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Big data empowering low-carbon smart tourism study on low-carbon tourism O2O supply chain considering consumer behaviors and corporate altruistic preferences

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ABSTRACT

This paper investigates a low-carbon tourism online-to-offline(O2O) supply chain consisting of a tourist spot(TS) that is responsible for providing low-carbon service and an online tourism agency(OTA) that is in charge of providing big-data marketing effort. Under the context of low-carbon smart tourism empowered by big data, the impacts of big-data empowerment, consumer reference effect, channel preference, and enterprise altruistic behavior on the optimal decision making and performance of enterprises are discussed. Then, the optimal decision and performance of the firms in three decision modes (centralized, decentralized, and altruistic) are obtained with the help of differential game theory and Bellman's continuous dynamic planning theory. Our findings as follows are acquired through comparative analysis and sensitivity analysis of essential parameters. First, big-data marketing technology can personalize more low-carbon travel plans for tourists and enhance tourists' awareness of environmental protection. Besides, the low-carbon smart tourism supply chain empowered by big data could also have greater market potential. Thus, this marketing technology can subvert the traditional tourism business model and provide a more low-carbon, sustainable, and smart development path for the future of the tourism supply chain. Moreover, TS can continuously improve the level of low-carbon service because of the inspiration of consumers' reference low-carbon service effect, contributing to forming a virtuous cycle and stimulating the low-carbon, efficient, and sustainable development of the tourism supply chain. Furthermore, the cooperation among tourism supply chain members can be deepened by the altruistic preference between TS and OTA, resulting in not only enhancing the low-carbon goodwill and environmental benefits but also bringing a better experience for tourists. The findings indicate that the altruistic preference can simultaneously promote the sustainable development of low-carbon tourism supply chain and achieve supply chain coordination. At the end of the article, we also give the ideal operating status of the low-carbon smart O2O tourism supply chain empowered by big data.

1. Introduction

Tourism is one of the world's largest and fastest-growing economic industries, but the large-scale population movements also make it an essential source of carbon emissions worldwide (Lee & Jan, 2019). In 2009, the United Nations World Tourism Organization officially released the report "Toward a low carbon travel and tourism sector", which proposed a reduction target for the tourism industry in the next 15–20 years to control the total annual growth of carbon emissions from the tourism industry within 2.7%, and promote the tourism industry to move towards a low carbon development path (World Economic Forum, 2009). Besides, more and more environmental enthusiasts begin to pay attention to and reduce their carbon emissions during tourism with the continuous enhancement of people's environmental awareness (Hsiao, 2016; Zhao et al., 2017; Vinzenz et al., 2019). Thus, the promotion of low-carbon tourism and the promotion of green and sustainable development of the tourism industry have become common goals of all sectors of society.

Since tourism is an essential part of the tertiary industry of the national economy, promoting the development of low-carbon tourism has a significant industrial driving force and social influence. From one perspective, the tourism supply chain involves various aspects such as

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clothing, food, housing, travel, shopping, and entertainment. The infiltration of low-carbon concepts in each link will contribute to the development of related industries from points and areas. That means each node in the tourism industry is not an isolated enterprise, and the complex interaction between them makes it impossible for us to independently view and analyze their role in the entire tourism process. Therefore, it is of high practical value to discuss the development of low-carbon tourism with the idea of supply chain management. Only in this way can we help each enterprise take a holistic view, better coordinate with upstream and downstream enterprises, and make positive responses conducive to low-carbon development. From another point of view, any enterprise in the tourism supply chain has the characteristics of facing consumers directly. Implementing a low-carbon tourism mindset into their operations has obvious guidance and leading role and can strengthen the continuous deepening of low-carbon concepts at the social level, leading to promoting the formation of low-carbon education and environmental awareness for people. Existing research on the tourism supply chain has focused on the two important players in the tourism supply chain, that is, competition and cooperation between TS and travel agencies. The low-carbon development goals have not been incorporated into the qualitative research of the tourism supply chain (Guo et al., 2013; Yang et al., 2016).

Besides, various online tourism service platforms have emerged with the continuous development of Internet technology. Data insight is continuously conducted to achieve accurate identification of tourists' portraits and accurate and personalized recommendation of tourism routes that meet tourists' travel habits by collecting and analyzing consumer terminal data using advanced technologies such as cloud computing and artificial intelligence, spending habits, and payment preferences; the intelligent tourism supply chain enabled by big data is taking shape (Nilashi et al., 2017). For example, the Huaxi Tourism Platform in China establishes a digital tourism economy model and forms a data sharing and exchange mechanism. Using the platform, the organic unification of information flow, business flow, and capital flow in the tourism industry chain can be completed, information sharing and online transactions can be realized, and the tourism consumption chain can be pictured (http://www.gthxdt.com/). With the continuous development of smart tourism, more and more tourist attractions tend to share tourist travel data to the online tourism agenda. The concept of low-carbon tourism is conveyed to tourists with the help of its big-data marketing technology. For example, some online tourism service platforms such as Fliggy.com, Ctrip.com, and Qunar.com that have been emerging in China in recent year intelligently recommend low-carbon travel solutions that match the preferences of tourists by integrating tourist travel tools, accommodation hotels, scenic tickets, surrounding restaurants, and other aspects of tourism recommendations and sales activities, as well as the image of tourists. Moreover, scenic spots themselves have begun to focus on the implementation of low-carbon tourism concepts by providing low-carbon services to tourists using environmentally friendly materials in the architectural design process, switching to clean and sustainable energy in the operation process, and optimizing the treatment of tourist travel waste (Vinzenz et al., 2019). The cooperation between scenic spots and online tourism in the context of big data could not only realize the implementation of the concept of low-carbon tourism in the tourism supply chain operation but also personalize low-carbon tourism programs for tourists to meet their travel preferences and habits, strengthen the promotion of low-carbon tourism, help tourists change the misconception that low-carbon tourism is low-quality tourism and promote the healthy development of low-carbon tourism.

Unlike the standard economics hypothesis that firms only seek to maximize their own profits, a large number of behavioral experiments prove the existence of altruistic preferences in the decision-making process, i.e., firms not only pay attention to their own profits, but also pay attention to the profits of counterparties to a certain extent, and will incorporate them into their decision-making goals and therefore adjust their decision making. Especially in tourism suppl chian, the traditional commission system and information sharing as a way of cooperation between TS and OTA can easily lead to conflicts of interest between them. Actually, more and more studies have revealed that the spontaneous altruistic behavior of the supply chain entities as a positive social preference can not only enable deeper cooperation among the various entities in the supply chain but also contribute to the achievement of goals when environmental protection and the promotion of sustainable development of the supply chain are targeted (Wang et al., 2020). Besides, consumers are very likely to have a reference effect on the consumption process of experiential products and services, that is, to produce quality and service level expectations based on brand goodwill (that is reference quality/service level), and to form a judgment on the brand goodwill and further affect consumer demand based on the difference between the experience level of the experience process and the reference level (Zhang et al., 2014; Liu et al., 2016; He et al., 2017). Tourism is a typical experience-based service industry, so it is more realistic to include consideration of tourists' reference service effects. The results will be more instructive for low-carbon tourism supply chain enterprises.

In summary, a low-carbon tourism supply chain consisting of a TS that provides low-carbon service and an OTA with big-data marketing technology is considered in this paper under the inspiration of the technological environment and practical business problems. TS has two ticket sales channel: selling tickets through independent offline and online travel platforms with commissions and selling tickets with its big data marketing technology. Specifically, the research questions in this paper are as follows.

- What are the optimal decisions and performance of enterprises in the low-carbon tourism supply chain under the three decision-making modes?
- How does consumers' preference for online and offline channels as an important indicator reflecting the degree of empowerment of big data affect corporate decision-making and performance?
- Using the level of performance under centralized and decentralized decision making as a reference point, what is the impact of the altruistic decision-making model of TS and OTA on the low-carbon tourism supply chain, and can the low-carbon performance be improved by deepening cooperation between the two?

In this paper, a differential game model under three decision-making modes (centralized decision-making, decentralized decision-making, and altruistic decision-making) is constructed to answer the above questions and consider the inherent dynamics of tourists' reference to low-carbon service effects. The solution obtains the optimal low-carbon service level of the scenic spot under the three decision-making modes, the big data marketing efforts strategy of the online travel service platform, the low-carbon goodwill of the scenic spot, and the profits of each subject and even the entire low-carbon supply chain. Besides, the optimal decision-making and performance levels of the three decision-making modes are further compared through comparative analysis to explore the impact of altruistic behavior. Moreover, the impacts of changes in environmental factors, consumer behavior, and corporate altruistic preferences on corporate decision-making and low-carbon supply chain operational performance are explored using sensitivity analysis and numerical examples; meanwhile, the effectiveness of altruistic cooperation for the sustainable development of the low-carbon tourism supply chain is verified.

The remaining of this paper is organized as follows. In Section 2, the relevant literature is reviewed. In Section 3, the problem is described and relevant assumptions are put forward. In Section 4, the differential game model under the three decision-making modes is established, and solution and sensitivity analysis are performed. Then, comparison and analysis of the model are conducted in Section 5. Next, numerical examples are used in Section 6 to verify the analytical results and perform further sensitivity analysis, giving the corresponding management enlightenment of the enterprise. Finally, the conclusions are drawn in Section 7.

2. Literature review

2.1. Low-carbon operations

With the rapid increase of consumers' environmental awareness, low-carbon consumption has become a consensus, consumers have begun to turn their attention to the low-carbon operation of enterprises, and more and more companies have begun to incorporate low-carbon concepts into their business processes (Tang et al., 2015; Chen et al., 2016; Shu et al., 2017; Hariga et al., 2017; Huang et al., 2020). Zhou et al. (2016) compared pure cooperative advertising contracts and cooperative advertising cost-sharing contracts with carbon-reduction effort, revealing that cost-sharing contract with carbon-reduction effort can coordinate the low-carbon supply chain. Luo et al. (2016) explored that cooperative behavior among enterprises can simultaneously reduce carbon emissions and increase corporate profits. Considering consumers 'environmental preferences and carbon tax policies, Ji, Zhang, and Yang (2017) concluded that companies can open online channel to obtain more profits when consumers' online channel preferences are high. Besides, Yang and Chen (2018) investigated the impact of the revenue sharing and cost-sharing mechanisms provided by retailers on the carbon emission reduction efforts of manufacturers and the profitability of the two companies when consumer environmental awareness and carbon taxes rise. Moreover, Taleizadeh et al. (2018) summarized that the market demand for low-carbon products depends on product prices and carbon reduction rates. Furthermore, a competition coordination model in which manufacturers implement low-carbon efforts and two competing retailers implement green efforts was proposed by Hosseini-Motlagh et al. (2019).

2.2. Tourism supply chain

The second research area closely related to the research in this paper is the tourism supply chain. A large number of empirical and case studies have focused on exploring the methods of tourism supply chain performance evaluation (Zhang et al., 2009; Kozicka et al., 2019; Huang, 2018; Palang & Tippayawong, 2019). In terms of theoretical research, Jena and Meena (2019) analyzed tourists' choice of travel packages from the perspective of price and service-sensitive demand and established three tourism supply chain models. Shi and Liu (2018) constructed a cruise tourism supply chain system consisting of one supplier and two retailers and explored the optimal ordering and pricing strategies of the two retailers and the profit distribution between the alliance. Besides, Liu et al. (2019) investigated the issues of corporate pricing, environmental governance, efficiency decision-making, and channel coordination in the tourism supply chain with corporate social responsibility. Moreover, Zhang and Song (2018) proposed a framework for collaborative tourism supply chain demand forecasting, promoted information sharing among enterprises, increased cooperation between industries, and improved demand forecasting performance. Jena and Jog (2017) explored the impact of advertising on the demand, pricing, and profit of channel members in the tourism supply chain, and designed two types of coordination contracts, cooperative advertising, and two-part tariff. Furthermore, Guo et al. (2014) analyzed the impact of the ratio of optional tourism to pre-designed tourism on corporate decision-making under three different consumer attitudes towards optional tourism.

In recent years, some researchers have started to introduce the idea of low-carbon operations into supply chain management, demonstrating the significance of reducing carbon emissions from manufacturing to supply chain sustainability (Cao et al., 2017; Yang et al., 2018; Zhang et al., 2019). By analogy with the manufacturing industry starting from the production process, tourism as a third industry and an important part of the service industry integrates low-carbon service concept into the management of the tourism supply chain, allowing tourism to go further on the path of low-carbon development. There are few theoretical studies on the low-carbon operation of tourism supply chains; besides, studies on low-carbon tourism mostly focus on individual enterprises or the evaluation of the low-carbon nature of tourism (Hsiao, 2016; Becken, 2017; Wang et al., 2019; Lee & Jan, 2019). The issue of low-carbon services in tourism and the development of marketing strategies has not been investigated with a supply chain management mindset, ignoring the impact of the consumer reference effect of tourism as an experiential activity on corporate decision making in the tourism supply chain. With the expanding access to information and the increasing diversity of products in the consumer market, the consideration of consumer behavior factors cannot be neglected in the formulation of any firm's operational strategy (East et al., 2016; Adele, 2016); the reference effect as a prevalent behavior of consumers when shopping has a significant impact on firm decision making (Zhang et al., 2014; Liu et al., 2016; He et al., 2017). Therefore, fully considering the consumption behavior of tourists will enable companies in the tourism supply chain to make more informed and market-compliant decisions. Besides, with the continuous development of big data analytics technology, the role of big-data marketing in accurately targeting consumers and personally recommending products for consumers has been widely accepted by enterprises as an important marketing tool (Xiang & Xu, 2019; Ma & Hu, 2020). However, this is still not found in the theoretical research of the tourism supply chain, not to mention the research of OTA to promote sustainable tourism development with its intelligent recommendation of low carbon tourism solutions.

Therefore, low-carbon service is incorporated into the management of the tourism supply chain in this paper. Under the background of big data empowerment, the coexistence of traditional sales channel and online channel relying on the big-data marketing technology of OTA is explored. The impact of consumer channel preference and the reference low-carbon service effect of the tourism process on the optimal decision-making of enterprises are considered and analyzed. The research scope of the tourism supply chain is further extended, its low-carbon, sustainable development is explored.

2.3. Altruistic preference

A large number of behavior experiment results have broken the assumption of "rational man" in traditional research and confirmed the various emotional preferences of people in decision-making (Sober & Wilson, 1998). Andreoni and Miller (2002) illustrated the existence of altruistic behavior through the ultimatum game and formally proposed his theory about altruism. Altruistic behavior, which indicates that firms not only pay attention to their own profits, but also pay attention to the profits of counterparties to a certain extent and will incorporate them into their decision-making goals to adjust their decision making, is common in supply chain management practice. Abundant studies indicate that altruistic behavior is a positive social preference that always contributes to enhancing the overall performance of the supply chain. Bassi, Pagnozzi, and Piccolo(2014) revealed that the degree of altruism has a positive correlation with a profit of the system in the principal-agent model. Ge et al. (2012) discovered that the manufacturer's altruistic behavior can raise the performance of the supply chain while the retailer's altruistic behavior may decrease the total performance of the supply chain in an evolutionary game. Ge and Hu (2012) explored that total efficiency with altruism is between that of decentralized and centralized decisions when exploring the effect of altruism in the vendor problem. Shi et al. (2013) found that manufacturer's altruism has a significant impact on pricing strategies in the dual-channel supply chain system. Besides, the higher the degree of the altruism one player, the more the profits acquired by the other player.

Recently, some researchers have started to incorporate altruistic behaviors into research on promoting sustainable aspects of supply chains, indicating that altruistic behaviors of companies have a positive contribution to low carbon efforts and can drive the sustainable development of supply chains (Huang, 2018; Wang et al., 2020). On this basis, altruistic behavior is further incorporated into the study of the low-carbon tourism supply chain in this paper, and the role of altruistic behavior preferences between scenic spots and online tourism service platforms for the sustainable development of low-carbon tourism supply chain is explored.

Furthermore, differential game theory is an essential method in terms of research methodology for dealing with the decision making of two and more players interacting over a continuous period (Jørgensen & Zaccour, 2012). Considering the research on consumer reference effect and the impact of enterprise decision on future profitability and sustainable development of scenic spots, the research on the interaction decision and long-term altruistic partnership between scenic spots and online tourism service platform through differential gaming theory is more in line with the actual operation process. Besides, the results obtained have practical guidance and reference value. Therefore, tourism supply chains and low-carbon operations and altruistic behavior are explored in this paper with the help of differential game theory from a dynamic perspective, different from the static strategy studies mentioned above.

3. Model description and assumption

In the context of big data empowering low-carbon smart tourism, consumers' reference low-carbon service effect is incorporated into the impacts on low-carbon goodwill and omnichannel tourism demand in this paper. Besides, a low-carbon tourism O2O supply chain composed of a tourist scene (TS) and an online travel agent (OTA) is established. The business model is illustrated in Fig. 1.

In the low-carbon tourism O2O supply chain, TS has two ticket sales channels: one is an online sales channel that he hires OTA in the form of revenue sharing and uses its big-data marketing effort to sell tickets online, the other is TS selling tickets directly to tourists offline. This O2O operation mode under the background of big data empowerment reflects a common marketing trend in the new retail era, that is, TS uses OTA's online big-data marketing to accurately locate consumer groups, complete the promotion of consumption transformation, and then attract tourists to complete the whole process of travel experience offline scenic spots. The emergence and prevalence of this online purchase and offline experience operation mode benefits from the background of the rapid development of mobile internet, upgrading of industry structure and the improvement of consumer demand for experience(Chang et al., 2018; Flavián et al., 2020). In the online sales channel, OTA conducts data mining on various types of information such as online search records, consumption records, travel methods, and dietary preferences of tourists, screens out useful information, and portrays portraits of tourists' behaviors to determine tourists' travel preferences and intelligently recommend local low-carbon tourist routes, foods, accommodation, shopping, and other information to tourists. It is worth noting that OTA's big-data marketing effort is designed to change people's misunderstandings about reducing the quality of experience of low-carbon tourism. Besides, the suitable environmentally friendly travel methods can be intelligently recommended to consumers based on consumer big-data mining, providing personalized and accurately customized clothing, food, housing, travel, travel, shopping, entertainment, and other travel according to consumer travel behavior preferences to achieve low-carbon goals while ensuring travel quality. For clarity, the basic parameters and variables used in this paper are summarized in Table 1.

Low carbon goodwill is co-led by the visitor's reference low carbon service effect and OTA's big-data marketing service. Based on Nerlove and Arrow's (1962) benchmark goodwill model and an extension of De

Table 1
Notations and definitions.

Notations	Definitions
γ_T	Impact factor of reference low-carbon service effect on low-carbon goodwill, $\gamma_T > 0$
γ_O	Impact factor of OTA's big-data marketing effort on low-carbon goodwill, $\gamma_O > 0$
σ	Decay factor of low-carbon goodwill, $\sigma > 0$
ξ	Correlation coefficient between consumer reference low-carbon service level and low-carbon goodwill, $\xi > 0$
χ	Tourists' preference for online sales channel,$\chi \in [0, 1]$
D_0	Basic market demand, $D_0 > 0$
λ_O	Impact factor of big-data marketing on online channel demand, $\lambda_O > 0$
λ_T	Coefficient of tourist reference low-carbon service effect on online channel demand, $\lambda_T > 0$
θ	Coefficient of low-carbon goodwill on demand, $\theta > 0$
μ_T	Coefficient of tourist reference low-carbon service effect on offline channel demand, $\mu_T > 0$
β_O	Tourists' sensitivity to online ticket price, $\beta_O > 0$
β_T	Tourists' sensitivity to offline ticket price, $\beta_T > 0$
η	Percentage of the commission received by OTA from TS, $\eta \in [0, 1]$
p_O	Unit ticket price online, $p_O > 0$
p_T	Unit ticket price offline, $p_T > 0$
c_O	OTA's marginal operating cost, $c_O > 0$
c_T	TS's marginal operating cost, $c_T > 0$
Decision variables:	
$S(t)$	The actual low-carbon service level of TS at time t, the control variable of TS
$B(t)$	Big-data marketing effort of OTA at time t, the control variable of OTA
State variables:	
$G(t)$	Low-carbon goodwill at time t, where$G_0 > 0$is the initial low-carbon goodwill
$R(t)$	Reference low-carbon service at time$t$

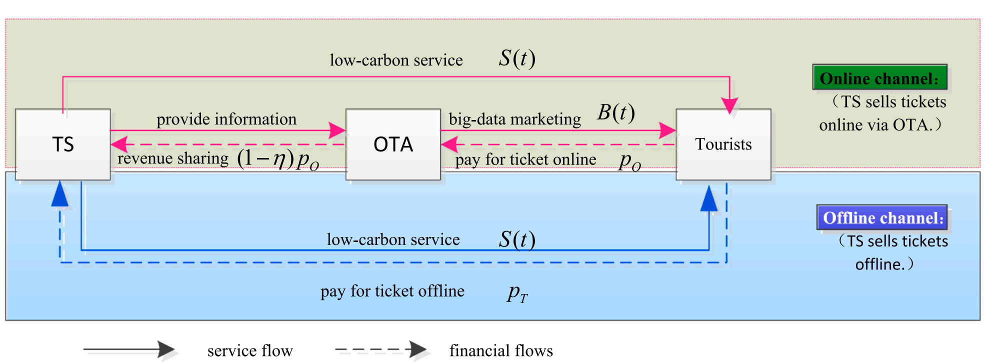


Fig. 1. Business model of low-carbon smart tourism SC.

Giovanni (2017) and Ma & Hu (2020) in terms of environmental aspect and consumer reference effect and combined with the actual research context of this paper, the dynamics model of low carbon goodwill can be described as a first-order differential equation as follows.

$$\dot{G}(t) = \gamma_T(S(t) - R(t)) + \gamma_O B(t) - \sigma G(t), G(0) = G_0 \tag{1}$$

where $G(t)$ represents the low-carbon goodwill of TS at time t, comprehensively measuring the carbon emissions, clean energy use, low-carbon equipment, and building construction achievements of TS in the minds of tourists. G_0 denotes the low-carbon goodwill at the initial moment. The most direct impact on low-carbon goodwill in the low-carbon tourism supply chain comes from the tourism attraction, namely, TS's low-carbon services and the big-data marketing efforts provided by the online tourism platform. From one perspective, TS's low-carbon goodwill is improved when the low-carbon service $S(t)$ provided by TS exceeds the visitor's expectation $R(t)$ and vice versa. That is a reference low-carbon service effect. Besides, $\gamma_T > 0$ represents the magnitude of the impact of this low-carbon service effect on low-carbon goodwill. From another perspective, OTA as a technology provider of smart low-carbon tourism empowered by big data makes use of the information provided by TS and its big-data marketing effort $B(t)$ (such as recommending low-carbon tourism itineraries based on user's accurate online image, selling tickets paperless, and reserving parking spaces online in advance (Nilashi et al., 2017) to enable tourists to feel the power of big data for low-carbon and smart tourism, promote high-quality, efficient, and personalized low-carbon tourism concepts to tourists, and encourage tourists to practice low-carbon tourism model, resulting in enhancing TS' low-carbon goodwill. Among them, $\gamma_O > 0$ is the impact of OTA's big-data marketing effort on low-carbon goodwill. Moreover, TS's low-carbon goodwill will also decay exponentially with time at a rate of σ if neither low-carbon service nor big-data marketing effort exists.

Based on the definition and assumptions of reference level by Hellofs and Jacobson (1999), and He et al. (2017), it is assumed in the context of the low-carbon tourism supply chain that tourists' expectations of TS low-carbon service level (i.e. reference low-carbon service level) always depends on TS's low-carbon goodwill. Tourists will generally expect a high level of low carbon service from a TS with high-low carbon goodwill, and will dynamically adjust their reference low carbon service level in response to the changes in TS low-carbon goodwill. The reference low-carbon service level can be expressed as

$$R(t) = \xi G(t) \tag{2}$$

where $\xi > 0$ is the degree of the correlation between the tourists' reference low-carbon service level and the low-carbon goodwill. The greater the ξ, the more visitor expectations of low-carbon service level in the TS depend on low-carbon goodwill.

Substituting equation (2) into dynamics (1), the low-carbon goodwill of TS can be further simplified as

$$\dot{G}(t) = \gamma_O B(t) + \gamma_T S(t) - \delta G(t), G(0) = G_0 \tag{3}$$

where $\delta = \gamma_T \xi + \sigma$.

Following He et al. (2016) and He et al. (2017), we extend the assumptions of the demand function to the low-carbon tourism supply chain, assuming that the demand of the online channel is jointly influenced by tourists' online channel preference, reference low-carbon service effect, OTA' s big-data marketing effort, low-carbon goodwill, and offline channel ticket price while the demand of traditional offline channel tickets is jointly influenced by tourists' reference low-carbon service effect, low-carbon goodwill, and offline ticket price. They can be constructed as follows:

$$D_{on}(t) = \chi[D_0 + \lambda_T(S(t) - R(t)) + \lambda_O B(t) + \theta G(t) - \beta_O p_O] \tag{4a}$$

$$D_{off}(t) = (1 - \chi)[D_0 + \mu_T(S(t) - R(t)) + \theta G(t) - \beta_T p_T] \tag{4b}$$

where $\chi > 0$ represents the proportion of tourists purchasing tickets through online channel and reflects the preference and acceptance of the online channel. $D_0 > 0$ denotes the basic demand for tickets; $\lambda_T, \mu_T > 0$ represents the impact of the reference low-carbon service effect on the demand online and offline, respectively. $\theta > 0$ denotes the impact of low-carbon goodwill on the demand online and offline. $\beta_O, \beta_T > 0$ indicate the sensitivity of visitors to the price of tickets online and offline, respectively. In this paper, it is assumed that TS and OTA are price acceptors (that is, retail prices are constant over the firm's operating period) in order to highlight the research focus. Besides, prices are only considered to be exogenous variables influencing demand. Moreover, the dynamic formulations of non-price influencing factors of demand such as low-carbon service strategy and big-data marketing effort strategy are discussed. Furthermore, the demand function can be further simplified by substituting equations (2) into equations (4a) and (4b), as expressed in Eqs. (5a) and (5b).

$$D_{on}(t) = \chi[D_0 + \lambda_O B(t) + \lambda_T S(t) + (\theta - \lambda_T \xi)G(t) - \beta_O p_O] \tag{5a}$$

$$D_{off}(t) = (1 - \chi)[D_0 + \mu_T S(t) + (\theta - \mu_T \xi)G(t) - \beta_T p_T] \tag{5b}$$

Based on the transaction relationship between TS and OTA in the low-carbon tourism O2O supply chain, it can be assumed that the marginal revenue of TS selling tickets directly through offline channel is $\pi_T = p_T - c_T$, where c_T is the marginal operating cost of TS; the marginal revenue of TS selling tickets through OTA is $\pi_{TO} = (1 - \eta)p_O - c_T$, where$\eta$denotes the percentage of the unit commission paid by TS to the online tourism platform; the marginal revenue of online service platform selling tickets is $\pi_O = \eta p_O - c_O$, where c_O represents its marginal operating cost.

Based on assumptions about the cost of services (He et al., 2020) and the cost of big-data marketing (Ma & Hu, 2020), the cost of low carbon service and big-data marketing service paid by TS and OTA to enhance TS goodwill and promote demand is expressed as $C_T(t) = \frac{1}{2}k_T S^2(t)$ and $C_O(t) = \frac{1}{2}k_O B^2(t)$, respectively.

In summary, the profit function of TS and OTA at each moment can be expressed as

$$\pi_T(t) = \pi_{TO} D_{on}(t) + \pi_T D_{off}(t) - C_T(t) \tag{6a}$$

$$\pi_O(t) = \pi_O D_{on}(t) - C_O(t) \tag{6b}$$

Meanwhile, it is supposed that the enterprises in the low-carbon tourism O2O supply chain operate within an unlimited plan period, the information in the supply chain is completely symmetrical, and enterprises discount their respective profits at a positive discount rate r.

4. Model analysis

Based on the assumptions in the previous sections, differential game models for TS and OTA under different decision modes in the context of the big data-empowered low-carbon tourism supply chain are established in this section. The optimal low-carbon service level, big-data marketing effort strategy, low-carbon goodwill time trajectory, and enterprise profit are solved. And the impact of various key exogenous factors on enterprise decision and performance is further analyzed. For the sake of model clarity, the superscripts C, N, and A represent the three decision modes of centralization, decentralization, and altruism, respectively. The subscripts T and O represent the main members of TS and OTA in the low-carbon tourism supply chain.

4.1. Model-C

The centralized decision mode (Model-C) is an ideal decision state for the low-carbon tourism supply chain and is manifested in the formation of a unified whole between TS and OTA, with the decision goal of maximizing the profit of the tourism supply chain system. It can be also considered that TS simultaneously establishes online ticketing channel on its own and adopts both online and offline channels to ticket consumers. However, it is difficult to achieve this decision-making model in the actual operation process due to the existence of different expertise, multiple leadership, and other problems; instead, it can be used as a reference ceiling to measure the effectiveness of cooperation between enterprises in the low-carbon tourism supply chain. In this model, the optimal control issues facing the low-carbon tourism supply chain system can be expressed as

$$\begin{aligned} \max_{S(\cdot),B(\cdot)} J^C &= \int_0^\infty e^{-rt}\left[(\pi_{TO}+\pi_O)D_{on}(t)+\pi_T D_{off}(t)-C_O(t)-C_T(t)\right]\mathrm{d}t \\ \text{s.t. } \dot{G}(t) &= \gamma_O B(t)+\gamma_T S(t)-\delta G(t), G(0)=G_0 \end{aligned} \tag{7}$$

Proposition 1.. *Under the centralized decision-making model, the system's strategies for optimal offline low-carbon services and optimal online big data marketing efforts are* $S^C = \frac{(\pi_{TO}+\pi_O)\chi\lambda_T+\pi_T(1-\chi)\mu_T+\gamma_T l_1}{k_T}$*and* $B^C = \frac{(\pi_{TO}+\pi_O)\chi\lambda_O+\gamma_O l_1}{k_O}$. *The total profit of the system is* $V^C = l_1 G^C + l_2$. *The time trajectory of low-carbon goodwill is* $G^C(t) = e^{-\delta t}\left[G_0 - G_\infty^C\right] + G_\infty^C$, *where*$G_\infty^C = \frac{1}{\delta}\left[\frac{(\pi_{TO}+\pi_O)\chi\gamma_O\lambda_O+\gamma_O^2 l_1}{k_O}+\frac{(\pi_{TO}+\pi_O)\chi\gamma_T\lambda_T+\pi_T(1-\chi)\gamma_T\mu_T+\gamma_T^2 l_1}{k_T}\right]$*is the steady-state low-carbon goodwill.*

Proof.. See the Appendix A.

Corollary 1.. *The sensitivity of the system's optimal low-carbon service, big-data marketing effort, and low-carbon goodwill for each key parameter under the centralized decision model is listed in Table 2.*

Corollary 1 suggests that TS and OTA form a unified whole to maximize system profits in the centralized decision model. Both low-carbon service levels and big data marketing effort strategies are positively influenced by both online and offline ticket prices and negatively influenced by marginal costs; this influence is transmitted to TS's low-carbon goodwill through strategy. This is an ideal scenario for the tourism supply chain, which can be regarded as a situation where TS opens up online channel on its own, and there is no transaction between TS and the online tourism platform, avoiding the existence of commission costs. However, the existence of industry barriers and the complexity of channel integration and other objective factors exist at this stage due to technical limitations; the TS autonomous opening of online channel is still difficult to achieve and can be used as a reference ceiling to explore the effect of altruistic cooperation, the study of which still has great significance. Furthermore, it can be found through analysis that the improvement of low-carbon service level and big-data marketing efforts will be stimulated by the increase in the correlation between the tourists' reference low-carbon level and low-carbon goodwill ξ. This is the benign performance of the tourists' reference low-carbon service effect in promoting the sustainable development of tourism supply chain. Specifically, tourists form an estimate of TS low-carbon service level through TS low-carbon goodwill before visiting TS and test this estimate through experience during the tour, resulting in influencing the market size of the tourism supply chain; this process can be regarded as the supervision of consumers on TS low-carbon construction. Therefore, the tourism supply chain will strive to improve its online and offline service levels to obtain the positive impact of this reference effect on the demand, as well as further optimize its service effects as the impact of the service level on the low-carbon goodwill γ_T,γ_O increases. Therefore, consumers will obtain a low-carbon tourism experience that exceeds their expectations and low-carbon goodwill growth while potential tourist groups will form new and higher low-carbon expectations based on the new and higher low-carbon goodwill. Consequently, a virtuous circle will be formed to stimulate the low-carbon, efficient, and sustainable development of the tourism supply chain.

4.2. Model-N

Different from the centralized decision-making model, TS and OTA operate independently in the decentralized model. TS uses a percentage of tickets as commission to expand the market scale with OTA's big data marketing efforts while it sells tickets through traditional offline channel. Each differential game model for with its profit maximization as the decision goal can be expressed as

$$\begin{aligned} \max_{S(\cdot)} J_T &= \int_0^\infty e^{-rt}\left[\pi_{TO}D_{on}(t)+\pi_T D_{off}(t)-C_T(t)\right]\mathrm{d}t \\ \max_{B(\cdot)} J_O &= \int_0^\infty e^{-rt}[\pi_O D_{on}(t)-C_O(t)]\mathrm{d}t \\ \text{s.t. } \dot{G}(t) &= \gamma_O B(t)+\gamma_T S(t)-\delta G(t), G(0)=G_0 \end{aligned} \tag{8}$$

Proposition 2.. *Under the decentralized decision-making model, the optimal low-carbon service for TS and the optimal big-data marketing effort for OTA are* $S^N = \frac{\pi_{TO}\chi\lambda_T+\pi_T(1-\chi)\mu_T+\gamma_T f_1}{k_T}$*and*$B^N = \frac{\pi_O\chi\lambda_O+\gamma_O g_1}{k_O}$, *respectively. The time evolution path for low carbon goodwill is* $G^N(t) = e^{-rt}\left(G_0 - G_\infty^N\right) + G_\infty^N$, *where*$G_\infty^N = \frac{1}{\delta}\left[\frac{\pi_O\chi\gamma_O\lambda_O+\gamma_O^2 g_1}{k_O}+\frac{\pi_{TO}\chi\gamma_T\lambda_T+\pi_T(1-\chi)\gamma_T\mu_T+\gamma_T^2 f_1}{k_T}\right]$. *The profits of TS and OTA are , where*

Proof.. See the Appendix B.

Corollary 2.. *The sensitivity of the TS's optimal low-carbon service, OTA's big-data-marketing effort, and low-carbon goodwill for each key parameter under the decentralized decision model are displayed in Table 3.*

Corollary 2 indicates that offline ticket pricep_T under the decentralized decision model only positively incentivizes TS low-carbon service level and does not affect OTA's big-data marketing effort. Besides, it is one of the channels through which TS sells tickets, and OTA's ticket price/marginal cost can have a positive/negative impact not only on its level of effort but also on the level of low-carbon service. The impact of tourists' reference to low-carbon service effects on TS and OTA decisions and low-carbon goodwill is the same as that under centralized decision making, and will also monitor and facilitate the development of the tourism supply chain under the decentralized decision-making model. Due to the double marginal effect inherent in decentralized decision-making, its environmental performance and economic performance will be lower than that under the centralized decision-making model, and the realization of big data for low-carbon tourism supply chain cannot be fully utilized. Therefore, new cooperation methods should be

Table 2
Sensitivity of system decisions and performance to key parameters in Model-C.

	p_T	p_O	c_T	c_O	k_T	k_O	ξ	γ_T	γ_O
S^C	↗	↗	↘	↘	↘	—	↗	↗	—
B^C	↗	↗	↘	↘	—	↘	↗	—	↗
G_∞^C	↗	↗	↘	↘	↘	↘	↗	↗	↗

Note; ↗ indicates positive correlation, ↘indicates negative correlation, — indicates irrelevant.

Table 3
Sensitivity of system decisions and performance to key parameters in Model-N.

	p_T	p_O	c_T	c_O	k_T	k_O	ξ	γ_T	γ_O
S^N	↗	↗	↘	↘	↘	—	↗	↗	—
B^N	—	↗	—	↘	—	↘	↗	—	↗
G_∞^N	↗	↗	↘	↘	↘	↘	↗	↗	↗

Note; ↗ indicates a positive correlation, ↘indicates a negative correlation, — indicates irrelevant.

explored for TS and OTA to realize the construction of a low-carbon smart tourism supply chain. Thus, an altruistic decision-making model is proposed in this paper to highlight the importance and effectiveness of further cooperation between TS and OTA for the sustainable development of themselves and the low carbon tourism supply chain in the context of big data empowerment.

4.3. Model-A

Following Bassi, Pagnozzi, and Piccolo (2014) and Wang et al. (2020) for the description of member altruistic behavior, the altruistic utility function of the member i in the low-carbon tourism supply chain is expressed as$U_i(t) = \pi_i(t) + \phi_i \pi_j(t)$, $i,j \in \{T,O\}, i \neq j$, where $\phi_i \in [0,1]$ indicates the degree of altruism. Assuming that its size does not exceed 1 (considering the concern for the interests of the other party does not exceed its own to ensure the normal operation of the enterprise). This bilateral altruistic behavior indicates that TS and OTA not only pursue their interests but also care about each other's interests when making decisions, using total channel profits as the goal of maximizing the altruistic utility of their operations. The existence of such altruistic behavior stems from the common social responsibility of tourism supply chain members, that is, low-carbon operations. Therefore, enterprises seek to further enhance TS's low-carbon goodwill by demonstrating altruistic preferences to counterparties to stimulate the formulation of their low-carbon strategies, bringing better low-carbon tourism experience to tourists and promoting their benefit growth while promoting a green economy and creating a win–win situation for tourism. Therefore, a differential game model between the two subjects of the low-carbon tourism supply chain (TS and OTA) is constructed to maximize the respective altruistic utility to explore the role of altruistic behavior.

$$\begin{aligned}
\max_{S(\cdot)} J_T^A &= \int_0^\infty e^{-rt}\left[\pi_{TO}D_{on}(t) + \pi_T D_{off}(t) - C_T(t) + \phi_T\left(\pi_O D_{on}(t) - C_O(t)\right)\right]\mathrm{d}t \\
\max_{B(\cdot)} J_O^A &= \int_0^\infty e^{-rt}\left[\pi_O D_{on}(t) - C_O(t) + \phi_O\left(\pi_{TO}D_{on}(t) + \pi_T D_{off}(t) - C_T(t)\right)\right]\mathrm{d}t \\
&\text{s.t. } \dot{G}(t) = \gamma_O B(t) + \gamma_T S(t) - \delta G(t), G(0) = G_0
\end{aligned} \tag{9}$$

Proposition 3.. *Under the altruistic decision-making model, the optimal low-carbon service strategy for TS is* $S^A = \frac{\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \phi_T\pi_O\chi\lambda_T + \gamma_T m_1}{k_T}$, *and OTA's big-data marketing effort is*$B^A = \frac{\pi_O\chi\lambda_O + \phi_O\pi_{TO}\chi\lambda_O + \gamma_O n_1}{k_O}$. *The time trajectory of low-carbon goodwill is*

$$G^A(t) = e^{-rt}\left(G_0 - G_\infty^A\right) + G_\infty^A$$

where$G_\infty^A = \frac{1}{\delta}\left[\frac{\pi_O\chi\gamma_O\lambda_O + \phi_O\pi_{TO}\chi\gamma_O\lambda_O + \gamma_O^2 n_1}{k_O} + \frac{\pi_{TO}\chi\gamma_T\lambda_T + \pi_T(1-\chi)\gamma_T\mu_T + \phi_T\pi_O\chi\gamma_T\lambda_T + \gamma_T^2 m_1}{k_T}\right]$.
The profits of TS and OTA are$V_T^A = u_1 G^A + u_2$, $V_O^A = v_1 G^A + v_2$. *The altruistic utilities are* $U_T^A = m_1 G^A + m_2$,$U_O^A = n_1 G^A + n_2$, *where,*

Proof.. See the Appendix C.

Corollary 3.. *The sensitivity of the TS's optimal low-carbon service, OTA's big-data-marketing effort, and low-carbon goodwill for each key parameter under the altruistic decision-making model is listed in* Table 4.

Table 4
Sensitivity of system decisions and performance to key parameters in Model-A.

	p_T	p_O	c_T	c_O	k_T	k_O	ξ	γ_T	γ_O
S^A	↗	↗	↘	↘	↘	——	↗	↗	——
B^A	↗	↗	↘	↘	——	↘	↗	——	↗
G_∞^A	↗	↗	↘	↘	↘	↘	↗	↗	↗

Note; ↗ indicates a positive correlation, ↘indicates a negative correlation, —— indicates irrelevant.

Corollary 3 suggests that the altruistic decision model not only retains the state of independent decision making of TS and OTA in the decentralized decision model but is more in line with the actual operational process of the low-carbon tourism supply chain; the influence of the external environmental parameters on it is more similar to the centralized decision model. Specifically, the increase in online and offline ticket prices and the reduction in marginal costs will incentivize TS to improve its low-carbon service levels and the online travel platform to improve its big data marketing efforts, resulting in collectively enhancing its low-carbon goodwill. This is because the decision-making goal of TS and OTA focuses on the interests of the partner at the same time and with the decision-making goal of improving both its own and each other's benefits instead of maximizing self-interest under the decentralized decision-making model. Under this decision-making model, the inefficient state of fragmentation can be changed, and the low-carbon tourism supply chain can be systematically targeted to obtain deeper incentives empowered by big data, contributing to the achievement of cooperation and mutual benefit among different industries in the new technological environment. Consequently, the sustainable development of low-carbon tourism would be promoted and the win–win situation would be achieved.

5. Comparison among different decision model

Proposition 4.. *As can be seen from* Table 5, *the magnitude relationship between the low carbon service level of TS for the three decision models is* $S^C \geqslant S^A \geqslant S^N$, *and OTA's big- data marketing relationship is* $B^C \geqslant B^A \geqslant B^N$.

Proof.. See the Appendix D.

It can be observed from proposition 4 that the size of the TS low-carbon service level is always the highest in the centralized decision mode, next to the altruistic decision mode, and the lowest in the decentralized decision mode. The level of low-carbon service under the altruistic decision-making model can be flush with that under centralized decision-making when TS is maximally altruistic, namely, $\phi_T = 1$. Its low-carbon service levels are not different from those in the decentralized decision-making model when there is no altruistic preference for TS, namely, $\phi_T = 0$. Besides, the TS low-carbon service level is not affected by OTA's altruistic preference. OTA's big data marketing efforts also the highest in the centralized decision among the three decision modes, followed by the altruistic decision, and the lowest in the decentralized decision. The difference is that the size of its big data marketing efforts depends on how altruistic the OTA is, independent of how altruistic the TS is. The level of the effort reaches the level of a centralized decision-making model when the OTA exhibits the highest degree of altruism, namely, $\phi_O = 1$. The level of effort is the same as in the decentralized decision-making model when it has no altruistic preference, namely, $\phi_O = 0$.

Proposition 5.. *The relationship between the size of TS's low-carbon goodwill for the three decision models is* $G_\infty^C \geqslant G_\infty^A \geqslant G_\infty^N$.

Proof.. See the Appendix D.

It can be seen from proposition 6 that decision mode is one of the key influences on the size of TS low-carbon goodwill; low-carbon goodwill in the centralized decision mode is always higher than that in the decentralized decision mode due to the intrinsic nature of the decision mechanism; besides, TS low-carbon goodwill in the altruistic decision model is always better than that in the decentralized decision when tourism supply chain members have altruistic preferences, namely, $\phi_T > 0$ or $\phi_O > 0$, because each party optimizes its own decisions, such as correspondingly improving low-carbon service levels or big data marketing efforts. Particularly, low-carbon goodwill in the altruistic decision model can reach the level in the centralized decision model when both parties are maximally altruistic, namely, $\phi_T = \phi_O = 1$.

Table 5
Comparisons of optimal decision making in different decision-making models.

Performance	Model-C	Model-N	Model-A
S	$\frac{(\pi_{TO}+\pi_O)\chi\lambda_T+\pi_T(1-\chi)\mu_T+\gamma_T l_1}{k_T}$	$\frac{\pi_{TO}\chi\lambda_T+\pi_T(1-\chi)\mu_T+\gamma_T f_1}{k_T}$	$\frac{(\pi_{TO}+\phi_T\pi_O)\chi\lambda_T+\pi_T(1-\chi)\mu_T+\gamma_T m_1}{k_T}$
B	$\frac{(\pi_{TO}+\pi_O)\chi\lambda_O+\gamma_O l_1}{k_O}$	$\frac{\pi_O\chi\lambda_O+\gamma_O g_1}{k_O}$	$\frac{(\pi_O+\phi_O\pi_{TO})\chi\lambda_O+\gamma_O n_1}{k_O}$
G_∞	$\frac{1}{\delta}\left[\frac{(\pi_{TO}+\pi_O)\chi\gamma_O\lambda_O+\gamma_O^2 l_1}{k_O}+\frac{(\pi_{TO}+\pi_O)\chi\gamma_T\lambda_T+\pi_T(1-\chi)\gamma_T\mu_T+\gamma_T^2 l_1}{k_T}\right]$	$\frac{1}{\delta}\left[\frac{\pi_O\chi\gamma_O\lambda_O+\gamma_O^2 g_1}{k_O}+\frac{\pi_{TO}\chi\gamma_T\lambda_T+\pi_T(1-\chi)\gamma_T\mu_T+\gamma_T^2 f_1}{k_T}\right]$	$\frac{1}{\delta}\left[\frac{\pi_O\chi\gamma_O\lambda_O+\phi_O\pi_{TO}\chi\gamma_O\lambda_O+\gamma_O^2 n_1}{k_O}+\frac{\pi_{TO}\chi\gamma_T\lambda_T+\pi_T(1-\chi)\gamma_T\mu_T+\phi_T\pi_O\chi\gamma_T\lambda_T+\gamma_T^2 m_1}{k_T}\right]$
$V_{T\infty}$	——	$V_{T\infty}^N=f_1G_\infty^N+f_2$	$V_{T\infty}^A=u_1G_\infty^A+u_2$
$V_{O\infty}$	——	$V_{O\infty}^N=g_1G_\infty^N+g_2$	$V_{O\infty}^A=v_1G_\infty^A+v_2$
V_∞	$V_\infty^C=l_1G_\infty^C+l_2$	$V_\infty^N=(f_1+g_1)G_\infty^N+f_2+g_2$	$V_\infty^A=(u_1+v_1)G_\infty^A+u_2+v_2$
$U_{T\infty}$	–	–	$U_{T\infty}^A=m_1G_\infty^A+m_2$
$U_{O\infty}$	–	–	$U_{O\infty}^A=n_1G_\infty^A+n_2$
U_∞	–	–	$U_\infty^A=(m_1+n_1)G_\infty^A+m_2+n_2$

As expressed in propositions 4 and 5, TS can provide visitors with a higher level of low-carbon services by demonstrating altruistic preferences to OTA, and the OTA can provide visitors with more complete big data marketing efforts, both of which are essential to the enhancement of TS' low-carbon goodwill. Therefore, altruistic preference is a positive preference in the tourism supply chain and is significant to increase members' motivation to serve tourists, maintain the TS environment, and achieve low-carbon sustainable development.

Proposition 6.. *In different decision modes, the profit size relationship between TS and OTA is $V_{T\infty}^A \geqslant V_{T\infty}^N, V_{O\infty}^A \geqslant V_{O\infty}^N$, The total profit size relationship of the low-carbon tourism supply chain is $V_\infty^C \geqslant V_\infty^A \geqslant V_\infty^N$.*

Proof.. See the Appendix D.

It can be observed from proposition 6 that altruism as a positive social preference could not only deepen the cooperation between TS and online tourism platforms to enable big data to fully empower the low-carbon smart tourism supply chain but also improve the economic efficiency of enterprises under the traditional decentralized decision-making model while maintaining the decentralized decision-making model in line with the actual operation model. Specifically, altruism can increase the profit level of both TS and OTA, resulting in increasing the profit level of the entire low-carbon tourism supply chain. It is even more noteworthy that the level of performance under altruistic decision-making can reach the level of a centralized decision-making model when both TS and OTA are most altruistic, namely, $\phi_T = \phi_O = 1$. Besides, cooperation can be achieved to the maximum extent, and supply chain coordination can be obtained by exhibiting the maximum altruistic preferences of low-carbon tourism supply chain members, contributing to forming an all-channel win–win situation.

6. Numerical analysis

In this section, the results of the previous analysis (such as the positive impact of altruistic preferences on members' decision making and TS low-carbon goodwill) are further validated. We also analyze the role of altruistic behavior in enhancing the economic performance of low-carbon tourism supply chain, the effectiveness of tourism supply chain coordination as well as the impact of various exogenous factors on TS and OTA decision making and performance. Besides, operational advice to enterprises at the nodes of the low-carbon tourism supply chain is provided. Regarding He et al. (2017) and He et al. (2020), the basic parameters of the centering are set, and the exogenous parameters are set as follows in conjunction with the specific research context of this paper.

$$\gamma_O=2,\gamma_T=1,\sigma=0.3,\xi=0.6,D_0=10,\lambda_T=1,\lambda_O=3,\theta=1,\mu_T=1.5,\beta_T=0.5,\beta_O=0.6,p_T=15,p_O=10,c_T=4,c_O=1,\eta=0.3,k_T=8,k_O=6,r=0.1.$$

6.1. Effect analysis of decision mode and time

Set the initial low carbon goodwill $G_0 = 0 < G_\infty^i$ and $G_0 = 10 > G_\infty^i$ separately, where $i \in \{C,N,A\}$; tourism supply chain operating hours are set as $t \in [0,5]$. Both TS and OTA are moderately altruistic, that is, $\phi_T = \phi_O = 0.5$. The time evolution trajectory of low-carbon goodwill for the three decision models is illustrated in Fig. 2.

It can be observed from Fig. 2 that the initial low-carbon goodwill of TS does not affect the final steady-state, and the steady-state equilibrium exists for the system in all three decision modes; this result is consistent with the $G_\infty^C \geqslant G_\infty^A \geqslant G_\infty^N$ proved by proposition 6; this size relationship is robust; besides, the time trajectory of the low-carbon goodwill in the three decision modes is always $G^C(t) > G^A(t) > G^N(t)$ when the initial low-carbon goodwill is the same. Moreover, the relationship between low-carbon service level and low-carbon goodwill can also be obtained by reference to the consumer's relationship equation (2) for $R^C(t) > R^A(t) > R^N(t)$. Furthermore, TS low-carbon goodwill is increased compared to the decentralized decision-making model while consumers' expectation of TS low-carbon service level is increased accordingly when the members of the low-carbon tourism supply chain have moderate altruistic attitudes. Since the size of the initial low-carbon goodwill does not affect the relationship between the size of the low-carbon goodwill under the three decision models, the initial low-carbon goodwill is set to be $G_0 = 0$. Then, the performance levels of firms in the low-carbon tourism supply chain under each of the three decision models are compared.

The time trajectory of firm performance levels for different decision models is illustrated in Fig. 3. It can be found that firm performance levels also gradually reach a steady state over time. As presented in Fig. 3(a)-(c), the online, offline, and even omnichannel visitor demand in a given planning period exhibits the highest under the centralized decision mode and the lowest under the decentralized decision mode;

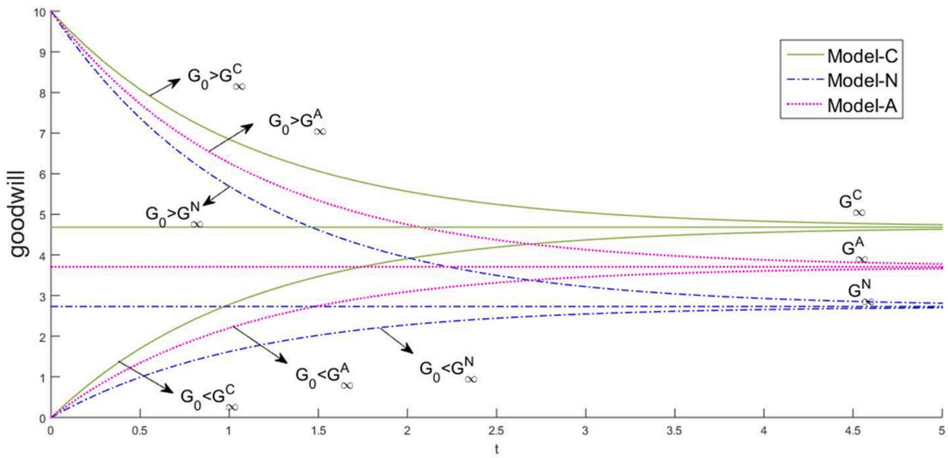


Fig. 2. Time trajectories of low-carbon goodwill under different decision models.

meanwhile, it can effectively increase the demand across channels under the decentralized decision mode when both TS and online travel service companies exhibit moderate altruistic preferences. The reason is that altruistic decision making can facilitate the cooperation between TS and OTA, and its altruistic preference is demonstrated by improving their decision-making level (low carbon service level/big data marketing efforts) and bringing visitors a better low carbon tourism experience, leading to indirectly enhancing TS's low carbon goodwill and increasing visitor traffic from all channels. It can be revealed by further analyzing the profits of enterprises under the three decision modes (Fig. 3(d)-(f)) and longitudinally comparing the profits of TS and OTA under the two decision modes that altruistic decision can effectively improve the profit level of enterprises in the tourism supply chain and the Pareto improvement of supply chain profits under the decentralized decision mode. To sum up, the altruistic preference of enterprises can not only improve the low-carbon goodwill of TS and environmental benefits but also bring a better experience to tourists through the construction of low-carbon tourism in TS, contributing to promoting the sustainable development of TS and increasing the number of visitors to TS to make itself more profitable.

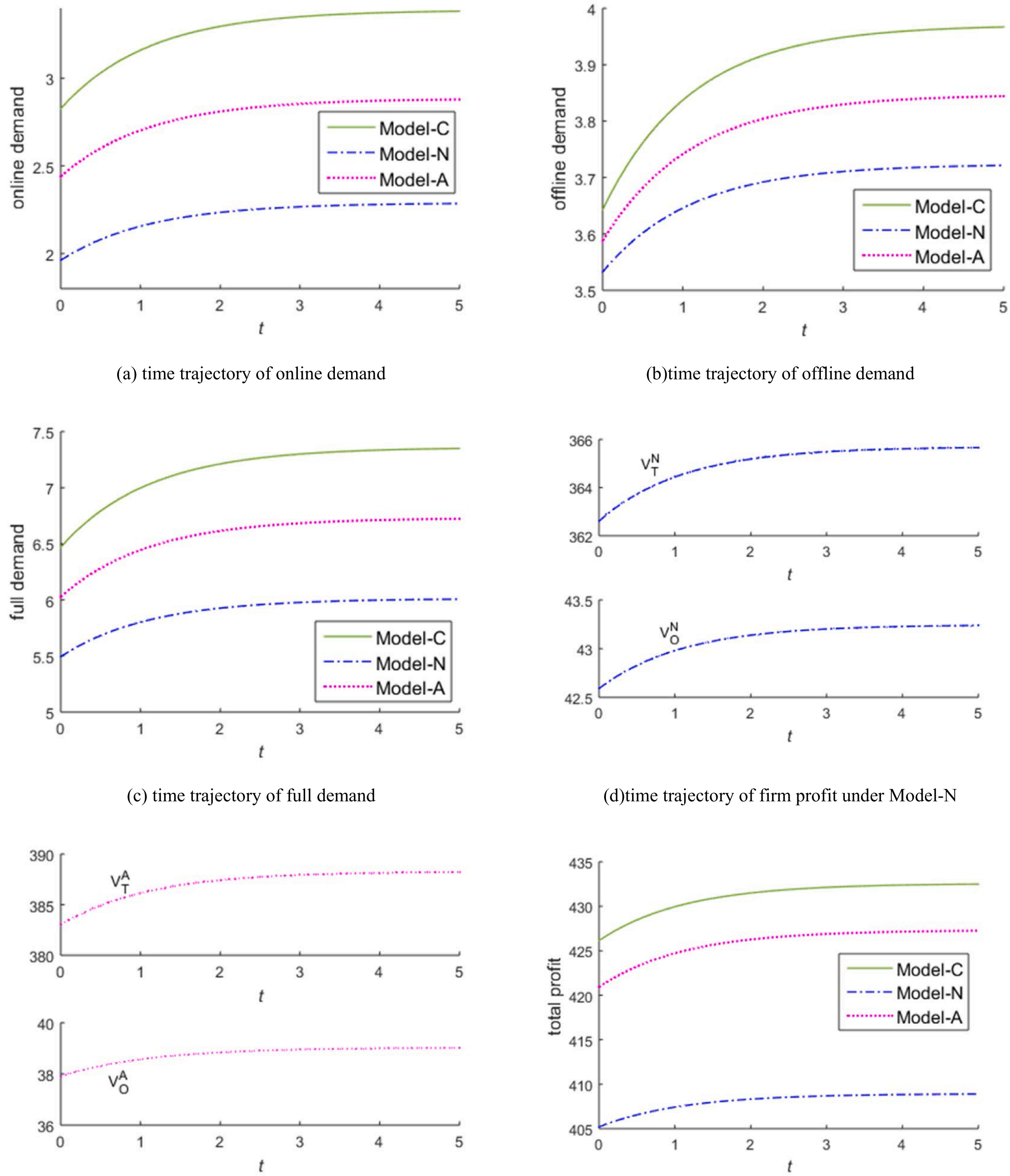
6.2. Effect analysis of channel preference parameter χ

Fixing the remaining benchmark parameters constant, the impact on the optimal decision making and performance of firms in the tourism supply chain for different decision modes is explored by adjusting the online channel preference coefficient for tourists. It is should be noted that the following analysis is performed from a system steady-state equilibrium perspective to highlight the impact of $\chi$by weakening the increased complexity of introducing time variables and consider that the time factor does not affect the final results of the analysis.

Fig. 4(a)-(b) indicates that the level of TS low-carbon service decreases in all three decision models and OTA big data marketing efforts increase as visitors' preference for online channel χ increases. The reasons for this can be analyzed from two aspects. From one perspective, offline tickets are still the main source of revenue compared to the sale of tickets through online channel in the current tourism TS situation due to the high pricing of tickets sold directly by TS, and the marginal cost of selling tickets through offline channel is high (such as the construction of visitor ticket centers, and the labor cost of ticket agents). Besides, the demand for offline channel decreases as the demand for online channel increases (Fig. 4(d)–(e)). At this time, TS to reduce the level of low carbon service can avoid unnecessary offline service costs. Therefore, an important OTA response is used to enhance big data marketing efforts to salvage TS's low-carbon goodwill and attract more visitors through accurate targeting and personalized recommendations in order to mitigate the negative impact of this on TS's low-carbon goodwill and ticket sales in both channels. In this way, more offline demand is shifted to online, more market potential is tapped, and omnichannel demand increases (e.g., Fig. 4(f)). From another perspective, the increase in online channel preference χ stimulates the online tourism platform to continuously improve the level of big-data marketing technology to serve tourists, suggesting that the online big data marketing to low-carbon tourism supply chain empowerment is deepened. Under more mature technology, tourists can choose to buy tickets through online channel and accept the online tourism platform to develop customized low-carbon tourism routes and low-carbon travel mode. Besides, the low-carbon construction of TS is also taking shape in the early stage. Meanwhile, tourists' travel becomes more efficient and intelligent with the empowerment of big data to low-carbon tourism; the travel mode of low-carbon tourism is also more acceptable and proactive. Therefore, TS can also use this empowerment of big data and the scale effect of initial construction to properly invest in low-carbon services, and more apply tourists' spontaneous awareness of low-carbon tourism to improve low-carbon goodwill (Fig. 4(c)) and promote the sustainable development of low-carbon tourism supply chain.

Although the addition of online tourism platform will cause the traditional business model of TS to be hit and the profit will be reduced accordingly at present, TS will find a new sustainable and environmentally friendly development potential. First, TS should not only use the online tourism platform to attract tourists but also deepen cooperation with OTAs in an altruistic manner to enhance the profit under the decentralized decision-making mode. Second, TS will find new profit growth points and further revitalize under the background of big data enabled low carbon tourism with the deepening (χincrease) and even comprehensive coverage enabled by big data under the altruistic cooperation mode (Fig. 4(g)). Besides, the increase of χ will further enhance their profitability and get sustained profit growth for online travel platforms. The altruistic decision-making model will increase its profit compared with the decentralized model (Fig. 4(h)). Besides, from the perspective of maximizing the altruistic effect and comprehensively enhancing the sustainability of the low-carbon smart tourism supply chain, its altruistic effect can also grow rapidly as the big data power deepens (Fig. 4(j)). Moreover, the whole low-carbon tourism supply chain will also adjust its development direction from the initial temporary losses introduced by the online channel to obtain the economic potential for sustainable development and economic growth above the traditional operating model (Fig. 4(i)).

It can be seen that online travel platforms are an essential bridge between tourists and TS. The introduction of OTA in the new technology environment can enable big data to empower low-carbon tourism; thus, the tourism supply chain can achieve low-carbon, sustainable, and



(a) time trajectory of online demand

(b)time trajectory of offline demand

(c) time trajectory of full demand

(d)time trajectory of firm profit under Model-N

(e)time trajectory of firm profit under Model-A

(f) time trajectory of SC profits

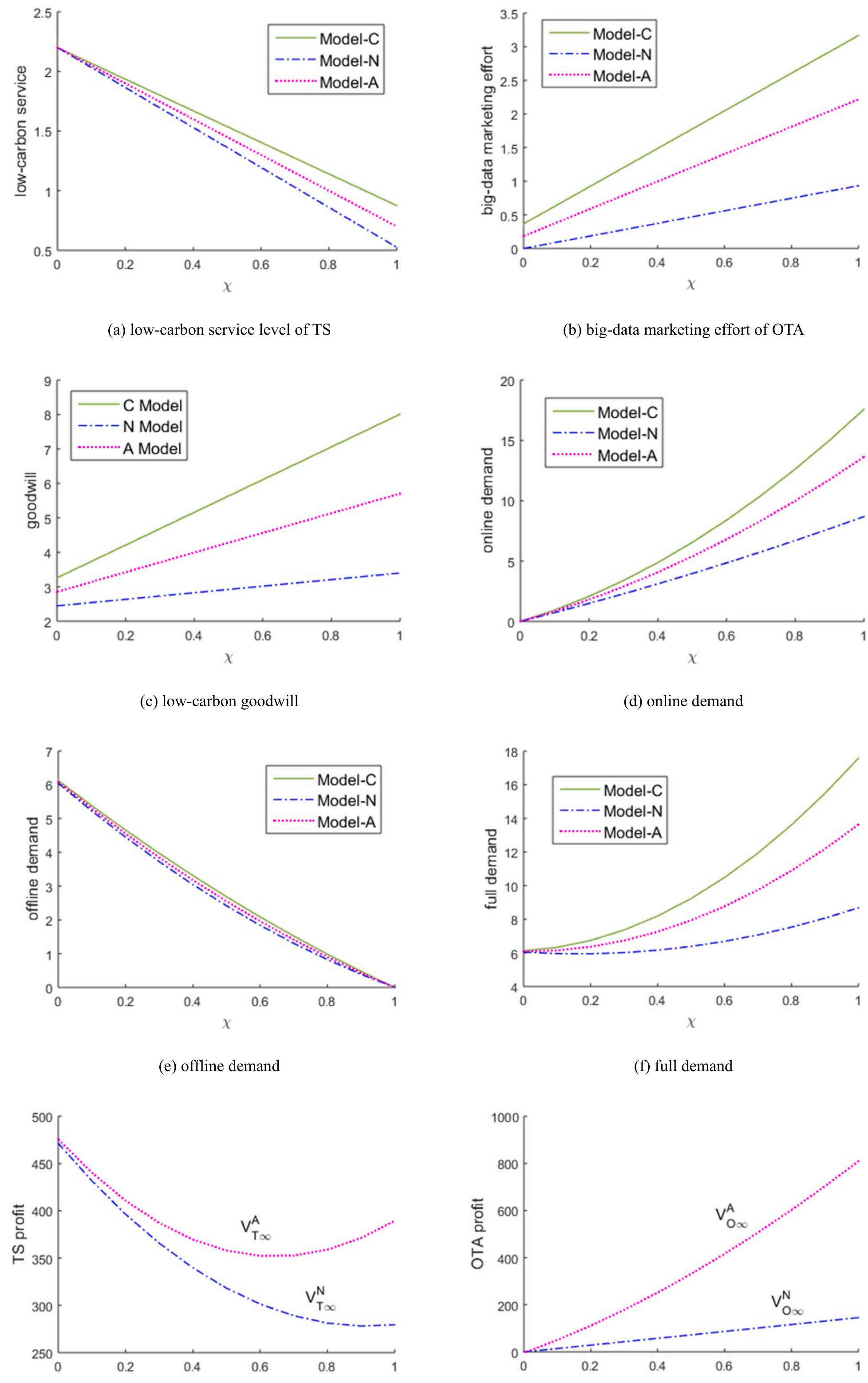
Fig. 3. Effects of decision mode and time on firms' performance.

intelligent development. With the deepening of online big data marketing's empowerment of low-carbon tourism supply chain, it will not only unlock greater market potential and revolutionize the traditional tourism business model but also find a more low-carbon, sustainable, and intelligent development path for the future of tourism supply chain.

6.3. Effect analysis of altruistic preference ϕ_T, ϕ_O

With the benchmark parameters set, the impact of the altruistic partnership between TS and OTA on the optimal decision making, performance, and even low-carbon tourism supply chain of the firm is further analyzed, as illustrated in Fig. 5.

In Fig. 5, the new technological environment has begun to empower the low-carbon tourism supply chain with considerable benefits and prospects in terms of the current stage of development (when tourists have a certain preference for online channel($\chi = 0.3$) and both online and offline channels exist). Meanwhile, the development of low-carbon smart tourism is still in the early stage; besides, low-carbon tourism supply chain enterprises can make altruistic decisions, deepen cooperative relationships, tap the potential of big data empowerment, and enhance its effectiveness. The market potential can be fully exploited through the altruistic cooperation between TS and OTA (Fig. 5(c)-(e)). Moreover, with the improvement of TS low-carbon service level and OTA big data marketing efforts, the construction of TS is more low-carbon, tourists have more low-carbon travel methods and low-carbon tourism paths, the playing environment of TS and tourists' playing



(a) low-carbon service level of TS

(b) big-data marketing effort of OTA

(c) low-carbon goodwill

(d) online demand

(e) offline demand

(f) full demand

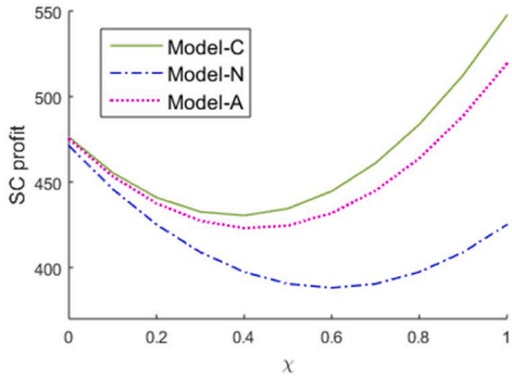
(g) TS profit

(h) OTA profit

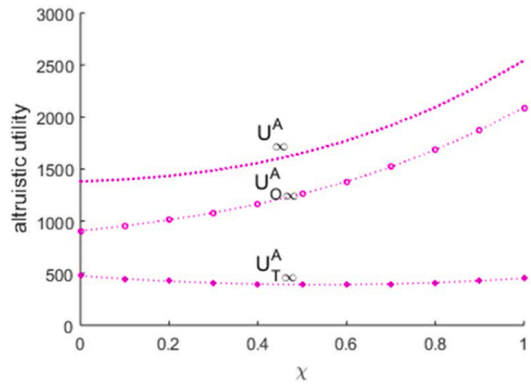
Fig. 4. The effect of χ on enterprise performance.

process is more low-carbon and environmentally friendly, and the low-carbon reputation of TS is rapidly improved (Fig. 5(f)).

It can be found by analyzing its reasons that tourists can better accept the high-quality, low-carbon tourism experience during the tour because TS's low-carbon service aims to regulate TS's low-carbon construction; this is the construction of the basic level of the tourism supply chain and



(i) SC profit



(j) altruistic utility

Fig. 4. (*continued*).

helps to stabilize the low-carbon tourism supply chain. OTA's big data marketing efforts can describe the user's image based on the personal information of tourists' consumption and browsing on the same platform to accurately locate consumers and recommend more intelligent and personalized low-carbon travel mode, accommodation, food and beverage, travel route, and other solutions while satisfying tourists' behavioral preferences and preferences. Meanwhile, the low-carbon concept of the whole process of tourism is instilled into tourists' minds; therefore, tourists can take the initiative in practicing personalized and customized low-carbon tourism and play their environmentally friendly tourism behavior, contributing to solving the fundamental level to avoid environmental damage behavior that traditional tourism does not realize. Besides, the efficiency and wisdom of big data tourism supply chain empowerment is a technological subversion of the traditional business model of low-carbon tourism supply chain, which will inevitably bring new development prospects different from the traditional business model.

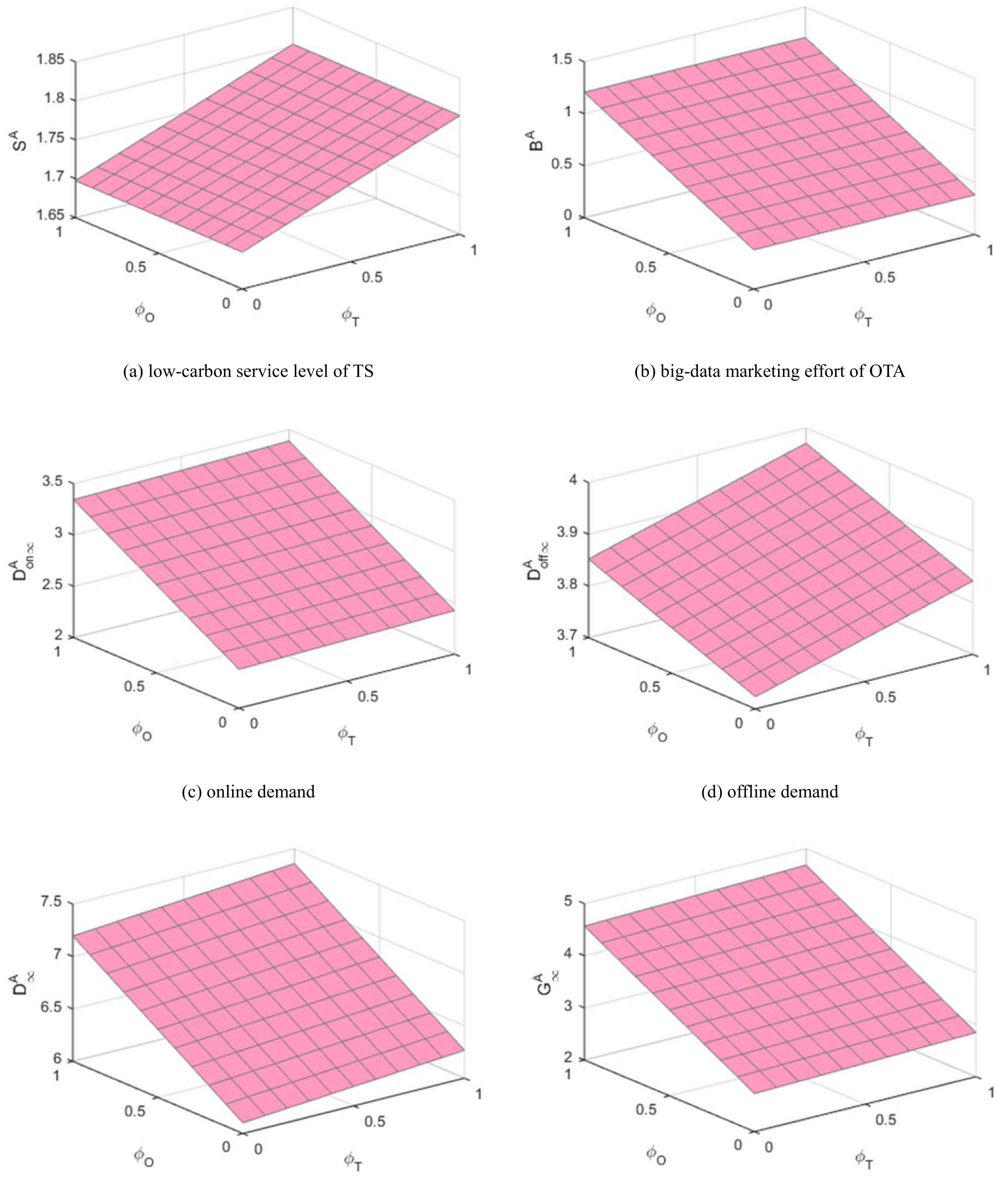
Moreover, altruistic decision making among members of the low-carbon tourism supply chain in the context of big data empowerment will not only bring environmental benefits over and above the traditional business model while it will enable companies to find new economic growth potential and social benefits, as illustrated in Fig. 5(g)-(l). Specifically, TS can obtain higher economic benefits as the online tourism platform becomes more altruistic, and the online service platform will receive temporary economic losses as the level of altruism deepens at the initial stage of construction; however, the entire low-carbon tourism supply chain has been developed rapidly, and the economic benefits have been increased significantly. Furthermore, OTAs' altruistic utility increases as their own and TS' altruistic preferences increase.

In summary, Rita's preference has not only inspired TS's low-carbon service level and OTA's big data marketing efforts but also enhanced TS's low-carbon goodwill and brought environmental benefits under the background of big data empowerment. Besides, it also makes TS and low-carbon tourism supply chains more economically efficient. Moreover, it is worth noting that big data marketing can not only recommend low-carbon tourism methods scientifically, intelligently, and efficiently but also have an implicit effect on the low-carbon tourism concept of tourists in the process. Therefore, consumers can change the traditional high-carbon and polluting travel methods, and enjoy high-quality tourism experience while practicing low-carbon tourism in all aspects of food, clothing, housing, and transportation, and then consider the enhancement of altruistic preferences for members themselves and even the entire tourism supply chain.

Given the positive impact of altruistic preferences and the context of the current big data-enabled low-carbon tourism, the following management advice is given to enterprises: TS should fundamentally change its operational thinking and implement low-carbon services throughout the operation process. First, it aims to make TS infrastructure construction more low-carbon and environmentally friendly through the use of environmentally friendly, clean, and recyclable materials instead of the original non-renewable raw materials, and to communicate this transformation as one of the promotional materials to tourists through OTA. Second, TS should operate based on more low-carbon and clean energy according to the low-carbon nature of the infrastructure, such as replacing the existing diesel or kerosene-based TS tour buses with electric or tourist-autonomous bicycle models while ensuring safety. Simultaneously, large quantities of high carbon emission items such as billboards, TS maps, and paper tickets will be online and electronic with the help of OTA. Besides, disposable shoe covers and raincoats provided to tourists for a fee will be exchanged for recyclable environmental materials and will be provided to tourists free of charge through post-consumer recycling; therefore, it could not only reduce tourist costs but also avoid the production of non-degradable waste. Meanwhile, electronic guides can gradually be made to replace manual guides, avoiding unnecessary carbon footprint. Moreover, TS should focus on creating a low-carbon tourism attraction that not only conforms to the TS culture but also demonstrates its value to attract consumers.

The main role of OTA is to act as a bridge between TS and the tourists to intelligently recommend more low-carbon and complete tourism solutions to the tourists through big data marketing technology and provide timely feedback to TS on the tourists' post-tour suggestions at the same time to continuously improve TS's low-carbon service capability. Particularly, OTA should widely integrate all aspects of the tourists' travel process. 1) Travel mode: the travel mode is recommended intelligently according to the tourists' image, and the carbon emissions of the travel mode are displayed to the tourists; the recommended order is walking > cycling > train > private car > airplane. 2) Hotel accommodation: the low-carbon accommodation with five-leaf environmental protection certification is recommended to the tourists first, and the low-carbon construction of cooperative hotels is also guided; the low-carbon accommodation concept is popularized to the tourists, such as bringing their toiletries and avoiding the use of disposable toiletries. 3) Travel route planning: low-carbon travel routes are designed and recommended for tourists through the information sharing of TS, and a post-experience evaluation system is opened for the tourists to feedback their suggestions to TS to make continuous improvement. 4) A reasonable membership mechanism is established for tourists, and the tourists are provided points through their acceptance of low-carbon travel mode accordingly; people who have not reached the points limit provide TS environmental activities such as tree planting experience.

The results of the above analysis can summarize the ideal operating model of the low-carbon smart tourism supply chain empowered by big data, as illustrated in Fig. 6.



(a) low-carbon service level of TS

(b) big-data marketing effort of OTA

(c) online demand

(d) offline demand

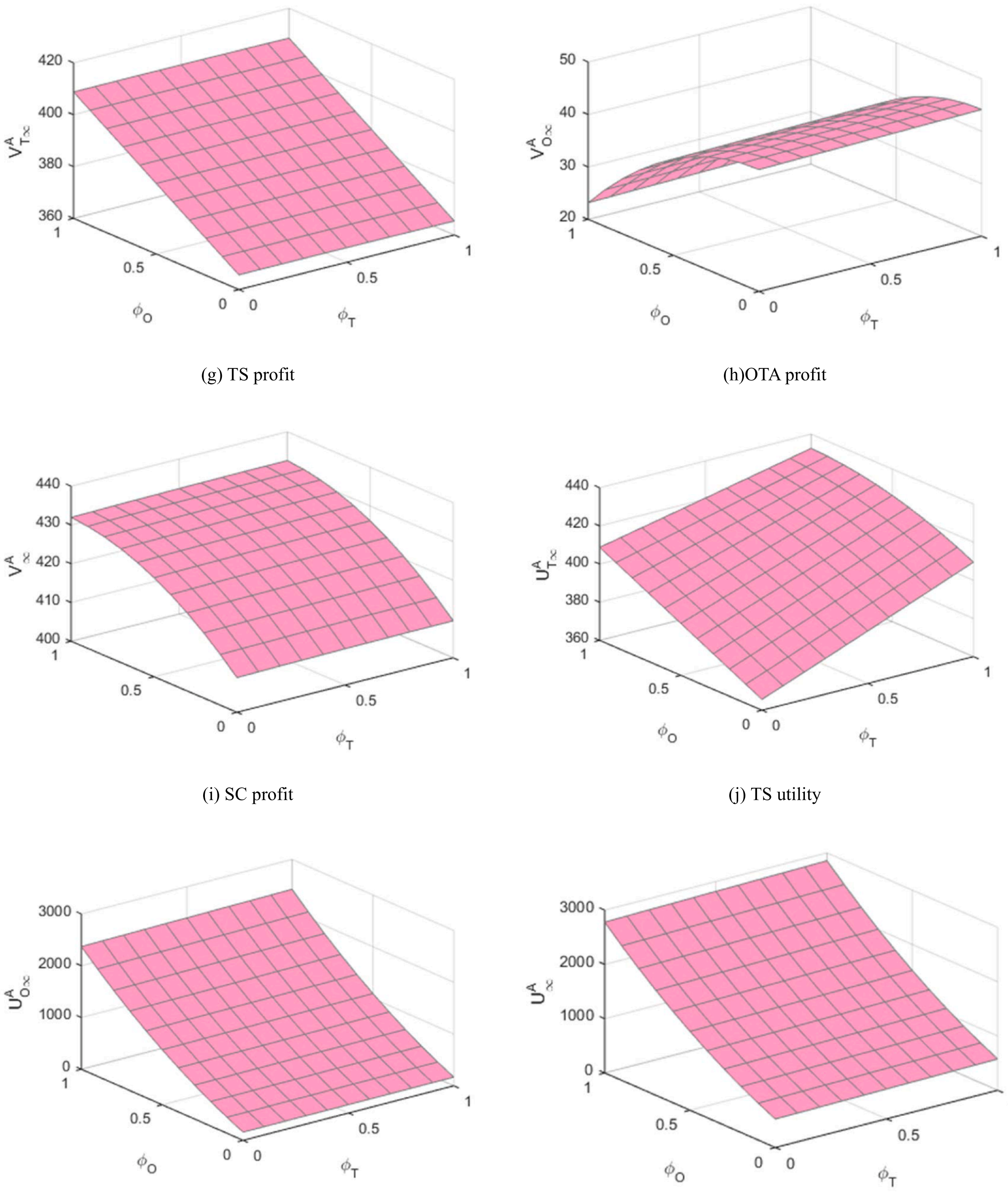
(e) full demand

(f) low-carbon goodwill

Fig. 5. The effects of factors ϕ_T, ϕ_O on the firm's optimal decision and performance.

7. Conclusions and managerial implications

In the context of big data-enabled low-carbon smart tourism, an O2O low-carbon tourism supply chain consisting of a TS that provides low-carbon services and an OTA providing big-data marketing efforts are considered in this paper. In the tourism supply chain, the TS can sell tickets to tourists through offline channel or sell tickets online with the help of OTA's big-data marketing technology through commission sharing. Both of them can make optimal decisions by incorporating the influence on tourists' shopping behavior about low-carbon service levels and channel preferences. Besides, a model of altruistic decision-making by TS and OTA with altruistic behavioral preferences is further proposed using the upper and lower bounds of decentralized and centralized decision making as a reference to promote low carbon sustainable discovery in the tourism supply chain. With the help of Bertelsmann's continuous dynamic planning theory, the optimal decision making and performance of the firm in three decision modes are solved. Through a comparative analysis, the effectiveness of the altruistic decision-making model for deepening member collaboration and coordination of the low-carbon tourism supply chain is tested and verified. Moreover, the impact



(g) TS profit (h)OTA profit

(i) SC profit (j) TS utility

(k) OTA utility (l) SC utility

Fig. 5. (*continued*).

of consumer channel preferences and corporate altruistic preferences on optimal decision making and profits and the important role of big data empowerment for the sustainable development of low-carbon tourism supply chains are further analyzed using numerical examples. Furthermore, the main contributions and conclusions of the paper are summarized below.

(1) The impact of big data marketing techniques on the sustainability of low-carbon tourism supply chains in an era of booming information technology is explored from a dynamic perspective. The study found that OTA with big data marketing technology is an indispensable bridge between tourists and TS. It integrates ticket ordering and all aspects of food, clothing, accommodation, and entertainment during the tour, and can not only share the factual information of TS and make intelligent and personalized recommendations on low-carbon tourism with the help of accurate images of tourists and promote the environmental protection concept behind low-carbon tourism to tourists but also provide real-time feedback to TS on tourists' comments and suggestions after visiting TS to promote the improvement of TS low-carbon service level. Although TS's traditional business model has been hit and profits have been reduced accordingly in the primary stage of big data empowerment, it will not only tap a greater market potential and completely change the traditional tourism

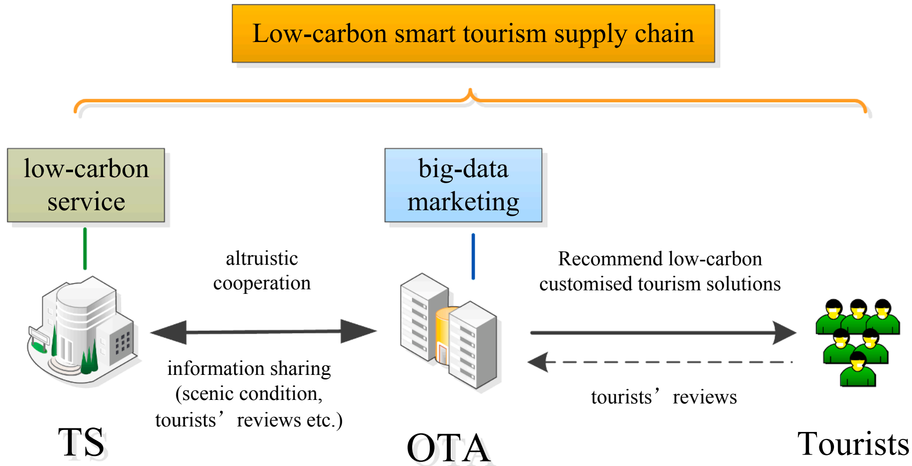


Fig. 6. The ideal operating status of the low-carbon smart tourism supply chain empowered by big data.

business model and find new profit growth points for TS but also find a more low-carbon, sustainable, and intelligent development path for the future of tourism supply chain with the deepening of online big data marketing's empowerment of low-carbon tourism supply chain.

(2) In the age of booming communication technology, consumer's access to information has become richer and more diversified, which results in a wider variety of options. Therefore, any business decision cannot be made without consideration of consumer shopping behavior. Tourism is a typical experiential-based service industry, and the consumer's reference service effect directly influences the enterprise's brand reputation and market demand. In the process of decarbonization of the tourism supply chain, the consideration of tourists' reference low-carbon service efficiency can enable TS and OTA to make decisions more in line with the market operation. This can be seen as consumers' supervision of TS low-carbon construction. Besides, the tourism supply chain will strive to improve its online and offline service levels to obtain the positive impact of this reference effect on demand. Therefore, consumers will have a lower-carbon tourism experience than expected, and the growth of low-carbon goodwill will be achieved. Meanwhile, potential tourist groups will form new and higher low-carbon expectations based on the new and higher low-carbon goodwill, resulting in forming a virtuous circle and stimulating low-carbon, efficient, and sustainable development of the tourism supply chain.

(3) Given that big data empowerment enables the low-carbon tourism bemome smarter, the fully consideration of tourists' behavior can enterprises make their decisions more in line with the actual operation of the market. Meanwhile, altruistic behavior is further incorporated into the decision-making process of enterprises in this paper. The study reveals that the altruistic preference between TS and OTA can not only improve the low-carbon goodwill of TS and environmental benefits but also bring a better experience to tourists through the construction of TS low-carbon tourism, leading to promoting the sustainable development of TS and increasing the number of visitors to TS to make itself more profitable.

To sum up, TS and OTA should also change the concept of competition in the traditional business model, make full use of the dividend of big data empowerment, carry out the real sense of strategic cooperation with altruistic decision-making behavior, improve the operation efficiency and service quality of low-carbon tourism supply chain through digital technology, work together to eliminate the misunderstanding of tourists about low-carbon tourism, and provide tourists with a good tourism experience by constantly improving the low-carbon service level of offline TS. Meanwhile, they should accelerate the continuous improvement of online big data marketing technology, position consumer preferences more precisely, and realize the customized and personalized low-carbon tourism program push. Therefore, tourists can feel that low-carbon tourism is a more experiential, efficient, and environmentally friendly tourism mode instead of at the expense of reducing tourism quality.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

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Appendix A

Proofo f Proposition 1.. According to the optimal control problem equation (7) and the Bellman continuum dynamic planning theory, there exists a continuously differentiable value function $V^C \geqslant 0$ satisfying Hamilton-Jacobi-Bellman(hereafter abbreviated as the HJB) function under Model-C that can be expressed as

$$rV^C = \max_{S(\cdot),B(\cdot)} \left\{ \begin{array}{c} (\pi_{TO} + \pi_O)\chi[D_0 + \lambda_O B + \lambda_T S + (\theta - \lambda_T \xi)G - \beta_O p_O] + \\ \pi_T(1-\chi)[D_0 + \mu_T S + (\theta - \mu_T \xi)G - \beta_T p_T] - \frac{1}{2}k_O B^2 - \frac{1}{2}k_T S^2 + V^{C'}[\gamma_O B + \gamma_T S - \delta G(t)] \end{array} \right\} \tag{A.1}$$

where V^C represents the optimal value function of the system under model C, and represents the total profit of the system during the planning period. $V^{C'}$ denotes the first partial derivatives of its value function with respect to low-carbon goodwill, which indicated the marginal contribution of low-carbon goodwill unit changes to overall profits.

The first-order optimality condition from the right end of the equation (A.1) gives that

$$\begin{cases} S = \dfrac{(\pi_{TO}+\pi_O)\chi\lambda_T + \pi_T(1-\chi)\mu_T + \gamma_T V^{C'}}{k_T} \\ B = \dfrac{(\pi_{TO}+\pi_O)\chi\lambda_O + \gamma_O V^{C'}}{k_O} \end{cases} \tag{A.2}$$

Substitute (A.2) into the HJB equation (A.1) and obtain

$$\begin{aligned} rV^C = {} & (\pi_{TO}+\pi_O)\chi\left[D_0 + \frac{(\pi_{TO}+\pi_O)\chi\lambda_O^2 + \gamma_O\lambda_O V^{C'}}{k_O} + \frac{(\pi_{TO}+\pi_O)\chi\lambda_T^2 + \pi_T(1-\chi)\mu_T\lambda_T + \gamma_T\lambda_T V^{C'}}{k_T} + (\theta-\lambda_T\xi)G - \beta_O p_O\right] + \\ & \pi_T(1-\chi)\left[D_0 + \frac{(\pi_{TO}+\pi_O)\chi\lambda_T\mu_T + \pi_T(1-\chi)\mu_T^2 + \gamma_T\mu_T V^{C'}}{k_T} + (\theta-\mu_T\xi)G - \beta_T p_T\right] \\ & -\frac{1}{2k_O}\left[(\pi_{TO}+\pi_O)\chi\lambda_O + \gamma_O V^{C'}\right]^2 - \frac{1}{2k_T}\left[(\pi_{TO}+\pi_O)\chi\lambda_T + \pi_T(1-\chi)\mu_T + \gamma_T V^{C'}\right]^2 \\ & + V^{C'}\left[\frac{(\pi_{TO}+\pi_O)\chi\gamma_O\lambda_O + \gamma_O^2 V^{C'}}{k_O} + \frac{(\pi_{TO}+\pi_O)\chi\gamma_T\lambda_T + \pi_T(1-\chi)\gamma_T\mu_T + \gamma_T^2 V^{C'}}{k_T} - \delta G\right] \end{aligned} \tag{A.3}$$

According to the structure of equation (A.3), it is supposed that the optimal value function under Model-C takes the form $V^C = l_1 G + l_2$, where l_1, $l_2 > 0$ are the pending coefficients of the value function. Further substituting the optimal value function into the HJB equation (A.3), and the pending coefficients can be obtained according to the constant relationship:

$$\begin{aligned} l_1 = {} & \frac{(\theta-\lambda_T\xi)}{r+\delta}\left[(\pi_{TO}+\pi_O)\chi + \pi_T(1-\chi)\right] \\ l_2 = {} & \frac{(\pi_{TO}+\pi_O)\chi}{r}\left[D_0 + \frac{(\pi_{TO}+\pi_O)\chi\lambda_O^2 + \gamma_O\lambda_O l_1}{k_O} + \frac{(\pi_{TO}+\pi_O)\chi\lambda_T^2 + \pi_T(1-\chi)\mu_T\lambda_T + \gamma_T\lambda_T l_1}{k_T} - \beta_O p_O\right] + \\ & \frac{\pi_T(1-\chi)}{r}\left[D_0 + \frac{(\pi_{TO}+\pi_O)\chi\lambda_T\mu_T + \pi_T(1-\chi)\mu_T^2 + \gamma_T\mu_T l_1}{k_T} - \beta_T p_T\right] \\ & -\frac{1}{2rk_O}\left[(\pi_{TO}+\pi_O)\chi\lambda_O + \gamma_O l_1\right]^2 - \frac{1}{2rk_T}\left[(\pi_{TO}+\pi_O)\chi\lambda_T + \pi_T(1-\chi)\mu_T + \gamma_T l_1\right]^2 \\ & + \frac{l_1}{r}\left[\frac{(\pi_{TO}+\pi_O)\chi\gamma_O\lambda_O + \gamma_O^2 l_1}{k_O} + \frac{(\pi_{TO}+\pi_O)\chi\gamma_T\lambda_T + \pi_T(1-\chi)\gamma_T\mu_T + \gamma_T^2 l_1}{k_T}\right] \end{aligned} \tag{A.4}$$

The optimal decisions are obtained by substituting the pending factor into equation (A.2)

$$\begin{aligned} S^C &= \frac{(\pi_{TO}+\pi_O)\chi\lambda_T + \pi_T(1-\chi)\mu_T + \gamma_T l_1}{k_T} \\ B^C &= \frac{(\pi_{TO}+\pi_O)\chi\lambda_O + \gamma_O l_1}{k_O} \end{aligned} \tag{A.5}$$

By substituting the optimal decision equation (A.5) into the low-carbon goodwill dynamics equation (1) and solving for this first-order linear differential equation, it can be obtained that$G^C(t) = e^{-\delta t}\left[G_0 - G_\infty^C\right] + G_\infty^C$, where

$G_\infty^C = \frac{1}{\delta}\left[\frac{(\pi_{TO}+\pi_O)\chi\gamma_O\lambda_O + \gamma_O^2 l_1}{k_O} + \frac{(\pi_{TO}+\pi_O)\chi\gamma_T\lambda_T + \pi_T(1-\chi)\gamma_T\mu_T + \gamma_T^2 l_1}{k_T}\right]$. ■

Appendix B

Proof of Proposition 2. The proof process of proposition 2 is similar to that of Proposition 1, with the difference that the HJB equations for TS and OTA are written separately as follows.

$$\begin{cases} rV_T^N = \max\limits_{S(\cdot)}\left\{\begin{array}{c} \pi_{TO}\chi[D_0 + \lambda_O B + \lambda_T S + (\theta-\lambda_T\xi)G - \beta_O p_O] + \pi_T(1-\chi)[D_0 + \mu_T S + (\theta-\mu_T\xi)G - \beta_T p_T] \\ -\frac{1}{2}k_T S^2 + V_T^{N'}[\gamma_O B + \gamma_T S - \delta G] \end{array}\right\} \\ rV_O^N = \max\limits_{B(\cdot)}\left\{\pi_O\chi[D_0 + \lambda_O B + \lambda_T S + (\theta-\lambda_T\xi)G - \beta_O p_O] - \frac{1}{2}k_O B^2 + V_O^{N'}[\gamma_O B + \gamma_T S - \delta G]\right\} \end{cases} \tag{B.1}$$

where V_T^N and V_O^N indicate the total profits of TS and OTA in model N respectively, $V_T^{N'}$ and $V_O^{N'}$ are the first partial derivatives of its value function with respect to low-carbon goodwill respectively. According to the first-order optimality condition on the right hand side of the equation (B.1), it can be obtained

$$\begin{cases} S = \dfrac{\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \gamma_T V_T^{N'}}{k_T} \\ B = \dfrac{\pi_O\chi\lambda_O + \gamma_O V_O^{N'}}{k_O} \end{cases} \tag{B.2}$$

In order to further solve the specific expression of the optimal value function, we substitute equation (B.2) into equation (B.1) to obtain the system of equations about the value function.

$$\begin{cases} rV_T^N = \left\{ \begin{aligned} &\pi_{TO}\chi\left[D_0 + \lambda_O\frac{\pi_O\chi\lambda_O + \gamma_O V_O^{N'}}{k_O} + \lambda_T\frac{\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \gamma_T V_T^{N'}}{k_T} + (\theta - \lambda_T\xi)G - \beta_O p_O\right] \\ &+\pi_T(1-\chi)\left[D_0 + \mu_T\frac{\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \gamma_T V_T^{N'}}{k_T} + (\theta - \mu_T\xi)G - \beta_T p_T\right] \\ &-\frac{1}{2}k_T\left(\frac{\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \gamma_T V_T^{N'}}{k_T}\right)^2 + V_T^{N'}\left[\gamma_O\frac{\pi_O\chi\lambda_O + \gamma_O V_O^{N'}}{k_O} + \gamma_T\frac{\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \gamma_T V_T^{N'}}{k_T} - \delta G\right] \end{aligned} \right\} \\ rV_O^N = \left\{ \begin{aligned} &\pi_O\chi\left[D_0 + \lambda_O\frac{\pi_O\chi\lambda_O + \gamma_O V_O^{N'}}{k_O} + \lambda_T\frac{\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \gamma_T V_T^{N'}}{k_T} + (\theta - \lambda_T\xi)G - \beta_O p_O\right] \\ &-\frac{1}{2}k_O\left(\frac{\pi_O\chi\lambda_O + \gamma_O V_O^{N'}}{k_O}\right)^2 + V_O^{N'}\left[\gamma_O\frac{\pi_O\chi\lambda_O + \gamma_O V_O^{N'}}{k_O} + \gamma_T\frac{\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \gamma_T V_T^{N'}}{k_T} - \delta G\right] \end{aligned} \right\} \end{cases} \tag{B.3}$$

And according to the structure of equation (B.3), it is supposed that the optimal value functions under Model-N take the form $V_T^N = f_1G + f_2, V_O^N = g_1G + g_2$, where f_1, f_2, g_1, g_2 are the pending coefficients of the value functions. Further substituting the optimal value functions into the HJB equation (B.3), and the pending coefficients can be obtained according to the constant relationship:

$$\begin{cases} f_1 = \dfrac{[\pi_{TO}\chi + \pi_T(1-\chi)](\theta - \mu_T\xi)}{r+\delta} \\ f_2 = \dfrac{\pi_{TO}\chi}{r}\left[D_0 + \dfrac{\pi_O\chi\lambda_O^2 + \gamma_O\lambda_O g_1}{k_O} + \dfrac{\pi_{TO}\chi\lambda_T^2 + \pi_T(1-\chi)\lambda_T\mu_T + \gamma_T\lambda_T f_1}{k_T} - \beta_O p_O\right] \\ \quad + \dfrac{\pi_T(1-\chi)}{r}\left[D_0 + \dfrac{\pi_{TO}\chi\lambda_T\mu_T + \pi_T(1-\chi)\mu_T^2 + \gamma_T\mu_T f_1}{k_T} - \beta_T p_T\right] \\ \quad -\dfrac{1}{2rk_T}[\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \gamma_T f_1]^2 + \dfrac{f_1}{r}\left[\dfrac{\pi_O\chi\gamma_O\lambda_O + \gamma_O^2 g_1}{k_O} + \dfrac{\pi_{TO}\chi\gamma_T\lambda_T + \pi_T(1-\chi)\gamma_T\mu_T + \gamma_T^2 f_1}{k_T}\right] \\ \begin{cases} g_1 = \dfrac{\pi_O\chi(\theta - \lambda_T\xi)}{r+\delta} \\ g_2 = \dfrac{\pi_O\chi}{r}\left[D_0 + \dfrac{\pi_O\chi\lambda_O^2 + \gamma_O\lambda_O g_1}{k_O} + \dfrac{\pi_{TO}\chi\lambda_T^2 + \pi_T(1-\chi)\lambda_T\mu_T + \gamma_T\lambda_T f_1}{k_T} - \beta_O p_O\right] \\ \quad -\dfrac{1}{2rk_O}[\pi_O\chi\lambda_O + \gamma_O g_1]^2 + \dfrac{g_1}{r}\left[\dfrac{\pi_O\chi\gamma_O\lambda_O + \gamma_O^2 g_1}{k_O} + \dfrac{\pi_{TO}\chi\gamma_T\lambda_T + \pi_T(1-\chi)\gamma_T\mu_T + \gamma_T^2 f_1}{k_T}\right] \end{cases} \end{cases} \tag{B.4}$$

Furthermore, we can obtain the specific decision set, through the function relationship in the expression (B.2)

$$\begin{cases} S^N = \dfrac{\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \gamma_T f_1}{k_T} \\ B^N = \dfrac{\pi_O\chi\lambda_O + \gamma_O g_1}{k_O} \end{cases}$$

And further obtain the time trajectory of low-carbon goodwill $G^N(t) = e^{-rt}\left(G_0 - G_\infty^N\right) + G_\infty^N, G_\infty^N = \frac{1}{\delta}\left[\frac{\pi_O\chi\gamma_O\lambda_O + \gamma_O^2 g_1}{k_O} + \frac{\pi_{TO}\chi\gamma_T\lambda_T + \pi_T(1-\chi)\gamma_T\mu_T + \gamma_T^2 f_1}{k_T}\right]$ and corporate profits. $V_T^N = f_1G^N + f_2, V_O^N = g_1G^N + g_2$. ■

Appendix C. .

Proof of Proposition. The process of solving the optimal utility value of U_T^A, U_O^A is similar to the process of solving the optimal value function in Proposition 1 and 2. First of all, we list the HJB equations of both firms as follows

$$rU_T^A = \max_{S(\cdot)} \left\{ \begin{array}{c} \pi_{TO}\chi[D_0 + \lambda_O B + \lambda_T S + (\theta - \lambda_T \xi)G - \beta_O p_O] + \pi_T(1-\chi)[D_0 + \mu_T S + (\theta - \mu_T \xi)G - \beta_T p_T] - \frac{1}{2}k_T S^2 \\ +\phi_T \left[\pi_O \chi[D_0 + \lambda_O B + \lambda_T S + (\theta - \lambda_T \xi)G - \beta_O p_O] - \frac{1}{2}k_O B^2 \right] \\ +V_T^{A'}[\gamma_O B + \gamma_T S - \delta G] \end{array} \right\}$$

$$rU_O^A = \max_{B(\cdot)} \left\{ \begin{array}{c} \pi_O \chi[D_0 + \lambda_O B + \lambda_T S + (\theta - \lambda_T \xi)G - \beta_O p_O] - \frac{1}{2}k_O B^2 \\ +\phi_O \left[\pi_{TO}\chi[D_0 + \lambda_O B + \lambda_T S + (\theta - \lambda_T \xi)G - \beta_O p_O] + \pi_T(1-\chi)[D_0 + \mu_T S + (\theta - \mu_T \xi)G - \beta_T p_T] - \frac{1}{2}k_T S^2 \right] \\ +V_O^{A'}[\gamma_O B + \gamma_T S - \delta G] \end{array} \right\} \tag{C.1}$$

In contrast to propositions 1 and 2, here, the optimal value function U_T^A and U_O^A represent the altruistic utility of TS and OTA, respectively. The rest of the solution process is the same as the previous propositional proof process, which will not be repeated here. We set $U_T^A = m_1 G + m_2, U_O^A = n_1 G + n_2$. And the corresponding expression of the optimal function coefficient of utility is directly given.

$$m_1 = \frac{\pi_{TO}\chi(\theta - \lambda_T \xi) + \pi_T(1-\chi)(\theta - \mu_T \xi) + \phi_T \pi_O \chi(\theta - \lambda_T \xi)}{r + \delta}$$

$$\begin{aligned} m_2 = {} & \frac{\pi_{TO}\chi}{r}\left[D_0 + \frac{\pi_O\chi\lambda_O^2 + \phi_O\pi_{TO}\chi\lambda_O^2 + \gamma_O\lambda_O n_1}{k_O} + \frac{\pi_{TO}\chi\lambda_T^2 + \pi_T(1-\chi)\lambda_T\mu_T + \phi_T\pi_O\chi\lambda_T^2 + \gamma_T\lambda_T m_1}{k_T} - \beta_O p_O\right] \\ & + \frac{\pi_T(1-\chi)}{r}\left[D_0 + \mu_T\frac{\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \phi_T\pi_O\chi\lambda_T + \gamma_T m_1}{k_T} - \beta_T p_T\right] - \frac{1}{2rk_T}[\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \phi_T\pi_O\chi\lambda_T + \gamma_T m_1]^2 \\ & + \phi_T \left[\begin{array}{c} \frac{\pi_O\chi}{r}\left[D_0 + \frac{\pi_O\chi\lambda_O^2 + \phi_O\pi_{TO}\chi\lambda_O^2 + \gamma_O\lambda_O n_1}{k_O} + \frac{\pi_{TO}\chi\lambda_T^2 + \pi_T(1-\chi)\lambda_T\mu_T + \phi_T\pi_O\chi\lambda_T^2 + \gamma_T\lambda_T m_1}{k_T} - \beta_O p_O\right] \\ -\frac{1}{2rk_O}[\pi_O\chi\lambda_O + \phi_O\pi_{TO}\chi\lambda_O + \gamma_O n_1]^2 \end{array} \right] \\ & + \frac{m_1}{r}\left[\frac{\pi_O\chi\gamma_O\lambda_O + \phi_O\pi_{TO}\chi\gamma_O\lambda_O + \gamma_O^2 n_1}{k_O} + \frac{\pi_{TO}\chi\gamma_T\lambda_T + \pi_T(1-\chi)\gamma_T\mu_T + \phi_T\pi_O\chi\gamma_T\lambda_T + \gamma_T^2 m_1}{k_T}\right] \end{aligned}$$

$$n_1 = \frac{\pi_O\chi(\theta - \lambda_T\xi) + \phi_O[\pi_{TO}\chi(\theta - \lambda_T\xi) + \pi_T(1-\chi)(\theta - \mu_T\xi)]}{r + \delta}$$

$$\begin{aligned} n_2 = {} & \frac{\pi_O\chi}{r}\left[D_0 + \frac{\pi_O\chi\lambda_O^2 + \phi_O\pi_{TO}\chi\lambda_O^2 + \gamma_O\lambda_O n_1}{k_O} + \frac{\pi_{TO}\chi\lambda_T^2 + \pi_T(1-\chi)\lambda_T\mu_T + \phi_T\pi_O\chi\lambda_T^2 + \gamma_T\lambda_T m_1}{k_T} - \beta_O p_O\right] \\ & - \frac{1}{2rk_O}[\pi_O\chi\lambda_O + \phi_O\pi_{TO}\chi\lambda_O + \gamma_O n_1]^2 \\ & + \phi_O \left[\begin{array}{c} \frac{\pi_{TO}\chi}{r}\left[D_0 + \frac{\pi_O\chi\lambda_O^2 + \phi_O\pi_{TO}\chi\lambda_O^2 + \gamma_O\lambda_O n_1}{k_O} + \frac{\pi_{TO}\chi\lambda_T^2 + \pi_T(1-\chi)\lambda_T\mu_T + \phi_T\pi_O\chi\lambda_T^2 + \gamma_T\lambda_T m_1}{k_T} - \beta_O p_O\right] \\ + \frac{\pi_T(1-\chi)}{r}\left[D_0 + \mu_T\frac{\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \phi_T\pi_O\chi\lambda_T + \gamma_T m_1}{k_T} - \beta_T p_T\right] \\ -\frac{1}{2rk_T}[\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \phi_T\pi_O\chi\lambda_T + \gamma_T m_1]^2 \end{array} \right] \\ & + \frac{n_1}{r}\left[\frac{\pi_O\chi\gamma_O\lambda_O + \phi_O\pi_{TO}\chi\gamma_O\lambda_O + \gamma_O^2 n_1}{k_O} + \frac{\pi_{TO}\chi\gamma_T\lambda_T + \pi_T(1-\chi)\gamma_T\mu_T + \phi_T\pi_O\chi\gamma_T\lambda_T + \gamma_T^2 m_1}{k_T}\right] \end{aligned} \tag{C.2}$$

And the optimal decision and time trajectory of low-carbon goodwill can also be obtained.

$$\begin{cases} S^A = \frac{\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \phi_T\pi_O\chi\lambda_T + \gamma_T m_1}{k_T} \\ B^A = \frac{\pi_O\chi\lambda_O + \phi_O\pi_{TO}\chi\lambda_O + \gamma_O n_1}{k_O} \end{cases} \tag{C.3}$$

$$\begin{cases} G^A(t) = e^{-rt}\left(G_0 - G_\infty^A\right) + G_\infty^A \\ G_\infty^A = \frac{1}{\delta}\frac{\pi_O\chi\gamma_O\lambda_O + \phi_O\pi_{TO}\chi\gamma_O\lambda_O + \gamma_O^2 n_1}{k_O} + \frac{\pi_{TO}\chi\gamma_T\lambda_T + \pi_T(1-\chi)\gamma_T\mu_T + \phi_T\pi_O\chi\gamma_T\lambda_T + \gamma_T^2 m_1}{k_T} \end{cases} \tag{C.4}$$

It is worth pointing out that the profit in the altruistic decision-making mode needs to be further solved. Set the TS and OTA profit value function $V_T^A = u_1G^A + u_2; V_O^A = v_1G^A + v_2$, respectively, where $u_1, u_2, v_1, v_2 > 0$ are pending coefficients. List the HJB equations for TS and OTA optimal values, and substitute the optimal decision S^A, B^A (C.3) and low-carbon goodwill G^A(C.4) into it the profit value funcions to obtain

$$r\left(u_1G^A + u_2\right) = \pi_{TO}\chi\left[D_0 + \frac{\lambda_O(\pi_O\chi\lambda_O + \phi_O\pi_{TO}\chi\lambda_O + \gamma_On_1)}{k_O} + \frac{\lambda_T(\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \phi_T\pi_O\chi\lambda_T + \gamma_Tm_1)}{k_T} + (\theta - \lambda_T\xi)G^A - \beta_Op_O\right]$$
$$+\pi_T(1-\chi)\left[D_0 + \frac{\mu_T(\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \phi_T\pi_O\chi\lambda_T + \gamma_Tm_1)}{k_T} + (\theta - \mu_T\xi)G^A - \beta_Tp_T\right] - \frac{1}{2k_T}(\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \phi_T\pi_O\chi\lambda_T + \gamma_Tm_1)^2$$
$$+u_1\left[\frac{\gamma_O(\pi_O\chi\lambda_O + \phi_O\pi_{TO}\chi\lambda_O + \gamma_On_1)}{k_O} + \frac{\gamma_T(\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \phi_T\pi_O\chi\lambda_T + \gamma_Tm_1)}{k_T} - \delta G^A\right]$$
$$r\left(v_1G^A + v_2\right) = \pi_O\chi\left[D_0 + \frac{\lambda_O(\pi_O\chi\lambda_O + \phi_O\pi_{TO}\chi\lambda_O + \gamma_On_1)}{k_O} + \frac{\lambda_T(\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \phi_T\pi_O\chi\lambda_T + \gamma_Tm_1)}{k_T} + (\theta - \lambda_T\xi)G^A - \beta_Op_O\right]$$
$$-\frac{1}{2k_O}(\pi_O\chi\lambda_O + \phi_O\pi_{TO}\chi\lambda_O + \gamma_On_1)^2$$
$$+v_1\left[\frac{\gamma_O(\pi_O\chi\lambda_O + \phi_O\pi_{TO}\chi\lambda_O + \gamma_On_1)}{k_O} + \frac{\gamma_T(\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \phi_T\pi_O\chi\lambda_T + \gamma_Tm_1)}{k_T} - \delta G^A\right]$$

According to the constant relationship at both ends of the equation, the pending coefficient of the profit value function can be found.

$$u_1 = \frac{\pi_{TO}\chi(\theta - \lambda_T\xi) + \pi_T(1-\chi)(\theta - \mu_T\xi)}{r+\delta}$$
$$u_2 = \frac{\pi_{TO}\chi}{r}\left[D_0 + \frac{\lambda_O(\pi_O\chi\lambda_O + \phi_O\pi_{TO}\chi\lambda_O + \gamma_On_1)}{k_O} + \frac{\lambda_T(\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \phi_T\pi_O\chi\lambda_T + \gamma_Tm_1)}{k_T} - \beta_Op_O\right]$$
$$+\frac{\pi_T(1-\chi)}{r}\left[D_0 + \frac{\mu_T(\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \phi_T\pi_O\chi\lambda_T + \gamma_Tm_1)}{k_T} - \beta_Tp_T\right] - \frac{1}{2rk_T}(\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \phi_T\pi_O\chi\lambda_T + \gamma_Tm_1)^2$$
$$+\frac{u_1}{r}\left[\frac{\gamma_O(\pi_O\chi\lambda_O + \phi_O\pi_{TO}\chi\lambda_O + \gamma_On_1)}{k_O} + \frac{\gamma_T(\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \phi_T\pi_O\chi\lambda_T + \gamma_Tm_1)}{k_T}\right]$$
$$v_1 = \frac{\pi_O\chi(\theta - \lambda_T\xi)}{r+\delta}$$
$$v_2 = \frac{\pi_O\chi}{r}\left[D_0 + \frac{\lambda_O(\pi_O\chi\lambda_O + \phi_O\pi_{TO}\chi\lambda_O + \gamma_On_1)}{k_O} + \frac{\lambda_T(\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \phi_T\pi_O\chi\lambda_T + \gamma_Tm_1)}{k_T} - \beta_Op_O\right] - \frac{1}{2rk_O}(\pi_O\chi\lambda_O + \phi_O\pi_{TO}\chi\lambda_O + \gamma_On_1)^2$$
$$+\frac{v_1}{r}\left[\frac{\gamma_O(\pi_O\chi\lambda_O + \phi_O\pi_{TO}\chi\lambda_O + \gamma_On_1)}{k_O} + \frac{\gamma_T(\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \phi_T\pi_O\chi\lambda_T + \gamma_Tm_1)}{k_T}\right]$$

The results in Corollaries 1–3 are obtained by biasing the optimal decision concerning exogenous parameters, which will not be repeated here. ■

Appendix D. .

Proof of Proposition. From Proposition 1–3, it can be easily obtained that

$$S^C - S^N = \frac{\pi_O\chi\lambda_T + \gamma_T(l_1 - f_1)}{k_T} > 0; S^C - S^A = (1-\phi_T)\left[\frac{\pi_O\chi\lambda_T}{k_T} + \frac{(\theta - \lambda_T\xi)\pi_O\chi\gamma_T}{(r+\delta)k_T}\right] \geqslant 0;$$
$$S^A - S^N = \phi_T\left[\frac{\pi_O\chi\lambda_T}{k_T} + \frac{\pi_O\chi(\theta - \lambda_T\xi)\gamma}{(r+\delta)k_T}\right] \geqslant 0;$$

$$B^C - B^N = \frac{\pi_{TO}\chi\lambda_O + \gamma_O(l_1 - g_1)}{k_O} > 0; B^C - B^A = (1-\phi_O)\left[\frac{\pi_{TO}\chi\lambda_O}{k_O} + \frac{\gamma_O(\theta - \lambda_T\xi)[\pi_{TO}\chi + \pi_T(1-\chi)]}{(r+\delta)k_O}\right] \geqslant 0$$
$$B^A - B^N = \phi_O\left[\frac{\pi_{TO}\chi\lambda_O}{k_O} + \frac{\gamma_O(\theta - \lambda_T\xi)[\pi_{TO}\chi + \pi_T(1-\chi)]}{(r+\delta)k_O}\right] \geqslant 0$$

Proof of Proposition. From Proposition 1–4, it can be easily obtained that

$$G_\infty^C - G_\infty^N = \frac{1}{\delta}\left[\frac{\pi_{TO}\chi\gamma_O\lambda_O + \gamma_O^2(l_1 - g_1)}{k_O} + \frac{\pi_O\chi\gamma_T\lambda_T + \gamma_T^2(l_1 - f_1)}{k_T}\right] > 0$$
$$G_\infty^C - G_\infty^A = \frac{1}{\delta}\left[(1-\phi_O)\gamma_O\left(\frac{\pi_{TO}\chi\lambda_O}{k_O} + \frac{\gamma_O(\theta - \lambda_T\xi)[\pi_{TO}\chi + \pi_T(1-\chi)]}{(r+\delta)k_O}\right) + (1-\phi_T)\gamma_T\left(\frac{\pi_O\chi\lambda_T}{k_T} + \frac{(\theta - \lambda_T\xi)\pi_O\chi\gamma_T}{(r+\delta)k_T}\right)\right] \geqslant 0$$
$$G_\infty^A - G_\infty^N = \frac{1}{\delta}\left[\phi_O\gamma_O\left(\frac{\pi_{TO}\chi\lambda_O}{k_O} + \frac{\gamma_O(\theta - \lambda_T\xi)[\pi_{TO}\chi + \pi_T(1-\chi)]}{(r+\delta)k_O}\right) + \phi_T\gamma_T\left(\frac{\pi_O\chi\lambda_T}{k_T} + \frac{\pi_O\chi(\theta - \lambda_T\xi)\gamma}{(r+\delta)k_T}\right)\right] \geqslant 0$$

Proof of Proposition. As obtained in Proposition1-3, $u_1 = f_1$, $v_1 = g_1$, then

$$V_{T\infty}^{A} - V_{T\infty}^{N} = f_1\left(G_\infty^A - G_\infty^N\right) + \frac{\pi_{TO}\chi}{r}\left[\frac{\phi_O\pi_{TO}\chi\lambda_O^2 + \gamma_O\lambda_O(n_1 - g_1)}{k_O} + \frac{\phi_T\pi_O\chi\lambda_T^2 + \gamma_T\lambda_T(m_1 - f_1)}{k_T}\right]$$

$$+\frac{\pi_T(1-\chi)}{r}\left[\frac{\phi_T\pi_O\chi\mu_T\lambda_T + \gamma_T\mu_T(m_1 - f_1)}{k_T}\right] + \frac{1}{2rk_T}\left[(\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \gamma_T f_1)^2 - (\pi_{TO}\chi\lambda_T + \pi_T(1-\chi)\mu_T + \phi_T\pi_O\chi\lambda_T + \gamma_T m_1)^2\right]$$

$$+\frac{f_1}{r}\left[\frac{\phi_O\pi_{TO}\chi\gamma_O\lambda_O + \gamma_O^2(n_1 - g_1)}{k_O} + \frac{\phi_T\pi_O\chi\gamma_T\lambda_T + \gamma_T^2(m_1 - f_1)}{k_T}\right] \geqslant 0$$

$$V_O^A - V_O^N = g_1\left(G_\infty^A - G_\infty^N\right) + \frac{\pi_O\chi}{r}\left[\frac{\phi_O\pi_{TO}\chi\lambda_O^2 + \gamma_O\lambda_O(n_1 - g_1)}{k_O} + \frac{\phi_T\pi_O\chi\lambda_T^2 + \gamma_T\lambda_T(m_1 - f_1)}{k_T}\right]$$

$$+\frac{1}{2rk_O}\left[(\pi_O\chi\lambda_O + \gamma_O g_1)^2 - (\pi_O\chi\lambda_O + \phi_O\pi_{TO}\chi\lambda_O + \gamma_O n_1)^2\right]$$

$$+\frac{g_1}{r}\left[\frac{\phi_O\pi_{TO}\chi\gamma_O\lambda_O + \gamma_O^2(n_1 - g_1)}{k_O} + \frac{\phi_T\pi_O\chi\gamma_T\lambda_T + \gamma_T^2(m_1 - f_1)}{k_T}\right] \geqslant 0$$

For the relationship of total profits, the proof is expressed as follows

$$V_\infty^C - V_\infty^A = l_1 G_\infty^C + l_2 - (u_1 + v_1)G_\infty^A - u_2 - v_2 = \frac{(\theta - \lambda_T\xi)}{r+\delta}\left[(\pi_{TO} + \pi_O)\chi + \pi_T(1-\chi)\right]\left(G_\infty^C - G_\infty^A\right)$$

$$+\frac{(\pi_{TO} + \pi_O)\chi}{r}\left[\frac{(1-\phi_O)\pi_O\chi\lambda_O^2 + \gamma_O\lambda_O(l_1 - n_1)}{k_O} + \frac{(1-\phi_O)\pi_O\chi\lambda_T^2 + \gamma_T\lambda_T(l_1 - n_1)}{k_T}\right]$$

$$\frac{\pi_T(1-\chi)}{r}\left[\frac{(1-\phi_O)\pi_O\chi\lambda_T\mu_T + \gamma_T\mu_T(l_1 - n_1)}{k_T}\right] + \frac{1}{2rk_O}\left[((\pi_O + \phi_O\pi_{TO})\chi\lambda_O + \gamma_O n_1)^2 - ((\pi_{TO} + \pi_O)\chi\lambda_O + \gamma_O l_1)^2\right] \quad \blacksquare$$

$$+\frac{1}{2rk_T}\left[((\pi_{TO} + \phi_T\pi_O)\chi\lambda_T + \pi_T(1-\chi)\mu_T + \gamma_T m_1)^2 - ((\pi_{TO} + \pi_O)\chi\lambda_T + \pi_T(1-\chi)\mu_T + \gamma_T l_1)^2\right]$$

$$+\frac{(\theta - \lambda_T\xi)}{r(r+\delta)}\left[(\pi_{TO} + \pi_O)\chi + \pi_T(1-\chi)\right]\left[\frac{(1-\phi_O)\pi_{TO}\chi\gamma_O\lambda_O + \gamma_O^2(l_1 - n_1)}{k_O} + \frac{(1-\phi_O)\pi_O\chi\gamma_T\lambda_T + \gamma_T^2(l_1 - n_1)}{k_T}\right] \geqslant 0$$

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