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The impact of cap-and-trade mechanism and consumers' environmental preferences on a retailer-led supply Chain

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ABSTRACT

Governments and consumers are paying more attention to environmental protection. China, Korea, and several European countries have implemented market-based cap-and-trade systems to reduce carbon emissions. At the same time, consumers are willing to pay more for low-carbon products. The decisions of manufacturers and retailers may be impacted by these factors. This paper considers a scenario with a model economy under the effects of a cap-and-trade policy, with consumers who prefer low-carbon products, and develops an evolutionary game (EG) model to examine the evolution of behaviors for powerful retailers (such as Amazon, Gome, Walmart, etc.) and manufacturers in a retailer-led supply chain. In such a supply chain, the retailers can choose whether or not to promote low-carbon products and manufacturers can choose whether or not to reduce carbon emissions. A Stackelberg game structure is used to identify the optimal decisions for manufacturers and retailers. A model is developed to investigate the stability of the equilibrium solutions of the evolutionary game. System dynamics is used to simulate and analyze dynamic and transient behaviors, and is used to simulate the evolutionary game in a Chinese appliance industry. The simulation results show that the emissions cap, the market price of carbon credits, and the consumers' preferences for low-carbon products are key factors influencing the retailers' and manufacturers' behavior. To increase long-term profits for both retailers and manufacturers, the retailers and the manufacturers should make sustainable decisions in tandem.

1. Introduction

With the rapid development of industrial capabilities in China and other parts of the world, more greenhouse gasses (GHGs) have been emitted due to industrial production processes, which damage the environment. After implementing the Kyoto Protocol in 1997 and the Paris Climate Agreement in 2015, Europe, China, and Korea have attempted to enact a variety of policies and legislation to reduce carbon emissions (Goulder and Schen, 2013; Zhang and Xu, 2013). For example, in China, the National Development and Reform Commission (NDRC) instructed Beijing, Shanghai, Guangdong, and four other cities to implement a carbon emissions trading mechanism. According to NDRC statistics, between the implementation of the program and September 2017, 197 million tons and more than 4.5 billion RMB of carbon credits were exchanged in these seven cities.

Under this cap-and-trade system, the government allocates a free limit on carbon emissions to an individual enterprise. If an enterprise produces a larger amount of carbon emissions than the emissions cap, it has to buy credits for the extra carbon emissions; otherwise, it can earn additional revenue by selling the unused carbon credits at the market price (Benjaafar et al., 2013). For example, in 2013, Foxconn invested less than 50 million RMB in energy-saving retrofits but gained 10 million RMB in profit (an increase of 60 million RMB in revenue) by selling the surplus carbon credits; this set of transactions accounted for nearly 30% of the annual surplus credits in Shenzhen. Therefore, the carbon trading market has created a new cost mechanism (Alhaj et al., 2016) for enterprises and could influence the enterprises' production planning and ordering strategies (Cheng et al., 2017; Drake et al., 2010).

Many customers are also concerned about environmental issues (Du et al., 2017; Manohar and Kumar, 2016; Xu and Wang, 2017) and are willing to pay more for low-carbon products (Du et al., 2015; Luo et al., 2014). Low-carbon products have lower embodied greenhouse gas emissions and are generally considered to have lower environmental impact (Janssen and Jager, 2002). A report by the AliResearch Institute, a non-profit agency in China, states that the total number of consumers

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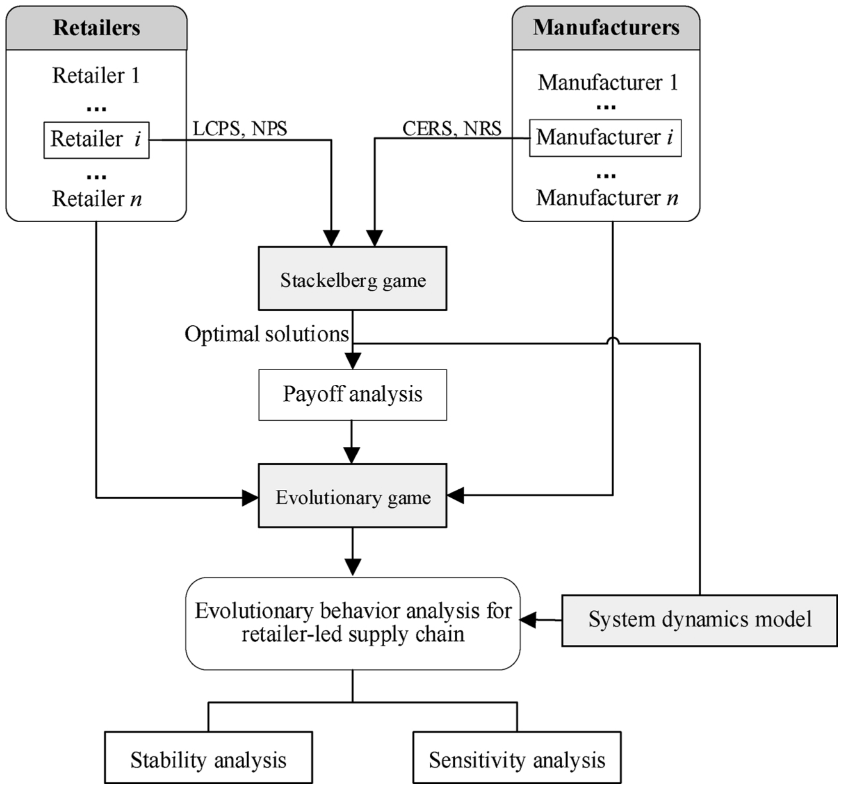

Fig. 1. Framework of this paper.

who prefer low-carbon products increased by a factor of 14 in the past four years and reached 65 million in 2015.

In view of these factors mentioned above, manufacturers may be incentivized to invest in sustainable/low-carbon technology to reduce carbon emissions, and use cleaner energy and eco-friendly materials (Swami and Shah, 2013). In response to these changing market conditions, several companies have adjusted their behavior. In 2016, Siemens adopted cleaner technologies and helped its upstream and downstream enterprises reduce carbon emissions by 521 million tons, which accounted more than 60% of the annual carbon emissions in Germany. Meanwhile, as market power (e.g., pricing power) has gradually shifted from manufacturers to powerful retailers (e.g. Walmart, Gome, Amazon) (Pu et al., 2007), some supply chains have become retailer-led. These powerful retailers are increasingly expected to take more responsibility for environmental damages (Lai and Tang, 2010; Styles et al., 2012). To this end, retailers promote their eco-friendly products by labeling products with carbon footprint information, and discounting the low-carbon products (Tuten, 2013). For instance, in recent years, Gome, the largest home appliances retailer in China, has actively popularized environmental knowledge and promoted energy-saving products to consumers.

However, each since stakeholder is concerned about maximizing its own profit, and does not act for the benefits of the overall supply chain. When one company invests in sustainable production technologies, all companies along the supply chain benefit from the ability to market their product as “sustainable”. This is a classic free rider problem, and as a result, supply chain spillover emerges. In fact, the supply chain members who act in an environmentally friendly manner do not receive all of the benefits of their strategies. Some of the supply chain enterprises will take a free ride and earn profits from other agents’ sustainability efforts. Over time, competitors will need to implement sustainable strategies to compete, and the market will evolve (Kusi-Sarpong and Sarkis, 2017).

In order to understand the expected changes to the market, methods are needed to predict the behavior of retailers and manufacturers. This market evolution can be modelled as a dynamic game (Liu et al., 2012). The equilibrium strategies for a dynamic game may not remain stable over time, similar to biological evolution. Thus, evolutionary game theory is an important method that can be used to investigate the dynamic impact of government incentive policies to reduce carbon emissions (Wu et al., 2017) on the strategies and behaviors of enterprises. Evolutionary game theory is based on the assumption of bounded rationality, which supposes that players have the ability to keep learning and adapt to the market environment (Du et al., 2017; Smith, 1976; Zhou and Deng, 2006). Barari et al. (2012) established an evolutionary game model between producers and retailers to analyze their strategies to incentivize sustainable practices and to maximize economic profits. (Naini et al., 2011) proposed a mixed performance measurement system using a combination of evolutionary game theory and a balanced score card method to solve environmental supply chain management (ESCM) problems. They found that the adoption of ESCM is limited by organizational factors and strategic myopia. Ji et al. (2015) developed an evolutionary game model to observe the long-term tendency for multiple stakeholders to cooperate in green purchasing. Zhao et al. (2016) proposed an evolutionary game model to investigate the responses of enterprises to a carbon reduction labeling scheme. Tian et al. (2014) utilized evolutionary game theory and system dynamics to explore the diffusion of sustainable supply chain management ideas between manufacturers.

By analyzing these existing studies, we conclude that prior research has mainly focused on investigating the influence of regulatory actions and macroeconomic policies on the evolution of the behavior of manufacturers and retailers. It is still unknown how carbon policies and consumer behavior impacts the selection of strategies and the evolution of the behavior of both the retailers and the manufacturers in an actual evolutionary game process. To address this gap, we consider cap-and-trade mechanism and the consumers’ preference for low-carbon products to develop an evolutionary game model to understand the evolutionary behavior of the retailers and the manufacturers in a retailer-led supply chain. As shown in Fig. 1, in such a retailer-led supply chain, the retailers have two strategies: a low-carbon promotion strategy (LCPS) and a non-promotion strategy (NPS) and the manufacturers can choose between a carbon emissions-reduction strategy (CERS) and a non-reduction strategy (NRS). Both LCPS and CERS cost more than their corresponding alternative strategies, but potentially can result in higher sales or more carbon credits in the long term. Since payoff analysis is very important in establishing an evolutionary game model, under each strategy combination, a Stackelberg game structure is applied to find optimal solutions for each manufacturer and each retailer to maximize their profits in the short term. In a Stackelberg game structure, the retailer moves first and the manufacturers adjust behavior based upon retailer actions. This is used to determine the optimal solutions for the various permutations of the two strategies available to retailers and the two strategies available to manufacturers. As these strategies can be chosen by retailers and manufacturers, and can be modelled using the relative probabilities of each choice, the EG model can be used to investigate the stability of the various equilibrium strategies and observe the interactions among stockholders and the effects of short-term optimal strategies on the long-term optimal solution.

One way that these evolutionary games are modelled is through system dynamics (SD) (Forrester, 1961). SD is a technique to simulate and analyze dynamic and transient behavior (Yang and Du, 2016), so many scholars have combined system dynamics with evolutionary game methods to study supply chain operations and management issues (Cai et al., 2009; Kim and Kim, 1997; Zhu et al., 2014). In this study, the system dynamics model for an evolutionary game is applied to a case study of the Chinese refrigerator industry to simulate the dynamic game process and investigate how the factors mentioned above influence their selection of a strategy and their evolving behavior. In particular, the evolutionary tendency of the enterprises' behavior when the emissions cap decreases has been observed and analyzed. The framework of this paper is shown in Fig. 1; the evolutionary game structure is outlined in Section 2 and the system dynamics model is discussed in Section 3.

2. The evolutionary game model

In this section, we develop an evolutionary game model to analyze the supply chain stakeholders' behavior while considering a cap-and-trade system and the consumers' preferences for low-carbon products. In a retailer-led supply chain, upstream manufacturers sell products to downstream retailers, who sell the products to the customers, as presented in Fig. 2. Specially, the enterprises' behavior is driven by carbon policies and the demand for low-carbon products (Tian et al., 2014; Zhao et al., 2016). The agents may also influence each other in the supply chain system, that is, organizational behavior may be influenced by competition between the manufacturers and the retailers.

As depicted in Figs. 1 and 2, each retailer acts as a leader in the Stackelberg game. The retailer first decides whether to adopt the LCPS or NPS strategy, then decides the retail margin and amount of promotional effort needed. Specifically, the promotional measures include increasing advertising investment, improving a salesmen's professional skills or displaying goods in the best locations; all of these measures require investment. In such a supply chain, each manufacturer acts as a follower in the game. According to the retailers' decisions, manufacturers decide whether to implement a CERS or NRS strategy, and then decide on the wholesale price and amount of investment in carbon emissions reduction technologies. If the manufacturer does not make effort to reduce carbon emissions, it only needs to decide on the optimal wholesale price.

Table 1
Payoff matrix for retailer and manufacturer.

Strategies of the retailer	Strategies of the manufacturer	
	CERS	NRS
LCPS	π_r^{PR}, π_m^{PR}	π_r^{PN}, π_m^{PN}
NPS	π_r^{NR}, π_m^{NR}	π_r^{NN}, π_m^{NN}

We construct four strategy combinations for the promotion (P), reduction (R) and non-promotion/reduction (N) scenarios: NN (NPS, NRS), PN (LCPS, NRS), NR (NPS, CERS), and PR (LCPS, CERS). The profits of both retailers and manufacturers are summarized in the payoff matrix, as shown in Table 1.

To develop the proposed model, we make the following assumptions.

Retailers, manufacturers, and customers exist in an oligopoly market.

The numbers of manufacturers and retailers are constant.

The manufacturers produce products based on make-to-order production, so that demand is considered to be equal to production quantity.

When utilizing a certain emissions reduction technology, the unit carbon emission is fixed and measurable.

Carbon credits that are allocated by the government for free cannot be transferred to the next production period. The manufacturers can trade carbon credits in the carbon market.

Customers can learn about the embodied carbon emissions of a product from "carbon labels" or other channels.

These assumptions are both useful and tenable in real domains, and enable the model to be analyzed. The parameters used in the model are shown below.

Δw Retail margin set by the retailer
τ_r Level of promotional effort decided by the retailer
w Wholesale price set by the manufacturer
τ_m Level of carbon emissions reduction decided by the manufacturer
a Potential market demand
b Price elasticity of demand
β Promotional effectiveness parameter
γ Emissions reduction effectiveness parameter
p Retail price per unit of product
q Production quantity
c_r Retail cost per unit of product
c_m Production costs per unit of product
h_r Promotion cost coefficient
h_m Emissions reduction investment coefficient
e_m Initial carbon emissions per unit of product
p_e Market price of carbon credits
C_g Emissions cap
π_j^i, $i = NN, PN, NR, PR$; $j = \gamma, m$ Profit of j in i strategy combination

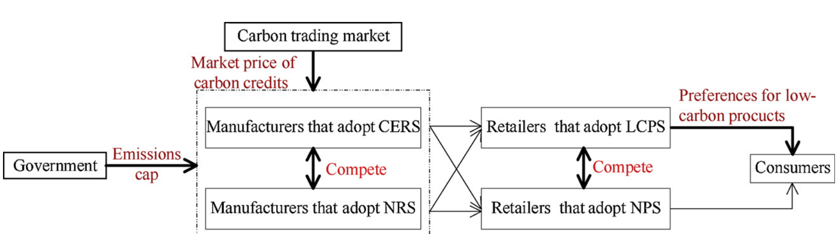

Fig. 2. Supply chain network structure.

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2.1. The model development

In the evolutionary game, each player chooses its strategy based on the probability to obtain evolutionary advantages for long-term development. According to Kim and Kim (1997), the probability of the players' behavior can be estimated as the proportion of retailers who promote low-carbon products and the proportion of manufacturers who reduce carbon emissions. We denote $x (0 \le x \le 1)$ as probability of that the retailers adopt the LCPS and y $(0 \le y \le 1)$ as the probability of that the manufacturers adopt the LCPS. The expected profits of the retailers that choose LCPS and NPS are set as E_r^P and E_r^N, which are described by Eqs. (1) and (2), respectively,

$$E_r^P = y\pi_r^{PR} + (1-y)\pi_r^{PN} \tag{1}$$

$$E_r^N = y\pi_r^{NR} + (1-y)\pi_r^{NN} \tag{2}$$

The average expected payoff of the retailers is

$$\bar{E}_r = xE_r^P + (1-x)E_r^N \tag{3}$$

Similarly, the expected profits of the manufacturers that choose CERS and NRS are given as follows, respectively,

$$E_m^R = x\pi_m^{PR} + (1-x)\pi_m^{NR} \tag{4}$$

$$E_m^N = x\pi_m^{PN} + (1-x)\pi_m^{NN} \tag{5}$$

and the average expected payoff of the manufacturers is:

$$\bar{E}_m = yE_m^R + (1-y)E_m^N \tag{6}$$

To describe the evolutionary game, replicator dynamic equations are used (Fudenberg and Maskin, 1990; Kim and Kim, 1997; Taylor, 1978). The replicator dynamic equations for the retailers who promote low-carbon products and the manufacturers who reduce carbon emissions are given as follows, respectively:

$$F(x) = \frac{dx}{dt} = x(E_r^P - \bar{E}_r) = x(1-x)[y(\pi_r^{PR} - \pi_r^{NR}) + (1-y)(\pi_r^{PN} - \pi_r^{NN})] \tag{7}$$

$$F(y) = \frac{dy}{dt} = y(E_m^R - \bar{E}_m) = y(1-y)[x(\pi_m^{PR} - \pi_m^{PN}) + (1-x)(\pi_m^{NR} - \pi_m^{NN})] \tag{8}$$

These systems of equations enable the simulation of manufacturer and retailer behavior.

2.2. Payoffs analysis

As mentioned above, in a retailer-led supply chain, the retailers and the manufacturers will attempt to maximize their economic profits under each one of the four strategy combinations. Therefore, Stackelberg game structure is applied to find the optimal solutions of the retailer and the manufacturer under each one of the four strategy combinations that are shown in Table 1.

(1) Strategy combination NN

In this combination, retailers do not promote low-carbon products and manufacturers do not reduce carbon emissions. As the leader in the game, each retailer first decides the retail margin per unit of product and then its upstream manufacturers decide the optimal wholesale price. According to Choi (1991), the product price is equal to the wholesale price plus the retail margin, that is, $p = w + \Delta w$. The demand function is given as

$$q(w, \Delta w) = D = a - b(w + \Delta w) \tag{9}$$

where Δw characterizes the retail margin that is decided by retailers. a and b denote the base market demand and price elasticity of demand, respectively. Based on the above description, by maximizing the players' profits, we formulate an unconstrained optimization model. Here, the profit function for each retailer is presented as:

$$\pi_r^{NN} = (p - w - c_r)q \tag{10}$$

and the profit function for each manufacturer is shown as:

$$\pi_m^{NN} = (w - c_m)q - (e_m q - C_g)p_e \tag{11}$$

where c_r and c_m represent the retail cost and production cost, respectively. e_m is the initial carbon emissions per unit of product when the reduction of carbon emissions is not incentivized (normal market conditions). C_g indicates the carbon emissions cap, as imposed by government policy.

(2) Strategy combination PN

In strategy combination PN, the manufacturers will not earn additional profits from reducing carbon emissions in the short term. These manufacturers prefer to buy carbon credits rather than invest in carbon emissions reduction technology. Thus, low-carbon products will not appear in the market and cannot be promoted by retailers. Under these circumstances, the sequence of decision making and the optimal solutions in PN are the same as the strategy combination NN.

(3) Strategy combination NR

In this case, the manufacturers provide themselves with surplus carbon credits through investment in emissions reduction technologies or carbon trading. Many retailers will have a strong tendency to be "free riders". These retailers contribute nothing toward the cost of the carbon emissions reduction technologies and the promotion of the low-carbon products, while enjoying their benefits as fully as manufacturers who invest (Kim and Walker, 1984). Therefore, demand is affected by the retail price per unit of product and the level of carbon emissions reduction. The demand function is given by Eq. (12).

$$q(w, \Delta w, \tau_m) = D = a - b(w + \Delta w) + \gamma\tau_m \tag{12}$$

where γ indicates an emissions reduction effectiveness parameter which represents the increase in consumer demand for a low carbon product for a given reduction in emissions by the manufacturer. In this case, after the retailer decides the retail margin, its upstream manufacturers will decide the wholesale price and level of carbon emissions reduction. The profit functions for each retailer and each manufacturer are presented in Eqs. (13) and (14).

$$\pi_r^{NR} = (p - w - c_r)q \tag{13}$$

$$\pi_m^{NR} = (w - c_m)q - [e_m(1-\tau_m)q - C_g]p_e - \frac{1}{2}h_m\tau_m^2 \tag{14}$$

where τ_m is the level of carbon emissions reduction, and h_m is the carbon emissions investment coefficient. Since the investment required to reduce carbon emissions has an increasing marginal cost, we assume that the investment costs can be modelled as a quadratic function, that is, $I_m = \frac{1}{2}h_m\gamma_m^2 (h_m > 0)$ (Gurnani and Erkoc, 2008; Petruzzi and Dada, 1999; Savaskan and Van Wassenhove, 2006). After investing in carbon emissions reduction technologies, the current emissions per unit of product is $e_m(1-\tau_m)$. If carbon emissions exceed the emissions cap, the manufacturer has to buy carbon credits in the carbon market; otherwise, it can sell its surplus credits to balance carbon reduction costs or gain additional revenue. If the manufacturer's carbon emissions in the production process exceeds the emissions cap C_g, the term $[e_m(1-\tau_m)q - C_g]p_e$ denotes the carbon trading cost; otherwise, the manufacturer will earn additional revenue.

(4) Strategy combination PR

When retailers sell products to customers, the retailers can quickly respond to the demand for low-carbon products and take measures to promote low-carbon products to further increase profits. The manufacturers are pushed by a cap-and-trade system and pulled by consumer demand for low-carbon products. Therefore, in strategy combination PR, the demand is affected by emissions reduction effort and promotional effort. The demand function is shown as follows:

$$q(w, \tau_m, \Delta w, \tau_r) = D = a - b(w + \Delta w) + \gamma\tau_m + \beta\tau_r \tag{15}$$

where β represents the promotional effectiveness parameter, which represents the increase in demand from customers in response to the promotional effort of retailers. The profit functions for each manufacturer and each retailer are provided as follows:

$$\pi_r^{PR} = (p - w - c_r)q - \frac{1}{2}h_r\tau_r^2 \tag{16}$$

$$\pi_m^{PR} = (w - c_m)q - [e_m(1 - \tau_m)q - C_g]p_e - \frac{1}{2}h_m\tau_m^2 \tag{17}$$

The promotional cost follows a quadratic function based on results from Laffont and Tirole (1993) and D'Aspremont and Jacquemin (1988), i.e. $I_r = \frac{1}{2}h_r\tau_r^2 (h_r > 0)$, where τ_γ is the level of promotional effort. In strategy combination PR, the retailer first decides the retail margin per unit Δw and the level of promotional effort, τ_r. The upstream manufacturers decide the optimal wholesale price w and the level of carbon emissions reduction τ_m.

Based on these profit functions established for each manufacturer and each retailer, the optimal solutions from the Stackelberg game structure are summarized in the following theorems.

Theorem 1. There exists a unique optimal solution to each combination.

See Appendix A for proof. The optimal solutions and important results in each case are shown in Appendix B. Note that there are only optimal solutions based on NR and PR if $2bh_m - (\gamma + be_mp_e)^2 > \frac{\beta^2 h_m}{2h_r} > 0$.

Theorem 1. allows us to calculate the unique optimal solutions for each strategy combination under specific conditions. A comparison of results between the optimal profits of the four strategy combinations are shown in theorem 2.

Theorem 2. *If* $2bh_m - (\gamma + be_mp_e)^2 > \frac{\beta^2 h_m}{2h_r} > 0$, *then* $(\pi_m^{NN})^* = (\pi_m^{PN})^* < (\pi_m^{NR})^* < (\pi_m^{PR})^*$ *and* $(\pi_r^{NN})^* = (\pi_r^{PN})^* < (\pi_r^{NR})^* < (\pi_r^{PR})^*$.

Proof. According to Theorem 1, we can determine the optimal solutions for the retailers' and the manufacturers' profits in each case:

The optimal profits for the retailer are:

$$(\pi_r^{NN})^* = (\pi_r^{PN})^* = \frac{[a - b(c_m + e_mp_e + c_r)]^2}{8b}$$

$$(\pi_r^{NR})^* = \frac{[a - b(c_m + e_mp_e + c_r)]^2}{8b - \frac{4(\gamma + be_mp_e)^2}{h_m}}, \quad (\pi_r^{PR})^* = \frac{[a - b(c_m + e_mp_e + c_r)]^2}{8b - \frac{4(\gamma + be_mp_e)^2}{h_m} - \frac{2\beta^2}{h_r}}$$

The profit functions will be greater than zero only when $2bh_m - (\gamma + be_mp_e)^2 > \frac{\beta^2 h_m}{2h_r} > 0$.

Since $\frac{2\beta^2}{h_r} > 0$, $\frac{4(\gamma + be_mp_e)^2}{h_m} > 0$, and $[a - b(c_m + e_mp_e + c_r)]^2 > 0$, we have $8b > 8b - \frac{4(\gamma + be_mp_e)^2}{h_m} > 8b - \frac{4(\gamma + be_mp_e)^2}{h_m} - \frac{2\beta^2}{h_r}$.

Therefore, $\pi_r^{NN} = \pi_r^{YN} < \pi_r^{NY} < \pi_r^{YY}$.

Similarly, we can get $\pi_m^{NN} = \pi_m^{PN} < \pi_m^{NR} < \pi_m^{PR}$.

Theorem 2. indicates that the most profitable strategy is PR, followed by NR. The least two profitable strategies are NN and PN. It is obvious that $\pi_m^{NN} + \pi_r^{NN} = \pi_m^{PN} + \pi_r^{PN} < \pi_m^{NR} + \pi_r^{NR} < \pi_m^{PR} + \pi_r^{PR}$, which indicates that the total supply chain profit in PR will be significantly greater than that in any other combination. Therefore, if supply chain enterprises take measures to promote low-carbon products and reduce carbon emissions, the profit of the company and the rest of the supply chain will increase.

However, as the retailers and the manufacturers update their strategies based on the perceived probability of changes in market circumstances (e.g., customers' preferences for low-carbon products, market price of carbon credits), the optimal solutions may not be constant or the time required to reach the optimal solutions may change. Thus, it is meaningful to analyze the stability of the evolutionary game.

2.3. Stability analysis of evolutionary game

As mentioned above, the evolutionary game process of the retailer-led supply chain system can be characterized by the replicator dynamic Eqs. (7) and (8). The following lemma is useful to derive the equilibrium points for this evolutionary game.

Lemma 1. With the dynamic evolution of the supply chain system, there are four Nash equilibrium points (0, 0), (0, 1), (1, 0) and (1, 1).

Proof. Since $\pi_r^{PN} = \pi_r^{NN}$ and $\pi_m^{PN} = \pi_m^{NN}$, then we can get

$$\begin{cases} F(x) = x(1 - x)(\pi_r^{PR} - \pi_r^{NR})y \\ F(y) = y(1 - y)[x(\pi_m^{PR} - \pi_m^{NR}) + (\pi_m^{NR} - \pi_m^{NN})] \end{cases}$$

Let $\begin{cases} F(x) = 0 \\ F(y) = 0 \end{cases}$, the equilibrium points of the supply chain system are (0,0), (0,1), (1,0), (1,1), (x_0, y_0), where $\begin{cases} x_0 = \frac{\pi_m^{NR} - \pi_m^{NN}}{\pi_m^{NR} - \pi_m^{NN} + \pi_m^{PN} - \pi_m^{PR}} = \frac{\pi_m^{NR} - \pi_m^{NN}}{\pi_m^{NR} - \pi_m^{PR}} < 0 \\ y_0 = \frac{\pi_r^{PN} - \pi_r^{NN}}{\pi_r^{PN} - \pi_r^{NN} - \pi_r^{PR} + \pi_r^{NR}} = 0 \end{cases}$ It is obvious that $x_0 < 0$ is contrary to the assumption that the values of all equilibrium points are greater than zero. Therefore, point $(x_0, y_0) = \left(\frac{\pi_m^{NR} - \pi_m^{NN}}{\pi_m^{NR} - \pi_m^{PR}}, 0\right)$ does not exist and there are only four equilibrium points of this system, that is (0, 0), (0, 1), (1, 0) and (1, 1).

Lemma 1. allows us to derive the four Nash equilibrium points of this supply chain system. The stabilities of these points are stated in the next theorem.

Theorem 3. Based on the system given by replicator dynamic Eqs. (7) and (8), it follows that

(a) The equilibrium (1, 1) is a unique ESS.
(b) The equilibrium (0, 1) is a saddle point.
(c) The equilibrium point (0, 0) and (1, 0) are unstable.

Proof. Friedman (1991) and Hofbauer and Sigmund (1998) put forward a local stability analysis method that utilizes a Jacobian matrix to analyze the stability of equilibrium points. The Jacobian matrix of the retailer-led supply chain system is

$$J = \begin{pmatrix} \frac{dF(x)}{dx} & \frac{dF(x)}{dy} \\ \frac{dF(y)}{dx} & \frac{dF(y)}{dy} \end{pmatrix}$$

$$= \begin{pmatrix} (1 - 2x)[y(\pi_r^{PR} - \pi_r^{NR}) + (1\text{-}y)(\pi_r^{PN} - \pi_r^{NN})] & x(1 - x)(\pi_r^{PR} - \pi_r^{NR} - \pi_r^{PN} + \pi_r^{NN}) \\ y(1 - y)(\pi_m^{PR} - \pi_m^{PN} - \pi_m^{NR} + \pi_m^{NN}) & (1 - 2y)[x(\pi_m^{PR} - \pi_m^{PN}) + (1 - x)(\pi_m^{NR} - \pi_m^{NN})] \end{pmatrix} \tag{18}$$

When the determinant of the Jacobian matrix is greater than 0 ($Det(J) > 0$) and the trace of the Jacobian matrix is less than 0 ($tr(J) < 0$), the equilibrium point that tends to a local asymptotic stability point is the evolutionary stability strategy (ESS) of the system.

Table 2
Stability of Equilibrium points.

Equilibrium point	*Det (J)*	*tr (J)*	Stability
(0, 0)	0	+	Unstable point
(0, 1)	–	+	Saddle point
(1, 0)	0	uncertain	Unstable point
(1, 1)	+	–	ESS

According to Lemma 1 and the Jacobian matrix of the system, the results are summarized in Table 2.

From Lemma 1 and Theorem 3, it can be seen that the system cannot reach a steady state when the manufacturers do not reduce carbon emissions or the retailers do not promote low-carbon products. In addition, from any point in the closed area of $[0, 1] \times [0, 1]$, the system converges to the (1, 1) point. The supply chain will then reach an evolutionary steady state. This means that all manufacturers will choose CERS and all retailers will select LCPS given time. However, the time the system takes to reach an evolutionary steady state depends on the changes in key factors such as the emissions cap, the market price of carbon credits, and the customers' preference for low-carbon products. These issues will be addressed in next section.

3. System dynamics model for an evolutionary game

3.1. The framework of system dynamics model

Based on the analysis of the manufacturers' and retailers' evolutionary behavior, we establish a system dynamics (SD) model for an evolutionary game using Vensim_DSS software. The SD model is a useful tool to simulate the dynamic game process and predict the dynamic evolution of a system using a convenient visual description (Wang et al., 2011). We established the SD model's stock-flow diagram for the supply chain system, as shown in Fig. 3. The subsystem modelling for the payoff of retailers and manufacturers in the SD model is shown in Fig. 4.

According to the Lyapunov function (Kelly et al., 1998) and Eqs. (16) and (17), the key equations in the system dynamics model are given as follows:

$$NMR = INTEG(AR, initial) \tag{19}$$

$$NRP = INTEG(AP, initial) \tag{20}$$

$$x = NRP/(NRP + NRN) \tag{21}$$

$$y = NMR/(NMR + NMN) \tag{22}$$

$$UMR = y\text{*Manufacturer's profit in strategy combination PR+}\\ (1 - y)\text{*Manufacturer's profit in strategy combination NR} \tag{23}$$

$$UMN = y\text{*Manufacturer's profit in strategy combination PN+}\\ (1 - y)\text{*Manufacturer's profit in strategy combination NN} \tag{24}$$

$$URP = x\text{*Retailer's profit in strategy combination PR} + (1 - x)\\ \text{*Retailer's profit in strategy combination NR} \tag{25}$$

$$URN = x\text{*Retailer's profit in strategy combination PN} + (1 - x)\\ \text{*Retailer's profit in strategy combination NN} \tag{26}$$

$$AP = \frac{dx}{dt} = x*(1 - x)*(URP - URN) \tag{27}$$

$$AR = \frac{dy}{dt} = y*(1 - y)*(UMR - UMN) \tag{28}$$

where *NMR* represents the number of manufacturers that invest in carbon emissions reduction technologies, *NMN* represents the number of manufacturers that do not invest in carbon emissions reduction technologies, *NRP* represents the number of retailers that promote low-carbon products, *NRN* represents the number of retailers that do not promote low-carbon products, *AR* represents the adoption rate of the manufacturers that choose CERS, *AP* represents the adoption rate of the retailers that choose LCPS, *UMR* represents the expected profits when the manufacturers select CERS, *UMN* represents the expected profit when the manufacturers select NRS, *URP* represents the expected profit when the retailers select LCPS, *URN* represents the expected profit when the retailers select NPS. As shown in Figs. 3 and 4, there are four levels of variables: *NRN*, *NRP, NMN* and *NMR*; two rate variables: *AR* and *AP*; two intermediate variables: *A Multiplier* and *B Multiplier*; and eleven exogenous variables.

To apply the SD model to a real world case, we examine the Chinese refrigerator industry. The initial parameters of the system dynamics model are mainly derived from information from the National Bureau of Statistics of the People's Republic of China (NBS), the China's National Development and Reform Commission (NDRC) and the China Household Electrical Appliances Association (CHEAA). In 2016, sales of sustainable refrigerators with a price of 4,000–6,000 RMB and over 6000 RMB were over 87,000 (CHEAA, 2016). Since China has launched the cap-and-trade system in Beijing, the unit market price of carbon credits in Beijing's Carbon Trading Center is 50 RMB/Ton (CHEAA,

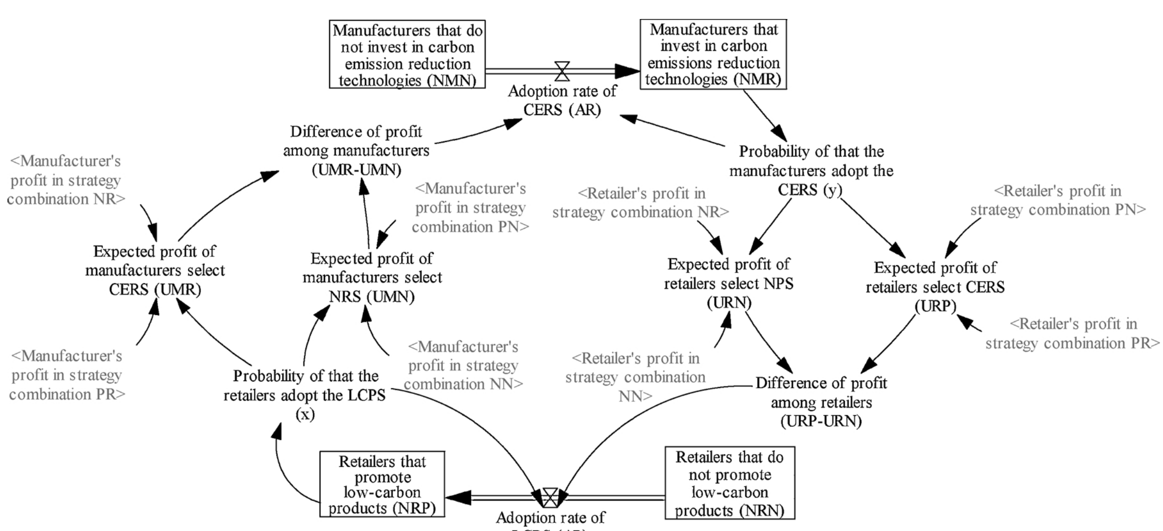

Fig. 3. The SD model for the evolutionary game.

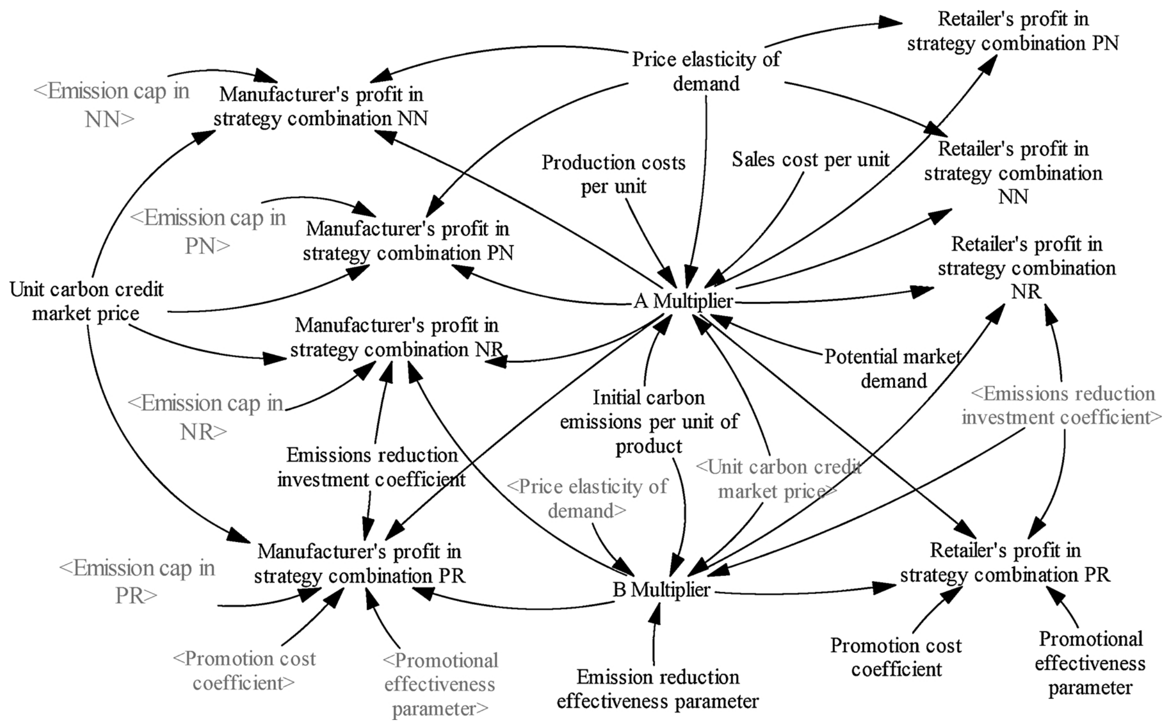

Fig. 4. The payoff of retailers and manufacturers.

Table 3
Input parameters of the simulation.

Variables	Type	Value	Unit
NRP	Level	0.01	
NRN	Level	0.99	
NMR	Level	0.01	
NMN	Level	0.99	
a	Constant	87	Thousand
b	Constant	0.8	
γ	Constant	0.8	
β	Constant	0.6	
c_m	Constant	0.9	Thousand RMB
c_r	Constant	0.6	Thousand RMB
e_m	Constant	0.01	Ton
h_m	Constant	50	
h_r	Constant	60	
p_e	Constant	50	RMB/Ton
C_g	Constant	1000	Thousand Ton

2016) and the emissions cap is calculated by using the baseline method (GFC and CBEEX, 2016). The emissions cap of each manufacturer that is regulated by the government is set as 1 million ton. According to Zhang et al. (2016), the production of each refrigerator consumes about 14 kW h. Thus, the initial carbon emissions of each refrigerator during manufacturing (kg) is equal to the power consumption (14 kg) multiplied by 0.785 (Calculation of carbon emissions, 2014). According to Zhang et al. (2016), the price of a refrigerator compressor is about 300 RMB, which accounts for one-third of the total manufacturing cost. Therefore, we set the production cost to be 900 RMB. Similar to Tian et al. (2014), the investment factors for carbon emissions reduction and promotion are set as 50 and 60, respectively. The values of these input parameters of the SD model are shown in Table 3. In the initial simulations, these numbers are used as benchmarks for the behavior of the retailers and manufacturers. The numbers are varied within reasonable limits (e.g., increases of 2x or 3x and a decrease of 2x) to understand the sensitivity of the behaviors to external forces.

3.2. Model validation of system dynamics

Model validation can help us build confidence in the inferences used to approximate the behavior of real system (Barlas, 1996). We conduct model validation from a structural validity and behavioral validity perspective by using Vensim_DSS software. We verified that this SD model does not have any mechanical or dimensional consistency errors.

Behavioral validity is important in SD model validation, and represents how consistently the model outputs match real world behavior (Barlas, 1996). In order to evaluate behavioral validity, we carry out a Monte-Carlo sensitivity test by using the Vensim_Dss software. A Monte-Carlo sensitivity test explores the expected behaviors of the model for a selected output variable, and estimates the probability of an action through repeated simulations (Musango et al., 2011). In this paper, the uncertain parameters include price elasticity of demand, a promotional effectiveness parameter, an emissions reduction effectiveness parameter, a promotion cost coefficient, and an emissions reduction investment coefficient. We assume that each parameter i can be modelled using a normal distribution. That is $i \sim N\,(\mu_i, \sigma_i)$, where μ_i is the mean value in the range $[a_i, b_i]$ and σ_i is the variance. The values of these parameters are shown in Table 4. The number of simulations was set at 200 scenarios.

Fig. 5 and Fig. 6 present the simulation-based confidence bounds for the probability of that the retailers adopt the LCPS (x) and the probability of that the manufacturers adopt the CERS (y), respectively. In the Monte-Carlo simulation, test cases were used to develop confidence

Table 4
Parameters used in sensitivity test.

Parameter (i)	Mean (μ_i)	Variance (σ_i)	Range
Price elasticity of demand (b)	0.8	0.1	[0.1, 1]
Emissions reduction effectiveness parameter (γ)	0.8	0.1	[0.1, 1]
Promotional effectiveness parameter (β)	0.6	0.1	[0.1, 1]
Emissions reduction investment coefficient (h_m)	50	10	[10, 100]
Promotion cost coefficient (h_r)	60	10	[10, 100]

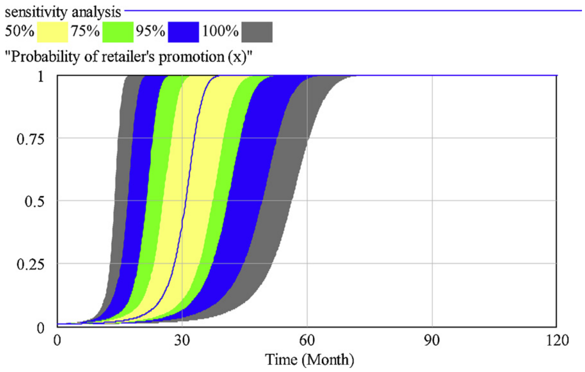

Fig. 5. A sensitivity analysis of the probability of that the retailers adopt the LCPS.

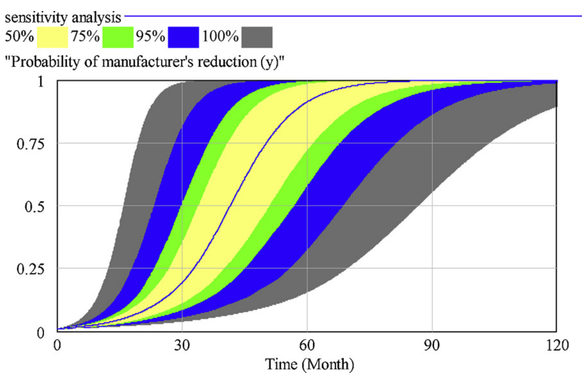

Fig. 6. A sensitivity analysis of the probability of that the manufacturers adopt the CERS.

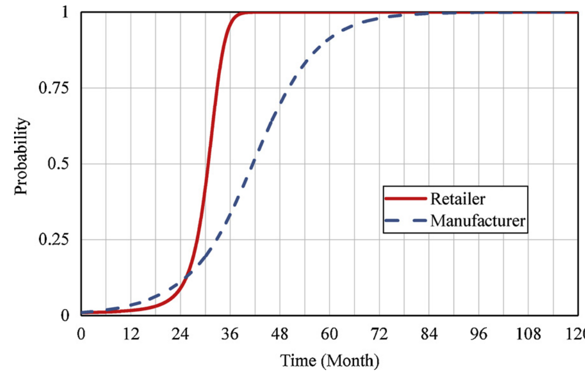

Fig. 7. The probability of that the retailers adopt the LCPS and that manufacturers adopt the CERS.

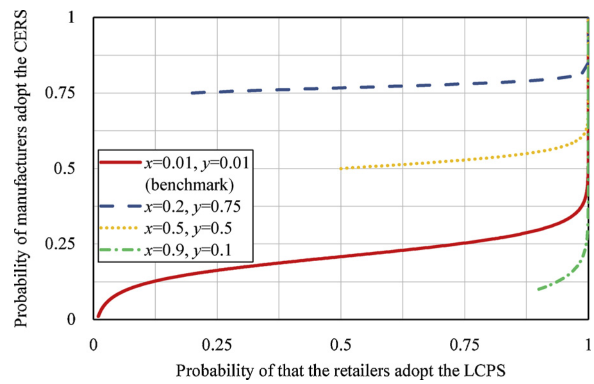

Fig. 8. The evolution and game process of the manufacturers and the retailers.

bounds and illustrate behavioral validity. In the simulations, if the confidence level is 50%, all the test cases are located within the yellow area. Similarly, all of the retailer's promotion test cases and all of the manufacturer emissions reduction test cases are located within the 100% confidence bounds represented by the gray area.

In summary, the system dynamics model for the evolutionary game is valid to simulate the evolution of behaviors between manufacturers and retailers and to investigate the influences of key parameters on the behavior of enterprises.

3.3. System dynamics simulation results

Based on the background of the refrigerator industry mentioned above, a system dynamics model is developed to simulate the evolutionary game process of a supply chain system and to investigate the impacts of key parameters (such as the market price of carbon credits and the elasticity coefficients related to demand) on the decisions of the manufacturers and retailers. The initial values of the simulation are shown in Table 3.

3.3.1. Simulation of evolutionary game process

The simulation of the evolutionary game was set up using a number of default parameters. The simulation interval is [0,120], that is, INITIAL TIME = 0, FINAL TIME = 120 Month, with a TIME STEP = 0.03125 months. The results of the simulation are shown in Table 3. In order to compare the simulation results with other scenarios, the initial simulation results of the model are set as benchmarks, which are shown in Fig. 7.

In the refrigerator industry situation, we simulate the behavioral evolution of supply chain stakeholders based on a random subset of initial strategies from the [0, 1] × [0, 1] space. For example, (0.2, 0.75) means the probability that a manufacturer adopts CERS is 0.2 and the probability that a retailer adopts LCPS is 0.75. The evolutionary simulation is shown in Fig. 8. We can see that the supply chain system eventually evolves to an equilibrium point (1, 1) and then stabilizes. Therefore, no matter how the initial strategies of the retailers and the manufacturers change, the system will eventually stabilize at the (1, 1) equilibrium point. Thus, the simulation results of the SD model are consistent with the theoretical proof of the evolutionary game model. To investigate the impacts of the environmental parameters of the system on the evolution of the behavior of the supply chain stakeholders, we will conduct a sensitivity analysis on these parameters.

3.3.2. Parameters related to customers' behavior

As consumer behavior is a key driver of market demand, we choose the price elasticity of demand, the emissions reduction effectiveness parameter, and the promotional effectiveness parameter to investigate the impacts of consumer behavior on the evolution of the manufacturers' and retailers' behavior over time.

(1) Price elasticity of demand

It is well known that different customers have different sensitivities to product prices. The price elasticity of demand is usually used to quantify the price sensitivity of consumers. In order to investigate the influence of the price elasticity of demand on the decision-making of the enterprises and observe the evolution of the game between the two stakeholders over time, we set values of price elasticity of demand as 0.4, 0.8, 1.6, and 2.4.

As shown in Fig. 9, increasing the price elasticity of demand does not linearly increase the probability that a retailer will promote low-carbon products. For example, when the price elasticity of demand is doubled from 0.4 to 0.8, the time required for the probability of LCPS adoption to reach 0.875 increases by 3.2 times (from 10.7 months to 34.3 months). Therefore, if consumers are price-insensitive, the fluctuation of product prices will have less impact on demand, and retailers will quickly promote low-carbon products. Otherwise, when the price

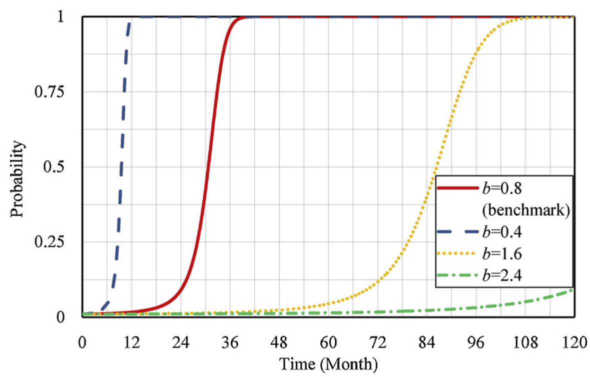

Fig. 9. The probability of that the retailers adopt the LCPS responses to the different values of price elasticity of demand.

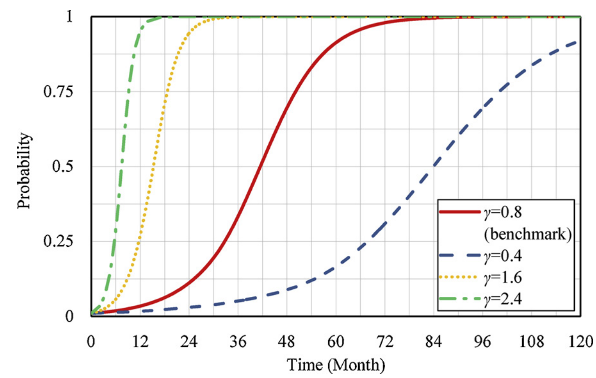

Fig. 11. The probability of that the manufacturers adopt the CERS (y) responses to the different values of emissions reduction effectiveness parameter (γ).

elasticity of demand is large, retailers will take longer to implement LCPS. Similarly, if the price elasticity of demand is low, the manufacturers do not need to care about the high cost of emissions reduction technologies. Therefore, the greater the price elasticity of demand, the more likely it is that a manufacturer will reduce carbon emissions.

From Fig. 9 and Fig. 10, it is seen that, compared to the probability of CERS adoption, the probability of LCPS adoption is more sensitive to variation in the price elasticity of demand. This is mainly because the retailers locate downstream of the supply chain and interact with consumers directly. When the price elasticity of demand changes, retailers are able to understand the movements of the market more quickly and can adapt their strategies first.

(2) Emissions reduction effectiveness parameter

In order to observe the impact of consumer preferences for low carbon products on the adoption of CERS by manufacturers, we set the emissions reduction effectiveness parameter as 0.4, 0.8, 1.6, and 2.4.

As can be seen from Fig. 11, the consumers' preferences for low-carbon products will affect the enthusiasm of manufacturers to reduce carbon emissions. The higher the emissions reduction effectiveness parameter is, the faster manufacturers choose CERS. When customers are highly sensitive to the embodied carbon emissions of a product, the amount of investment from the manufacturer in carbon emissions reduction technology will increase the demand accordingly. Therefore, many manufacturers may choose to invest in carbon emissions reduction to increase revenue.

(3) Promotional effectiveness parameter

With increasing numbers of low-carbon products in the market, more large supermarkets, shopping malls, and other powerful retailers hope to use a variety of promotional methods to increase demand (Familmaleki et al., 2015; Krishnamurthi and Raj, 1985). In this simulation, in order to observe the effects of consumer sensitivity to a retailer's promotional effort for low-carbon products, the promotional

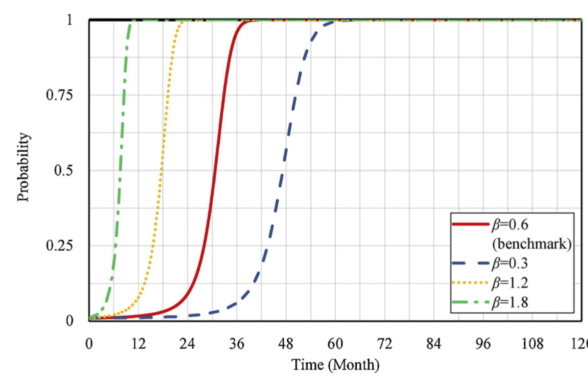

Fig. 12. The probability of that the retailers adopt the LCPS (x) responses to the different values of emissions reduction effectiveness parameter (β).

effectiveness parameter is set as 0.3, 0.6, 1.2, and 1.8.

Fig. 12 shows that the less receptive the customers are to product promotion, the more time it will take for the probability of retailer adoption of the LCPS to reach a certain value. Under these experimental circumstances, all retailers will eventually invest in promoting low-carbon products. If customers are sensitive to the level of promotional effort, there will be an increase in the number of customers buying the low-carbon products once the retailers choose LCPS. In contrast, when the parameter is small, the retailers are less likely to promote low-carbon products. Therefore, when the promotional effectiveness parameter is large, it is beneficial for the retailers to promote their low-carbon products. Fig. 13

3.3.3. Emissions cap

According to GFC and CBEEX (2016), the emissions cap is calculated

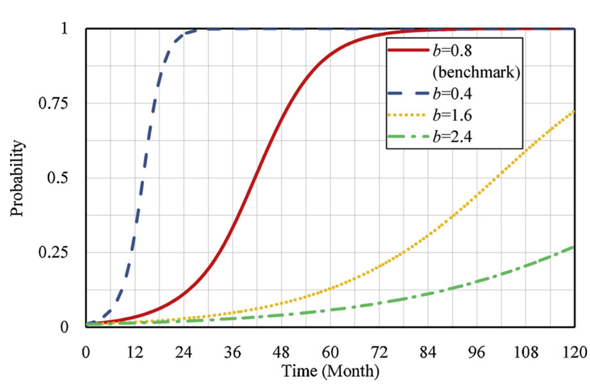

Fig. 10. The probability of that the manufacturers adopt the CERS (y) responses to the different values of price elasticity of demand (b).

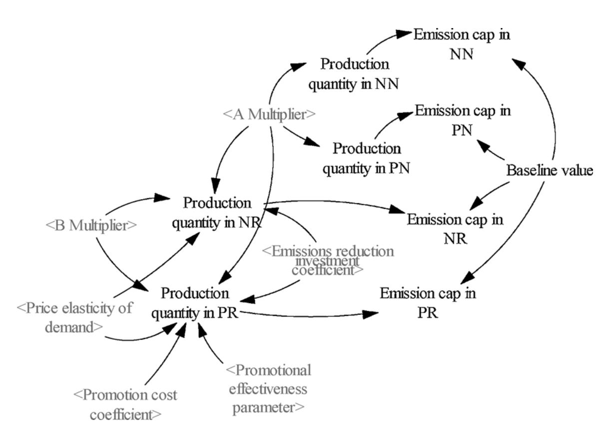

Fig. 13. Emissions cap in each strategy combination.

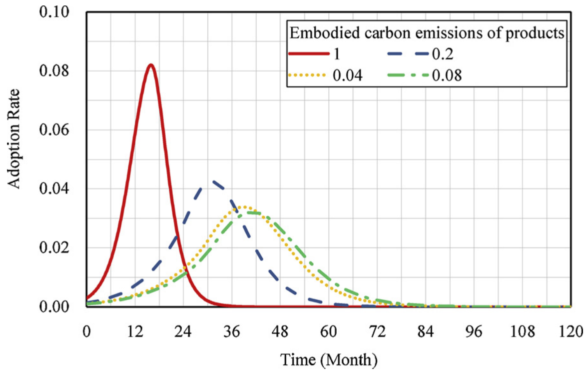

Fig. 14. Manufacturers adopt CERS at different rates based on the embodied carbon emissions of the products.

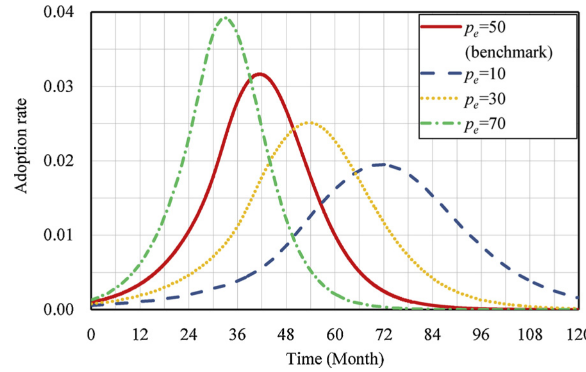

Fig. 15. The adoption rate of the manufacturers that choose CERS responses to the different values of market price of carbon credits.

by using the baseline method, where the baseline value for the average carbon emissions of a unit of product is multiplied by the production quantity. When the emissions reduction technologies are improved, the baseline value will decrease, which indirectly leads to a decrease of the emissions cap. Thus, the relationship between the emissions cap (set by the government) and the quantity of products produced has changed. Based on these circumstances, the stock-flow diagram of the module for the emissions cap in each strategy is established to observe and analyze the evolution of the enterprises' behavior when the baseline value decreases. This module is connected to the module for the payoff of retailers and manufacturers (see Fig. 14).

We assume that the baseline value of embodied carbon is normalized from 0 to 1. To facilitate the sensitivity analysis, average carbon emissions during the production per unit of product in an industry is set at 1, 0.2, 0.04, and 0.008 to examine a range of possible industry behaviors. The simulation results are shown in Fig. 14.

From Fig. 14, we see that when the average carbon emissions of a given product are higher, the manufacturers are incentivized to adopt carbon emissions reduction strategies more quickly. At high product emissions values, all manufacturers adopt carbon emissions reduction strategies within 36 months, but at low carbon emissions values, manufacturers respond in twice the time.

This response indicates that there is a linear relationship between the emissions cap and the baseline value, if the product quantity remains unchanged, the level of carbon emissions reduction of an industry can be improved by reducing the free carbon credits that are allocated by the government. Under extreme situations, if the baseline is very high, the government will reduce the emissions cap to control carbon emissions. In this circumstance, all manufacturers will choose CERS. In contrast, when the baseline value is low, many manufacturers find it more difficult to reduce carbon emissions because the effects are small. All of the manufacturers will adopt NRS even if the market price of carbon credits is very high.

3.3.4. Market price of carbon credits

According to CHEAA (2016), the unit market price of carbon credits in Beijing's Carbon Trading Center is 50 RMB/Ton. In order to understand the behavior of manufacturers in markets with different carbon credit prices, we set the market price of carbon credits to 10, 30, 50, and 70. As shown in Fig. 15, we can see that the higher the market price of carbon credits is, the faster the manufacturers choose to shift to lower emissions technologies, as emphasized by sharper, earlier peaks in high credit cost situations. Due to the high investment cost for carbon emissions reduction technologies, it will take a long time for the manufacturers to realize the benefits from carbon emissions reduction technologies. If the price of carbon credits is low, the manufacturers will choose to buy carbon credits to comply with carbon policies. If the trading cost is high, the manufacturers will choose to invest in emissions reduction technologies and sell surplus credits at a higher carbon credit price to realize higher profits. Based on a shortage of free carbon credits allocated by the government and an increased market price of carbon credits, the manufacturers will implement carbon reduction technologies quickly. The simulation results indicate that when the government allocates few free carbon credits, the carbon trading market plays a major role in regulating the supply chain system; if more free carbon credits are allocated, the government will play a larger regulatory role.

However, as motioned above, the market price of carbon credits is not constant. To simulate this, we determine the market price of carbon credits using a normal distribution with a mean value of 50 and a covariance of 10, that is $p_e \sim N(50, 10)$.

Fig. 16 shows that when carbon price fluctuates around 50, the adoption rate of the number of manufacturers choosing to reduce carbon emissions will fluctuate in response to the price difference and the rate will approach zero. During the initial stage of carbon trading, manufacturers hesitate to invest in reducing carbon emissions to meet the carbon limits provided by the government because the carbon price is uncertain. Companies are likely to wait and understand how the market evolves rather than make a large initial investment. With the development of a carbon trading mechanism, manufacturers will sell surplus carbon credits to earn higher profits after investing in emissions reduction technologies.

Through the use of sensitivity analysis, the influence of several variables on the behavior of the manufacturers and retailers is examined. The evolution of the stakeholders' behavior is affected by the emissions cap, the market price of carbon credits, and consumer preferences for low-carbon products. There are several implications:

(1) If consumers are sensitive to the market price of the product and their purchasing preferences can be influenced by promotional activities (the promotional effectiveness parameter), the retailers will earn higher profits when they promote low-carbon products, as they have influenced the demand for those products. When customers are

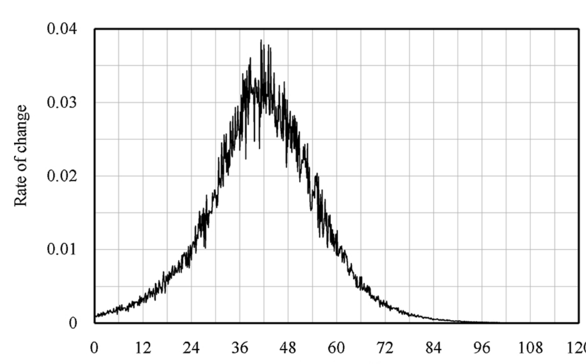

Fig. 16. The adoption rate of CERS in response to p_e.

sensitive to the embodied carbon of the product, it is beneficial for manufacturers to invest in emissions reduction technologies to earn higher profits.

(2) If there is a shortage of carbon credits, the manufacturers will only benefit by selling the carbon credits that are offset by implementing carbon emissions reduction technologies. However, as the investment costs for these technologies are high, it takes a long time for the manufacturers to realize the benefits from the reduction in carbon emissions. We also find that there are still many manufacturers who choose to reduce carbon emissions when the market price of carbon credits is high, even when there are sufficient carbon credits available on the market. Therefore, manufacturers should adjust their strategies based on the emissions cap and the market price of carbon credits.

4. Conclusions and limitations

In recent years, governments, enterprises, and consumers have given more attention to environmental issues, such as carbon emissions from the manufacturing of products. Specifically, among other strategies, the cap-and-trade system has incentivized the reduction of carbon emissions. Consumers are also willing to pay more for low-carbon products. In this study, we considered the cap-and-trade system and consumer preferences for low-carbon products to develop an evolutionary game model which demonstrates the simulated behaviors of manufacturers and retailers in a retailer-led supply chain. We find that the supply chain system will eventually reach an evolutionary steady state, which means that eventually manufacturers will choose to reduce emissions and retailers will promote low-carbon products, given appropriate market incentives. In particular, this will increase the benefits for both stakeholders and for enterprises of the supply chain.

By applying a system dynamics model to the sensitivity analysis, we find that the cap-and-trade system and the demand-related elasticity coefficients can influence the evolution of the behavior of manufacturers and retailers. When customers are sensitive to promotional effort and carbon emissions reduction technologies, more manufacturers will invest in carbon emissions reduction technologies and retailers may quickly adopt promotional strategies for low-carbon products to increase revenue. Furthermore, simulation results show that manufacturers are willing to invest in the reduction of carbon emissions when the market price of carbon credits is high. However, with a decrease of the emissions cap, it will take time for all manufacturers to adopt a strategy which reduces emissions. These findings can be useful for both the retailers and the manufacturers of low-carbon products.

There are a number of interesting extensions to this work. First, we assume that (1) all low-carbon products have the same carbon emissions and have the same effects on the market, (2) the customers are homogeneous with regard to their environmental preference, (3) carbon emissions reduction incurs the same investment cost for all manufacturers and (4) all retailers pay for the same amount to effect the promotion cost coefficient. However, since the stakeholders and consumers are heterogeneous, more nuanced models can be developed to understand market behavior. Second, in a real market, carbon credits can be saved and can be transferred for use in the next production period. Another set of models could be developed to identify how a manufacturer should choose between selling carbon credits, saving carbon credits, or investing in additional reduction technology. These methods can help governments and industries understand how market conditions can change and make better long-term decisions.

Acknowledgments

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Appendix A

For ease of reference, Equation (x) in the paper is referred to as (E.x) in this appendix.

Theorem 1. We use the Stackelberg game approach to present the optimal solutions. The calculation process for the optimal solutions based on strategy NN is shown below. We first determine the best response function of the manufacturers from the first derivative of π_m^{NN}. Then π_m^{NN} and w are the functions of $\triangle w$. Eq. (11) and can be rewritten as

$$\pi_m^{NN} = (w - c_m)[a - b(w + \Delta w)] - \{e_m[a - b(w + \Delta w)] - C_g\}p_e \tag{A.1}$$

For (A.1), the second derivative for w is $\frac{\partial^2 \pi_m^{NN}}{\partial w^2} = -2b < 0$ (1) is a concave function of$w$. The first-derivative for π_m^{NN} then yields optimal values of w, that is, let $\frac{\partial \pi_m^{NN}}{\partial w} = a - b(w + \Delta w) - b(w - c_m - e_m p_e) = 0$ We can get

$$w = \frac{a - b(\Delta w - c_m - e_m p_e)}{2b} \tag{A.2}$$

Then the retailer's profit function can be rewritten as

$$\pi_r^{NN} = (\Delta w - c_r)\frac{a - b(c_m + \Delta w + e_m p_e)}{2} \tag{A.3}$$

Then the best response function of the retailers from the first derivative of π_r^{NN} is shown as follows:

$$\frac{\partial \pi_r^{NN}}{\partial \Delta w} = \frac{a - b(c_m + e_m p_e - c_r) - 2b\Delta w}{2} \tag{A.4}$$

For (A.3), the second derivative for $\triangle w$ is $\frac{\partial^2 \pi_r^{NN}}{\partial \Delta w^2} = -b < 0$. Then (A.3) is a concave function of $\triangle w$.

We can then determine that the optimal retail margin is

$$(\Delta w^{NN})^* = \frac{a - b(c_m + e_m p_e + c_r)}{2b} + c_r \tag{A.5}$$

Then we can determine the optimal wholesale price and production, respectively, as

$$(w^{NN})^* = \frac{a - b(c_m + e_m p_e + c_r)}{4b} + c_m + e_m p_e \tag{A.6}$$

$$(q^{NN})^* = \frac{a - b(c_m + e_m p_e + c_r)}{4} \tag{A.7}$$

After the optimal retail margin, the wholesale price and production have been inserted in equations (A.1) and (A.2), we can determine the optimal profits of retailers and manufacturers respectively:

$$(\pi_r^{NN})^* = \frac{[a - b(c_m + e_m p_e + c_r)]^2}{8b},\ (\pi_m^{NN})^* = \frac{[a - b(c_m + e_m p_e + c_r)]^2}{16b} + C_g p_e$$

Since analogous proofs leads to optimal solutions for the different combination strategies we omit the details of the derivations, and the results are shown in Appendix B.

Appendix B

Optimal solutions	Strategy NN and Strategy PN	Strategy NR	Strategy PR
π_r^*	$\frac{[a-b(c_m+e_m p_e+c_r)]^2}{8b}$	$\frac{h_m[a-b(c_s+e_m p_e+c_r)]^2}{2[4bh_m-2(\gamma+be_m p_e)^2]}$	$\frac{h_r h_m[a-b(c_m+e_m p_e+c_r)]^2}{4h_r[2bh_m-(\gamma+be_m p_e)^2]-2\beta^2 h_m}$
π_m^*	$\frac{[a-b(c_m+e_m p_e+c_r)]^2}{16b} + C_g p_e$	$\frac{h_m[a-b(c_m+e_m p_e+c_r)]^2}{4[4bh_m-2(\gamma+be_m p_e)^2]} + C_g p_e$	$\frac{h_r^2 h_m[a-b(c_m+e_m p_e+c_r)]^2[2bh_m-(\gamma+be_m p_e)^2]}{2\{2h_r[2bh_m-(\gamma+be_m p_e)^2]-\beta^2 h_m\}^2} + C_g p_e$
w^*	$\frac{a-b(c_m+e_m p_e+c_r)}{4b} + c_m + e_m p_e$	$\frac{[h_m-e_m p_e(\gamma+be_m p_e)][a-b(c_m+e_m p_e+c_r)]}{4bh_m-2(\gamma+be_m p_e)^2} + c_m + e_m p_e$	$\frac{h_r[h_m-e_m p_e(\gamma+be_m p_e)][a-b(c_m+e_m p_e+c_r)]}{2h_r[2bh_m-(\gamma+be_m p_e)^2]-\beta^2 h_m} + c_m + e_m p_e$
Δw^*	$\frac{a-b(c_m+e_m p_e+c_r)}{2b} + c_r$	$\frac{a-b(c_m+e_m p_e+c_r)}{2b} + c_r$	$\frac{h_r[a-b(c_m+e_m p_e+c_r)][2bh_m-(\gamma+be_m p_e)^2]}{b\{2h_r[2bh_m-(\gamma+be_m p_e)^2]-\beta^2 h_m\}} + c_r$
τ_r^*	——	——	$\frac{\beta h_m[a-b(c_m+e_m p_e+c_r)]}{2h_r[2bh_m-(\gamma+be_m p_e)^2]-\beta^2 h_m}$
τ_m^*	——	$\frac{(\gamma+be_m p_e)[a-b(c_m+e_m p_e+c_r)]}{4bh_m-2(\gamma+be_m p_e)^2}$	$\frac{h_r(\gamma+be_m p_e)[a-b(c_m+e_m p_e+c_r)]}{2h_r[2bh_m-(\gamma+be_m p_e)^2]-\beta^2 h_m}$
q^*	$\frac{a-b(c_m+e_m p_e+c_r)}{4}$	$\frac{bh_m[a-b(c_m+e_m p_e+c_r)]}{4bh_m-2(\gamma+be_m p_e)^2}$	$\frac{bh_r h_m[a-b(c_m+e_m p_e+c_r)]}{2h_r[2bh_m-(\gamma+be_m p_e)^2]-\beta^2 h_m}$

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