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# Designing coordination contract for biofuel supply chain in China

Fei Ye, Yina Li*, Qian Yang

*School of Business Administration, South China University of Technology, Guangzhou, 510640, China*

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ABSTRACT

To ensure the sustainable supply of agricultural feedstock for biofuel production and improve the performance of biofuel supply chain, coordination along the biofuel supply chain in a random yield environment is studied. Three types of coordination contract are examined, namely, an over-production risk-sharing contract (OPC), an under-production risk-sharing contract (UPC), and a mixed contract (MC) with an asymmetric Nash bargaining model. Though an OPC and a UPC can correct the farmers' over-production and under-production behavior, the expected increase in profit may not be realized by the biofuel producer or the farmers. The MC is feasible because it achieves an efficient supply chain, where supply chain optimization as well as the interests of all individual actors are respected simultaneously. The proposed contracts are tested with data from the cassava-based biofuel industry in China. The findings help practitioners and policy makers understand when and how to implement coordination contracts to achieve the sustainable supply of agricultural feedstock for biofuel production and supply chain Pareto improvement as well.



## 1. Introduction

With the China's rapid economic growth, the country has become the largest primary energy consumer in the world, relying heavily on coal and petroleum (see Fig. 1), and, also the largest emitter of greenhouse gases in the world (Dong et al., 2016). The interruptions in energy supply, environmental contamination, and growing dependence on energy imports (especially for crude oil, which imported accounts for about 60% of China's total need in 2015) combine to make energy security and environmental protection to be two major problems faced by China (Ren et al., 2015; Ren and Sovacool, 2015).

To have a sustainable future, China is seeking the adjustment on its energy structure by accelerating the use of renewable and environmentally friendly energy sources to substitute the traditional fossil fuels (Wen and Zhang, 2015; Dong et al., 2016). Biofuels are viewed as one of the most utilized sources of renewable energy and the promising alternatives to fossil fuels, especially in the transportation sector, due to their high potential to enhance energy security and mitigate environmental pollutions (Papapostolou et al., 2011; Ren et al., 2016). Moreover, as a leading agricultural nation, the development of the biofuel industry is conducive to promote the rural development in China.

In recent years, China has launched programs to promote the production and supply of biofuel. The biofuel output has been increased by about fivefold between 2005 and 2015 (see Fig. 2). However, this amount accounts for only 3.25% of the global total biofuel output in 2015 (see Fig. 3), and is still very small comparing to the apparent consumption of petroleum product. Thus, the limited production of biofuels in China cannot fill the gap between energy demand and supply (Chen et al., 2016).

Hence, for the sake of energy security and environmental protection, China's biofuel production should be increased remarkably. To increase biofuel production, the stable and abundant supply of feedstock is indispensable and the first priority (Chen et al., 2016). However, China is suffering an undersupply of agricultural feedstock for biofuel production. For example, cassava, one of the most important biofuel crops in China, relies heavily on imports: imported cassava accounts for more than 60% of China's total domestic need (Liu et al., 2013). Consequently, the design of sustainable biofuel supply chains to ensure the sustainable supply of agricultural feedstock, so as to enhance biofuel production is becoming more and more important nowadays.

With this circumstance, this study aims to investigate how to enhance the supply of agricultural feedstock from a supply chain management perspective using analytical approaches. We suppose a biofuel supply chain consisting of a biofuel producer

* Corresponding author.
*E-mail address:* bmliyina@scut.edu.cn (Y. Li).

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and multiple small-scale farmers for the supply of agricultural feedstock and the production of biofuel. Since the biofuel producer and small-scale farmers belong to separate entities, they will have conflicting objectives and reach different decisions, leading to double-marginalization and inefficiency with less supply of agricultural feedstock in the whole supply chain. The present studies on supply chain coordination contracts provide us with good insights into designing benefit and risk-sharing coordinate contracts for biofuel supply chains to overcome the double-marginalization effect. Unfortunately, they cannot be applied to the biofuel supply chain directly, as that supply chain has unique characteristics (Sharma et al., 2013). For example, traditionally, in the agricultural industry, an independent buyer and an independent supplier will sign a purchasing contract before the growing season, specifying the purchasing quantity and wholesale price for the agricultural products. Then the supplier sells the actual yielded products to the buyer at harvest time. However, the yield of agricultural products, which is greatly affected by natural conditions, such as weather, pests and disease, is highly uncertain (Jones et al., 2001; Kazaz, 2004; Deo and Corbett, 2009; Ren et al., 2016). Consequently, the actual yielded products often differ greatly from that expected from the initial input, they might be over or under the quantity earlier specified in the contract. Hence, the supplier bears the risk of over-production, while the buyer bears the risk of under-production in yield uncertainty environment (Inderfurth and Clemens, 2014).

Therefore, in light of the characteristics of biofuel supply chain, designing fair, mutually beneficial, and risk-sharing coordination contracts to enhance the supply of agricultural feedstock and the performance of the whole biofuel supply chain is the objective of this study. Specially, we intend to answer the following research questions. Can the traditional supply chain coordination contracts still work for the biofuel supply chain? If not, what factors will affect the design of effective coordinate contracts for the biofuel supply chain? Whether and under what conditions various types of contracts are capable of achieving supply chain coordination and a win–win situation? How does the yield uncertainty of agricultural feedstock post impacts on the decision making behavior of biofuel supply chain actors and the coordination contracts?

The rest of this paper is organized as follows. Section 2 reviews the literature on the bioenergy supply chain and supply chain coordination in random yield environments. Section 3 defines the problem and presents the optimal decisions for a centralized and a decentralized biofuel supply chain. In Section 4, three types of coordination contracts, OPC, UPC, and MC, are proposed and the optimal coordination factors are obtained. Then in Section 5, we present an empirical application of the proposed coordination contracts with data from the cassava-based biofuel industry in China; the results and implications for both practitioners and policy makers are provided. Finally, the main conclusions are summarized in Section 6.

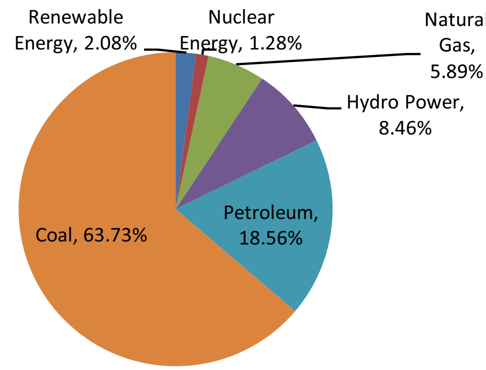


**Fig. 1.** China's primary energy consumption structure in 2015. Source: http://www.bp.com.

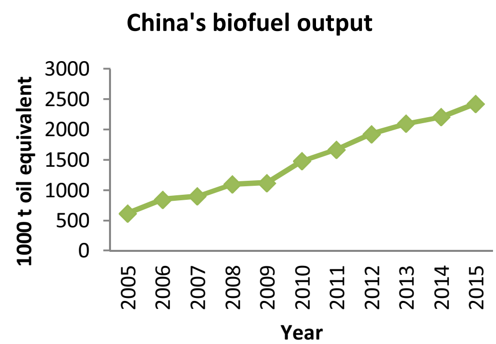


**Fig. 2.** China's biofuel output from 2005 to 2015. Source: http://www.bp.com.

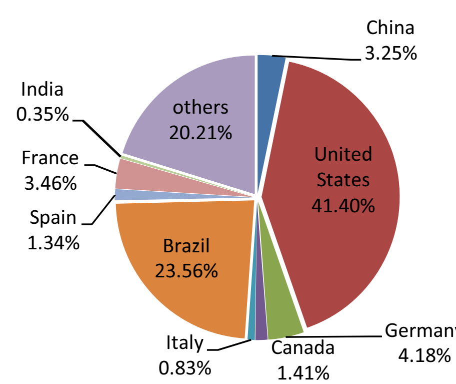


**Fig. 3.** The global distribution of biofuel output in 2015.

## 2. Literature review

There have been some studies of the bioenergy supply chain, but most of them have focused on its energy and greenhouse gas performance to see whether it is energy efficient (Dai et al., 2006; Liu et al., 2013; Holmgren et al., 2015; Jakrawatana et al., 2016). Only a few have focused on supply chain coordination among the actors. For example, Nasiri and Zaccour (2009) proposed a game-theoretic approach to model and analyze the process of utilizing biomass for power generation. Sharma et al. (2013) provided a comprehensive review of biomass supply chain design and modeling. Sun et al. (2013) developed a game-theoretic model to analyze the competitive agri-biomass supply chain. Wen and Zhang (2015) designed a 'straw acquisition' model for China's straw power plants, based on supply chain coordination. Ren et al. (2015) developed a mixed-integer non-linear programming model to design a biodiesel supply network to optimize the emergy sustainability index. However, these studies did not take the random yield environment into consideration.

The random yield problem has been well studied in the single-firm setting. Yano and Lee (1995) reviewed the studies on the ordering and producing problems in a random yield environment. Kazaz (2004) investigated olive oil production planning in a random yield and demand environment, where there were yield-dependent costs and prices. Kazaz and Webster (2011) further assumed the selling price is endogenous and affected by initial invested quantity to extend Kazaz's (2004) work. Ben-Zvi and Grosfeld-Nir (2007) provided efficient myopic heuristics for serial production systems with random yields and rigid demand. Keren (2009) studied a single-period inventory problem with known demand and stochastic supply. Deo and Corbett (2009) studied Cournot competition under yield uncertainty using the US influenza vaccine case. Ren et al. (2016) developed a bi-objective interval mix integer programming model to design biofuel supply chain under uncertainties for feedstocks, transportation capacities, yields of crops, and market demands. Unlike these studies, we focus on the design of a supply chain coordination contract for a decentralized biofuel supply chain with independent parties.

Setting a supply chain contract between individual parties has received much attention (Cachon, 2003). Our study is related to the literature on supply chain coordination in a random yield environment. In this setting, Gurnani and Gerchak (2007) studied the coordination problem in an assembly system. They showed that a shortage penalty contract for failure in delivery performance and a surplus subsidy contract for success in delivery performance can ensure the coordination across even a decentralized supply chain. Yan et al. (2010) extended the work by considering the situation where the buyer accepts all the output of the supplier and explored the properties of the over-production risk-sharing contract. Chick et al. (2008) investigated the coordination problem in the manufacture of influenza vaccinations. They assessed the performance of a pay-back contract in coordinating the supply chain. Tang and Kouvelis (2014) showed that a payback contract can coordinate the supply chain where there is random supply. Inderfurth and Clemens (2014) developed an over-production risk-sharing contract and a penalty contract to coordinate the buyer's ordering and the supplier's production decisions in the random yield setting. However, the models we presented are quite different from these studies. First, these studies assumed that the random yield rate is distributed on [0,1], that is, the realized yield will certainly be lower than the input quantity. In our study, however, the realized yield may be higher or lower than the input quantity due to unpredictable weather, a main factor behind the yield uncertainty for agricultural feedstock. Thus, the actual yield may be more or less than the input quantity ordered. Secondly, the present studies assumed that the supply chain actors own equal bargaining powers during their cooperation. In practices, however, due to unequal resources (capital, technology, purchased inputs, and others) owned by the biofuel producer and small-scale farmers, their bargaining powers are quite unbalanced with the biofuel producer being much more powerful than the farmers (Bijman, 2008). In response, we therefore develop a coordination contract incorporating the unbalanced bargaining powers of supply chain actors, so as to achieve supply chain coordination and a win–win situation.

## 3. Problem formulation

In this study, we consider a biofuel supply chain consisting of a biofuel producer and $n$ small-scale farmers for the supply of agricultural feedstock and the production of biofuel in a random yield environment. Facing market energy demand $D_0$, the biofuel producer purchases agricultural feedstocks from the $n$ small-scale farmers first, then prosses them to be biofuel products with per unit processing cost $c_E$ and sells the biofuel products to the market at per unit price $p$. Let $r\,(0 < r \le 1)$ represent the transfer output rate (i.e. the quantity of biofuel produced from a unit of feedstock). Hence the biofuel producer needs to purchase $D_0/r$ of feedstock from the $n$ small-scale farmers in order tet thmarket demand. Here, we assume the $n$ small-scale farmers are homogenous and the biofuel producer purchases the same amount, $D_0/rn$, from each farmer at per unit wholesale price $w$. Let F denote the biofuel producer's overall cost of cooperation with each farmer (expenditure on contracts, training, technical support, etc.). After receiving tfuel pducer's order, each farmer has to decide the input quantity, Q, associated with aeunit pduction cost, $c_F$. Similar to Kazaz and Webster (2011), we assume the realized yield of crop is random, due to natural conditions, such as weather, pests, diseases, etc. Thus, for each farmer's input quantity $Q$, the realized yield is $Q\mu$, where the random yield rate $\mu$ is distributed on $[\mu_1, \mu_2]$, and has a continuous probability density function $\varphi(\cdot)$ and a cumulative distribution function $\phi(\cdot)$, $E(\mu) = \bar{\mu}$, $VaR(\mu) = \delta^2$. Because the realized yield is uncertain, it may be either above or below the input size. Based on the above assumptions, we can get the following expected profit functions for the biofuel producer and the farmers.

Eer's expected profit function is

$$\pi_F(Q) = E_\mu\left[w \cdot \min\left\{\frac{D_0}{nr}, Q\mu\right\}\right] - c_{F\ Q} \quad (1)$$

The biofuel producer's expected profit function is

$$\pi_E(Q) = E_\mu\left[(pr - w - c_E)\min\left\{\frac{D_0}{r}, nQ\mu\right\}\right] - n \cdot {}_F \quad (2)$$

### 3.1. Centralized system

According to Eqs. (1) and (2), the optimization of the centralized system can be expressed as:

$$\max_Q \{\pi_{SC}(Q) = E_\mu\left[(pr - c_E)\min\left\{\frac{D_0}{r}, nQ\mu\right\}\right] - n\cdot(F + c_F Q)\} \quad (3)$$

where $E_\mu[\min\{\frac{D_0}{r}, nQ\mu\}] = nQ\int_{u_1}^{\frac{D_0}{rnQ}} \varphi(u)du + \frac{D_0}{r}\bar{\Phi}(\frac{D_0}{nrQ})$.

Due to the concavity characteristic of Eq. (3), the centralized system's optimal input quantity is obtained by taking the first-order derivative and setting it equal to zero. Then, we can characterize the centralized system's optimal input quantity as follows:

**Theorem 1.** *The centralized system's optimal input quantity* $\boldsymbol{Q^*_{SC}}$ *satisfies:*

$$\boldsymbol{\Omega\left(\frac{D_0}{nrQ^*_{SC}}\right) = \frac{c_F}{pr - c_E}} \quad (4)$$

where $\boldsymbol{\Omega(x) = \int_{\mu_1}^{x} \mu\varphi(\mu)d\mu}$.

**Proposition 1.** *If the random yield rate follows a uniform distribution with, then the farmer's optimal input quantity under the centralized system is .*

Then the centralized system's optimal expected profit can be expressed as:

$$\pi_{SC}(Q^*_{SC}) = (pr - c_E)\cdot\frac{D_0}{r}\cdot\bar{\Phi}(\frac{D_0}{nrQ^*_{SC}}) - n\cdot F \quad (5)$$

For a given wholesale price, each farmer's and the biofuel producer's expected profits under the centralized system without coordination are respectively

$$\pi_F(Q^*_{SC}) = w\cdot\frac{D_0}{rn}\cdot\bar{\Phi}(\frac{D_0}{nrQ^*_{SC}}) - (pr - w - c_E)\cdot Q^*_{SC}\cdot\Omega(\frac{D_0}{nrQ^*_{SC}}) \quad (6)$$

$$\pi_E(Q^*_{SC}) = (pr - w - c_E)\cdot\frac{D_0}{r}\cdot\bar{\Phi}(\frac{D_0}{nrQ^*_{SC}}) + (pr - w - c_E)\cdot nQ^*_{SC}\cdot\Omega(\frac{D_0}{nrQ^*_{SC}}) - n\cdot F \quad (7)$$

### 3.2. Decentralized system

From Eq. (1), we can get each farmer's optimal input quantity under the decentralized system:

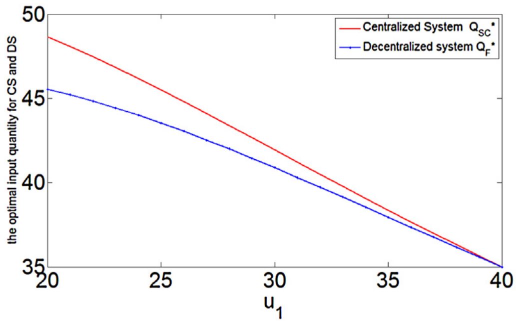


**Fig. 4.** The optimal input quantity of the centralized and decentralized supply chain.

**Theorem 2.** *Each farmer's optimal input quantity under the decentralized system satisfies:*

$$\Omega\left(\frac{D_0}{nrQ_F^*}\right) = \frac{c_F}{w} \tag{8}$$

**Proposition 2.** *If the random yield rate follows a uniform distribution with, then the farmer's optimal input quantity under decentralized system is .*

Since $pr > w + c_E$, then $\Omega\left(\frac{D_0}{nrQ_F^*}\right) > \Omega\left(\frac{D_0}{nrQ_{SC}^*}\right)$. This suggests that each farmer's optimal input quantity under the decentralized system is less than that under the centralized system. This observation is consistent with practices: under a decentralized system, farmers bear the risk of yield uncertainty alone, and so set a lower input quantity. Fig. 4 shows the optimal input quantity under the centralized and decentralized system given uniform distributed random yield rate.

Under the decentralized system, each farmer's expected profit is

$$\pi_F(Q_F^*) = w \cdot \frac{D_0}{rn} \cdot \bar{\Phi}(\frac{D_0}{nrQ_F^*}) \tag{9}$$

The biofuel producer's expected profit is

$$\pi_E(Q_F^*) = (pr - w - c_E) \cdot \frac{D_0}{r} \cdot \bar{\Phi}(\frac{D_0}{nrQ_F^*})$$
$$+(pr - w - c_E) \cdot nQ_F^* \cdot \Omega(\frac{D_0}{nrQ_F^*}) - n \cdot F \tag{10}$$

Hence, the expected overall profit for the whole supply chain under the decentralized systeis

$$\pi_{SC}(Q_F^*) = (pr - c_E) \cdot \frac{D_0}{r} \cdot \bar{\Phi}(\frac{D_0}{nrQ_F^*})$$
$$+(pr - w - c_E) \cdot nQ_F^* \cdot \Omega(\frac{D_0}{nrQ_F^*}) - n \cdot F \tag{11}$$

According to the above discussion, we can obtain Proposition 3 as follows.

**Proposition 3.** *For a given wholesale price w, we have* $\pi_F\left(Q_F^*\right) > \pi_F\left(Q_{SC}^*\right)$; $\pi_E\left(Q_F^*\right) < \pi_E\left(Q_{SC}^*\right)$; $\pi_{SC}\left(Q_F^*\right) < \pi_{SC}\left(Q_{SC}^*\right)$.

**Proof.** It is easy to verify that $Q_F^* < Q_{SC}^*$ for $pr > w + c_E$. From Eq. (8) we know that $\pi_F\left(Q_F^*\right) < \pi_F\left(Q_{SC}^*\right)$ since $\pi_F(Q)$ is increasing on $(0, Q_F^*]$ and $(Q_F^*, \infty)$. Similarly, it is easy to know that $\pi_{SC}\left(Q_{SC}^*\right) > \pi_{SC}\left(Q_F^*\right)$ for $Q_F^* < Q_{SC}^*$. As a result, $\pi_E\left(Q_{SC}^*\right) = \pi_{SC}\left(Q_{SC}^*\right) - n\pi_F\left(Q_{SC}^*\right) > \pi_{SC}\left(Q_F^*\right) - n\pi_F\left(Q_F^*\right) = \pi_E\left(Q_F^*\right)$. Thus$\pi_E\left(Q_{SC}^*\right) > \pi_E\left(Q_F^*\right)$.

Propositions 1–3 verify that the double marginalization effect of the decentralized system, which highlights the need for coordination to improve the input quantity and the performance of the supply chain.

## 4. Methods for designing coordination contracts

### 4.1. Over-production risk-sharing contract (OPC)

Under this contract, we assume that if the farmers' realized yield is more than the biofuel producer's order quantity due to random factors, the biofuel producer nonetheless purchases a yielded feedstocks. The biofuel producer pays the full wholesale price, $w$, for the actual order quantity, but pays a discounted wholesale price, $\alpha \cdot w$ $(0 \le \alpha < 1)$, for all the excess quantity. In this way, the biofuel producer will bear a higher risk than under the decentralized system, by sharing the risk of over-production with the farmers together.

Therefore, under this contract, the farmer's optimal input quantity, $Q_s$ can be deteined by lving Eq. (12):

$$\max_{Q_s}\{\pi_F(Q_s, \alpha) = E_\mu\left[w \cdot \min\left\{\frac{D_0}{nr}, Q_s\mu\right\}\right]$$
$$+E_\mu\left[\alpha \cdot w \cdot \max\left(Q_s\mu - \frac{D_0}{nr}, 0\right)\right] - c_F Q_s\} \tag{12}$$

where $E_\mu[\max(Q_s\mu - \frac{D_0}{nr}, 0)] = Q_s\int_{\frac{D_0}{rnQ}}^{u_2}\mu\varphi(u)du - \frac{D_0}{nr}\bar{\Phi}(\frac{D_0}{nrQ_s})$.

And the biofuel producer's expected profit function is

$$\pi_E(Q_s, \alpha) = E_\mu\left[(pr - w - c_E)\min\left\{\frac{D_0}{r}, nQ_s\mu\right\}\right] -$$
$$E_\mu\left[\alpha \cdot w \cdot \max\left(nQ_s\mu - \frac{D_0}{r}, 0\right)\right] - n \cdot {}_F \tag{13}$$

From Eq. (12), we can get the farmer's optimal input quantity with the OPC:

**Theorem 3.** *With the OPC, each farmer's optimal input quantity* $\mathbf{Q_S^*}$ *satisfies:*

$$\boldsymbol{\Omega(\frac{D_0}{nrQ_S^*}) = \frac{c_F - \bar{\mu} \cdot \alpha \cdot w}{w - \alpha \cdot w}} \tag{14}$$

According to Eq. (14), we know that $\alpha < \in (0, min(1, \frac{c_F}{\bar{\mu}w}))$.

**Proposition 4.** *If the random yield rate $\mu$ follows a uniform distribution with $\mu \sim [\mu_1, \mu_2]$, then the farmer's optimal input quantity with the OPC is* $Q_S^* = \frac{D_0}{nr\sqrt{{\mu_1}^2 + \frac{2(c_F - \bar{\mu}\cdot\alpha\cdot w)(\mu_2 - \mu_1)}{(w - \alpha \cdot w)}}}$.

**Proposition 5.** *For a given wholesale price w, then an OPC where* $\alpha^* = \frac{c_F(pr - c_{E-w})}{w(\bar{\mu}(pr - c_E) - c_F)}$ *coordinates the decentralized supply chain.*

**Proof.** Let $Q_S^* = Q_{SC}^*$, we can obtain $\alpha^* = \frac{c_F(pr - c_{E-w})}{w(\bar{\mu}(pr - c_E) - c_F)}$.

Thus, with the OPC, each farmer's expect profit is

$$\pi_F(Q_{SC}^*; \alpha^*) = w(1 - \alpha^*) \cdot \frac{D_0}{nr} \cdot \bar{\Phi}(\frac{D_0}{nrQ_{SC}^*}) \tag{15}$$

And the biofuel producer's expected profit can be expressed as

$$\pi_E(Q_{SC}^*; \alpha^*) = (pr - w(1 - \alpha^*) - c_E) \cdot \frac{D_0}{r} \cdot \bar{\Phi}(\frac{D_0}{nrQ_{SC}^*})$$
$$+(pr - c_E) \cdot nQ_{SC}^* \cdot \Omega(\frac{D_0}{nrQ_{SC}^*}) - n(F + c_F Q_{SC}^*) \tag{16}$$

### 4.2. Under-production risk-sharing contract (UPC)

With the UPC, we assume that if the farmers' realized yield is less than the biofuel producer's order quantity due to random factors,

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then the farmers will be penalized for each unit of unfulfilled order at a penalty price $\beta \cdot w$ $(0 \leq \beta < 1)$. Thus the farmers will bear a higher risk than under the decentralized system, by sharing the risk of under-production with the biofuel producer.

With the UPC, each farmer's expected profit function can be expressed as:

$$\max_{Q_P}\{\pi_F\left(Q_P,\beta\right)=E_\mu\left[w\cdot\min\left\{\frac{D_0}{nr},Q_P\mu\right\}\right]-$$
$$E_\mu\left[\beta\cdot w\cdot\max\left(\frac{D_0}{nr}-Q_P\mu,0\right)\right]-c_FQ_P\} \quad (17)$$

where $E_\mu[\max(\frac{D_0}{nr}-Q_P\mu,0)]=\frac{D_0}{nr}\bar{\Phi}(\frac{D_0}{nrQ_P})-Q_P\int_{u_1}^{\frac{D_0}{rnQ_P}}\mu\varphi(u)du$.

And the biofuel producer's expected profit function is

$$\pi_E\left(Q_P,\beta\right)=E_\mu\left[(pr-w-c_E)\cdot\min\left\{\frac{D_0}{r},nQ_P\mu\right\}\right]$$
$$+E_\mu\left[\beta\cdot w\cdot\max\left(\frac{D_0}{r}-nQ_P\mu,0\right)\right]-nF \quad (18)$$

The farmer's optimal input quantity with the UPC can be characterized as follows:

**Theorem 4.** *With the UPC, each farmer's optimal input quantity* $\mathbf{Q_P^*}$ *satisfies:*

$$\boldsymbol{\Omega}\left(\frac{\boldsymbol{D}_0}{\boldsymbol{nrQ_P^*}}\right)=\frac{\boldsymbol{c_F}}{\boldsymbol{w}\left(1+\boldsymbol{\beta}\right)} \quad (19)$$

**Proposition 6.** *For a given wholesale pricew, then an UPC where* $\beta^*=\frac{(pr-c_E-w)}{w}$ *coordinates the decentralized supply chain.*

**Proof.** Let $Q_P^*=Q_{SC}^*$, we can obtain $\beta^*=\frac{(pr-c_E-w)}{w}$.

With the UPC, each farmer's expect profit is

$$\pi_F(Q_{SC}^*,\beta^*)=\frac{D_0}{nr}\cdot w(1+\beta^*)\cdot\bar{\Phi}(\frac{D_0}{nrQ_{SC}^*})-\frac{D_0}{nr}\cdot w\cdot\beta^* \quad (20)$$

The biofuel producer's expected profit can be expressed as

$$\pi_E(Q_{SC}^*,\beta^*)=(pr-w(1+\beta^*)-c_E)\cdot\frac{D_0}{r}\cdot\bar{\Phi}(\frac{D_0}{nrQ_{SC}^*})$$
$$+(pr-c_E)\cdot nQ_{SC}^*\cdot\Omega(\frac{D_0}{nrQ_{SC}^*})+\frac{D_0}{r}\cdot w\cdot\beta^*-n(F+c_FQ_{SC}^*) \quad (21)$$

### 4.3. *The mixed contract with asymmetric Nash bargaining model (MC)*

From Sections 4.1 and 4.2, we can see that, with the OPC or the UPC, either the biofuel producer or the farmers bear a higher risk than they do in the decentralized system. Thus, the participation constraints of either of them cannot hold. So we develop a MC to incorporate key aspects of the above two contracts and achieve supply chain coordination by ensuring that there is a win–win situation for farmers and the biofuel producer. With the MC, each farmer's expected profit function can be expressed as:

$$\max_{Q_M}\{\pi_F\left(Q_M,\alpha,\beta\right)=E_\mu\left[w\cdot\min\left\{\frac{D_0}{nr},Q_M\mu\right\}\right]$$
$$+E_\mu\left[\alpha\cdot w\cdot\max\left(Q_M\mu-\frac{D_0}{nr},0\right)-\right.$$
$$\left.\beta\cdot w\cdot\max\left(\frac{D_0}{nr}-Q_M\mu,0\right)\right]-c_FQ_M\} \quad (22)$$

The biofuel producer's expected profit function can be expressed as:

$$\pi_E\left(Q_M,\alpha,\beta\right)=E_\mu\left[(pr-w-c_E)\cdot\min\left\{\frac{D_0}{r},nQ_M\mu\right\}\right]-$$
$$E_\mu\left[\alpha\cdot w\cdot\max\left(nQ_M\mu\right.\right.$$
$$\left.\left.-\frac{D_0}{r},0\right)-\beta\cdot w\cdot\max\left(\frac{D_0}{r}-nQ_M\mu,0\right)\right]-n\cdot\mathrm{F} \quad (23)$$

The optimal input quantity with the MC can be characterized as follows:

**Theorem 5.** *With the MC, the optimal input quantity* $\mathbf{Q_M^*}$ *satisfies:*

$$\boldsymbol{\Omega}(\frac{\boldsymbol{D_0}}{\boldsymbol{nrQ_M^*}})=\frac{\boldsymbol{c_F}-\boldsymbol{\bar{\mu}}\cdot\boldsymbol{\alpha}\cdot\boldsymbol{w}}{\boldsymbol{w}(\mathbf{1}+\boldsymbol{\beta}-\boldsymbol{\alpha})} \quad (24)$$

**Proposition 7.** *For a given wholesale price w, then a MC where* $\left(\alpha^{**}\left(\bar{\mu}\left(pr-c_E\right)-c_F\right)+\beta^{**}c_F\right)=\frac{c_F(pr-c_{E-w})}{w}$ *coordinates the decentralized supply chain.*

**Proof.** Let $Q_M^*=Q_{SC}^*$, we have $\left(\alpha^{**}\left(\bar{\mu}\left(pr-c_E\right)-c_F\right)+\beta^{**}c_F\right)=\frac{c_F(pr-c_{E-w})}{w}$.

Under MC, each farmer's expected profit is:

$$\pi_F(Q_{SC}^*,\alpha^{**},\beta^{**})=\frac{D_0}{nr}\cdot w(1+\beta^{**}-\alpha^{**})\cdot\bar{\Phi}(\frac{D_0}{nrQ_{SC}^*})-\frac{D_0}{nr}\cdot w\cdot\beta^{**} \quad (25)$$

The biofuel producer's expected profit is

$$\pi_E(Q_{SC}^*,\alpha^{**},\beta^{**})=(pr-w(1+\beta^{**}-\alpha^{**})-c_E)\cdot\frac{D_0}{r}\cdot\bar{\Phi}(\frac{D_0}{nrQ_{SC}^*})$$
$$+(pr-c_E)\cdot nQ_{SC}^*\cdot\Omega(\frac{D_0}{nrQ_{SC}^*})+\frac{D_0}{r}\cdot w\cdot\beta^{**}-n(F+c_FQ_{SC}^*) \quad (26)$$

Now the problem is to determine the optimal $\alpha^{**}$ and $\boldsymbol{\beta^{**}}$. In practice, the optimal $\alpha^{**}$ and $\boldsymbol{\beta^{**}}$ are negotiated by both actors. Recall that the biofuel producer and the sll-scale fmers have unbalanced bargaining powers due to their unequal resources (capital, technology, purchased inputs, and others), in this study, we use an asymmetric Nash bargaining model, one of the most popular methods used to coordinate possible benefits from a system, by taking the bargaining powers of both actors into consideration (Nash, 1950; Harsanyi and Selten, 1972).

To define a bargaining problem, first, we need to appoint the disagreement points of the negotiation actors, the farmers and the biofuel producer in this study. In many situations, the disagreement points are set to be the negotiation actors' profits when the negotiation breaks down (Feng and Lu, 2012). Here, we set the famers and the biofuel producer's profits under the decentralized system (non-cooperation scenario), denoted by $n\pi_F\left(Q_F^*\right),\pi_E\left(Q_F^*\right)$, respectively, as the disagreement points. Second, we need to define the famers and the biofuel pducer's profits after negotiation, which refer their profits under mixed contract (cooperation scenario), denoted by $n\pi_F\left(Q_{SC}^*,\alpha^{**},\beta^{**}\right),\pi_E\left(Q_{SC}^*,\alpha^{**},\beta^{**}\right)$, respectively. Third, we let $k$ and (1-$k$) represent the farmers' and the biofuel producer's bargaining power, respectively. An asymmetric Nash bargaining model can incorporate the individual rationalities of both actors while optimizing the supply chain. Then the bargaining model can described as

$$\max_{\alpha^{**},\beta^{**}}\{H=\{(n\pi_F(Q_{SC}^*,\alpha^{**},\beta^{**})-n\pi_F(Q_F^*))^k\cdot(\pi_E(Q_{SC}^*,\alpha^{**},\beta^{**})-\pi_E(Q_F^*))^{(1-k)}\}$$
$$\text{s.t.}\begin{cases}(\alpha^{**}(\bar{\mu}(pr-c_E)-c_F)+\beta^{**}c_F)=\dfrac{c_F(pr-c_E-w)}{w}\\ \pi_F(Q_{SC}^*,\alpha^{**},\beta^{**})\geq\pi_F(Q_F^*)\\ \pi_E(Q_{SC}^*,\alpha^{**},\beta^{**})\geq\pi_E(Q_F^*)\end{cases} \quad (27)$$

From Eq. (27), we can get the optimal

$$\alpha^{**} = \frac{k\left(G_3 - n\pi_F\left(Q_F^*\right) - \pi_E\left(Q_F^*\right)\right) + n\pi_F\left(Q_F^*\right) - G_1 - (G_1 - G_2)G_5}{G_2G_4 - (G_1 + G_1G_4)} \tag{28}$$

$$\beta^{**} = G_5 - \alpha^{**}G_2 \tag{29}$$

where $G_1 = \frac{D_0 w}{r}\bar{\Phi}(\frac{D_0}{nrQ_{SC}^*})$, $G_2 = \frac{D_0}{r} \cdot w$, $G_3 = (pr - c_E) \cdot \{nQ_{SC}^* \cdot \Omega(\frac{D_0}{nrQ_{SC}^*}) + \frac{D_0}{r}\bar{\Phi}(\frac{D_0}{nrQ_{SC}^*})\} - n(F + c_F Q_{SC}^*)$, $G_4 = \frac{(\bar{\mu}(pr-c_E)-c_F)}{c_F}$, $G_5 = \frac{(pr-c_E-w)}{w}$.

## 5. Case study and results discussion

In this section, we present a case study of the above proposed contracts. The key parameters are set as the industry average values from the cassava-based biofuel industry in China. The characteristics of the crop, such as high drought and heal tolerance, high starch content and little requirement for agricultural fertilizers, make cassava one of the most attractive plants for biofuel production (Jansson et al., 2009). Moreover, cassava is a non-staple crop in China, avoiding direct competition with food. Therefore, cassava is viewed as an important and highly attractive biofuel crop in China. Four provinces of South China, Guanagxi, Guangdong, Yunnan, and Hainan, account for more than 90% of the national production of cassava. However, more than 60% of China total domestic need for cassava is met by imports, from Thailand for example (Liu et al., 2013).

Ava-based biofuel supply chain consisting of a biofuel producer and 2000 small-scale farmers ($n = 2000$) has the following characteristics: demand $D_0 = 400,000$ t/year; the rdom yield rate $\mu$. follows a uniform distribution with $\mu \sim [20, 40]$ $\left(\text{t/ha}\right)$; planting costs of the farmers $c_F = RMB7500$/ha; the biofuel producer's processing cost $c_E = RMB100$/t; cassava market price $p = RMB5600$/t; wholesale price for cassava $w = RMB550$/t; biofuel producer's cooperation cost $F = RMB300/year$; transfer output rate $r = 0.12$. In addition, we let the farmer's bargaining power $k = 0.5$.

### 5.1. The overall results

Using the cassava-based biofuel supply chain case in China, we get the optimal input quantity, the coordination factors, as well as the expected profits of each farmer, the biofuel producer, and the whole biofuel supply chain, as shown in Table 1. Table 1 confirms the main conclusions of the above discussions. The optimal input quantity under the centralized system is higher than that under the decentralized system. Due to the double marginalization effect, the profits of the biofuel producer and of the whole supply chain are greater under the centralized system than that under the decentralized system; while the farmer's profit is less under the centralized system. Further, from Table 1 we can see that, though both the OPC and UPC can achieve the optimization of the whole supply chain, either the biofuel producer or the farmer fails to see an improvement in profits. Only the MC can satisfy both actors' participation constraints and achieve supply chain coordination simultaneously.

### 5.2. Sensitivity analyses

In the above empirical application of the proposed contracts, we used the average industry data for the cassava-based biofuel industry of China. However, in the same industry, the real parameters for specific companies vary. For example, the average industry transfer output rate from cassava to biofuel is 12%, but it differs for specific biofuel producers as they have made different investments in equipment and human resources, etc. Then, the question that arises is: to what extent does varying the parameter values (to match those of specific companies) influence the decision-making behavior and the profit of each actor in the supply chain? To answer this question, we perform sensitivity analyses on the main parameters – yield uncertainty, the biofuel producer's transfer output rate, as well as costs – to see their effect on the optimal input quantity, coordination factors and profits.

When the biofuel producer's transfer output rate varies from 12% to 24%, we can see that the higher the transfer output rate is, the lower the input quantity will be, and the higher the coordination factors for the OPC and UPC will be (Fig. 5). This phenomenon makes sense in the real world. To satisfy a given end market (energy) demand, as the biofuel producer's transfer output rate becomes higher, the size of the cassava purchasing order will be less. Accordingly, the farmers will decrease their input quantity. As a consequence, the risk of under-delivery and shortage will be increased, due to the yield uncertainty. In this situation, to mitigate the risk of lost energy sales, the biofuel producer will choose to commit to purchase all the excess cassava, at a higher discount on the wholesale price, and to penalize each unit of unfulfilled order at a higher penalty price, so as to provide incentives to the farmers to increase the input quantity. Intuitively, the higher the transfer output rate is, the more the biofuel producer's profit and the less the farmer's profit will be.

The effects of yield uncertainty are shown in Fig. 6. We use the coefficients of variation of the yield $\zeta_\mu = \delta/\bar{\mu}$ to represent the extent of yield uncertainty. Obviously, a larger $\zeta_\mu$ represents a higher yield uncertainty. We can see from Fig. 3 that, the higher yield uncertainty is, the larger the input quantity will be under both the centralized system and the decentralized system. This result is intuitive: a larger input quantity should be set to meet a given level of demand where the yield uncertainty is greater. With a higher yield uncertainty, the actual quantity of output might be larger for a larger input quantity. Then, the farmer's risk of over-production will be increased. In response, the biofuel producer should set a higher discount price $\alpha$ in the OPC to commit to purchase all excess output, to encourage the farmers to increase their input quantity.

In addition, from Fig. 7 we can see that the optimal input quantity in both the centralized system and the decentralized system decrease in the farmer's per unit production cost, while the coordination factor with the OPC increases in the farmer's per unit production cost. This supports the real-world finding that, as farmers' production costs increase, they will decrease the input quantity because they are small-scale and have a limited amount of capital, which confirms Theorem 1 and Theorem 2. In this situation, the biofuel producer will increase the coordination factors on the whole price in purchasing the excess quantity, in order to encourage the farmers to increase their input quantity. However, if the biofuel producer's processing costs increase, the input quantity under the centralized system will be decrease, while that under the decentralized system remains the same, which can be easily seen to follow from Theorem 1 and Theorem 2. Consequently, the biofuel producer will set a lower coordination factors to correct the farmers' input quantity aligning that of centralized system.

### 5.3. Implications

The empirical application on cassava-based biofuel supply chain in China provides several interesting observations and implications for both practitioners and policy-makers regarding how to enhance the supply of agricultural feedstock and the performance of the whole biofuel supply chain under random yield environment. ***First,*** the results suggest that, the input quantity of the agricultural feedstock and the profit of the whole supply chain in centralized system are higher than that in decentralized system, specifying the need for the design of effective coordination contract to achieve the optimization and coordination of the biofuel supply chain. ***Second***, an effective coordination contract should

**Table 1**
Empirical Results.

| | Optimal coordination factor | Optimal input quantity (acre) | Each farmer's expected profit ($10^3$RMB) | Biofuel producer's expected profit ($10^3$RMB) | The whole supply chain's expected profit ($10^3$RMB) |
|---|---|---|---|---|---|
| CS | – | $Q_{SC}^* = 48.6366$ | 353.61 | 391,250 | 1,098,470 |
| DS | – | $Q_F^* = 45.5311$ | 356.19 | 379,950 | 1,092,330 |
| OPC | $\alpha^* = 0.1515$ | $Q_S^* = 48.6366$ | 366.36 | 365,760 | 1,098,480 |
| UPC | $\beta^* = 0.2727$ | $Q_P^* = 48.6366$ | 339.54 | 419,400 | 1,098,480 |
| MC | $\alpha^{**} = 0.1028$ $\beta^{**} = 0.0878$ | $Q_M^* = 48.6366$ | 357.73 | 383,020 | 1,098,480 |

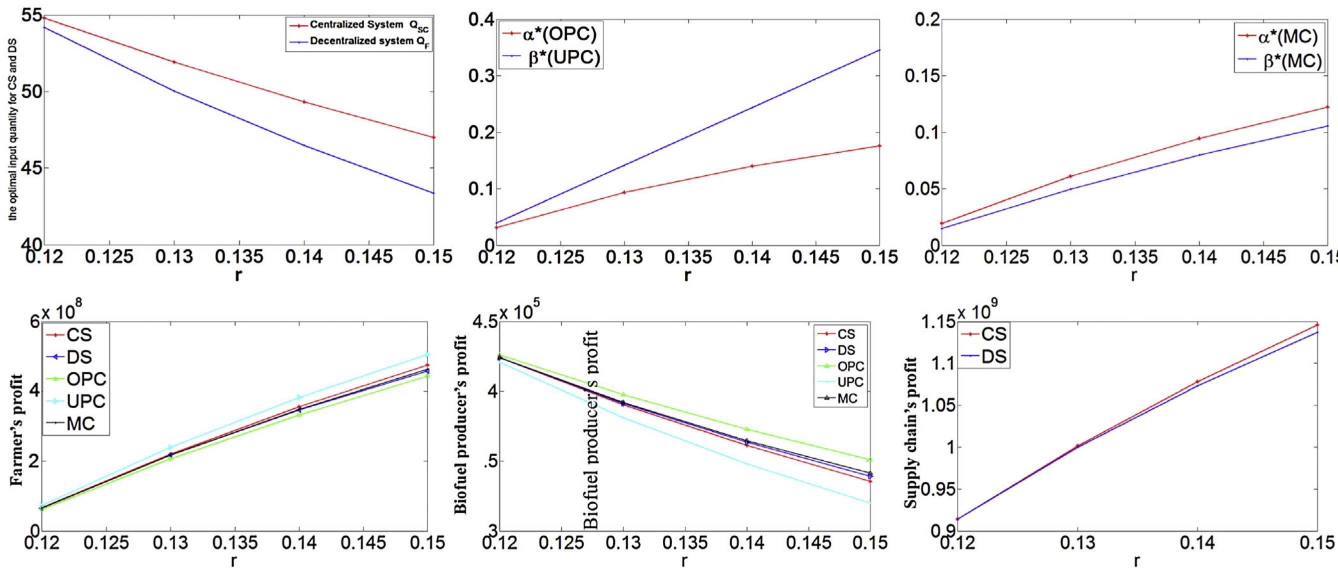


**Fig. 5.** The impact of transfer output rate on optimal decisions and profits.

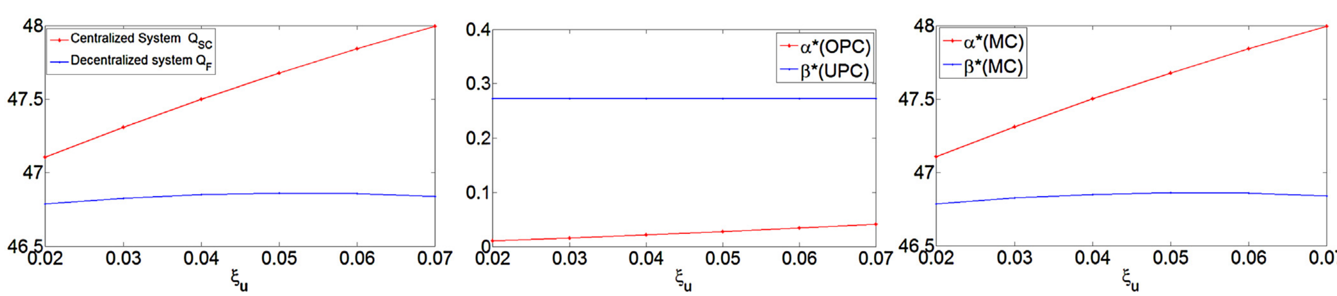


**Fig. 6.** The impact of yield uncertainty on optimal decisions.

incorporate the unique characteristics of the biofuel supply chain (the uncertainty for yield of agricultural crops and the unbalanced bargaining powers of supply chain actors for example) (like MC contract), otherwise, the coordination contracts might not work (like OPC and UPC contracts). ***Third***, the sensitive analyses indicate that as the improvement achieved by supply chain optimization and coordination will be increased as the yield uncertainty becomes higher, that is, the pratitioners should value the cooperation with the actors in the biofuel supply chain to achieve the win–win situation for both benefit and risk sharing, this point is particularly important under the environment with uncertainties. In addtion, we find that as the biofuel producer's transfer output rate from cassava to biofuel enhances, the achieved improvement through supply chain coordiantion will be more. Then, the government should adopt policies or provide incentive to induce and encourage the biofuel producer to enhance the transfer output rate through innovation, so as to improve the economic performance of biofuel supply chain, and consequently, achieve the green and sustainable development. On the other hand, we find the higher production cost will force the farmers to decrease the input quantity of agricultural feedstock, which is not conducive to the sustainable development of biofuel industry and rural development, therefore, how to offer financial and policy supports to encourage the farmers to increase the input quantity of agricultural feedstock is an improtant issue for the government.

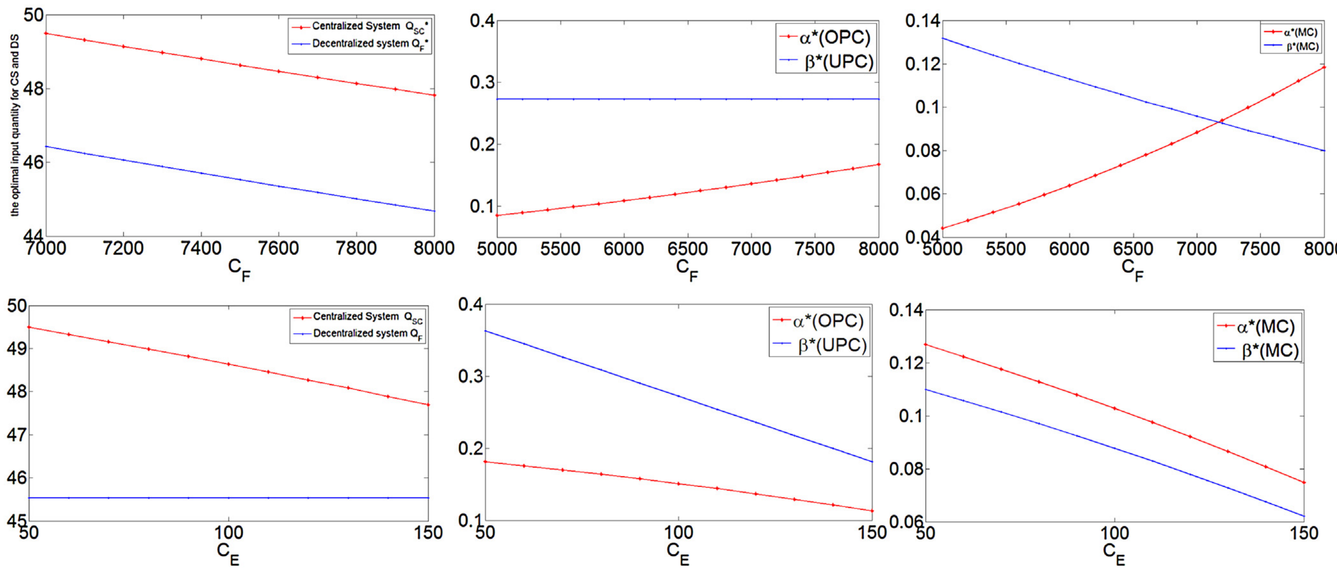


**Fig. 7.** The impact of production costs on optimal decisions.

## 6. Conclusions

This paper has investigated the use of coordination contracts between a biofuel producer and multiple small-scale farmers in a random yield environment, as such contracts might ensure the sustainable supply of agricultural feedstock for biofuel production and improve the performance of the biofuel supply chain as a whole. First, both the over-production risk-sharing contract (where the biofuel producer pays a discount price for the farmers' excess units) and the under-production risk-sharing contract (where the farmers are penalized by a penalty price for the under-delivery of units) are developed to provide incentives or penalties for the farmers to increase or decrease their production, so as to align it to that required in a centralized supply chain. However, the results show that either the biofuel producer or the farmers will do less well (will profit less) with use of these two types of contract than they would have done under a decentralized system, with no contracts. Building upon this result, we further put forward a mixed contract, with an asymmetric Nash bargaining model, to achieve supply chain coordination and to satisfy both actor' participation constraints. An empirical case for the cassava-based biofuel industry in China is applied to illustrate the proposed contracts. The results show that the proposed mixed contract with an asymmetric Nash bargaining model is conducive to the sustainable supply of agricultural feedstock and achieves Pareto improvement in the supply chain. Moreover, sensitivity analyses are conducted to reveal the effects of varying the yield uncertainty, the biofuel producer's transfer output rate, as well as the cost parameters on the optimal input quantity, coordination factors and profits. The findings should help practitioners understand when and how to implement these coordination contracts to increase the efficiency of both the individual actors and the biofuel supply chain as a whole. The practitioners must also be aware of the possible impacts of individual conditions (price, cost, capacity) on decision-making behavior.

Our study contributes to the literature on supply chain coordination in random yield environments, which is of practical relevance to the agricultural industry. The proposed mixed contract with an asymmetric Nash bargaining model is easy to implement in practice. This study has several limitations. ***First***, we assume all decision makers are risk-neutral, and their objectives are optimizing the expected profit. In practices, however, numerous examples indicate that the decision makers in a supply chain would have different kinds of risk preferences (Li et al., 2015). For example, the small-scale farmers, who are often lack of the necessary financial reserves and information about market opportunities, will often have risk-averse behavior, especially under uncertain environment. Therefore, further research may take the risk preferences of decision makers in the biofuel supply chain into consideration in the design of the coordinate contract. ***Second***, to ease the computational burden, we assume all small-scale farmers are homogeneous in terms of cost structure and capacity, whereas, in practice, heterogeneous farmers with unequal resources (e.g. land and capital) will make quite different decisions, and this would also be an interesting point to explore. ***Third***, we only consider the biofuel supply chain consisting of a biofuel producer and farmers in this study. Incorporating the role of external actors into the biofuel supply chain decision making model would be of interest, notably the external influence of government, which is in reality an important additional actor in the system giving the importance of renewable energy in sustainable development.

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