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A Novel Scoring Auction for Agricultural Supply Chain Trading

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Abstract

Due to the various and obsolete nature, fresh agricultural product has enormous unused value. It is significant to design multi-attribution auction for agricultural supply chain trading (ASCT). This paper proposes a novel scoring auction for agricultural supply chain trading. In such a mechanism, poverty alleviation is considered. A second-preferred-score and a Vickrey-Clarke-Groves score (VCG-score) auctions for both single-unit and multi-unit multi-attribute cases are used to realize incentive compatible, allocatively efficient, individually rational, budget balanced. Additionally, two types of auction models have incorporated poverty alleviation, which also achieve the same properties. The effectiveness and robustness of our mechanism are verified by numerical study.

Subject Areas

Supply Chain Management

Keywords

Agricultural Supply Chain Trading, Scoring Auction, Poverty Alleviation, Multi-Attribution Auction

1. Introduction

Fresh produce is a necessity of people's life (such as vegetables, fruits, aquatic products, meats, etc.), which always plays an important role in the market [1]. On the one hand, fresh produce has a high yield. For instance, China has a total 749.12 million tons of vegetables, 286.92 million tons of fruits, 77.48 million tons of meats and 65.49 million tons of aquatic products in 2020 [2]. On the other hand, more than 150 types of vegetables have circulated in food market. The huge yield and a large number of varieties of fresh produce require an efficient supply chain to discover additional market value. Similar to classical perishable products (such as hotels, airlines, gifts, toys, consumption electronics, etc.), fresh produce has a long-time delivery, finite shelf-life. However, fresh produce, as a special perishable product, has a high circulation loss, easily decays, and has no salvage value after the selling season [1]. For example, the circulation loss of fruits and vegetables is approximately 200 million tons. The performance of produce supply chains has a significant effect on both the economic development and the standard of living.

In general, agricultural supply chain trading (ASCT) involves exchanging commodities, delivering commodities, support services and the flow of information across produce supply chain. It owns the same advantages with usual supply chain trading such as matching supply and demand, facilitating transactions and providing an institutional infrastructure, and is usually consisted of sellers, buyers and a market intermediary [3]. Supply chain trading is only based on price, not incorporated those characteristics of produce such as high fluctuation both supply and demand, long delivery time and a short shelf-life. Therefore, more non-money attributes should be considered into ASCT such as quality, quantity, delivery time, and location of the products [4]. Meanwhile, supply chain trading selects trading mechanisms to lower transaction costs only, neglecting transaction time incurred in exchanging products [5]. A novel comprehensive produce supply chain trading mechanism is imperative in order to improve both standard of living and economic development.

Auction is defined as "a market institution with an explicit set of rules determining resource allocation and prices based on bids of market participants" [6]. Auction mechanisms make two contributions to produce market: eliminate haggling and efficient allocation. To date, auction mechanisms for ASCT are mainly open-cry auctions, involving English auction and Dutch auction [7] [8] [9] [10] where bidders can observe their competitors' bids. However, sealed-bid auctions will come to dominate the stable long-time market since e-commerce has been one of the key drivers of evolution in trading [11]. An efficient auction that realizes maximal social welfare is imperative to ensure the stability and long-term of produce market.

As standard of living and economic improving, people give more requirement on produce and produces are pretty various and heterogeneous. It is significant to study multi-attribute auction where bidders compete both price and non-price attributes. In the economics and operations research literature, multi-attribute auctions can be divided two streams of studies: optimal auctions and efficient auctions. In an optimal multi-attribute auction, the buyer maximizes her expected utility given the beliefs about the costs of sellers via announcing a scoring rule [12] [13] [14]. In an efficient multi-attribute auction where one buyer announces her utility function and sellers submit their cost function to an auctioneer. Such a mechanism maximizes social welfare. Mechanism design upon efficient multi-attribute auction is in infancy. Parkes and Kalagnanam proposed several efficient iterative auctions for single-unit procurement via a linear programming approach [11]. Xiao and Wang proposed efficient multi-attribute auctions for multi-unit trading. In this study, we also aim to design efficient multi-attribute auctions both single-unit and multi-unit procurement. From a practical view, the higher the market efficiency is, the larger revenues third-party auction platform gains in long-term run [15].

To our best knowledge, this study is the first paper that considers auction incorporated poverty alleviation. In particular, this article attempts to address the following questions: 1) How to take more non-price attributes into consideration for the ASCT? 2) How to realize efficient multi-attribute auctions for ASCT? 3) How can our auction mechanisms be extended to incorporate CSR under poverty alleviation policy? We first consider the case where each grower submit bid to compete one produce procurement order, that is, only one unit of produce procurement order is bided in one auction. In this case, a second-preferred-score auction is proposed to sort bids that consisted of both price and attribute bundle, and determine the winner and payment via designed scoring rule. Consequently, we extend single-unit to the multi-unit case where each grower submits a vector bid for multi-unit produce orders. In such a multi-unit case, not only the price and attribute bundle but also the quantity attribute (*i.e.*, the number of produce orders that grower desire to win) should be contained into bids. Quantity is a special attribute since it preferentially depends on price. The more procurement orders grower win, the lower unit price the grower is willing to accept. Hence, a VCG-score auction is proposed to overcome this plight. The outcome of this auction is determined by converting each grower's bid into a new vector score. Both the second-preferred-score auction and VCG-score auction can ensure IC, IR, BB and AE, which provide a support for sustaining a long-term stable produce market.

The reminder of this study is organized as follows. In Section 2, we review the literature related to fresh produce supply chain, multi-attribute auction, and auction-based ASCT. Section 3 describes the base model. In Section 4.1 and Section 4.2, we propose the SUMA and the MUMA auction mechanisms, respectively. In Section 4.3, auction mechanisms be extended to incorporate CSR under poverty alleviation policy. To evaluate the efficiencies of mechanisms and obtain optimal poverty alleviation schemes for both corporation and government, computational analyses are conducted in Section 5. Finally, our contributions and some directions for future research are summarized in Sections 6 and 7.

2. Literature Review

2.1. Fresh Produce Supply Chain

The question of fresh produce supply chain has been widely studied, such as, supply chain design [16] [17], supply chain coordination [18] [19] [20], and reviews of literature [21] [22]. Joseph and Gary take the example of melons and sweet corn, use the product's marginal value of time (MVT) to examine supply chain design strategies. They find a hybrid of a responsive model from post-harvest to cooling minimize lost value in the supply chain [16]. Soto-Silva *et al.* note that the supply chain is characterized by long supply lead times combined with significant supply and demand uncertainties, and relatively thin margins in the food and agribusiness sector [17]. Cai *et al.* propose a wholesale-market clearance contract between the producer and the distributor, and a wholesale-price-discount sharing contract between the producer and the 3PL provider to coordinate the supply chain and find that contracts can eliminate the two sources of "double marginalization" [18].

Wu *et al.* develop two novel incentive mechanisms to coordinate the decentralized channel considering the risk preference of the third-party logistics service provider and achieve full channel coordination and win–win outcomes [19]. Ma *et al.* poposed the coordination mechanism in a three-echelon supply chain for fresh products under cap-and-trade regulation improve sales volume and balance the supply chain members' profit [20]. Ahumada and Villalobos review the contributions in the field of production and distribution planning for agri-foods based on agricultural crops and diagnose some of the future requirements for modeling the supply chain of agri-foods [21]. Borodin *et al.* proposed a structured overview of the use of operations research methodologies for handling uncertainties in the framework of produce supply chain management. They aim to identify the existing state of the art, gaps in current research, and future directions on the topic [22].

The above works mainly explores the fresh produce flow from upstream suppliers to retailers for sale. However, we also improve the circulation efficiency via an efficient allocating and pricing scheme for fresh produce.

2.2. Auction-Based ASCT

The second stream focuses on auction have been utilized in practice on fresh produce for allocating and pricing. Cramton *et al.* point that the most fundamental questions auctions ask and answer in economics are who should get the goods and at what prices [23]. In past, the Dutch auctions have existed for over a century as the premier mechanism for the trading of flowers in Europe [8]. The produce markets are mainly dependent on some onsite auctions, such as, traditional Dutch auction [5] [7] [8] dual Dutch auction [9] Japanese Dutch auction [10]. In a Dutch auction a single selling agent lowers the price sequentially until a buyer agrees to pay the seller's price. Often the prices are indicated by a clock, which falls over a price scale until a buyer presses a button to stop the clock. The first buyer to do this obtains a unit at the price in effect at the time that the clock was stopped. McCabe *et al.* prove that multiple-unit Dutch, used for produce, fish, or cut flowers, have the same theoretical properties as corresponding sing-unit Dutch clock [7]. Kambil and van Heck propose a novel trading driven by information technology will be a tool for organizing price determination and transactions to partly replace and replenish the traditional Dutch auction [8]. Crawford and Kuo studied a dual Dutch fish auction [9], that is conventional Dutch auction with bundling. Minoru and Ogawa point that Japanese Dutch auction has "Mari"-stages. To begin with, the price drops continuously until a buyer stops the clock [10]. Then, "Mari" signal appears for a short time (usually a few seconds) for other buyers to compete the products at the same price. Kambil and van Heck discussed the disadvantages of the traditional Dutch auctions [5]. To overcome the limit of onsite space and time, online auctions for produce are studied [24] [25]. Miyashita develop an online double auction for produce that prioritizes bids of bidders according to their time-urgency in order to realize efficient and fair allocations among participants [24].

2.3. Multi-Attribute Auction

The last theme concentrates on multi-attribute auction. McAfee *et al.* point that an auction is a market institution with an explicit set of rules determining resource allocation and prices on the basis of bids from the market participants [6]. Based on McAfee and McMillan's works, the pioneering paper of generalized the auction to be multi-attribute auctions where bids include other non-money attributes related to the auction objects such as quality [12]. Branco extended Che's auction by relaxing an essential assumption, the correlation across sellers. He finds that contrary to the case of independent-costs model, the optimal outcome can be acquired by a two-stage auction: in the first stage the procurer selects one firm; in the second stage he bargains to readjust the level of quality to be provided [13]. Asker *et al.* further investigated Che's auctions that is scoring auctions by proving utility equivalence in cases where nonmoney attributes are multiple, the buyer's utility is quasi-linear and sellers are symmetric. They show that the buyer is willing to distort qualities away from their efficient levels and the scoring rule in which price is linear is no longer optimal. When suppliers' private information is two-dimensional such as price and quality, a scoring auction that is linear in price is the optimal mechanism. In addition, they show that scoring auctions dominate several other procedures for buying differentiated products, such as menu auctions, beauty contests, and price-only auctions with minimum quality thresholds [14]. Nishimura study the optimal scoring auctions where quality is multidimensional [26]. Papakonstantinou *et al.* introduced a novel multi-dimensional procurement auction where the agents' qualities are uncertain and the principal can only check them after the project is completed [27]. Chetan *et al.* proposes a two-stage multi-attribute auction mechanism for market price discovery and to determine the winning bidder [28]. Lorentziadis studied competitive bidding in asymmetric multidimensional public procurement [29]. All those above works concentrated on single-unit case in which auction object is only one, so they do not consider the allocation efficiency of the auctions. There are some studies focused on both the single-unit and multi-unit cases and analysis the allocation efficiency of the auction. Cheng *et al.* introduced a multi-unit multi-attribute double auctions with high allocative efficiency for perishable supply chain trading. However, there are few works upon the design of efficient multi-attribute auctions [30].

It can be observed from above literature that although those models can improve circulation efficiency and obtain more social welfare, it cannot achieve the maximal social welfare and truthful information revelation for ASCT. However, previous research has made the foundation for our work on auction mechanisms for produce procurement. Some research gaps from the review of existing literature are followed. Thus, we have developed model of these direction to solve the above research gaps.

3. Problem Description

This study considers a produce procurement system in which procurers purchase multiple produces from growers on an e-commerce platform. A large number of online orders between growers and procurers are generated. The procurers draw those online orders from demand of customers and growers can deliver these online orders by providing produces. We propose a novel produces procurement frame. There exists a procurer, a lot of growers include poor area and nonpoor area, and an e-commerce auction platform. Trade orders are created and released to be transformed into procurement order by auction platform, which is fulfilled via the growers.

Usually, the prices of produces are mainly regulated by government and influenced by the supply and demand of agricultural product market. The pricing of produces should consider the all attributes, especially the non-money attributes. Those present e-commerce platforms about agricultural products have only considered a few attributes such as price, source place, demand volume. More attributes should be considered in trading, especially demand- satisfy attributes. Each online order in our paper has three dimensions of non-money attributes: *Demand-satisfy* attributes, *safety* attributes, and *surface* attributes. Demand-satisfy attributes are used to meet the essential requirements of customers such as moisture, sugar, vitamin, pulp texture and so on. Safety attributes include diseases, insect pests, agricultural residues and surface attributes are freshness, color, appearance, packaging, source place and so on. The above-mentioned characteristic attributes can be classified and grading by authority and provide the basis of trading. An important challenge faced by e-commerce platform is how to transfer the trade orders to procurement orders with an effective and efficient way. For the attributes of produces, each procurement order may specify which growers should provide the multi-attribute products which meet requirements from procurer (*i.e.*, demand-satisfy attributes, safety attributes, and surface attributes). Hence, the e-commerce auction platform should deal with the fresh agriculture products procurement problem to fulfill trading.

Auction-based fresh produces procurement model is mainly discussed in this study for solving fresh produces procurement problem. In this section, we introduce the framework and summarize the multi-attribute auction problem as mechanism design problem. We consider a single procurer seeking to procure q units of fresh produces for various attributes from multiple risk neutral growers, where q is a fixed and positive integer. If $q=1$, then the fresh produces procurement problem reduces to the *single-unit situation.* Since most of agricultural products may be need of daily life, q is usually more than one (*i.e.*, multi-unit situation). In the problem, one unit is a predefined agricultural product with special attributes. We assume that each grower can supply one unit of fresh produces. Therefore, there are $q(q \geq 1)$ growers in the final trading of either the single-unit or multi-unit case.

In fresh produces procurement auction market, considering a procurement operation between a single procurer and a set of growers *I*. A grower is referred to as "he", and a procurer as "she". Each bid from growers specifies an offer consisted of promised attribute bundle $\theta_i \in \Theta$, and price. The final outcome is defined in term of some winning growers, their produces with levels for each of *K* attributes and their income. In our provided model, the *K* attributes all refer to nonmoney attributes. Suppose that each attribute *k* has an attribute space Θ_k, where $k \in \{1, \cdots, K\}$. Each space Θ_k have a finite domain of discrete attribute valuations. For example, $\Theta_k = \{\text{rich}, \text{middle}, \text{little}\}$, which represent that the nutrition of a produce has three levels. Let $\Theta = \Theta_1 \times \cdots \times \Theta_k$ be the joint space of attributes.

Since planting attribute *k* of produces for each grower needs spending different raw material, manpower, time-period, logistics costs and so on, he has a *planting cost function* for each attribute bundle *θ*, which has a non-negative valuation, denoted by $c_i(\theta) \geq 0$. Since the cost function is private information, the price of bid is not always the truthful cost and the bidding strategy is complex. The auctioneer only knows the distribution function of the cost. We assumed that c_i is independently and identically distributed over $[\underline{c}, \overline{c}]$ ($0 < \underline{c} < \overline{c} < \infty$), according to a distribution function *C* for which there exists a positive, continuously differentiable density *c* [12]. Suppose that one grower only provides one bundle attributes, so the growers' costs for the other bundle attributes may be regarded as infinity. The procurer has a non-negative valuation function with various bundle attributes, denoted by $v(\theta) \geq 0$.

We assume there is a *private-values* model with independently distributed growers' planting costs and procurer's valuation. All participants are assumed to have quasi-linear utility functions [30] [31] [32]. In other words, if he receives a payment $\pi_i \in \mathbb{R}^+$ from procurer for the attribute bundle θ_i, where $\mathbb{R}^+$ is the set of non-negative real numbers, then his utility is the difference between his cost incurred during the planting process and the payment, that is $u_i = \pi_i - c_i(\theta_i)$. The procurer's utility is the difference between her valuation and the payment paid to the growers. Let I^* denote the set of growers from contracts, where

$I^* \subseteq I$ and $|I^*| \le q$. Since procurer's utility from one contract of grower $i \in I^*$ is $v(\theta_i) - \pi_i$, then all utility is $u_p = \sum_{i \in I^*} [v(\theta_i) - \pi_i]$, where θ_i implies that grower $i(i \in I^*)$ get the contract to provide product with attribute bundle θ, and the letter p denotes the procurer. If $u_p, u_i(\forall i \in I) > 0$, then the trade succeeds; otherwise, the trade fails.

The challenge faced by the third-party procurement platform is how to devise an efficient multi-attribute auction that maximizes the total value. Given the auction mechanism, the problem of the growers is to find the optimal strategy and obtain the maximal valuation. Some key parameters are showed as Table 1.

4. Mechanism Design

4.1. SUMA Auction Mechanism

A single-unit multi-attribute auction-based mechanism is proposed in this section, where the auctioneer receives the procurement order from procurer ($q = 1$) in each auction. Potential growers submit bids consisted of prices and intended attribute bundle θ. Then, the platform chooses a single winner and calculate the payment from the winner based on grower's bids. The grower's cost $c_i(\cdot)$ for offered multi-attribute produce is private information. The challenge we face is how to devise auction rules to ensure that growers bid truthfully and social welfare is maximized.

4.1.1. The Second-Preferred-Offer Auction

In the SUMA auction, growers submit multi-attribute bids consisted of price and

Table 1. Notations.

Notations	
q	The quantity of procurement
I	The set of growers
I^*	The winner set of growers
K	The set of nonmoney attributes
θ_i	The attribute bundle selected by grower i
Θ_k	Discrete valuations space of attribute k
$c_i(\theta)$	Planting cost function of grower i for each attribute bundle θ
$v(\theta)$	The valuation function of the procurer
p_i	The price submitted by grower i for one unit produce
p_i^q	The price submitted by grower i for q unit of produces
B_i	The multidimensional bid of grower i
y_i^q	The constructed score of grower i
y_*^q	The q_{th} highest score in the constructed

cost information to compete a single produce of procurement order. Based on the announced auction rules, the third-party procurement platforms evaluate the bids from all growers and decide the winner for whom he will fulfill the produce order and the price that the winner pay.

The outcomes of SUMA auction depend heavily on the devise of the rules, including scoring rule, the winner determination rule and the payment rule. According to Che's work [12], in single-attribute price-only auctions, the winner determination problem (WDP) is easily solved by selecting the winner who declares the highest price among bidders. While in our multi-attribute auction, growers need to report attribute bundle in addition to the price in their bids. It can be seen that the nonmoney attributes influence the procurer's value, so the winner cannot be simply determined by only ranking prices among all bidder. In SUMA auction, we convert a multi-attribute bid into one dimensional score based on the scoring rule. Then, the platform ranks bids based on their corresponding scores and determine winner and pricing on the basis of their scores. Hence, a scoring rule should be well evaluated growers' multidimensional bids.

According to multi-dimension auctions designed by Che [12], we construct a linear scoring function based on any bid $B_i = (\theta_i, p_i)$ from grower i in SUMA auctions, which is given by

$$s_i = f(\theta_i) - p_i \tag{1}$$

where satisfies the requirement that $f(\theta_i)$ is non-decreasing as θ_i increases. It is fairly obvious that lower price and higher multi-attribute yields higher score, thus having higher probability to win. the growers' and procurer's utility function defined above, the grower can yield more utility by increasing the price and decreasing the attribute bundle level, while the procurer minimize the cost by decreasing price and increase the attribute bundle level. Hence, the construction of scoring function becomingly reflects bidders' preference for price and attribute bundle. Since growers submit their bids after the auction rules are announced, growers' bidding behavior are influenced auction rules. Therefore, the challenge faced by the platform is to devise proper auction rules to achieve desirable outcome. Concretely, the auction rules designed ensure truthful bidding and allocating efficiency.

In addition, the winner determination rule defines that the bidder who submits the bid with the highest score wins, that is,

$$i^* = \arg\max_{i \in I} \left[f(\theta_i) - p_i \right] \tag{2}$$

Consequently, the payment rule is that the required payment of winner i^* is equal to the price that achieves the second largest score with the winner's attribute bundle θ_{i^*}, that is,

$$\pi^* = f\left(\theta_{i^*}\right) - \max_{i \in I / i^*} s_i \tag{3}$$

Notice that $f(\cdot)$ not only plays an important role in the auction rules but also influences growers' optimal bidding strategies. Specifically, the auction outcome depends on the concrete expression of function $f(\cdot)$. Consequently, the auction platform can devise the function of $f(\cdot)$ to obtain desirable auction results. In order to find an efficient multi-attribute mechanism for produce procurement, we construct the form of $f(\cdot)$ as

$$f(\theta)=v(\theta) \tag{4}$$

where $v(\theta)$ refers to the procurer's business valuation for multi-attribute produces, and $v(\theta)$ is non-decreasing as θ increases.

Consider the procurement market with one single procure, one procurer, and I growers. If all of growers bid truthfully, the maximal social welfare can be obtained by solving the following binary integer programming (IP) problem:

$$\text{IP:}\quad \max \sum_{\theta\in\Theta}\sum_{i\in I} x_i(\theta)\left[v(\theta)-c_i(\theta)\right] \tag{5}$$

$$\text{s.t.}\quad \sum_{i\in I}\sum_{\theta\in\Theta} x_i(\theta)\le 1, \tag{6}$$

$$\sum_{\theta\in\Theta} x_i(\theta)\le 1, \forall i\in I, \tag{7}$$

$$x_i(\theta)\in\{0,1\}, \forall i\in I, \forall\theta\in\Theta$$

Setting $x_i(\theta)=1$ implies that procurer contracts with the grower i and procurer the product with attribute bundle θ. For those unselected θ, the growers' valuations, that is $c_i(\theta)$, are regarded as infinity. Constraint (6) ensures that all of growers compete at most one procurement item. Constraint (7) guarantees that each grower selects at most one attribute bundle among a set of attribute bundles. Based on the scoring rule, the objective function (5) can be rewritten as

$$\max \sum_{\theta\in\Theta}\sum_{i\in I} s_i(\theta) \tag{8}$$

It indicates that the total value problem can be transformed into score ranking problem. The winner can be determined by sorting the score of bids submitted from growers. To deal with above questions, we propose a second-preferred-score auction to induce truthful bidding from the growers. We define the second-preferred-score auction as follow. Ties are broken arbitrarily.

Definition 1. The second-preferred-score auction for fresh produce procure as follow:

1) The e-commerce auction platform announces auction rules, include scoring rule, winner determination rule, and payment rule.

2) The growers submit their sealed bids $B=\left(B_i(\theta_i,p_i),\forall i\in I\right)$ to platform, where θ_i and p_i represent respectively the declared attribute bundle and the price she is willing to pay, to the platform.

3) The platform computes the score of bids according to scoring rule, solves the (IP) and chooses the winner i^* of auction based on winner determination rule. An attribute bundle θ_{i^*} is allocated to grower i^*. If the procurer's utility is positive ($u_p>0$), he will give a payment according to the payment rule, that is, $\pi^*=f\left(\theta_{i^*}\right)-\max\limits_{i\in I/i^*} s_i$. In this case, grower i^*'s utility is $u_{i^*}=\pi^*-c_{i^*}\left(\theta_{i^*}\right)$ and procurer's utility is $u_p=v\left(\theta_{i^*}\right)-\pi^*$. If $u_{i^*},u_p\le 0$, then the trade fails.

4) The grower i^* provides a single produce for the procurer with the

attribute bundle θ_{i^*}.

4.1.2. Properties

Theorem 1. Truthful bidding is the optimal strategy for grower *i* with a given attribute bundle θ_i in the second-preferred-score auction, in other word, the bidding price is his real cost, denoted by

$$p_i = c_i(\theta_i) \tag{9}$$

This result implies that it is dominant for each grower to submit his real costs for attribute bundles, which means that the proposed second-preferred-score auction mechanism can achieve truthful bidding. Finally, the problem of computing prices of bids reduces to the problem of estimating cost for attribute bundles.

Proof. If grower *i* bids truthfully on the price $p_i = c_i(\theta_i)$ for any given attribute bundle θ_i, then the score of his bid is denoted by $s_i = f(\theta_i) - c_i(\theta_i)$ and the expected utility is denoted by u_i. If he doesn't tell the truth, that is $\hat{p}_i \neq c_i(\theta_i)$, then the score of his bid is $\hat{s}_i = f(\theta_i) - \hat{p}_i$, and the expected utility is denoted by $\hat{u}_i$. According to the above defined auction rules, if grower *i* is the winner i^*, his utility

$$u_i^* = \pi^* - c_i(\theta_i) = \left[f(\theta_{i^*}) - \max_{i \in I/i^*} s_i \right] - c_i(\theta_i) = s_i - \max_{i \in I/i^*} s_i$$

If $\hat{p}_i \neq p_i$ or $c_i(\theta_i)$, we discuss four cases to prove $u_i \geq \hat{u}_i$, which indicates that grower *i* cannot obtain a larger utility via bidding at price $\hat{p}_i$.

1) If grower *i* wins the auction with both score s_i and $\hat{s}_i$, we have $u_i = \hat{u}_i = u_i^*$.

2) If grower *i* wins the auction with score s_i and loses with $\hat{s}_i$, we have $u_i = u_i^* = s_i - \max_{i \in I/i^*} s_i > 0$; $\hat{u}_i = 0$.

3) If grower *i* wins the auction with score $\hat{s}_i$ and loses with s_i, we have $\hat{u}_i = u_i^* = s_i - \max_{i \in I/i^*} s_i < 0$; $u_i = 0$.

4) If grower *i* loses the auction with both score s_i and $\hat{s}_i$, we have $u_i = \hat{u}_i = u_i^* = 0$.

By summarizing above four cases, we have a conclusion that grower *i* will tell the real cost.

Theorem 2. In the second-preferred-score auction, grower *i*'s optimal bidding attribute bundle is denoted by

$$\theta_i = \arg\max_{\theta \in \Theta} \left[f(\theta) - c_i(\theta) \right] \tag{10}$$

Theorem 2 implies that grower *i* chooses the attribute bundle that maximize the difference between procurer's valuation function $f(\theta)$ and the grower *i*'s real cost $c_i(\theta)$. According to scoring rule specified in Equation (1), grower *i* selects the θ_i to obtain the maximal score of his bid.

Proof. We suppose that for grower *i*'s any bid $\hat{B}_i = (\hat{\theta}_i, \hat{p}_i)$ with an expected utility $\hat{u}_i(\hat{\theta}_i)$, there always exists a bid $\bar{B}_i = (\bar{\theta}_i, \bar{p}_i)$ with an expected utility

$\bar{u}_i(\bar{\theta}_i)$ satisfying $\bar{u}_i(\bar{\theta}_i) \geq \hat{u}_i(\hat{\theta}_i)$. Considering the bid $\bar{B}_i$, $\bar{\theta}_i$ is obtained based on (9) and $\bar{p}_i$ is determined by making the bid $\bar{B}_i$ has the same score s^* with $\hat{B}_i$. If score s^* is the highest score among all bidders, bidder *i* can win the auction with both bid $\bar{B}_i$ and $\hat{B}_i$. If score s^* is not the highest score among all bidders, bidder *i* fails to win with his utility is zero. According to the payment rule defined in Equation (3), the required payments under the two bids are $f(\hat{\theta}_i) - \max_{i \in I/i^*} s_i$ and $f(\bar{\theta}_i) - \max_{i \in I/i^*} s_i$, respectively. The inequality $\bar{u}_i(\bar{\theta}_i) \geq \hat{u}_i(\hat{\theta}_i)$ can be rewritten as

$$\left[f(\bar{\theta}_i) - \max_{i \in I/i^*} s_i\right] - c_i(\bar{\theta}_i) \geq \left[f(\hat{\theta}_i) - \max_{i \in I/i^*} s_i\right] - c_i(\hat{\theta}_i).$$

The above equality proves this equation: $\bar{\theta}_i = \arg\max_{\theta \in \Theta}\left[f(\theta) - c_i(\theta)\right]$.

Theorem 3. The second-preferred-score auction is allocatively efficiency when

$$f(\theta) = v(\theta)$$

Proof. According to the objective of (IP), the second-preferred-score auction obtains the maximal total social value given procurer's demand order and growers' bids. Based on the optimal bidding strategy characterized in Theorem 1 and Theorem 2, the grower *i* declares the attribute bundle as $\theta_i = \arg\max_{\theta \in \Theta}\left[f(\theta) - c_i(\theta)\right]$ and reports his true cost given by $p_i = c_i(\theta_i)$ in his bid. When $f(\cdot)$ is constructed as $f(\theta) = v(\theta)$, the score of growers *i*'s bid is computed by

$$s_i = \max_{\theta \in \Theta}\left[v(\theta) - c_i(\theta)\right] \tag{11}$$

According to the winner determination rule specified in the second-preferred-score auction, the winner is the bidder who realizes the highest score bid, that is $i^* = \arg\max_{i \in I} s_i$, and the winning attribute bundle is $\theta_{i^*} = \arg\max_{\theta \in \Theta}\left[v(\theta) - c_{i^*}(\theta)\right]$. Therefore, the corresponding social welfare of auction is given by

$$s = v(\theta_{i^*}) - c_{i^*}(\theta_{i^*}) = \max_{i \in I, \theta \in \Theta}\left[v(\theta) - c_i(\theta)\right] \tag{12}$$

Hence, the second-preferred-score auction realizes the maximal social welfare with winner i^* bidding $B_{i^*}\left(\theta_{i^*}, c_{i^*}(\theta_{i^*})\right)$.

Theorem 3 implies that the second-preferred-score auction is suitable for FPT since it realizes maximum market efficiency, and can be as an important basis to support the devise of stable long-term e-commerce produce markets.

4.2. MUMA Auction Mechanism

In this section, we extend the single-unit procurement case to multi-unit procurement case. Consider a more general situation where a procurer purchase *q* (*q* > 1) unit produces from growers by e-commerce auction platform. In this MUMA auction, growers can't only submit price and attribute bundle information in their bids but also give specify quantity they intend to win. The decision a grower face is how many produce procurements he intend to win in addition to price and attribute bundle. The essential core for designing auction is to induce growers to declare their real cost in their bids and yield maximal social welfare in order to support a long-term stable system.

Note that the marginal cost cannot be fixed since grower secures lower average cost as the production scale. For the sake of analysis, we adopt vector bids to clearly specify three related information in growers' bids, which is price, attribute bundle, and quantity, respectively. Grower i submits a vector bid B_i, defined by

$$B_i = \left(b_i^1, b_i^2, \cdots, b_i^Q\right), \tag{13}$$

where b_i^q is the bid when he provides a total of q units. Similar to single-case, the b_i^q is denoted by $b_i^q = \left(\theta_i, p_i^q\right)$ in which θ_i means the grower i chooses attribute bundle θ and p_i^q represents the total price that procurer purchases q produces from grower i. All the bidders submit their "dividable" bids, called OR bids In order to signify conveniently, the winner set of the total of q produces are denoted by

$$I^* = \left\{i_1^*, i_2^*, \cdots, i_Q^*\right\}, \tag{14}$$

where i_q^* is the grower winning the q_{th} produce procurement order. The payment set includes the payment the procure pay to each grower, denoted by

$$\pi^* = \left\{\pi_1^*, \pi_2^*, \cdots, \pi_I^*\right\}, \tag{15}$$

In the second-preferred-score auction, a grower's multidimensional bid is converted to single-dimensional score by a scoring function. But, in the MUMA auction, a vector bid which grower submits can't be directly figure out a corresponding score via a scoring function. Hence, we construct a vector score to rank the vector bids and decide the auction outcomes. Note that the vector bid B_i contains Q bids. We give each bid a score via a scoring function, denoted by

$$s_i^q = qf\left(\theta_i\right) - p_i^q, \tag{16}$$

where s_i^q represents the score when grower i wins q produce procurement order in this auction. Then, grower i has Q scores for his vector bids, *i.e.*, s_i^q, $\forall q \in Q$. To solve the problem of ranking those scores among growers, we convert all scores into a new vector score. Following [10] [31] [32], s_i^q is concave as the quantity of winning order q increasing, and those equations are confirmable, *i.e.*, $s_i^{q+1} - s_i^q \geq s_i^q - s_i^{q-1}$, $2 \leq q \leq Q$. Therefore, we use s_i^q to construct a new vector score, given by

$$Y_i = \left\{y_i^1, y_i^2, \cdots, y_i^Q\right\}, \tag{17}$$

where the equation satisfies $y_i^1 \leq y_i^2 \leq \cdots \leq y_i^Q$ and y_i^q is given by

$$y_i^q = \begin{cases} s_i^1, & q = 1, \\ s_i^q - s_i^{q-1}, & 2 \leq q \leq Q, \end{cases} \tag{18}$$

All of the vector scores are sorted by descending and the first Q scores are selected, denoted by $Y^* = \left\{y_*^1, y_*^2, \cdots, y_*^Q\right\}$, where y_*^q is the q_{th} highest score.

Let Y^{-i} be the set of first q rest scores excluding grower *i*'s score, denoted by $Y_{-i} = \left\{y_{-i}^1, y_{-i}^2, \cdots, y_{-i}^Q\right\}$, where y_{-i}^q represents the q_{th} highest score without grower *i*.

The growers, realizing the first Q scores, are selected to win the auction. For sake of analyzing simply, we utilize a revised winner set I^{*} to replace the set I^*, given by

$$I^{*} = \left\{\rho_1, \rho_2, \cdots, \rho_I\right\}, \tag{19}$$

where ρ_i is the total number of produce orders that grower *i* wins and satisfies the equation $\sum_{i=1}^{I} \rho_i = Q$.

The VCG-Score Auction

In order to address the sorting and allocating problem in the multi-unit situation, we propose a VCG-score auction where a multi-unit multi-attribute vector bids is converted to a vector score. Based on the above definition, we follow define the scoring rule in MUMA auction: For any vector bid $B_i = \left(b_i^1, b_i^2, \cdots, b_i^Q\right)$ of grower *i*, each bid $b_i^q = \left(\theta_i, p_i^q\right)$ is converted into single-dimensional score via scoring function $s_i^q = qf\left(\theta_i\right) - p_i^q$. According to Equation (18), A new vector score of B_i is given by

$$Y_i = \left\{y_i^1, y_i^2, \cdots, y_i^Q\right\}$$

Different from the SUMA auction, the winner determination rule is defined as follow: The set of Y_i is converted into $Y^* = \left\{y_*^1, y_*^2, \cdots, y_*^Q\right\}$ via ranking scores in a decreasing order. Thus, the relationship between y_*^q and y_i^q can be given by

$$y_{i_q^*}^{\lambda} = y_*^q, 1 \le \lambda \le Q \tag{20}$$

where $y_{i_q^*}^{\lambda}$ represents the λ_{th} score value in the vector score $Y_{i_q^*}$. The above equation means that the grower with the q_{th} highest score y_*^q is the winner i_q^* of the q_{th} produce procurement order.

In the MUMA auction, the payment rule is more complicated than above SUMA auction: For the winning grower *i* who wins ρ_i procurement orders, the required payment achieves the total score with his declared attribute bundle when grower *i* is excluded in auction, that is,

$$\pi_i^* = qf\left(\theta_i\right) - \sum_{i'=1}^{\rho_i} y_{-i}^{Q-\rho_i+i'} \tag{21}$$

where $\sum_{i'=1}^{\rho_i} y_{-i}^{Q-\rho_i+i'}$ refers to the score change imposed by grower *i* to other growers.

The VCG-score auction for FPT problem progresses as follows:

1) The auctioneer announces auction rules for procurer's multi-unit produce procurement orders, including the scoring rule, the winner determination rule and the payment rule.

2) The grower $i \in I$ submits a vector bid B_i for the Q produce orders to e-commerce auction platform.

3) The auctioneer computes the vector score Y_i of grower *i*'s based on scoring rule. According to winner determination rule, the winner set I^* is obtained based on all growers' vector scores. An attribute bundle θ_i is allocated to grower $i \in I^*$, where $\{\rho_i, \theta_i\}_{i\in I^*}$ is an efficient allocation realizing the maximum social welfare.

4) According to the payment rule, each grower *i* receives a payment π_i^* from procurer. If $u_{i^*}, u_p \le 0$, then the trade fails.

5) Grower *i* provides ρ_i produces for procures in the winner set I^* with the declared attribute bundle θ_i.

Note that growers bid for multi-unit and report more complicated private information in the VCG-score than in the second-preferred-score. Grower's behaviors are influenced by the auction rules. To realize the maximal expected utility, we next analyze each grower optimal bidding behavior, including price and attribute bundle.

4.3. Multi-Unit Auction under Poverty Alleviation Policy

Under poverty alleviation policy, it is significantly important to procure more from poor area via multi-attribute auction mechanism. In present, fresh produce e-commerce auction platform have three categories: integrated platform, professional platform, and interactive social platform. Integrated platform greatly promoted the circulation and transaction of agricultural products through mass flow of customers (e.g., Alibaba.com, pinduoduo.com). Professional platforms help the poor growers boost their income via auctioning their produces (e.g., fupin823.com, cnhnb.com). Meanwhile, the produces from remote country were sold by interactive social platform (e.g., the moments of Wechat, Tiktok). Those e-commerce platforms have reduced the transaction cost of FAPs by information technology, especially in rural produces, and take social responsibility into account via settling the vendition problem of the poor's produces. Hence, auction platform should procure more produces from poor area to undertake more social responsibilities.

Suppose Q' ($Q' \le Q$) be the quantity of procuring from poor area, and μ be the subsize coefficient resulted from social responsibilities. The μ implies that the increment of social welfare is realized by the social responsibility of sing-unit procurement from poor area. Let I' be the set of growers from poor area. Under poverty alleviation policy, there exists two cases we prepare to discuss:

1) Given the value of μ based on government's policy, how auction platform determines Q', the quantity of produces auctioned in poor area, to maximize the total social welfare.

2) Given the all quantity Q competed both in poor area and nonpoor area, how to adjust the subsize degree of policy (*i.e.*, μ) in order to not only attain the goal of poverty alleviation, but also guarantee maximum social welfare.

Note that in the case 1, auction platform hosts twice auctions, respectively in poor area and nonpoor area. The total social welfare of two auctions is given by

$$\max_{Q'} \sum_{i=1}^{Q'} \dot{y}_*^i + \mu Q' + \sum_{i=1}^{Q-Q'} \ddot{y}_*^i,$$

where $\dot{y}_*^i$ is the outcome of Q' produces auctioned among the growers set I', and $\ddot{y}_*^i$ is the outcome of $Q-Q'$ produces auctioned in I/I'.

Different to case 1, there is only once auction in case 2. The subsize coefficient μ is incorporated into VCG-score auction as increment of vector scores of growers in the poor area, given by

$$Y_i = \left\{ y_i^1 + \mu, y_i^2 + \mu, \cdots, y_i^Q + \mu \right\}, i \in I',$$

while vector scores of growers in I/I' are changeless. Thus, the allocated produces to poor area changes as subsize coefficient gets larger. Assume that the goal of poverty alleviation policy is to assist vendition of Q^* produces from poor area. The government can reach the goal via adjusting the value of μ, then, the maximal social welfare with social responsibility can be realized by the following integer program (IP):

$$\text{IP-1} \quad \max_{\mu} \sum_{i \in I'} \sum_{q \in Q} x_i^q \left(y_i^q + \mu \right) + \sum_{i \in I/I'} \sum_{q \in Q} x_i^q y_i^q$$

$$\sum_{i \in I'} \sum_{q \in Q} x_i^q \ge Q^* ;$$

$$\sum_{i \in I/I'} \sum_{q \in Q} x_i^q \le Q ;$$

$$x_i^q \in \{0,1\}, i \in I, q \in Q$$

Theorem 1. The VCG-score auction for poverty alleviation is IC, BB, and IR.

In case1, no matter what auction in poor growers or in non-poor growers, the subsidy does not influence their bidding strategies, and the stable of third-part. In case2, since the growers from poor area may obtain extra subsidy, their bidding strategies should equal to the difference between their real cost and subsidy. Thus, the VCG-score auction for poverty alleviation is IC, BB and IR.

5. Computational Analyses

Although both the second-preferred-offer auction and VCG-score auction have been proved to be IC, IR, BB and AE, the performance of both mechanisms due to the impacts of various factors are not clear. In this section, we focus on the outcome of MUMA mechanism that may reduce to SUMA mechanism when k = 1. Firstly, we compare the performance of VCG-score auction to that of just-price attribute auction. Then, we discuss the impact of different parameters on the VCG-score auction outcome. Last but not least, we investigate the impact of subsize and the procurement quantity auctioned for poor area on poverty alleviation and corporation social responsibility.

This study considers one case where a procurer purchase produces from multiple growers via the third-party auction platform. Three non-price key attributes that are incorporated into auctions are *demand-satisfy* attribute, *safety* attributes, and *surface* attributes. Assume that all attributes are assessed into five grades by third-party auction platform. If a grower is willing to accept $15 for

offering one unit with demand-satisfy grade no higher than A2, safety grade lower than B1, and surface no higher than C3, his bid for one unit is expressed as ($15, 1, A2, B1, C3). In each auction scenario, such cost parameters and multi-attributes bundles are randomly chosen. Based on IC, the product cost for the grower is $15 for the produce with A2, B1, C3 grade of attributes, that is $c_i(\theta_i) = \$15$. For the valuation function for produces with various attribute bundles, we set it as $v(\theta_i) = w_1 * A + w_2 * B + w_3 * C$, where *A*, *B*, and *C* represent their orders in five attribute grades and w_1, w_2, and w_3 is corresponding weigh with *A*, *B*, and *C*, respectively. For example,
$v(\theta_i)_{\text{A2,B1,C3}} = w_1 * 4 + w_2 * 5 + w_3 * 3$. Meanwhile, a grower's cost function for produces is $c_i(\theta_i) = a \cdot \sqrt{A + B + C}$, where *a* is the cost parameter and uniformly distributed over $(\underline{a}, \overline{a})$ ($0 < \underline{a} < \overline{a} < \infty$).

Firstly, we compare multi-attribute auction with single-attribute auction (Vickrey auction) and a fixer price mechanism. The Vickrey auction is characterized as single attribute auction and widely serviced in trading system. The greatest difference among three auction mechanisms is their pricing strategy. The payment is determined by the second highest price in the Vickrey auction, while under the multi-attribute auction, the payment is determined by both price and three non-money attributes and under the fixed rate mechanism, the payment is based on a pre-fixed market price and grower are first come, first purchase which follows the principle of time priority.

Table 2 compares the social welfare of the VCG-score auction with that of Vickrey auction. "AVG" and "STD" represent the average and standard deviation values of social welfare, respectively. In our experiments, we set the number of produces a procurer can procure to be 5 (*i.e.*, $q = 5$), *a* is uniformly distributed over (1, 10), and having w_1, w_2, w_3 to be 5, 3, 2, respectively. All results are derived from 10,000 randomly generated auction scenarios. Specifically, with the number of growers varying from 10 to 140, the average social welfare of multi-attribute and single-attribute auctions increase from 211.67 to 230.63 and from 185.50 to 191.33, respectively, but that of the fixed price mechanism retains relatively stable. Such outcome demonstrates that no matter what the number of participants is, the proposed VCG-score auction is more socially beneficial for produces trading system than the other trading mechanisms. This result is consistent with theorem 7, which confirms that our proposed VCG-score auction can maximize social welfare for produce trading. What's more, with the number of participating growers increases, the average social welfare in VCG-score auction increases while its standard deviation decreases. This finding indicates that the multi-attribute auction outperforms other mechanisms in a market with a large number of growers, which is consistent with our intuition that auction is appropriate to select the growers with high trading valuation. The social welfare of fixed price mechanism is unfluctuating since it obeys the rule of first come, first served and is unable to screen out growers with high trading valuation.

The impact of the maximum number of produces that a grower can provide, that is the dimensionality of vector bid, is reported in Table 3. In our experiment,

Table 2. Social welfare of different mechanisms.

# of growers	Multi-attribute		Single-attribute		Fixed price	
	AVG	STD	AVG	STD	AVG	STD
10	211.67	15.14	185.50	7.65	121.21	7.54
40	227.37	4.11	190.84	1.11	120.47	7.55
70	230.09	1.57	191.26	0.29	121.44	7.51
100	230.56	0.52	191.32	0.13	121.37	7.57
140	230.63	0.04	191.33	0.01	120.65	7.59

Table 3. The impact of the number of produces.

q	Social welfare				
	# of growers = 10	# of growers = 40	# of growers = 70	# of growers = 100	# of growers = 140
Growers' cost parameter distribution [1, 10]					
1	207.21	224.55	227.36	227.85	227.91
2	207.73	224.98	227.66	228.13	228.20
3	208.82	225.45	228.24	228.72	228.78
4	209.68	226.04	228.85	229.30	229.37
5	211.67	227.37	230.09	230.56	230.63
Growers' cost parameter distribution [2, 11]					
1	184.00	201.73	205.12	205.71	205.83
2	184.71	202.48	205.59	206.33	206.40
3	185.37	203.83	206.69	207.46	207.56
4	187.22	204.92	208.08	208.63	208.76
5	189.90	207.65	210.56	211.10	211.26
Growers' cost parameter distribution [3, 12]					
1	159.29	179.41	182.70	183.56	183.73
2	160.21	180.17	183.62	184.41	184.59
3	164.43	181.87	185.25	186.17	186.34
4	165.37	183.98	187.22	187.94	188.13
5	170.14	187.83	190.91	191.69	191.90

the values of w_1, w_2, w_3 are same **Table 2**. Note that the dimensionality of vector bid the grower provides also increases as q increases. Two findings in MUMA auction outcome can be observed. One is that the social welfare increases as the maximum number of produces q the grower provides increases in any setting. The another is that no matter what the marker size is, the growth in social welfare slower than the rate of k increases. This is because the grower's cost function is concave while the procurer's valuation function is linear with regard to multi-attributes. Note that the total social welfare of produce trading decreases with the distribution range of a increases. The reason behind the outcome is the social welfare is the difference between the procurer's valuation and the grower's cost. Moreover, the social welfare in Table 3 is always higher in large-sized markets, which implying that our proposed VCG-score auction is more beneficial with more growers.

In conclusion, all those result show that our proposed VCG-score auction outperforms the Vickrey auction and the fixed price mechanism in produce procurement and maximizes the social welfare. The VCG-score auction is more beneficial with a large number of growers, low level of distribution range for grower's cost.

6. Conclusions

In multi-attribute auctions, growers are allowed to complete over both price and nonprice attributes. The key point to form a long-term and stable produce procurement system is an efficient mechanism that obtains maximal social welfare for the system. In this paper, we propose VCG-score auctions that can achieve truthful bidding and obtain maximal social welfare, which provides a strong theoretical basis for running a long-term stable produce trading system.

To our best knowledge, this study is the first one to consider poverty alleviation in multi-attribution auctions for produce trading systems. This paper shows that under the SUMA auction, a second-preferred-score auction with a proper scoring function can obtain truthful bidding and allocative efficiency. Then, under MUMA auction, a VCG-score auction is proposed to well achieve an efficient outcome with the devised scoring function. Furthermore, we take poverty alleviation into produce auction and proposed two extended models to maximize both social welfare and CSR.

Finally, our computational study verifies the allocative efficiency of the proposed mechanisms in produce trading system. This result shows that our multi-attribute auction outperforms the single-attribute auction and the fixed rate mechanism on allocative efficiency. Additionally, the mechanism is more likely to be preferred in a market with a large number of growers. From a practical point of view, our model offers a feasible alternative to existing auction mechanisms (e.g., only-price auctions, forward auctions) for ASCT.

7. Contributions

This paper serves as effort in mechanism design for produce trading systems. Since produce trading systems are complex in real-trading application, this work is likely to be extended along several directions. As far as the proposed models are concerned, each grower may have different multiple units of supplies. This word only regards the grower as unit-supply growers that provide one multi-attribute. Additionally, we can also incorporate other essential attributes into our model, such as on-time performance of delivery serve and customer demand uncertainty. Another extension is to consider multiple growers and procurers competing for produces, which have higher requirement for auction mechanism to achieve truthful and efficient. Last, growers may adjust their bidding strategies via previous auction outcomes. Procurers may intentionally modify their cost functions by learning previous auction results for more benefit. A more complex mechanism is required to apply a case when learning from previous auction outcomes. However, those extensions will introduce the required analytical effort increasing, and need further learn and explorations.

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Conflicts of Interest

The authors declare no conflicts of interest.

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