* e_3^* 
\]  
(19)

\[
\delta \geq \frac{\beta^* k e_1^* e_2^* e_3^*}{\beta^* k e_1^* e_2^* e_3^* - \beta k e_1^* e_2^* e_3^* - \alpha^* - \frac{\gamma}{2}(1 - \beta^*) k e_1^* e_2^* e_3^*}
\]  
(20)

First, considering the optimal income distribution ratio \(\beta^*\), according to equation (15), then:

\[
\frac{\partial \beta^*}{\partial \gamma^*} < 0, \frac{\partial \beta^*}{\partial \lambda} > 0, \frac{\partial \beta^*}{\partial \eta} > 0
\]  

Thus, there is proposition 1: the optimal income distribution ratio is inversely proportional to the producer's knowledge sharing effort elastic coefficient \(\gamma\), directly proportional to distributor's customer big data knowledge sharing effort elastic coefficient \(\lambda\), and also directly proportional to distributor's customer small data knowledge sharing effort elastic coefficient \(\eta\).

Using the similar methods, we get the following propositions:

**Proposition 2:** When the discount factor \(\delta^*\), the informal incentive contract promised by the producer can be trusted by the distributor. At this time, the optimal income distribution ratio is \(\beta^*\), and the fixed payment is \(\alpha^*\).

**Proposition 3:** The critical discount factor \(\delta^*\) decreases as the distributor's income distribution ratio \(\beta_4\) of customer big data knowledge increases; the critical discount factor \(\delta^*\) is directly proportional to the distributor's income distribution ratio \(\beta_4\) of customer big data knowledge.

**Proposition 4:** The critical discount factor \(\delta^*\) is negatively correlated to the optimal income distribution ratio \(\beta^*\).

5. Numerical Analysis

In this section, based on the previous model, the contract \((\alpha^*, \beta^*)\) is designed by numerical analysis and the relationship between the contract and other variables is analyzed. Let the marginal benefit \(k = 0.6\).

First, we'll discuss the relationship between the optimal distribution ratio \(\beta^*\) and producer knowledge sharing output elastic coefficient \(\gamma\), the distributor output elastic coefficient \(\lambda\) in customer big data knowledge sharing effort, and the distributor output elastic coefficient \(\eta\) in customer small data knowledge sharing effort.

Let \(\lambda = 0.5\), \(\eta = 0.1, 0.5, 0.9\), and plot the curve graph of the optimal distribution ratio \(\beta^*\) in relation to producer's knowledge sharing output elastic coefficient \(\gamma\). Then we can get the corollary 1.
**Corollary 1:** The optimal distribution ratio $\beta^*$ decreases with the increase of producer's knowledge sharing output elastic coefficient, which decreases sharply at first, then tends to be stable. Moreover, with the increase of $\lambda + \eta$, the optimal distribution ratio $\beta^*$ shows slower and slower decrease rate, and the decrease interval gets narrower, that is, the incentive to the distributor becomes larger.

This shows that once a producer has the ability to transform knowledge, he will choose to increase his own income distribution ratio to lower his moral hazard.

Let $0.5 \leq \gamma$ , then we obtain the relation graph between the optimal distribution ratio $\beta^*$ and the distributor's output elastic coefficient $\lambda$ in customer big data knowledge acquisition and sharing, the distributor's output elastic coefficient $\eta$ in customer small data knowledge acquisition and sharing:

Further, $\eta$ is any value in the interval $[0, 1)$, let $\eta = 0.1, 0.5, 0.9$ , then we can obtain the relation between the optimal distribution ratio $\beta^*$ and the distributor's output elastic coefficient in customer big data knowledge acquisition and sharing. When $\lambda = 0$, the distributor's income distribution ratio $\beta_1$ of customer small data knowledge can be obtained. Moreover, since $\beta^* = \beta_1 + \beta_2$, the relation between the distributor's income distribution ratio $\beta_1$ of customer big data knowledge and elastic coefficient $\lambda$ can be gotten.

Figure 1. Relation curve of the optimal distribution ratio $\beta^*$ and elastic coefficient $\lambda, \eta$

According to the above analysis, combining Fig. 1 and above analysis, the following conclusions can be drawn:

**Corollary 2:** Producers have “preconceptions”: when the producer first observes the distributor's ability $\eta$ to transform customer small data knowledge, regardless of the size of $\gamma$ and his own customer knowledge transformation ability $\gamma$, he will always consider the distributor's customer small data knowledge transformation ability when providing incentive to the distributor, and lower concern or dependence on the distributor's customer big data knowledge transformation ability $\lambda$. In this way, when $\lambda = \eta$, the distributor's income distribution ratio $\beta_1$ of customer big data knowledge is lower than income distribution ratio $\beta_2$ of customer small data knowledge.

It can be seen from Fig. 1 and above analysis that the optimal distribution ratio $\beta^*$ and the distributor's income distribution ratio of customer big data knowledge increase with the increase of the distributor's output elastic coefficient in customer big data knowledge acquisition and sharing. When $0.1 \leq \eta < \gamma = 0.5$ (can be generalized to $\eta < \gamma$), $\beta^*$ has slower and slower growth rate, also $\beta_1$ growth rate has slowed down. When $0.9 \leq \eta > \gamma = 0.5$ (can be generalized to $\eta > \gamma$), $\beta^*$ has faster and faster growth rate, also $\beta_1$ growth rate gets faster. Combining the above analysis, it can be obtained that:

**Corollary 3:** When the distributor's output elastic coefficient $\eta$ of customer small data knowledge (i.e., small data knowledge transformation ability) is low, that is, when the producer is less dependent on
the distributor’s customer small data knowledge, he will be even less dependent on the distributor’s customer big data knowledge; when the producer’s output elastic coefficient $\eta$ of customer small data knowledge (i.e., small data knowledge transformation ability) is high, that is, when the producer is more dependent on the distributor’s customer small data knowledge, he will be even more dependent on the distributors’ customer big data knowledge.

6. Conclusions

In this paper, targeting at how producers away from market end in the agricultural product supply chain share customer big data and small data knowledge with distributors, an incentive contract model for producers and distributors to share customer big data knowledge and customer small data knowledge is established, and the model results are analyzed, with the following conclusions drawn: when designing big data customer knowledge sharing incentive contracts, producers tend to have preconceptions, always giving priority to incentives of first-observed customer data knowledge transformation ability, which leads to distributors’ lower income distribution ratio of customer big data knowledge than retailers’ income distribution ratio of customer small data knowledge when transformation ability equals for customer big data knowledge and customer small data knowledge; producers are more dependent on customer big data knowledge when greatly depending on distributors’ customer small data knowledge. In the process of big data customer knowledge sharing, agricultural producers actively learn to improve ability to transform big data customer knowledge, increase their income distribution ratio without affecting distributors' income distribution ratio, that is, achieving win-win cooperation. Agricultural producers’ expectation of future income and distributors’ customer knowledge sharing default cost jointly determine whether the producers need design informal relationship incentive contract.

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References


