1. Introduction. With the increase of people’s awareness of low carbon, people have focused on the problem of environmental pollution, especially carbon emissions. Carbon emissions have led to serious pollution problems such as the greenhouse effect in the process of economic development. Under the carbon emissions trading scheme (cap-and-trade regulation), manufacturers can obtain free emission caps from government agencies, and the emission quotas can be traded through external markets. Specifically, the manufacturer must purchase carbon emission rights if its actual output exceeds the prescribed capacity, otherwise, it can sell its excess carbon credits through the market (Du et al. [8]). Cap-and-trade regulation
is now generally regarded as one of the most effective market mechanisms (Hua et al. [15]). It has been applied in the United States, Japan, Europe, and other developed countries. As a developing country, China has begun to implement the “cap-and-trade” policy in 7 provinces and cities including Beijing, Shanghai and so on, and established a national carbon trading platform covering multiple manufacturing industries in 2017, such as steel, electricity, petro chemical, and cement.

The development of the remanufacturing industry can effectively reduce energy consumption and carbon emissions. It is known as the closed-loop supply chain (CLSC), where forward channel sells new products to meet the customer demands, while reverse channel recycles used products for remanufacturing. More and more companies are using reverse supply chain. It helps to reduce the consumption of raw materials, energy usage, soil pollution, water pollution, and air pollution, etc. Many manufacturers (e.g., Xerox, HP, Lenovo and Epson) have actively participated in the remanufacturing of used products. Besides recycling and remanufactured, some manufacturers consider reducing carbon emissions in the CLSC management process. Many manufacturers are actively exploring carbon emission reduction technologies in the production process under the pressure of carbon tax. Retailers, as one of the important members of CLSC, also play an important role in guiding consumers’ buying habits to low-carbon alternatives. For example, Bosch has built a new fast firing kiln at its new plant to produce ceramic spark plugs in Nanjing China in 2011. Although the new type of sintering furnace cost exceeds 14 million dollars, it can reduce carbon emissions by approximately 1,100 tons of CO₂ per year. Some large retailers, such as Wal-Mart, Carrefour and Suning, have already taken actions to guide customers’ low-carbon concepts by displaying and promoting energy-saving products in their offline stores (Ji et al. [17]). From the above research, the research on remanufacturing products and reducing carbon emissions is of great significance to economic development and environmental protection.

Most of the literatures focus on the pricing and recycling problems in the supply chain with cap-and-trade regulation under the deterministic environment. However, in fact, there are many nondeterministic factors which cannot be ignored. Today, some products, especially new products and high-tech equipment, are usually updated very quickly. It is difficult to obtain sufficient and effective data of market demands. If the distribution of these non-deterministic factors can be accurately obtained, they can be described as random variables. Then, probability theory can be used to deal with these random factors. When the distribution of some nondeterministic factors cannot be obtained, they can be described as fuzzy variables. In the CLSC system, the retailer sales costs, collecting costs, consumer demands, the manufacturer’s total carbon emissions, and the quantities of recycled products often have no historical data or we cannot collect enough data of them. Their distributions can only be estimated by experts or managers. In this case, human belief degree should be treated as an uncertain variable rather than a random variable. In this paper, we use uncertainty theory to study the behavior of non-deterministic phenomena. Uncertainty theory was initiated by Liu [23] and refined by Liu [24] that can be used to process the parameters estimated by human belief degrees.

The previous literature is based on a supply chain without considering recycling and remanufacturing, they also don’t consider the nondeterministic factors in the supply chain. This paper has three contributions to previous studies. Firstly, our paper study the pricing and recycling decision problems of CLSC with cap-and-trade
regulation which consisting of a manufacturer, a downstream retailer, and a third-party. The manufacturer needs to decide the optimal its wholesale prices, carbon emission reduction rate and the retailer attracts end consumers by choosing its own sales price, and the third-party determines its recovery rate. Remanufacturing could reduce energy consumption, but many references don’t take into account the CLSC. Secondly, we analyze the third-party collects the used products directly from the customers, as raw materials to produce new products. By game theory, three decentralized pricing models based on uncertainty theory are discussed. Thirdly, the demands, total carbon emissions, and recovery of these products often lack certain historical data and uncertain theory is used for solving the above problems.

The rest of this paper is built as follows. We will briefly review the relevant literature in the next section. Section 3 describes the definition of the problem, including some necessary hypothetical symbols involved in the problem, demand function, and the crisp form of expected profit function. And discussion, is performed in Section 4. In Section 5, we give some numerical experiments. Section 6 gives some conclusions and directions for future research.

2. Literature review. The literature covering CLSC management and carbon emissions is relatively insufficient. Some scholars have taken great interest in the issue of green supply chain management. The subsequent literature review focuses on pricing decisions and carbon emissions in the supply chain. Cruz [4] shows the optimal conditions for retailers and manufacturers based on the supply chain network by constructing their carbon emissions, risk, and profits models. Under the cap-and-trade system, Du et al. [7] explore the optimal price and carbon emission decisions based on the emission permit supplier. Ghosh and Shah [12] study the impact of consumer sensitivity and green costs on green clothing and coordinate the green channel by constructing a coordination contract. Under the cap-and-trade system, Du et al. [8] further study the optimal production decision in the emission-dependent supply chain. By using the linear programming model, Benjaafar et al. [2] minimize the emission cost of a single enterprise across multiple periods. Under the cap-and-trade scheme, Yang et al. [45] study their impact on channel coordination by comparing four low-carbon policies. Bazan et al. [1] study a reverse logistics model, in which the optimal decision of price and carbon emission of remanufactured products is considered by recycling old products from the market. Yang and Xiao [44] discuss two competitive supply chain game models, each of which is composed of a manufacturer and a retailer. In the vertical direction, the manufacturer is the leader of the Stackelberg game, and the retailer acts as the follower. In the horizontal direction, manufacturers make emission reduction decisions in the Nash game. At last, it is best to analyze and solve the model and compare the equilibrium solutions of the supply chain under several different structures. In MTO (make-to-order) supply chain, Xu et al. [42] discuss production and pricing issues in a supply chain that included a manufacturer and a retailer. The manufacturer was subjected to quota trading control and determines the wholesale prices of the two products. In order to comply with regulations, emission permits can be purchased or sold by manufacturers through external markets. Li et al. [21] consider a CLSC with the manufacturer directly recycled second-hand products and reduced carbon emissions. By experimental analysis and comparison, the optimal decision-making results and profits of different cooperation modes were compared. However, their
work is not based on the CLSC, not taking recycling and remanufacturing into account.

In recent years, in order to make full use of raw materials and environmental protection, some researchers have studied the recycling and remanufacturing of CLSC in different recycling channels. Ferrer and Swaminathan [9] study the different preferences of the remanufactured product and the new product, and proposed a pricing decision model related to this problem. There are many studies that considered pricing issues in their models for planning the CLSC e.g., Souza [34], Daniel et al. [5], Shi et al. [30], Chen and Chang [3] and Gan et al. [10]. In a CLSC composed of a retailer, a manufacturer and a third-party recycling center, based on short life cycle products, Gan et al. [11] propose an optimal pricing model. Two scale factors were introduced into the model. Meng et al. [29] study a decision-making problem between remanufacturing and dismantling of used products. Liu and Xu [27] construct the manufacturer-Stackelberg game. In terms of reverse recycling, manufacturer recycling, retailer recycling and third-party recycling are discussed separately. Huang et al. [16], Hong et al. [14] and Xiong et al. [41] study the CLSC coordination model based on changes in product advertising investment and used product recovery rate. They showed that advertising investment has a certain impact on channel members’ pricing strategies, used product collection decisions, and total profits. Based on game theory, Yi et al. [48] propose a CLSC optimal decision model with dual recycling channels, exploring how remanufacturing companies can reasonably allocate recycling efforts to the third-party and the retailer. In a CLSC, Giri et al. [13] study the price decision model by processing two dual-channel. The forward dual-channel means that the manufacturer sells products to customers through the traditional retail channel and the online channel, and the reverse dual-channel includes recycling products from customers through the third-party recycling channel and the online channel. The above-mentioned work generally focuses on recycling and remanufacturing, without considering carbon emission constraints, not taking the uncertain factor into account.

Under an uncertain environment, price and remanufacturing decisions related to the CLSC have been studied in the literature of Vorasayan and Ryan [36] and Li et al. [22]. Vorasayan and Ryan [36] model the sales, recycling, refurbishment and resale processes in the open queuing network and studied the optimal price and the proportion of refurbished used products. Market demand is assumed to be random. Li et al. [22] study the pricing and remanufacturing decision-making in a random environment where both remanufacturing rate of return and demand are random. Wang and Chen [37] develop a newsvendor model to study the impact of customer returns on corporate pricing and order decisions when a company faces price-dependent stochastic demand. In recent supply chain studies, some researchers have already adopted fuzzy set theory to depict indeterminacies in the supply chain model. Zhao et al. [49] and Wei and Zhao [39] study the production and price problems of two substitutable products in a supply chain with two competitive retailers and one manufacturer. Yang et al. [46] establish a three-game model of the green supply chain under government intervention and study the impact of channel leadership and government intervention on green levels, product prices, and expected profits. Consumer demand and manufacturing costs are described by fuzziness. However, fuzzy set theory is not rigorous in mathematical theory. There are still some shortcomings in dealing with uncertain problems. Nowadays, Production costs and demand for new products are often with no historical data
or we can’t collect enough valuable data, whose distributions are only estimated by experienced experts or supply chain managers. Therefore, the belief degree should not be regarded as a random variable or a fuzzy variable. When some nondeterministic factors show neither randomness nor fuzziness, for modeling human’s belief degree in mathematics, uncertainty theory is initiated by Liu [23] and refined by Liu [24] that will be a useful tool. Uncertainty theory has developed in a variety of directions and dealt with subjective uncertainty (Ding [6], Ke et al. [19], Yan et al. [43] and Song et al. [33]).

However, these studies are based on a single supply chain structure, not taking total carbon emissions, recycling and remanufacturing, nondeterministic factors in CLSC into account. This paper fill the gap as mentioned. Based on uncertainty theory and game theory, we formulate the pricing decision problem in a CLSC with cap-and-trade regulation. The main interest of this research is to discuss how the manufacturer makes his own pricing decision and carbon emission reduction rate, the downstream retailer makes his own retail markups, the third-party makes his recovery rate when facing an uncertain environment. In this paper, both the insights and the main model setting are different from those in the above-mentioned literature.

3. Model assumptions and notations. We consider a CLSC system under the cap-and-trade scheme, which consists of one manufacturer, one retailer, and one third-party recycling center. Figure 1 shows the CLSC structure in this paper. The manufacturer sells a single remanufactured product to the retailer at a wholesale price $\omega$, and then the retailer chooses its own markup policy $r$. Note that the sales price can be decided by $p = \omega + r$. In the reverse supply chain, the recycling of used products is mainly discussed in this research by the third-party collected from customers. For example, some large-scale machines, the dangerous goods that require high recycling conditions, etc. The third-party determines its collection rate $\tau$. As more and more people pay more attention to protecting the environment, low-carbon products on the market have received a large number of consumers’ preferences. A growing number of manufacturers are formulating and implementing relevant low-carbon policies to curb carbon emissions and improve product cleanliness. Therefore, the manufacturer considers about carbon emissions and determines its carbon emission reduction rate $\theta$. Under the cap-and-trade system, manufacturers can buy and sell emission permits through an external carbon trading market.

In reality, some parameters can not be collected or there are no historical data about them. We must invite some domain experts or managers to evaluate the degree of confidence that each event will occur. For example, the retailer sales costs $\hat{s}_r$, market sizes $\hat{d}$, price elasticity coefficients $\hat{\beta}$, and $\hat{\gamma}$ are usually unknown to the CLSC managers. We use uncertain variables to model those parameters. Some parameters used are shown in Table 1.

Further, the objective functions $\pi_i$ represent the expected profit of supply chain members, where $i = m, r, t$ represent the manufacturer, retailer, and the third-party, respectively. To better analyze this model, several reasonable assumptions are proposed and made as follows.

**Assumption 1.** We suppose that the linear demand function is

$$\tilde{q}(p, \theta) = \hat{d} - \hat{\beta}p + \hat{\gamma}\theta.$$
• Decision variables
  \( \omega \): Unit wholesale price to retailer, the manufacturer’s decision variable.
  \( r \): Unit markup price of retailer, the retailer’s decision variable.
  \( p \): Unit retail price of retailer, where \( p = \omega + r \).
  \( \tau \): Recovery rate through third-party channel,
  \( \tau \in [0,1] \), the third-party’s decision variable.
  \( \theta \): Carbon emission reduction rate of manufacturer,
  \( \theta \in [0,1] \), the manufacturer’s decision variable.

• Parameters
  \( c_n \): Unit cost of manufacturing the product from raw materials.
  \( c_r \): Unit manufacturing cost of the product from return products.
  \( \tilde{s}_r \): Unit sales cost of retailer, an uncertain variable.
  \( \tilde{d} \): The market base of product, an uncertain variable.
  \( \tilde{C} \): Total emissions of the manufacturer, an uncertain variable.
  \( p_e \): Average recycling price for used product from the third-party to the manufacturer.
  \( A \): Average recycling price for used products through the third-party channel.
  \( e \): Initial carbon emission of unit product.
  \( \Omega \): Total carbon free permits from government.
  \( \rho \): Cost coefficient of emissions reduction investment.
  \( \lambda \): Coefficient of carbon emissions reduction unit recovery rate.
  \( b \): Carbon buying price of unit product.
  \( s \): Carbon selling price of unit product.

This form of linear demand function is widely used in various references, such as Savaskan et al. [31] and Tsay and Agrawal[35]. The parameter \( \tilde{d} \) is the market base (the potential market size with all the prices equaling 0). The market size \( \tilde{d} \) is often with no historical data, which is an uncertain variable. The parameters \( \tilde{\beta} \) and \( \tilde{\gamma} \) represent the price elasticity coefficient and the product’s demand sensitivity to the
greening level, respectively, which are also uncertain variables. As the demand for new products is more sensitive to changes in their own prices than to changes in the level of greening, we assume that the expected value of elasticity coefficients $\hat{\beta}$ and $\hat{\gamma}$ satisfy $E[\hat{\beta}] > E[\hat{\gamma}] > 0$.

**Assumption 2.** The third-party collects the used products with collecting cost $\hat{c}(t)$. The collecting cost function can be denoted as

$$\hat{c}(t) = k\tau^2 + A\tau \hat{q}(p, \theta),$$

where $k\tau^2$ denotes the fixed collecting cost, and $\tau \hat{q}(p, \theta)$ denotes the collecting quantity of used products by third-party. A similar approach was used by Savaskan et al. [31] and Savaskan and Wassenhove [32].

**Assumption 3.** Based on the findings in the literature (e.g. Kotchen [20], Du et al. [7]), we assume that the total emissions function of the manufacturer is

$$\hat{C}(\theta, \tau) = e(1 - \theta)\hat{q}(p, \theta) - \lambda \tau,$$

where $e(1 - \theta)\hat{q}(p, \theta)$ represents the total carbon emissions of the manufacturer by employing low carbon technology, $\lambda \tau$ represents reduced carbon emissions by recycling and remanufacturing.

**Assumption 4.** The emission reduction process is related to the reduction rate. The higher the emission reduction rate means the more difficult the emission reduction process. Therefore, when the emission reduction rate is slightly improved, the investment cost of carbon emission reduction will increase sharply. Thus, similar to the previous literature (Wei et al. [38], Xiao and Yang [40] and Yang and Xiao [44]), the carbon reduction cost function can be expressed as $f(\theta) = \rho\theta^2 / 2$.

**Assumption 5.** The manufacturer uses virgin raw materials to produce new products at a unit cost of $c_n$. The cost of producing from the used materials is denoted by $c_r$. Note that $c_r$ includes all the disassembly and remanufacturing costs. Thus, for the feasibility of the proposed model, we assume that $c_n - c_r > p_c > A > 0$.

**Assumption 6.** All uncertain parameters are assumed to be non-negative and independent of each other.

**Assumption 7.** Consumers in these demand markets can return their used products to manufacturers at a price. All recycled products can be used to produce remanufactured products at the same quality. The manufacturer only produces a single-brand product and all activities occur within a single period. All the CLSC members are risk-neutral.

**Assumption 8.** In this study, the carbon trading price is an exogenous variable determined by the carbon trading market Yang and Xiao [44]. We assume that $b \geq s > 0$. The cost of carbon emission reduction is a one-time investment, and the investment has no impact on the unit production cost.

**Assumption 9.** The wholesale prices and the retailer’s unit markup price should exceed the unit cost of sales. The market demands and carbon emissions are always positive. The relative constraints are presented as follows:

$$\omega > c_n + be(1 - \theta),$$

$$M\{r - \hat{s}_r \leq 0\} = 0,$$

$$M\left\{ \hat{d} - \hat{\beta}(r + \omega) + \hat{\gamma}\theta \leq 0 \right\} = 0,$$
\[ M \left\{ e(1 - \theta) \left( \tilde{d} - \tilde{\beta}(r + \omega) + \tilde{\gamma} \theta \right) - \lambda \tau \leq 0 \right\} = 0. \]

Let \( \Omega \) be the total emissions quota of the manufacturer. In order to meet market demand for their products, the manufacturer decides to buy or sell carbon emission credits from the carbon trading market. The two cases of the manufacturer’s expected profit function are considered in this paper.

**Case 1:** Buying carbon quotas with cap-and-trade regulation. When the total carbon emissions are more than the total carbon quota \( \Omega \), the manufacturer is allowed to buy emission permits from other firms or government agencies through an outside carbon trading market. Then, the manufacturer’s expected profit function can be given as follows,

\[
\pi_m^b(\omega, \theta) = E \left[ (\omega - c_n + (c_n - c_r - p_c) \tau - be(1 - \theta)) (\tilde{d} - \tilde{\beta}(r + \omega) + \tilde{\gamma} \theta) \right. \\
- \rho \theta^2/2 - b(\tilde{C}(\theta, \tau) - \Omega) \left. \right]
\]

\[
= E \left[ (\omega - c_n + (c_n - c_r - p_c) \tau - be(1 - \theta)) \times (\tilde{d} - \tilde{\beta}(r + \omega) + \tilde{\gamma} \theta) - \rho \theta^2/2 + b\lambda \tau + b\Omega \right].
\]

By Assumptions 5 and 9, we find that \( \pi_m^b(\omega, \theta) \) is a monotone increasing function of \( \tilde{d} \), \( \tilde{\gamma} \) and a monotone decreasing function of \( \tilde{\beta} \). Thus,

\[
E[\xi] = \int_0^1 \Phi^{-1}(\alpha)d\alpha,
\]

where \( \Phi^{-1} \) is an uncertainty inverse distribution of uncertain variable \( \xi \) (Liu [25]). Referring to Liu and Ha [28]

\[
E[\xi] = \int_0^1 f(\Phi^{-1}_1(\alpha), \ldots, \Phi^{-1}_m(\alpha), \Phi^{-1}_{m+1}(1 - \alpha), \ldots, \Phi^{-1}_n(1 - \alpha))d\alpha,
\]

where \( \xi_i \) are independent uncertain variables. \( \Phi_i \) \((i = 1, 2, \ldots, n)\) are the regular uncertainty distributions of \( \xi_i \), respectively. \( f(x_1, x_2, \ldots, x_n) \) is strictly increasing to \( x_1, x_2, \ldots, x_m \) and strictly decrease to \( x_{m+1}, x_{m+2}, \ldots, x_n \).

The crisp form of \( \pi_m^b(\omega, \theta) \) can be attained as follows,

\[
\pi_m^b(\omega, \theta) = \int_0^1 \left[ (\omega - c_n + (c_n - c_r - p_c) \tau - be(1 - \theta)) (\Phi^{-1}_d(\alpha) \\
- (r + \omega)\Phi^{-1}_\beta(1 - \alpha) + \theta \Phi^{-1}_\gamma(\alpha)) - \rho \theta^2/2 + b\lambda \tau + b\Omega \right]d\alpha
\]

\[
= (\omega - c_n + (c_n - c_r - p_c) \tau - be(1 - \theta)) (E[\tilde{d}] \\
- (r + \omega)E[\tilde{\beta}] + \theta E[\tilde{\gamma}]) - \rho \theta^2/2 + b\lambda \tau + b\Omega.
\]

where \( \Phi^{-1}_d, \Phi^{-1}_\beta, \) and \( \Phi^{-1}_\gamma \) are the inverse uncertainty distribution functions of \( \tilde{d}, \tilde{\beta}, \) and \( \tilde{\gamma}, \) respectively.

**Case 2:** Selling carbon quotas

When the total carbon emissions in the actual production process are lower than the total carbon quota, the manufacturer may sell surplus emission permits. Similarly, the crisp form of the expected profit function \( \pi_m^s(\omega, \theta) \) can be attained
as follows,
\[
\pi_m^b(\omega, \theta) = E\left[ (\omega - c_n + (c_n - c_r - p_c)\tau) (\bar{d} - \bar{\beta}(r + \omega) + \bar{\gamma}\theta) - \rho\theta^2/2 + s(\Omega - \bar{C}(\theta, \tau)) \right]
\]
\[
= (\omega - c_n + (c_n - c_r - p_c)\tau - se(1 - \theta)) (E[\bar{d}] - (r + \omega)E[\bar{\beta}] + \theta E[\bar{\gamma}]) - \rho\theta^2/2 + s\lambda\tau + s\Omega.
\]

From the above crisp form of \(\pi_m^b(\omega, \theta)\) and \(\pi_m^a(\omega, \theta)\), the expected profit of the manufacturer can be described as follows,
\[
\pi_m(\omega, \theta) = (\omega - c_n + (c_n - c_r - p_c)\tau - ae(1 - \theta)) (E[\bar{d}] - (r + \omega)E[\bar{\beta}] + \theta E[\bar{\gamma}]) - \rho\theta^2/2 + a\lambda\tau + a\Omega,
\]

where
\[
a = \begin{cases} 
b, \text{when the manufacturer buys carbon quotas} 
\end{cases}
\]
\[
\begin{cases} 
s, \text{when the manufacturer sells carbon quotas.}
\end{cases}
\]

Similarly, the crisp form of the expected profit function of the retailer can be expressed as
\[
\pi_r(r) = E\left[ (r - \bar{s}_r)(\bar{d} - \bar{\beta}(r + \omega) + \bar{\gamma}\theta) \right]
\]
\[
= \int_0^1 (r - \Phi_{s_r}^{-1}(1 - \alpha)) (\Phi_d^{-1}(\alpha) - (r + \omega)\Phi_{\beta}_r^{-1}(1 - \alpha) + \theta\Phi_{\gamma}^{-1}(\alpha))d\alpha
\]
\[
= rE[\bar{d}] - (r^2 + r\omega)E[\bar{\beta}] + r\theta E[\bar{\gamma}] + (r + \omega)E[\bar{s}_r^{1-\alpha}\bar{\beta}^{1-\alpha}] - \theta E[\bar{s}_r^{1-\alpha}\bar{\gamma}^{\alpha}] - E[\bar{s}_r^{1-\alpha}\bar{\beta}^{1-\alpha}]
\]

where
\[
E[\xi^{1-\alpha}\eta^\alpha] = \int_0^1 \Phi_{\xi}^{-1}(1 - \alpha)\Phi_{\eta}^{-1}(\alpha)d\alpha,
\]
\[
E[\xi^{1-\alpha}\eta^{1-\alpha}] = \int_0^1 \Phi_{\xi}^{-1}(1 - \alpha)\Phi_{\eta}^{-1}(1 - \alpha)d\alpha,
\]
\(\Phi_{\xi}^{-1}\) and \(\Phi_{\eta}^{-1}\) are the inverse uncertainty distribution functions of independent uncertain variables \(\xi\) and \(\eta\), respectively.

The third-party’s expected profit function can be written as
\[
\pi_t(\tau) = E\left[ (p_c - A)\tau(\bar{d} - \bar{\beta}(r + \omega) + \bar{\gamma}\theta) - k\tau^2 \right]
\]
\[
= (p_c - A)\tau(E[\bar{d}] - (r + \omega)E[\bar{\beta}] + \theta E[\bar{\gamma}]) - k\tau^2.
\]

4. Models and discussions. In this section, we investigate three decentralized game models: (1) Manufacturer Stackelberg (MS) game. The market is dominated by a large manufacturer (like Intel, Apple, and Microsoft) who can play a dominant role. In MS, the manufacturer is the leader of the Stackelberg game, where the retailer and the third-party are followers. (2) Retailer Stackelberg (RS) game. The retailer (like Walmart, Suning, and Carrefour) has more bargaining power than the other members in CLSC. Thus, the manufacturer and the third-party are Stackelberg followers. (3) Vertical Nash (VN) game. In this scenario, each member has equal bargaining power, and they make their own decisions at the same time.
4.1. MS model. In the first case, with cap-and-trade regulation, we assume that the manufacturer plays a leading role in the supply chain members and announces its wholesale price $\omega$ and carbon emission reduction rate $\theta$ to maximize its own profit. Observing the manufacturer’s decision, the retailer and the third-party non-cooperatively choose their own markup pricing scheme $r$ and recovery rate $\tau$ respectively to maximize their own profits. Thus, a Stackelberg-Nash game model is formulated as

\[
\begin{align*}
\max_{\omega, \theta} & \quad \pi_m(\omega, \theta) = (\omega - c_n + (c_n - c_r - p_c)r^* - ae(1 - \theta)) (E[\tilde{d}]) \\
& - (r^* + \omega)E[\tilde{\beta}] + \theta E[\tilde{\gamma}] - \rho \theta^2/2 + a\lambda\tau^* + a\Omega
\end{align*}
\]

where $r^*$ and $\tau^*$ derives from problem:

\[
\begin{align*}
\max_r & \quad \pi_r(r) = rE[\tilde{d}] - (r^2 + r\omega)E[\tilde{\beta}] + r\theta E[\tilde{\gamma}] + (r + \omega)E[\tilde{\gamma} \tilde{\beta}^{1-\alpha}] \\
- & \theta E[\tilde{\gamma} \tilde{\beta}^{1-\alpha}] - E[\tilde{\gamma} \tilde{\beta}^{1-\alpha} \tilde{d}] \\
\max_\tau & \quad \pi_\tau(\tau) = (p_c - A)\tau (E[\tilde{d}] - (r + \omega)E[\tilde{\beta}] + \theta E[\tilde{\gamma}]) - k\tau^2
\end{align*}
\]

Based on MS model, we state the following proposition.

**Proposition 1.** In the MS model, the manufacturer first gives certain decision price $(\omega, \theta)$, the retailer’s optimal decision $r^*$ can be obtained as follows

\[
r^* = \frac{E[\tilde{d}] - \omega E[\tilde{\beta}] + \theta E[\tilde{\gamma}] + E[\tilde{\gamma} \tilde{\beta}^{1-\alpha}]}{2 E[\tilde{\beta}]}.
\] (1)

**Proof.** Referring to the retailer’s expected objective function with the given earlier decisions $\omega$ and $\theta$, we can get

\[
\frac{d\pi_r}{dr} = E[\tilde{d}] - (2r + \omega)E[\tilde{\beta}] + \theta E[\tilde{\gamma}] + E[\tilde{\gamma} \tilde{\beta}^{1-\alpha}],
\] (2)

\[
\frac{d^2\pi_r}{dr^2} = -2E[\tilde{\beta}] < 0.
\]

Hence, $\pi_r(r)$ is concave in $r$. By setting Eq. (2) to zero and solving it, Proposition 1 is proved.

**Proposition 2.** In the MS model, we can easily obtain the third-party’s optimal decision

\[
\tau^* = \frac{(p_c - A)\left(E[\tilde{d}] - \omega E[\tilde{\beta}] + \theta E[\tilde{\gamma}] - E[\tilde{\gamma} \tilde{\beta}^{1-\alpha}]\right)}{4k}.
\] (3)

**Proof.** The first and second order derivatives of $\pi_\tau(\tau)$ to $\tau$ are

\[
\frac{d\pi_\tau}{d\tau} = (p_c - A)\left(E[\tilde{d}] - (r + \omega)E[\tilde{\beta}] + \theta E[\tilde{\gamma}]\right) - 2k\tau,
\] (4)

\[
\frac{d^2\pi_\tau}{d\tau^2} = -2k < 0,
\]

respectively. Hence, $\pi_\tau(\tau)$ is concave in $\tau$. By setting the Eq. (4) to zero and substituting $r^*$ into $r$, Proposition 2 can be easily obtained.

**Proposition 3.** When the manufacturer receives the cap from the government agency, we can obtain the following conclusions given the optimal responses of the
The manufacturer expected profit \( \pi_m(\omega, \theta) \) is concave in \((\omega, \theta)\), if
\[
    k > \max \left\{ \frac{B_1}{4}, \frac{\rho B_1 E[\tilde{\beta}]^2}{4\rho E[\tilde{\beta}] - (E[\hat{\gamma}] + aeE[\tilde{\beta}])^2} \right\}
\]
and
\[
    \rho > \frac{(E[\hat{\gamma}] + aeE[\tilde{\beta}])^2}{4E[\tilde{\beta}]}. \tag{5}
\]

(ii) The manufacturer’s optimal decision are as follows,
\[
    \omega^* = \frac{B_3 B_6 - B_4 B_5}{B_2 B_4 - B_3^2}, \tag{6}
\]
\[
    \theta^* = \frac{B_3 B_5 - B_2 B_6}{B_2 B_4 - B_3^2},
\]
where
\[
    B_1 = (c_n - c_r - p_c)(p_c - A),
\]
\[
    B_2 = 2B_1E[\tilde{\beta}]^2 - 8kE[\tilde{\beta}],
\]
\[
    B_3 = 4kE[\hat{\gamma}] - 4kaeE[\tilde{\beta}] - 2B_1E[\tilde{\beta}]E[\hat{\gamma}],
\]
\[
    B_4 = 8kaeE[\hat{\gamma}] + 2B_1E[\hat{\gamma}]^2 - 8k, \rho,
\]
\[
    B_5 = 4kE[\hat{d}] - 2B_1E[\hat{d}]E[\tilde{\beta}] + (2B_1E[\tilde{\beta}] - 4k)E[\hat{\gamma}^1 - \alpha \tilde{\beta}^1 - \alpha]
    + (4kc_n + 4kae - 2a\lambda p_c + 2a\lambda A)E[\tilde{\beta}],
\]
\[
    B_6 = 4kaeE[\hat{d}] + 2B_1E[\hat{d}]E[\hat{\gamma}] - (2B_1E[\hat{\gamma}] + 4kae)E[\hat{\gamma}^1 - \alpha \tilde{\beta}^1 - \alpha]
    - (4kc_n + 4kae - 2a\lambda p_c + 2a\lambda A)E[\hat{\gamma}],
\]

Proof. By substituting the retailer and the third-party’s reaction functions Eqs. (1) and (3) into the manufacturer’s profit function \( \pi_m(\omega, \theta) \), we can get the Hessian matrix with the second derivative corresponding of the manufacturer’s expected profit function \( \pi_m(\omega, \theta) \),
\[
    H = \begin{bmatrix}
    \frac{\partial^2 \pi_m}{\partial \omega^2} & \frac{\partial^2 \pi_m}{\partial \omega \partial \theta} \\
    \frac{\partial^2 \pi_m}{\partial \omega \partial \theta} & \frac{\partial^2 \pi_m}{\partial \theta^2}
\end{bmatrix}
\]
\[
    = \begin{bmatrix}
    -E[\tilde{\beta}] + B_1E[\tilde{\beta}]^2/4k & (E[\hat{\gamma}] - aeE[\tilde{\beta}])/2 - B_1E[\tilde{\beta}]E[\hat{\gamma}]/4k \\
    (E[\hat{\gamma}] - aeE[\tilde{\beta}])/2 - B_1E[\tilde{\beta}]E[\hat{\gamma}]/4k & B_1E[\hat{\gamma}]^2/4k + aeE[\hat{\gamma}] - \rho
\end{bmatrix}.
\]
Under assumptions, the Hessian matrix is negative definite
\[
    k > \max \left\{ \frac{B_1}{4}, \frac{\rho B_1 E[\tilde{\beta}]^2}{4\rho E[\tilde{\beta}] - (E[\hat{\gamma}] + aeE[\tilde{\beta}])^2} \right\}
\]
and
\[
    \rho > \frac{(E[\hat{\gamma}] + aeE[\tilde{\beta}])^2}{4E[\tilde{\beta}]}.
\]
that $\pi_m(\omega, \theta)$ is concave in $(\omega, \theta)$. Therefore, setting the first order derivatives of $\pi_m(\omega, \theta)$ equal to zero, we have
\[
\frac{\partial \pi_m}{\partial \omega} = E[\tilde{d}] - (r + \omega)E[\tilde{\beta}] + \theta E[\tilde{\gamma}] - (\omega - c_n - ae + ae\theta)E[\tilde{\beta}] / 2 \\
- B_1 E[\tilde{\beta}] \left( E[\tilde{d}] - (r + \omega)E[\tilde{\beta}] + \theta E[\tilde{\gamma}] \right) / 4k - (c_n - c_r - p_c)\tau E[\tilde{\beta}] / 2 \\
- a\lambda(p_c - A)E[\tilde{\beta}] / 4k = 0.
\]
Solving Eqs. (7) and (8) simultaneously, we can easily gain the Proposition 3.

Based on Propositions 1, 2 and 3, it is easy to get the equilibrium price of the retailer and the equilibrium recovery rate of the third-party:
\[
\begin{align*}
r^* &= \frac{E[\tilde{d}] - \omega^* E[\tilde{\beta}] + \theta^* E[\tilde{\gamma}] + E[\tilde{s}_r^{1-\alpha}\tilde{\beta}^{1-\alpha}]}{2E[\tilde{\beta}]}, \\
\tau^* &= \frac{(p_c - A) \left( E[\tilde{d}] - \omega^* E[\tilde{\beta}] + \theta^* E[\tilde{\gamma}] - E[\tilde{s}_r^{1-\alpha}\tilde{\beta}^{1-\alpha}] \right)}{4k}.
\end{align*}
\]

4.2. RS model. In the second scenarios, the retailer is assumed to be the leader of the Stackelberg game model, where the manufacturer and the third-party act as the Stackelberg followers. The third-party first gives the best countermeasures, and then the manufacturer feeds back its response to the retailer. Then, the RS game model is formulated as
\[
\begin{align*}
\max_{r} \pi_r(r) &= rE[\tilde{d}] - (r^2 + r\omega^*)E[\tilde{\beta}] + r\theta^* E[\tilde{\gamma}] + (r + \omega^*)E[\tilde{s}_r^{1-\alpha}\tilde{\beta}^{1-\alpha}] \\
&\quad - \theta^* E[\tilde{s}_r^{1-\alpha}\tilde{\beta}^{1-\alpha}] - E[\tilde{s}_r^{1-\alpha}\tilde{\beta}^{1-\alpha}]
\end{align*}
\]
where $\omega^*$ and $\theta^*$ derive from problem:
\[
\begin{align*}
\max_{\omega, \theta} \pi_m(\omega, \theta) &= (\omega - c_n + (c_n - c_r - p_c)\tau^* - ae(1 - \theta))E[\tilde{d}] \\
&\quad - (r + \omega)E[\tilde{\beta}] + \theta E[\tilde{\gamma}] \right) / 2 + a\lambda\tau^* + a\Omega
\end{align*}
\]
where $\tau^*$ derives from problem:
\[
\max_{\tau} \pi_r(\tau) = (p_c - A)\tau \left( E[\tilde{d}] - (r + \omega)E[\tilde{\beta}] + \theta E[\tilde{\gamma}] \right) - k\tau^2
\]
Similarly, we can obtain Propositions 4, 5 and 6.

**Proposition 4.** In the RS model, given earlier decisions made by the manufacturer and the dominant retailer are $\omega$, $\theta$ and $r$ respectively, the third-party optimal recovery rate $\tau^*$ is
\[
\tau^* = \frac{(p_c - A) \left( E[\tilde{d}] - (r + \omega)E[\tilde{\beta}] + \theta E[\tilde{\gamma}] \right)}{2k}.
\]

**Proof.** Similar to the proof of Proposition 2, we can easily proof that Proposition 4 holds.
Proposition 5. In the RS model, after observing the third-party decision, we can obtain the following conclusions by given retail price \( r \),

(i) The manufacturer expected profit \( \pi_m(\omega, \theta) \) is concave in \( (\omega, \theta) \), if

\[
k > \frac{B_1 E[\tilde{\beta}]}{2}
\]

and

\[
\rho > \frac{k \left( E[\tilde{\gamma}] + aeE[\tilde{\beta}] \right)^2}{(2k - B_1 E[\tilde{\beta}]) E[\tilde{\beta}]}. \tag{10}
\]

(ii) The optimal decisions of the manufacturer are as follows,

\[
\begin{align*}
\theta^* &= \frac{C_1 C_7 - C_2 C_6}{C_2 - C_1 C_3} + \frac{(C_1 C_5 - C_2 C_4)r}{C_2 - C_1 C_3}, \tag{10} \\
\omega^* &= \frac{C_3 C_6 - C_2 C_7}{C_2 - C_1 C_3} + \frac{(C_3 C_4 - C_2 C_5)r}{C_2 - C_1 C_3}. \tag{11}
\end{align*}
\]

where

\[
\begin{align*}
C_1 &= 2B_1 E[\tilde{\beta}]^2 - 4k E[\tilde{\beta}]^2, \\
C_2 &= 2k E[\tilde{\gamma}] - 2B_1 E[\tilde{\beta}] E[\tilde{\gamma}] - 2kae E[\tilde{\beta}], \\
C_3 &= 2B_1 E[\tilde{\beta}]^2 + 4kae E[\tilde{\gamma}] - 2k \rho, \\
C_4 &= 2B_1 E[\tilde{\beta}]^2 - 2k E[\tilde{\beta}]^2, \\
C_5 &= -(2B_1 E[\tilde{\gamma}] + 2kae) E[\tilde{\beta}], \\
C_6 &= 2k(c_n + ae) E[\tilde{\beta}] - 2B_1 E[\tilde{d}] E[\tilde{\beta}] - a \lambda(p_e - A) E[\tilde{\beta}] + 2k E[\tilde{d}], \\
C_7 &= (2B_1 E[\tilde{\gamma}] + 2kae) E[\tilde{d}] - 2k(c_n + ae) E[\tilde{\gamma}] + a \lambda(p_e - A) E[\tilde{\gamma}].
\end{align*}
\]

Proof. Referring to the \( \pi_m(\omega, \theta) \) with the given earlier decisions \( r \), by substituting the third-party’s reaction functions Eq. (9) into the manufacturer’s profit function, we can get the Hessian matrix with the corresponding second-order derivatives of the equivalent objective function,

\[
H = \begin{bmatrix}
\frac{\partial^2 \pi_m}{\partial \omega^2} & \frac{\partial^2 \pi_m}{\partial \omega \partial \theta} \\
\frac{\partial^2 \pi_m}{\partial \theta^2}
\end{bmatrix}
= \begin{bmatrix}
-2E[\tilde{\beta}] + B_1 E[\tilde{\beta}]^2/k & E[\tilde{\gamma}] - B_1 E[\tilde{\beta}] E[\tilde{\gamma}] / k - ae E[\tilde{\beta}] \\
E[\tilde{\gamma}] - B_1 E[\tilde{\beta}] E[\tilde{\gamma}] / k - ae E[\tilde{\beta}] & B_1 E[\tilde{\gamma}]^2 / k + 2ae E[\tilde{\gamma}] - \rho
\end{bmatrix}.
\]

Then, the Hessian matrix is negative definite with the assumptions

\[
k > \frac{B_1 E[\tilde{\beta}]}{2}
\]

and

\[
\rho > \frac{k \left( E[\tilde{\gamma}] + aeE[\tilde{\beta}] \right)^2}{(2k - B_1 E[\tilde{\beta}]) E[\tilde{\beta}]}.
\]
Hence, $\pi_m(\omega, \theta)$ is concave in $(\omega, \theta)$. Then, by deriving the first-order condition, we can get the optimal response function to $(\omega, \theta)$.

$$\frac{\partial \pi_m}{\partial \omega} = C_1\omega/2k + C_2\theta/2k + C_4r/2k + C_6/2k = 0,$$

$$\frac{\partial \pi_m}{\partial \theta} = C_2\omega/2k + C_3\theta/2k + C_5r/2k + C_7/2k = 0. \quad (13)$$

By solving Eqs. (12) and (13), we can obtain Proposition 5.

**Proposition 6.** In the RS model, the total expected profit $\pi_r(r)$ is concave in $r$. When

$$k > \frac{B_1\rho E[\hat{\beta}]^2}{2\rho E[\hat{\beta}] - E[\hat{\gamma}]^2 - a^2c^2E[\hat{\beta}]^2 - 2aeE[\hat{\beta}]E[\hat{\gamma}]},$$

and

$$\rho > \frac{E[\hat{\gamma}]^2 + a^2c^2E[\hat{\beta}]^2 + 2aeE[\hat{\beta}]E[\hat{\gamma}]}{2E[\hat{\beta}]}$$

the optimal $r^*$ can be obtained as follows

$$r^* = \frac{C_8E[\hat{d}] - C_{12}E[\hat{\beta}] + C_{10}E[\hat{\gamma}] + (C_8 + C_{11})E[\hat{s}_r^{1-\alpha}\hat{\beta}^{1-\alpha}] - C_9E[\hat{s}_r^{1-\alpha}\hat{\gamma}]}{2(C_8 + C_{11})E[\hat{\beta}] - 2C_9E[\hat{\gamma}]} \quad (14)$$

where

$$C_8 = C_2^2 - C_1C_3,$$

$$C_9 = C_1C_5 - C_2C_4,$$

$$C_{10} = C_1C_7 - C_2C_6,$$

$$C_{11} = C_3C_4 - C_2C_5,$$

$$C_{12} = C_3C_6 - C_2C_7.$$

**Proof.** Substituting the manufacturer’s reaction functions Eqs. (10) and (11) into the retailer’s profit function, we obtain

$$\frac{d \pi_r}{dr} = E[\hat{d}] - [2r + \omega + r(C_3C_4 - C_2C_3)/(C_2^2 - C_1C_3)]E[\hat{\beta}]$$

$$+ r(C_1C_5 - C_2C_4)/(C_2^2 - C_1C_3)E[\hat{\gamma}] - (C_1C_5 - C_2C_4)/(C_2^2 - C_1C_3)$$

$$\times E[\hat{s}_r^{1-\alpha}\hat{\gamma}^\alpha] + [1 + (C_3C_4 - C_2C_5)/(C_2^2 - C_1C_3)]E[\hat{s}_r^{1-\alpha}\hat{\beta}^{1-\alpha}]$$

$$+ \theta E[\hat{\gamma}]. \quad (15)$$

When

$$k > \frac{B_1\rho E[\hat{\beta}]^2}{2\rho E[\hat{\beta}] - E[\hat{\gamma}]^2 - a^2c^2E[\hat{\beta}]^2 - 2aeE[\hat{\beta}]E[\hat{\gamma}]},$$

and

$$\rho > \frac{E[\hat{\gamma}]^2 + a^2c^2E[\hat{\beta}]^2 + 2aeE[\hat{\beta}]E[\hat{\gamma}]}{2E[\hat{\beta}]}$$

we can obtain

$$\frac{d^2 \pi_r}{dr^2} < 0.$$ 

Hence, $\pi_r(r)$ is concave in $r$. By setting Eq. (15) to zero and solving it, we can easily get Proposition 6.
Based on Propositions 4, 5 and 6, we can obtain the equilibrium price and equilibrium carbon emission reduction rate of the manufacturer and the third-party's equilibrium recovery rate as follows,

\[
\omega^* = \frac{C_3C_6 - C_2C_7}{C_2^2 - C_1C_3} + \frac{(C_3C_4 - C_2C_5)r^*}{C_2^2 - C_1C_3},
\]

\[
\theta^* = \frac{C_1C_7 - C_2C_6}{C_2^2 - C_1C_3} + \frac{(C_1C_5 - C_2C_4)r^*}{C_2^2 - C_1C_3},
\]

\[
\tau^* = \frac{(p_c - A)\left(E[\tilde{d}] - (r^* + \omega^*)E[\tilde{\beta}] + \theta^*E[\gamma]\right)}{2k}.
\]

4.3. VN model. In the CLSC, when each member has equal bargaining power, we assume that the three players move simultaneously. Then, a three-player Nash game model can be established as follows,

\[
\max_{\omega, \theta, r} \pi_m(\omega, \theta) = (\omega - c_n + (c_n - c_r - p_c)r - ac(1 - \theta))(E[\tilde{d}]
\]

\[-(r + \omega)E[\tilde{\beta}] + \theta E[\gamma]) - \rho \theta^2 / 2 + a\lambda r + a\Omega\]

\[
\max_\tau \pi_r(r) = rE[\tilde{d}] - (r^2 + r\omega)E[\tilde{\beta}] + r\theta E[\gamma] + (r + \omega)E[\tilde{s}_r^{1-\alpha}\tilde{\beta}^{1-\alpha}]
\]

\[-\theta E[\tilde{s}_r^{1-\alpha}\tilde{\gamma}^{1-\alpha}] - E[\tilde{s}_r^{1-\alpha}\tilde{d}^{1-\alpha}]\]

\[
\max_\tau \pi_\tau(\tau) = (p_c - A)\tau (E[\tilde{d}] - (r + \omega)E[\tilde{\beta}] + \theta E[\gamma]) - k\tau^2.
\]

From the above model, we can state the following proposition.

**Proposition 7.** In the Nash equilibrium of the three-player game, when \(\rho > (acE[\tilde{\beta}] + E[\tilde{\gamma}])^2/2E[\tilde{\beta}]\), the equilibrium prices are obtained as follows

\[
\omega^* = \frac{(D_1D_4 - D_2D_3)E[\tilde{d}] + (D_2 - D_1)E[\tilde{d}] - 2(D_4 - D_3)E[\tilde{\beta}] + (D_2 - D_1)E[\tilde{s}_r^{1-\alpha}\tilde{\beta}^{1-\alpha}]}{(D_2 - D_1)E[\tilde{\beta}]},
\]

\[
\tau^* = \frac{(p_c - A)\left[(D_4 - D_3)E[\tilde{\beta}] - (D_2 - D_1)E[\tilde{s}_r^{1-\alpha}\tilde{\beta}^{1-\alpha}]\right]}{2k(D_2 - D_1)},
\]

\[
\theta^* = \frac{D_1D_4 - D_2D_3}{D_2 - D_1},
\]

\[
r^* = \frac{D_4 - D_3}{D_2 - D_1},
\]

where

\[
D_1 = (E[\tilde{\beta}]E[\tilde{\gamma}] + acE[\tilde{\beta}]^2)/\rho E[\tilde{\beta}],
\]

\[
D_2 = (6kE[\tilde{\beta}] - B_1E[\tilde{\beta}]^2)/2k(E[\tilde{\gamma}] + acE[\tilde{\beta}]),
\]

\[
D_3 = (E[\tilde{\gamma}] + acE[\tilde{\beta}])E[\tilde{s}_r^{1-\alpha}\tilde{\beta}^{1-\alpha}]/\rho E[\tilde{\beta}],
\]

\[
D_4 = -(2kc_nE[\tilde{\beta}] + 2E[\tilde{d}] - 2kE[\tilde{d}] - 4kE[\tilde{s}_r^{1-\alpha}\tilde{\beta}^{1-\alpha}]
\]

\[+ B_1E[\tilde{\beta}]E[\tilde{s}_r^{1-\alpha}\tilde{\beta}^{1-\alpha}])]/2k(E[\tilde{\gamma}] + acE[\tilde{\beta}]).\]
Table 2. Parameters for the model

| Parameters | $c_n$ | $c_r$ | $p_c$ | $A$ | $b$ | $s$ | $e$ | $k$ | $\lambda$ | $\rho$ | $\Omega$ |
|------------|-----|-----|-----|-----|-----|-----|-----|-----|---------|-------|--------|
| Value      | 20  | 10  | 5   | 13  | 6   | 2.5 | 1200| 1500| 10000   | 5000  | 10000  |

Proof. Obviously, $\pi_r(r)$ is concave in $r$ and $\pi_t(\tau)$ is concave with respect to $\tau$. With Assumption 1, the Hessian matrix

$$
\begin{bmatrix}
\frac{\partial^2 \pi_m}{\partial \omega^2} & \frac{\partial^2 \pi_m}{\partial \omega \partial \theta} \\
\frac{\partial^2 \pi_m}{\partial \omega \partial \theta} & \frac{\partial^2 \pi_m}{\partial \theta^2}
\end{bmatrix}
$$

is negative definite since $\rho > (aeE[\tilde{\beta}] + E[\tilde{\gamma}])^2/2E[\tilde{\beta}]$, so $\pi_m(\omega, \theta)$ is jointly concave with respect to $(\omega, \theta)$. Setting the first-order derivatives equaling zero as follows,

$$
\frac{\partial \pi_m}{\partial \omega} = -rE[\tilde{\beta}] - 2\omega E[\tilde{\beta}] + \theta(E[\tilde{\gamma}] - aeE[\tilde{\beta}]) - (c_n - c_r - p_c)\tau E[\tilde{\beta}] + E[\tilde{d}] + (c_n + ae)E[\tilde{\gamma}] = 0,
$$

(16)

$$
\frac{\partial \pi_m}{\partial \theta} = -rE[\tilde{\beta}] + \omega(E[\tilde{\gamma}] - aeE[\tilde{\beta}]) + \theta(2aeE[\tilde{\gamma}] - m) - (c_n - c_r - p_c)\tau E[\tilde{\gamma}]
$$

+ $aeE[\tilde{d}] - (c_n + ae)E[\tilde{\gamma}] = 0$,

(17)

$$
\frac{d\pi_r}{dr} = -2rE[\tilde{\beta}] - \omega E[\tilde{\beta}] + \theta E[\tilde{\gamma}] + E[\tilde{d}] + E[\tilde{s}^{1-a}\tilde{\beta}^{1-a}] = 0,
$$

(18)

$$
\frac{d\pi_t}{dr} = -r(p_c - A)E[\tilde{\beta}] - \omega(p_c - A)E[\tilde{\beta}] + \theta(p_c - A)E[\tilde{\gamma}] - 2k\tau + (p_c - A)E[\tilde{d}] = 0.
$$

(19)

Proposition 7 can be obtained by solving Eqs.(16, 17, 18, 19).

5. Numerical experiments. In this section, some numerical experiment are performed to analysis of the above three models. Our paper was motivated by a Chinese company which produces an electronic product. We utilize a hypothetical dataset to show the underlying relationship of the model structure. The used value of the parameter satisfies a certain assumptions of our research and is consistent with the previous literature, as shown in Table 2.

The model structure is quite complex since it involves uncertain demand, uncertain carbon emissions, and uncertain cost. In this case, we estimate uncertain variables by relying on the belief degrees given by experienced experts or managers. Interested readers can refer to Liu [23] (Chapter 16: Uncertainty Statistics) for more details on how to effectively collect expert data and how to estimate the empirical distribution of uncertain variables from experimental data. For simplicity, the specific distributions of uncertain parameters are given in Table 3.

We use

$$
E[\xi] = \int_0^1 \Phi^{-1}(\alpha)d\alpha
$$
### Table 3. Distributions of uncertain variables

| Parameters | Distribution | Expected value |
|------------|--------------|----------------|
| $\tilde{\beta}$ | $\mathcal{L}(0.4, 0.8)$ | 0.6 |
| $\tilde{\gamma}$ | $\mathcal{L}(0.2, 0.4)$ | 0.3 |
| $\tilde{d}$ | $\mathcal{Z}(700, 950, 1000)$ | 900 |
| $\tilde{s}$ | $\mathcal{L}(3, 5)$ | 4 |

### Table 4. The optimal decisions of the three structures under buying carbon quotas

| Structure | $\omega^*$ | $\theta^*$ | $\pi^b_m$ | $r^*$ | $\pi_r$ | $\tau^*$ | $\pi_t$ |
|-----------|-----------|-----------|-----------|------|-------|------|-------|
| MS        | 753.7486  | 0.7351    | 224163.5012 | 375.3678 | 82851.5121 | 0.1856 | 41.3482 |
| RS        | 1161.6480 | 0.2598    | 143452.4000 | 222.6841 | 15340.8000 | 0.0579 | 4.0227 |
| VN        | 512.1873  | 0.9743    | 210343.7000 | 496.2082 | 145447.5000 | 0.2460 | 72.6462 |

### Table 5. The optimal decisions of the three structures under selling carbon quotas

| Structure | $\omega^*$ | $\theta^*$ | $\pi^b_m$ | $r^*$ | $\pi_r$ | $\tau^*$ | $\pi_t$ |
|-----------|-----------|-----------|-----------|------|-------|------|-------|
| MS        | 758.6526  | 0.3429    | 193461.0000 | 372.8177 | 81719.3100 | 0.1844 | 40.7821 |
| RS        | 1156.2150 | 0.1368    | 107485.1000 | 229.5259 | 15617.3600 | 0.0572 | 3.9213 |
| VN        | 516.9945  | 0.4553    | 174966.9000 | 493.6749 | 143955.4000 | 0.2448 | 71.9002 |

To calculate the expected value of uncertain variables, where $\xi$ is an uncertain variable with regular uncertainty distribution $\Phi$ (Liu [25]). With $E[\xi] = \frac{a + b}{2}$, where $\xi \sim \mathcal{L}(a, b)$ is a linear uncertain variable (Yao [47]) and $E[\xi] = \frac{a + 2b + c}{4}$, where $\xi \sim \mathcal{Z}(a, b, c)$ is a zigzag uncertain variable (Yao [47]), we can obtain $E[\tilde{\beta}] = 0.6, E[\tilde{\gamma}] = 0.3, E[\tilde{d}] = 900, E[\tilde{s}] = 4$, and

\[
E[\tilde{s}^{1-\alpha \tilde{\beta}^{1-\alpha}}] = \int_0^1 \Phi_{s_r}^{-1}(1-\alpha)\Phi^{-1}_{\tilde{\beta}}(1-\alpha)d\alpha = 2.4667,
\]

\[
E[\tilde{s}^{1-\alpha \tilde{\gamma}^{\alpha}}] = \int_0^1 \Phi_{s_r}^{-1}(1-\alpha)\Phi^{-1}_{\tilde{\gamma}}(\alpha)d\alpha = 1.1667,
\]

\[
E[\tilde{s}^{1-\alpha \tilde{d}^{\alpha}}] = \int_0^1 \Phi_{s_r}^{-1}(1-\alpha)\Phi^{-1}_{\tilde{d}}(\alpha)d\alpha = 3550.
\]

In the following analysis, we consider the manufacturer has to buy/sell carbon quotas through carbon trading market in order to meet the market demand of his product. The corresponding results are shown in Tables 4 and 5.

From Tables 4 and 5, the following results are obtained,

(i) In the MS game scenario, no matter the manufacturer buys/sells carbon quotas, he can get the highest expected profit. The lowest expected profit is achieved
Table 6. Effects of the retailer sales costs $\tilde{s}_r$ on the optimal results under buying carbon quotas

| Structure | $\tilde{s}_r$ | $\omega^*$ | $\theta^*$ | $\pi_m$ | $\pi_r$ | $\tau^*$ | $\pi_t$ |
|-----------|--------------|-----------|-----------|-------|-------|--------|-------|
| MS        | $\mathcal{L}(2.5, 5.5)$ | 753.7224  | 0.7351    | 224152.9000 | 375.4051 | 82890.7900 | 0.1856 | 41.3454 |
|           | $\mathcal{L}(3, 5)$     | 753.7486  | 0.7351    | 224163.5012 | 375.3678 | 82851.5121 | 0.1856 | 41.3482 |
|           | $\mathcal{L}(3.5, 4.5)$ | 753.7789  | 0.7351    | 224176.7000 | 375.3218 | 82777.9400 | 0.1856 | 41.3517 |
| RS        | $\mathcal{L}(2.5, 5.5)$ | 1161.6360 | 0.2598    | 143442.6000 | 222.7092 | 15407.3100 | 0.0579 | 4.0218  |
|           | $\mathcal{L}(3, 5)$     | 1161.6480 | 0.2598    | 143452.4000 | 222.6841 | 15340.8000 | 0.0579 | 4.0227  |
|           | $\mathcal{L}(3.5, 4.5)$ | 1161.6620 | 0.2599    | 143464.5000 | 222.6533 | 15264.5700 | 0.0579 | 4.0239  |
| VN        | $\mathcal{L}(2.5, 5.5)$ | 512.1714  | 0.9743    | 210333.8000 | 496.2412 | 145507.4000 | 0.2460 | 72.6412 |
|           | $\mathcal{L}(3, 5)$     | 512.1873  | 0.9743    | 210343.7000 | 496.2082 | 145447.5000 | 0.2460 | 72.6462 |
|           | $\mathcal{L}(3.5, 4.5)$ | 512.2070  | 0.9743    | 210355.9000 | 496.1676 | 145379.4000 | 0.2460 | 72.6524 |

In the RS game case. As the leader of the Stackelberg game model, the manufacturer will obtain more profit than as a follower. For the common retailer, in the VN game case, she achieves her highest expected profit and achieves her lowest expected profit in the RS game case although she acts as Stackelberg leader. The third-party gains the highest expected profit and recovery rate in the VN game case.

(ii) In addition to the RS game case, the markup price of retailer, carbon emission reduction rate, and the retailer’s expected profit in buying carbon emissions quotas are higher than that of selling carbon quotas. No matter what kind of game structure, recovery rate, the expected profit of the manufacturer and the third-party are higher in buying carbon emissions quotas. Under a cap-and-trade regulation, the results show that the manufacturer is willing to buy carbon quotas in order to make greater profits.

In order to further study the influence of uncertain parameters on the optimal decision under three possible structures, including the retailer sales costs $\tilde{s}_r$ and greening level elastic coefficient $\tilde{\gamma}$, we make sensitivity analysis by varying the standard deviation of these parameters and keeping the other parameters unchanged as shown in Tables 6, 7, 8 and 9. We present the following four tables to show the optimal results under buying/selling carbon quotas.

Referring to Tables 6 and 7, we get the following results,

(i) When the variance of its sales cost becomes higher, no matter the manufacturer buys/sells carbon quotas, the maximally expected profits of the third-party and the manufacturer will drop, while the retailer’s maximal expected profits will drop as the variance of parameter $\tilde{s}_r$ decreases.

(ii) The retailer can charge a higher markup price when the variance of parameter $\tilde{s}_r$ increases. No matter what kind of strategies, the manufacturer’s wholesale price changes slightly, the carbon emission reduction rate and recovery rate of used products keep the same under buying/selling carbon quotas.

Referring to Tables 8 and 9, one can find the following results.

(i) Regardless of the leadership, when the manufacturer buys/sells carbon quotas, the wholesale price, carbon emission reduction rate, recovery rate, and the expected profits of the third-party keep the same, showing that no matter who holds the power has no effect on them. (ii) The retailer’s maximal expected profit and sales price change slightly as the variance of parameter $\tilde{\gamma}$ decreases.
Table 7. Effects of the retailer sales costs $\tilde{s}_r$ on the optimal results under selling carbon quotas

| Structure | $\tilde{s}_r$ | $\omega^*$ | $\theta^*$ | $\pi_m$ | $\tau^*$ | $\pi_r$ | $\tau^*$ | $\pi_t$ |
|-----------|----------------|-------------|------------|--------|---------|--------|---------|--------|
| MS | $L(2.5, 5.5)$ | 758.6278 | 0.3429 | 193450.0000 | 372.8552 | 81758.7700 | 0.1840 | 40.7793 |
| | $L(3, 5)$ | 758.6526 | 0.3429 | 193461.0000 | 372.8177 | 81719.3100 | 0.1844 | 40.7821 |
| | $L(3.5, 4.5)$ | 758.6834 | 0.3429 | 193474.6000 | 372.7715 | 80964.4000 | 0.1844 | 40.7556 |
| RS | $L(2.5, 5.5)$ | 1158.2020 | 0.1368 | 107475.7000 | 229.5509 | 15952.6800 | 0.0572 | 3.9204 |
| | $L(3, 5)$ | 1156.2150 | 0.1368 | 107485.1000 | 229.5259 | 15617.3600 | 0.0572 | 3.9213 |
| | $L(3.5, 4.5)$ | 1156.2300 | 0.1368 | 107496.8000 | 229.4951 | 15541.0800 | 0.0572 | 3.9223 |
| VN | $L(2.5, 5.5)$ | 516.9780 | 0.4553 | 174957.1000 | 493.7081 | 143955.3000 | 0.2448 | 71.8953 |
| | $L(3, 5)$ | 516.9945 | 0.4553 | 174966.9000 | 493.6749 | 143889.4000 | 0.2448 | 71.9002 |
| | $L(3.5, 4.5)$ | 517.0149 | 0.4553 | 174979.1000 | 493.6339 | 143887.0000 | 0.2448 | 71.9062 |

Table 8. Effects of the greening level elastic coefficient $\tilde{\gamma}$ on the optimal results under buying carbon quotas

| Structure | $\tilde{\gamma}$ | $\omega^*$ | $\theta^*$ | $\pi_m$ | $\tau^*$ | $\pi_r$ | $\tau^*$ | $\pi_t$ |
|-----------|----------------|-------------|------------|--------|---------|--------|---------|--------|
| MS | $L(0.15, 0.45)$ | 753.7486 | 0.7351 | 224163.5000 | 375.3678 | 82826.4400 | 0.1856 | 41.3482 |
| | $L(0.2, 0.4)$ | 753.7486 | 0.7351 | 224163.5012 | 375.3678 | 82851.5121 | 0.1856 | 41.3482 |
| | $L(0.25, 0.35)$ | 753.7486 | 0.7351 | 224163.5000 | 375.3678 | 82851.4700 | 0.1856 | 41.3482 |
| RS | $L(0.15, 0.45)$ | 1161.6480 | 0.2598 | 143452.4000 | 222.6842 | 15340.7800 | 0.0579 | 4.0227 |
| | $L(0.2, 0.4)$ | 1161.6480 | 0.2598 | 143452.4000 | 222.6841 | 15340.8000 | 0.0579 | 4.0227 |
| | $L(0.25, 0.35)$ | 1161.6480 | 0.2598 | 143452.4000 | 222.6841 | 15340.7900 | 0.0579 | 4.0227 |
| VN | $L(0.15, 0.45)$ | 512.1873 | 0.9743 | 210343.7000 | 496.2082 | 145447.5000 | 0.2460 | 72.6462 |
| | $L(0.2, 0.4)$ | 512.1873 | 0.9743 | 210343.7000 | 496.2082 | 145447.5000 | 0.2460 | 72.6462 |
| | $L(0.25, 0.35)$ | 512.1873 | 0.9743 | 210343.7000 | 496.2082 | 145447.5000 | 0.2460 | 72.6462 |

Table 9. Effects of the greening level elastic coefficient $\tilde{\gamma}$ on the optimal results under selling carbon quotas

| Structure | $\tilde{\gamma}$ | $\omega^*$ | $\theta^*$ | $\pi_m$ | $\tau^*$ | $\pi_r$ | $\tau^*$ | $\pi_t$ |
|-----------|----------------|-------------|------------|--------|---------|--------|---------|--------|
| MS | $L(0.15, 0.45)$ | 758.6554 | 0.3429 | 193462.2000 | 372.8136 | 81714.9800 | 0.1844 | 40.7825 |
| | $L(0.2, 0.4)$ | 758.6554 | 0.3429 | 193461.0000 | 372.8177 | 81719.3100 | 0.1844 | 40.7825 |
| | $L(0.25, 0.35)$ | 758.6554 | 0.3429 | 193462.2000 | 372.8136 | 81714.9600 | 0.1844 | 40.7825 |
| RS | $L(0.15, 0.45)$ | 1156.2150 | 0.1368 | 107485.1000 | 229.5259 | 15617.3600 | 0.0572 | 3.9213 |
| | $L(0.2, 0.4)$ | 1156.2150 | 0.1368 | 107486.1000 | 229.5232 | 15612.7800 | 0.0572 | 3.9214 |
| | $L(0.25, 0.35)$ | 1156.2150 | 0.1368 | 107486.1000 | 229.5232 | 15612.7800 | 0.0572 | 3.9214 |
| VN | $L(0.15, 0.45)$ | 516.9945 | 0.4553 | 174966.9000 | 493.6749 | 143955.4000 | 0.2448 | 71.9002 |
| | $L(0.2, 0.4)$ | 516.9945 | 0.4553 | 174966.9000 | 493.6749 | 143955.4000 | 0.2448 | 71.9002 |
| | $L(0.25, 0.35)$ | 516.9945 | 0.4553 | 174966.9000 | 493.6749 | 143955.4000 | 0.2448 | 71.9002 |

6. Conclusion and future research. In this paper, we research the pricing and recycling decisions in a CLSC with cap-and-trade regulation, which consisting of a retailer, a manufacturer, and a third-party. The manufacturer produces new products using both virgin materials and some used products returned from the
customers in a reverse supply chain. The manufacturer asks a third-party to recycle used products directly from the customer. To comply with the regulation, the manufacturer buys or sells emission permits from external markets. Many non-deterministic factors are considered, such as the retailer sales costs, collecting costs, consumer demands, the manufacturer’s total carbon emissions, and the quantities of recycled products. Subsequently, we analyze three decentralized game models: MS model assumes that the manufacturer is the leader of Stackelberg game and other players (retailer and third-party) are the followers; RS model assumes that the retailer plays a dominant role as the Stackelberg leader, while the third-party and the manufacturer are the Stackelberg followers; in the VN model, each member had equal bargaining power, they make their decisions simultaneously. Meanwhile, a clear equivalent model is given respectively and we get the corresponding analytical solution. Numerical experiments are given to verify the effectiveness of the model.

In order to simplify the model and calculation process, some assumptions are proposed in this paper. In the future, research can focus on some more general issues to meet the real situation. Firstly, several reasonable assumptions in the model can be further relaxed for further study. For example, product demand is affected by many factors, so nonlinear or more complex demand function can be considered in the future study. Secondly, we assume the same quality of the remanufactured product for all accepted used products. Modeling different quality levels for remanufactured products would be a meaningful extension of the current study. Thirdly, we consider a single product in our model. Future studies may extend our modeling approach to consider multiple products. Finally, this model assumes carbon emissions and costs in transport don’t exist, which deviates from the real world. The future research on supply chain can focus on the above more complicated pricing decision problems.

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