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Full Length Article

Dynamic decision intelligence for pricing and delivery time in sustainable supply chains with strategic consumers

Ata Allah Taleizadeh [a,b], Hossein Choopani [a], Madjid Tavana [c,d,*], Hamidreza Abedsoltan [e]

[a] School of Industrial Engineering, College of Engineering, University of Tehran, Tehran, Iran
[b] Department of Industrial Engineering, Istinye University, Istanbul, Turkey
[c] Business Systems and Analytics Department, Distinguished Chair of Business Analytics, La Salle University, Philadelphia, USA
[d] Business Information Systems Department, Faculty of Business Administration and Economics, University of Paderborn, Paderborn, Germany
[e] The Center for Research in Economics and Management (CREM), University of Rennes, Rennes, France

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ABSTRACT

Understanding the joint effects of consumers' strategic behavior and their sensitivity to delivery time, price, and environmental impact remains a crucial yet underexplored issue in supply chain (SC) management. This study investigates a green SC comprising an online retailer, a manufacturer, and consumers who may behave strategically and value shorter delivery times, lower prices, and reduced carbon emissions. We develop analytical models to determine optimal retail pricing, delivery times, wholesale pricing, and carbon emission reduction strategies. In the first model, retail prices are dynamically adjusted, while delivery time is fixed. In contrast, the second model dynamically quotes both the delivery time and the retail price. The analysis also reveals the economic mechanisms by which delivery time flexibility influences pricing incentives, consumer purchasing behavior, and carbon-reduction decisions within the supply chain. The results indicate that when consumers are susceptible to delivery time but less strategic, a dynamic delivery time strategy enhances the retailer's profit while consistently improving the manufacturer's profit across all scenarios. To further align incentives, we propose a cost-sharing contract in which the manufacturer supports the retailer's delivery system costs. This mechanism improves the profitability of both parties and expands the conditions under which the retailer benefits. The findings provide actionable managerial insights into how delivery time, pricing strategies, and carbon-reduction decisions interact within a green SC context.

1. Introduction

Online retailing has become a dominant channel for retailers worldwide, making the study of pricing decisions in this context increasingly important. These decisions are critical for both members of the supply chain, namely the producer and the online retailer [1]. Profitability in online retailing, however, is not solely determined by price. Delivery time has emerged as a key factor shaping consumer purchasing behavior, leading retailers to invest strategically in their delivery systems [1–4].

At the same time, heightened public concern about climate change has strengthened consumer preference for environmentally friendly products. A prominent measure of environmental impact is the carbon indicator, which reflects CO_2 emissions generated during production. Studies have shown that consumers are increasingly inclined to select products with lower carbon emissions [5].

Consumer demand is also affected by strategic purchasing behavior, where buyers postpone purchases in anticipation of future price reductions. Such consumers exhibit patience and are willing to delay purchases to maximize their surplus [6]. To address this behavior, retailers have adopted strategies such as dynamic pricing, in which prices are adjusted across time periods [7,8], and pre-announced pricing, in which a price schedule is set at the start of the selling season [9,10]. Despite this progress, the literature has yet to consider how delivery time quotation strategies, whether fixed, pre-announced, or dynamic, can be used in conjunction with pricing to manage strategic consumers

* Corresponding author at: Business Systems and Analytics Department, Distinguished Chair of Business Analytics, La Salle University, Philadelphia, PA 19141, United States.

E-mail addresses: taleizadeh@ut.qac.ir (A.A. Taleizadeh), h.choopani@ut.ac.ir (H. Choopani), tavana@lasalle.edu (M. Tavana), hamidreza.abedsoltan@univ-rennes.fr (H. Abedsoltan).

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in online retailing.

Although consumer sensitivities to delivery time and carbon emissions have been studied independently, only a limited number of studies have examined both simultaneously [1,11]. More broadly, prior studies have typically investigated subsets of the key factors influencing supply chain decisions, such as delivery time and pricing decisions or carbon emission reduction and strategic consumer behavior. Consequently, the joint interaction among strategic consumer behavior, delivery-time sensitivity, carbon-emission considerations, and pricing decisions has rarely been analyzed within a unified supply chain framework.

To address this gap, this study develops a unified analytical framework that jointly incorporates consumer sensitivities to delivery time, price, and carbon emissions, as well as strategic purchasing behavior, in a supply chain setting. Considering these dimensions simultaneously provides deeper insights into the interactions among delivery time quotations, strategic waiting behavior, and carbon-emission-reduction decisions. In particular, the interaction between delivery time decisions and strategic consumer behavior alters equilibrium pricing incentives, while consumer sensitivity to carbon emissions affects the manufacturer's optimal carbon-reduction effort and the resulting demand structure. These interactions generate new implications for supply chain profitability, environmental performance, and coordination between manufacturers and retailers.

This paper addresses these gaps by:

- Modeling strategic consumers' sensitivities to delivery time, carbon emissions, and price simultaneously;
- Identifying the optimal dynamic delivery time (DDT) strategy that maximizes supply chain profit;
- Proposing coordination contracts between manufacturers and online retailers to enhance joint profitability.

This study contributes to the literature by developing a game-theoretic framework to analyze supply chain decisions involving strategic consumers who are sensitive to multiple factors, including price, delivery time, and carbon emissions. In particular, the proposed model integrates dynamic pricing and delivery time quotation strategies within a two-echelon supply chain comprising a manufacturer and an online retailer. While prior studies often examine these factors separately, this study incorporates them jointly within a unified analytical framework and evaluates the role of a cost-sharing contract (CSC) in coordinating supply chain decisions. The analysis reveals several important insights. First, allowing delivery time to be dynamically adjusted alters the equilibrium structure of pricing and demand compared with fixed delivery time (FDT) policies. Second, the results show that DDT strategies can increase total demand and consistently benefit the manufacturer, while the retailer's profitability depends on consumer patience and sensitivity to delivery time. Third, the model demonstrates that DDT decisions may also lead to greater carbon emissions reductions, linking operational decisions to environmental outcomes. Finally, the study shows that a cost-sharing contract can align incentives between supply chain members when DDT benefits the manufacturer but not the retailer, thereby improving overall supply chain profitability.

This study advances the existing literature in several important ways. First, from a theoretical perspective, it develops a unified analytical framework that integrates strategic consumer behavior, delivery-time sensitivity, carbon-emission considerations, and pricing decisions. While prior studies typically examine these dimensions in isolation or in partial combinations, this study explicitly models their joint interaction and reveals how these factors collectively shape equilibrium outcomes. Second, from a methodological perspective, the paper integrates dynamic delivery time quotations into a Stackelberg game-theoretic framework with strategic consumers, allowing delivery time to serve as an endogenous decision variable alongside pricing and carbon-reduction efforts. This extends existing models that treat delivery time as exogenous or static. Third, from a managerial perspective, the study identifies conditions under which dynamic delivery time strategies improve supply chain performance and proposes a cost-sharing contract to align incentives among supply chain members. These contributions provide new insights into the design of pricing, logistics, and sustainability strategies in modern e-commerce supply chains. In addition, unlike prior studies, this paper explicitly captures the interaction between delivery time flexibility and strategic consumer waiting behavior, which serves as the central mechanism driving our results.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on delivery time quotations, green supply chains, and strategic consumer behavior. Section 3 develops the base model with FDT and presents the game-theoretic analysis and equilibrium results. Section 4 extends the analysis to the DDT model and derives the corresponding equilibrium solutions. Section 5 compares the outcomes of the FDT and DDT models using numerical experiments. Section 6 introduces a cost-sharing contract designed to coordinate the supply chain and improve joint profitability. Section 7 presents sensitivity analyses and discusses the managerial insights derived from the results. Finally, Section 8 concludes the paper and highlights the limitations and directions for future research.

2. Literature review

In the following subsections, the literature on online retailing is reviewed across three key areas: delivery time quotation, consumer sensitivity to product greenness, and strategic consumer behavior.

2.1. Delivery time

In the literature, delivery lead-time quotation problems may refer to either the time required for product manufacturing, particularly in Make-to-Order (MTO) systems [12], or the time needed to deliver products from retailers or manufacturers to end consumers. In this subsection, the focus is on delivery time to consumers.

Zhao et al. [13] investigate the price and delivery time of two competing online retailers. They considered product returns when products are delivered later or earlier than the promised delivery times. Their results showed that, under certain conditions, when the competitor's product return rate increases, the firm's profit does not increase. A similar counterintuitive conclusion was made by Sun et al. [14]. They studied an SC with multiple sellers competing on price and delivery time. Their results showed that when competition intensity differs across price and delivery time, heightened competition in the weaker dimension (price or delivery time) leads to higher profits for firms. These studies demonstrate that competition on price and delivery time is not necessarily detrimental to firms.

Other researchers have studied supply chain settings with uncertainty and delivery time quotation. Noori-Daryan et al. [15] analyzed an international pharmaceutical supply chain with multiple producers and a single retailer under uncertainty to address time constraints. Using game theory, they compared decentralized, centralized, and cooperative approaches, concluding that decentralization yields the lowest profit, while centralization and cooperation achieve the same higher level of profitability.

The role of third-party logistics providers (3PLs) has also been explored in relation to pricing and delivery strategies. Zhang et al. [16] developed an SC in which the retailer sets prices while the 3PL determines delivery capacity, finding that retailers may strategically lower prices to discourage 3PLs from expanding capacity. In a related context, Ye et al. [17] analyzed an online channel and presented that 3PL capacity critically influences retailer profitability. Their results also suggest that retailers with larger market shares are more likely to benefit from online channels under competitive pressure.

A parallel stream of research has examined dual-channel SCs. Modak and Kelle [18] investigated a system in which producers sell through both a retailer and their own online channel, accounting for demand uncertainty and deriving optimal ordering, delivery time, and pricing decisions, as well as SC coordination mechanisms. Similarly, Xu et al. [19] analyzed a dual-channel setting with a platform-based online channel and demonstrated that wholesale and cost-sharing contracts can coordinate the SC under specific conditions. Karthick and Uthayakumar [20] extended this analysis by incorporating demand uncertainty modeled with trapezoidal fuzzy numbers and validated their framework through numerical experiments.

More recently, studies have focused on integrating dynamic pricing with delivery and operational decisions. Stamer and Lanza [21] proposed a dynamic pricing system that enables customers to choose delivery times and prices according to their preferences. Wang et al. [22] developed a stochastic optimization model that integrates dynamic pricing with demand-driven supply planning to enhance overall SC efficiency. Köhler et al. [23] examined a retailer's pricing and delivery time window decisions, considering both static and dynamic pricing strategies. Leng et al. [24] extended this work by modeling optimal pricing, promised delivery times, and investments in delivery reliability information. In parallel, Wang et al. [25] studied a two-echelon fulfillment system such that demand depends on price, delivery time, and structure of a distribution network, while Yang et al. [26] explored a producer–retailer SC with random demand, in which the producer, acting as a Stackelberg leader, decides delivery times during retailer shortages. Recent studies have increasingly emphasized the role of analytics-driven delivery decisions in carbon-constrained online retail environments. For example, Chen et al. [27] investigate delivery-promise optimization using business analytics approaches under carbon-constrained online retail supply chains, highlighting how delivery commitments interact with environmental considerations and operational efficiency. Their findings reinforce the growing importance of integrating delivery-promise strategies with sustainability objectives and data-driven decision systems. These developments further motivate the analytical examination of delivery-time decisions in environmentally conscious supply chains.

Additional research highlights the interplay between customer preferences, operational constraints, and sustainability considerations. Zhang and Zhang [28] analyzed the effects of dynamic pricing and delivery time strategies in multi-variant production systems, emphasizing the need to balance customer preferences with operational constraints. He et al. [29] investigated optimal delivery strategies and retail pricing in a green SC that incorporates consumer responsiveness to delivery time and carbon emissions. They demonstrated that dynamic strategies can improve both environmental and economic outcomes.

2.2. Green issues and delivery time

Environmental considerations have become increasingly important in supply chain research, particularly in studies examining pricing, carbon emission reduction, and delivery time decisions. Several studies examine how carbon emission regulations influence pricing and delivery time decisions in supply chains [30–33]. However, relatively few studies jointly incorporate pricing and delivery time decisions under environmental considerations. Ding and Jin [34] examined decisions regarding price and delivery time (i.e., service time) for an online retailer subject to carbon taxation. Consumers were assumed to be responsive to price and service time, although not directly to carbon emissions. Their analysis, which incorporated consumer welfare and a carbon compensation index, revealed that carbon taxation plays a critical role in shaping social welfare outcomes. Jamali and Rasti-Barzoki [11] investigated a green SC comprising two producers, one retailer, and a 3PL responsible for delivery. Consumers in their model were sensitive to both product greenness and 3PL carbon emissions, as well as retail price and delivery time.

More recently, He et al. [1] analyzed a manufacturer–retailer SC in which consumers were sensitive to retail delivery and to producers' carbon emissions. Their model simultaneously determined optimal retail and delivery times, wholesale prices, and carbon emission reductions. The study highlighted cross-effects in consumer sensitivities, such as how retail delivery time influenced efforts to reduce emissions. These interdependencies led to a free-rider problem between supply chain members, motivating the authors to propose a cost-sharing contract. Their findings demonstrated that such a contract could enhance profitability for both firms under certain conditions.

2.3. Consumers' strategic behavior

The interaction between pricing and strategic consumer behavior is widely explored, often in combination with other operational or marketing decisions. Prior studies have examined quality adjustment [35,36], advertising [7,37–39], carbon emission reduction [40,41], and delivery time quotation [42] alongside pricing. In line with the scope of this study, we focus on studies that incorporate carbon-emission reduction and delivery-time sensitivity in the context of strategic consumer behavior.

Jiang and Chen [41] considered a producer–retailer supply chain where the producer is subject to cap-and-trade carbon regulations and the retailer faces strategic consumers. Their model determined optimal production, pricing, and carbon trading decisions under both centralized and decentralized structures. Similarly, Che et al. [40] studied a retailer selling to strategic consumers who value low-carbon products. They compared scenarios in which the retailer offers only low-carbon (LC) products versus both regular and LC products, demonstrating how consumer preferences for greenness influence profitability.

Strategic consumer behavior has also been studied in connection with delivery time. Liu et al. [42] analyzed an SC in which a producer introduces an online direct channel, with consumer preference for the channel depending on delivery time. They compared pay-on-delivery and pay-before-delivery schemes, finding that pay-on-delivery yields higher profitability. Lei et al. [10] also examined consumer choice between a direct channel with lead time and an indirect channel with immediate delivery. However, in their model, delivery time was not treated as a decision variable, limiting its managerial implications.

Regardless of the scope of the problems, various strategies were deployed to address consumers' strategic behavior. Dynamic pricing, fixed pricing, and pre-announced pricing are among the most utilized strategies. While these strategies have primarily been used in pricing problems [6], their application to other problems, such as retail delivery time quotation in the presence of strategic consumers, has been largely neglected. Additionally, studies by Chen et al. [43], Jiang et al. [44], Liu [45], Baardman et al. [46], Sadeghi et al. [47], and Allaei et al. [48] explore personalized pricing mechanisms, highlighting the importance of data-driven decision-making in catering to strategic consumers. These advancements underscore the growing sophistication of consumers in navigating the marketplace, prompting businesses to adapt their strategies accordingly. Similarly, Xu and Zheng [49] explore the impact of taste projection on markdown pricing, revealing that consumers' perceptions of others' preferences can influence their own purchasing decisions.

Recent research has increasingly focused on the strategic consumers' behavior in dynamic pricing and SC management. Hou et al. [50] explore pricing strategies incorporating strategic behavior and consumer fairness concerns to optimize supply chain outcomes. Chen and Xu [51] examine dynamic competitive pricing among some retailers, accounting for platform costs and the influence of consumer behavior on decision-making. Yang and Liu [26] analyze optimal pricing strategies in the context of sequential innovation, highlighting implications for closed-loop SC. Wang et al. [52] investigate the role of SC leadership in pricing under information asymmetry regarding consumer patience, emphasizing strategic consumer responses. Yin et al. [53] examine the effects of strategic consumers and direct channels on SC contracting, offering insights into contractual efficiency. Jiang et al. [54] focus on pricing mechanisms with strategic consumers and social learning,

Table 1
Comparison between existing works.

	Variable delivery time	Variable pricing	Consumer green sensitivity	Supply chain context	Strategic consumer behavior	Competition
Zhao et al. [13]	✓					✓
Jiang & Chen [41]		✓	✓	✓	✓	
Zhang & Zhang [33]	✓	✓	✓			✓
Jamali and Rasti-Barzoki [11]	✓		✓	✓		✓
Ding & Jin [34]	✓	✓				
Liu et al. [42]	✓			✓		✓
Sun et al. [14]		✓				✓
He et al. [1]	✓	✓	✓	✓		✓
Leng et al. [24]	✓	✓				
Che et al. [40]		✓	✓			
Yang et al. [26]	✓			✓		
Ye et al. [17]	✓	✓				✓
Wang et al. [25]	✓	✓		✓		
Stamer & Lanza [21]	✓	✓				
Köhler et al. [23]	✓	✓				
This paper	✓	✓	✓	✓	✓	

evaluating contingent pricing and price guarantees. Morlotti and Mantin [55] integrate price strategies into yield management, exploring trade-offs between strategic consumer responsiveness and price fluctuations. Parilina et al. [56] consider dynamic advertising and pricing in SC, where consumers are concerned about fairness and the environment, and exhibit strategic tendencies. Wei et al. [57] assess inventory and pricing strategies, incorporating strategic consumers and cost effects to enhance operational resilience. Zhou and Dai [58] analyze pricing strategies for software vendors, accounting for strategic consumer waiting times and their impact on SC dynamics.

Emerging research has investigated contractual coordination mechanisms in environmentally sensitive e-commerce supply chains involving strategic consumers. Huang et al. [59] develop green innovation contracts for carbon-sensitive e-commerce supply chains in which consumers exhibit strategic waiting behavior, underscoring the importance of aligning environmental investments and consumer response mechanisms through contractual arrangements. Their findings highlight the growing relevance of coordination contracts in sustainable online retailing. While these studies advance understanding of green contractual design and strategic consumer behavior, delivery-time quotation remains largely underexplored as a dynamic strategic decision interacting simultaneously with carbon reduction and consumer waiting behavior. The present study addresses this gap by jointly modeling dynamic delivery-time decisions, pricing, and carbon-emission reduction within a unified analytical framework.

Overall, the existing literature has significantly advanced the understanding of pricing strategies, delivery time quotations, green supply chain decisions, and strategic consumer behavior. However, several limitations remain. First, many studies examine these factors independently or consider only partial combinations of them. For example, some studies focus on pricing and delivery time decisions without considering environmental factors. In contrast, others analyze carbon-emission reduction and green-product strategies without incorporating delivery-time quotations or strategic consumer behavior. Second, several studies treat delivery time as an exogenous parameter rather than a strategic decision variable that interacts with pricing and consumer waiting behavior. Third, the joint impact of delivery time sensitivity, carbon emission reduction decisions, and strategic consumer purchasing behavior within a unified supply chain framework remains relatively underexplored.

To address these limitations, this study develops a unified analytical framework that incorporates dynamic pricing, delivery-time quotation strategies, consumer sensitivity to carbon emissions, and strategic consumer behavior within a two-echelon supply chain. By comparing FDT and DDT strategies, the proposed model provides new insights into how delivery time decisions affect pricing incentives, carbon-reduction efforts, and supply chain coordination mechanisms. The study further proposes a cost-sharing contract that can mitigate incentive misalignment between supply chain members and expand the conditions under which dynamic delivery strategies become beneficial.

In addition to analytical supply chain models, recent research has emphasized the increasing role of digital technologies and advanced analytics in supply chain management. Emerging studies highlight how data-driven and digital technologies can enhance decision-making and coordination in supply chains. For example, Yang et al. [60] investigate how large language models (LLMs) can be integrated into blockchain-based supply chain finance systems to improve information processing and financing efficiency. They show that LLMs' natural-language understanding capabilities can support decision-making and information sharing among supply chain participants on blockchain platforms. Similarly, digital supply chain studies emphasize the growing importance of Industry 4.0 technologies and analytics-driven decision systems in managing complex supply chain environments [61]. In parallel, big data analytics has been shown to significantly improve operational decision-making and firm performance by enabling firms to process large volumes of supply chain data and develop more adaptive strategies [62]. These developments reflect the increasing role of data-driven decision systems in supply chains. While these studies focus on digital infrastructure and coordination mechanisms, they underscore the importance of decision systems in supply chains. The analytical framework developed in this study complements this emerging research stream by focusing on strategic operational decisions related to pricing, delivery time quotations, and environmental performance within a unified supply chain model.

Table 1 summarizes the main characteristics of representative studies in the literature and highlights the research gap this paper addresses.

While prior research has made significant progress in understanding pricing, delivery time decisions, environmental considerations, and strategic consumer behavior, these elements have largely been studied in isolation or in limited combinations. In particular, existing studies typically treat delivery time as an exogenous parameter or examine it independently of strategic consumer behavior. Similarly, research on green supply chains often focuses on pricing and carbon emission reduction without incorporating delivery time quotation as a strategic decision variable.

Table 1 summarizes the key characteristics of representative studies and highlights these gaps. As shown, no prior work has simultaneously considered dynamic delivery-time decisions, strategic consumer behavior, and carbon-emission reduction within a unified analytical framework.

To address this gap, this study introduces a novel mechanism that jointly models delivery-time flexibility and strategic consumer waiting behavior. Specifically, we show how allowing delivery time to be

Table 2
Notations.

Indices	
i	Time periods, $i = 1, 2$
j	Model, j=FDT, DDT, CSC (DDT with Cost-sharing)
Parameters	
v	Valuation of consumer on product, uniform on $[0, 1]$
γ	Consumer's sensitivity to the time of delivery
δ	Sensitivity of consumers to the reduction effort of carbon emissions
φ	Consumer patience factor
r_0	Fixed expense for delivery
r_1	Marginal operational cost for the delivery network
α	The rate of the carbon tax
k	Carbon reduction cost
c	Unit cost of manufacturing the product
Decision variables	
p_i	Retail price within period i
t_i	Promised delivery time in period i
e	The manufacturer's effort to reduce carbon emissions
w	Wholesale price
Dependent variables	
u_i^j	Purchase utility of a consumer in period i of model j
q_i^j	Demand in period i of model j
π_{Ri}^j	Retailer's profit within period i of model j (π_R^j is for the sum of the retailer's profit in two periods)
π_M^j	Manufacturer's profit in model j

* Since in the base model $t_1 = t_2$ so, for convenience, we consider $t_1 = t_2 = t$.

dynamically adjusted alters consumers' intertemporal purchasing decisions, which in turn affect pricing strategies, demand allocation across periods, and incentives for carbon-emission reduction. This interaction generates new equilibrium structures and coordination challenges that are not captured in existing models.

3. Model with fixed delivery time (FDT)

We study an SC comprising a manufacturer and an online retailer that sells a single seasonal item. The manufacturer provides the products to the retailer, who sells and delivers them to end consumers. The selling season is separated into two periods, during which both SC members make their decisions. To capture different strategic settings, we develop two models: an FDT model**,** in which the retailer commits to a single delivery time throughout the season, and a DDT model, in which the retailer may adjust delivery times across periods. This section introduces and analyzes the FDT model.

Consumers have different valuations for the products they purchase, which are uniformly distributed on [0, 1]. The market size is normalized to 1. Consumer preferences are influenced by both the product's delivery time and its carbon footprint during production. Consumers get information about a product's carbon emissions from its carbon label. We model consumers' utility function based on the manufacturer's efforts to reduce CO_2 emissions. Therefore, if the producer increases its efforts to reduce carbon emissions, consumers will derive greater utility. Consumers are also strategic, meaning that, based on their expectations, they may wait to buy an item in the second period to increase their surplus. In other words, consumers' strategic behavior leads them to consider both periods when purchasing the product. We assume consumers have a patience factor of $0 \le \varphi < 1$, which means the utility derived from purchasing the product in period 2 is discounted by the factor 1-φ. If $\varphi = 0$, the consumers are myopic and buy in period 1 if the product is priced below their valuation.

In the base model, the retailer determines price dynamically in two periods; however, the delivery time is defined in the first period and remains fixed throughout both periods. Moreover, the manufacturer statically determines the carbon-reduction efforts and the selling price at the start of period 1 and does not change them throughout the selling season.

Given the descriptions above and using the notations in Table 2, the consumer's utility function is influenced by the purchase period as follows:

$$u_1 = v - p_1 - \gamma t + \delta e \tag{1}$$

$$u_2 = \varphi(v - p_2 - \gamma t + \delta e) \tag{2}$$

The modeling assumptions adopted in this study are consistent with standard practices in the supply chain and pricing literature and reflect key characteristics of real-world e-commerce environments. The assumption of uniformly distributed consumer valuations captures heterogeneous customer preferences in large online markets. Normalizing market size to one enables analytical tractability without loss of generality. The quadratic cost structure for carbon emission reduction reflects increasing marginal costs associated with sustainability investments, which is commonly observed in practice. Similarly, the delivery cost function captures the tradeoff between faster delivery and higher operational costs, reflecting real-world logistics systems in which expedited delivery requires additional resources. These assumptions allow the model to balance analytical solvability with practical interpretability.

To analyze consumers' purchase preferences in both the first and second periods, we use the Hoteling model. Similar approaches have been employed by researchers [14,63,64]. It can be shown that there exists an indifferent consumer, and consumers with a valuation greater than the indifference valuation will purchase the items within period one, and vice versa. In more exact terms, we have *Lemma 1*.

Lemma 1. *If a customer with a valuation v' prefers to purchase a product within period 1, then all customers who have higher value than v' Will also choose to buy in the first period. Conversely, if a customer with valuation v' opts to purchase in period 2; then, all customers with lower valuations will likewise buy in the second period, provided their net utility remains non-negative. As a result, a unique threshold or indifference valuation exists that separates consumers who purchase in period 1 from those who postpone their purchase to the next period.*

Proof. *See Appendix.*

All proofs are presented in the appendices. From *Lemma 1*, we have the indifference valuation $\hat{v} = \frac{p_1 - \varphi p_2 + \gamma t(1-\varphi) + \delta e(\varphi - 1)}{1-\varphi}$. Since customers buy the product if their utility is positive, we calculate another threshold valuation, denoted by $\tilde{v}$. So, if consumers have a valuation greater than $\tilde{v}$ they will still purchase the product in period 2. In other words, if $v > \tilde{v} = p_2 + \gamma t - \delta e$, then $u_2 > 0$. We do not consider such a threshold valuation for period 1 because valuations in period 1 exceed those in period 2. So, we have the demand functions of two periods as follows:

$$q_1^{FDT} = 1 - \hat{v} = 1 - \frac{p_1 - \varphi p_2 + \gamma t(1-\varphi) + \delta e(\varphi - 1)}{1-\varphi} \tag{3}$$

$$q_2^{FDT} = \hat{v} - \tilde{v} = \frac{p_1 - \varphi p_2 + \gamma t(1-\varphi) + \delta e(\varphi - 1)}{1-\varphi} - p_2 + \gamma t - \delta e \tag{4}$$

3.1. Boundary conditions and managerial insights

The modeling assumptions adopted in this study are designed to balance analytical tractability with practical relevance. In particular, the two-period selling horizon captures the essence of many real-world retail settings in which firms adjust pricing and operational decisions over a limited number of decision stages, such as seasonal sales, promotional campaigns, or short product life cycles. This structure is particularly well-suited to industries such as fashion, consumer electronics, and other time-sensitive goods, where demand is concentrated

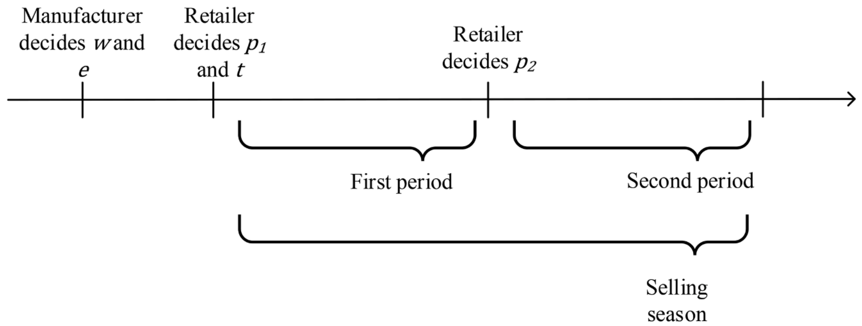

Fig. 1. Timeline of decisions.

within a pre-determined selling season.

The assumption of clearly defined delivery time commitments reflects common practices in e-commerce platforms, where customers are provided with promised delivery windows at the time of purchase. Similarly, modeling delivery time as a controllable decision variable captures the increasing operational flexibility enabled by modern logistics systems and data-driven fulfillment technologies.

The analytical framework also assumes deterministic demand and rational consumer behavior, which enables us to derive closed-form equilibrium solutions and isolate the fundamental economic mechanisms underlying the interactions among pricing, delivery time, and carbon-reduction decisions. While real-world environments may involve demand uncertainty and behavioral heterogeneity, the current model provides a foundational benchmark that can be extended in future research.

Therefore, the results of this study are most applicable to supply chain settings characterized by (i) seasonal or finite selling horizons, (ii) relatively predictable demand patterns, (iii) well-defined delivery commitments, and (iv) centralized decision-making structures with clear leader–follower interactions. These boundary conditions help clarify the scope of applicability of the model while preserving its ability to generate meaningful managerial insights.

In addition to the previously mentioned assumptions, the following are used to derive the profit functions and analyze the game in the FDT model.

- To avoid trivial solutions, we assume $\gamma < r_1\sqrt{\frac{2(2-\varphi)}{1-\varphi}}$. This is reasonable for realistic problems since cost factors are larger than other parameters. Similar conditions were assumed by He et al. [1] and Saha et al. [2].
- The CO_2 reduction investment expense, k, is significantly greater than the other parameter's value. The same assumption was made by He et al. [1] and Xia et al. [4]. Also, since the whole market size is 1, we assume other parameters are significantly <1, which is similar to commonly adopted assumptions [1–4].
- Total costs of a delivery system for a delivery time of t is $(r_0 - r_1 t)^2$ where $r_0 > r_1 t$. This cost function has been applied in many other studies [1,2,18,19].
- The amount of carbon emission, denoted by e, without any carbon reduction effort is 1. After the reduction effort $e > 0$, it will be $1 - e$.

Game-theoretic analysis is applied to the base model. Game theory is typically applied to analyze strategic interactions among rational players, such as manufacturers, retailers, and consumers in our model, and to predict the outcomes of these interactions [65]. Its primary focus is on a decision-making framework consisting of two or more parties with potentially conflicting objectives, which aligns naturally with the problem addressed in this study.

We develop an SC interaction as a Stackelberg game, in which the retailer and manufacturer act as the follower and leader, respectively. The decision sequence is depicted in Fig. 1.

At the beginning of period 1, the manufacturer specifies the selling price and the level of CO_2 reduction effort. Then, the seller responds by setting the retail price for period 1 and the delivery times for both periods, placing a single order to cover the entire demand. When the second period begins, the retailer establishes the retailing price for that period.

The game is solved using backward induction. The retailer's best-response strategies are first derived and then used to determine the manufacturer's optimal decisions. Since the retail price is dynamic, we initially compute the optimal price in the second period, assuming the retailer observes the first-period decisions. This optimum price within the second period is then incorporated into the first-period profit function, allowing the retailer's overall profit-maximization problem to be solved sequentially. The profit functions of the retailer are formally presented below:

$$\pi_{R2}^{FDT} = (p_2 - w)\ q_2 \tag{5}$$

$$\pi_{R1}^{FDT} = (p_1 - w)q_1 - (r_0 - r_1 t)^2 \tag{6}$$

Since the delivery time decision is made in the first period, we consider all its costs in the first period. Using the first-order conditions and ensuring the concavity of the functions, we obtain the retailer's best response, as described in *Propositions 1 and 2*.

Proposition 1. *The best response of the retailer in the second period for a given w, α, and p_1 is* $p_2^* = \frac{p_{1+w}}{2}$.

Proof. *See Appendix.*

Proposition 2. *The best response of the retailer (within period 1) to e andw, is*

$$p_1^* = \frac{2r_1^2 w + (1-\varphi)(2r_1(r_1(1+\delta e) - \gamma r_0)) - \gamma^2 w)}{2r_1^2(2-\varphi) - \gamma^2(1-\varphi)} \tag{7}$$

$$t^* = \frac{2r_0 r_1(2-\varphi) - \gamma(1-\varphi)(1 - w + \delta e)}{2r_1^2(2-\varphi) - \gamma^2(1-\varphi)} \tag{8}$$

Proof. *See Appendix.*

The profit function of the manufacturer is shown in Eq. (9). The term $ke^2/2 = C(e)$ represents the quadratic carbon reduction effort cost function and the term $\alpha(1-e)$ shows the amount of carbon tax paid per unit of product.

$$\pi_M^{FDT} = (w - c - \alpha(1-e))\ (q_1 + q_2) - ke^2/2 \tag{9}$$

By substituting the retailer's best responses into Eq. (9), we obtain the first-order conditions in *Proposition 3*. The expressions for A_i and B_i $\forall i$ are shown in Appendix B.

Proposition 3. *The equilibrium values of the e^* and w^* are:*

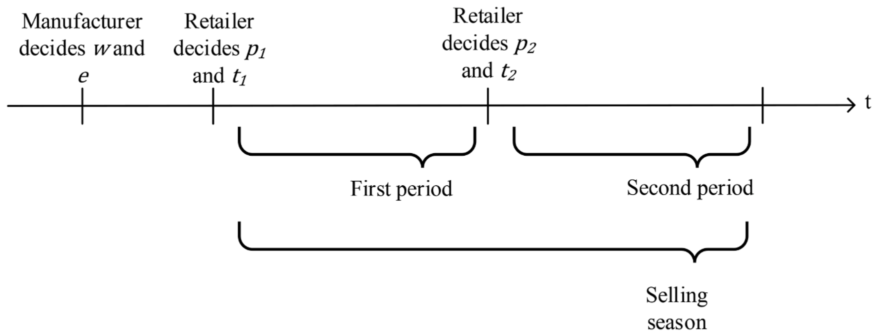

Fig. 2. Timeline of the decision in the DDT model.

$$w^* = \frac{(3-\varphi)A_1 - A_2\left(2r_1^2(2-\varphi) - \gamma^2(1-\varphi)\right)}{r_1 A_3} \tag{10}$$

$$e^* = \frac{r_1(\alpha + \delta)(3-\varphi)(r_1(\alpha + c - 1) + \gamma r_0)}{A_3} \tag{11}$$

Proof. *See Appendix.*

After substituting the equilibrium values of the manufacturer into the best responses, demand, and profit functions, we have the final equilibrium values in the FDT model as follows:

$$\begin{aligned}
p_1^* &= \frac{r_1^2(\varphi-3)A_1 + A_2\left(2r_1^2 - \gamma^2(1-\varphi)\right) + 4kr_1^2(1-\varphi)(r_1 - \gamma r_0))}{r_1^3\left(4k(2-\varphi) - (\alpha+\delta)^2(3-\varphi)\right) - 2\gamma^2 k r_1(1-\varphi)}\\
p_2^* &= \frac{A_1 r_1^2(\varphi-3) + A_2\left(r_1^2(3-\varphi) - \gamma^2(1-\varphi)\right) - 2kr_1^2(1-\varphi)(\gamma r_0 - r_1)}{r_1^3\left(4k(2-\varphi) - (\alpha+\delta)^2(3-\varphi)\right) - 2\gamma^2 k r_1(1-\varphi)}\\
t^* &= \frac{-\left(r_0 r_1^2(\alpha+\delta)^2(3-\varphi) + k\left(\gamma(1-\varphi)(\gamma r_0 + r_1(1-\alpha-c)) + 4r_0 r_1^2(\varphi-2)\right)\right)}{r_1^3\left(4k(2-\varphi) - (\alpha+\delta)^2(3-\varphi)\right) - 2\gamma^2 k r_1(1-\varphi)}\\
\pi_M^{FDT*} &= \frac{k(\varphi-3)(r_1(\alpha+c-1)+\gamma r_0)^2}{2A_3}\\
\pi_R^{FDT*} &= -\frac{k^2(\varphi-1)(r_1(\alpha+c-1)+\gamma r_0)^2\left(\gamma^2(\varphi-1) + r_1^2(5-2\varphi)\right)}{{A_3}^2}\\
Q_1^{FDT*} &= \frac{-kr_1(\varphi-2)(r_1(\alpha+c-1)+\gamma r_0)}{A_3}\\
Q_2^{FDT*} &= \frac{kr_1(r_1(\alpha+c-1)+\gamma r_0)}{A_3}
\end{aligned} \tag{12}$$

Consider an example with the following: $\alpha = 0.01$, $\delta = 0.1$, $k = 0.95$, $c = 0.01$, $r_1 = 0.15$, $r_0 = 0.2$, $\varphi = 0.5$, $\gamma = 0.1$. Using equilibrium solutions, we obtain the following results: $p_1^* = 0.5986$, $p_2^* = 0.5220$, $w^* = 0.4453$, $t^* = 0.9927$, $e^* = 0.0444$, $\pi_{R1}^* = 0.0326$, $\pi_{R2}^* = 0.0117$, $\pi_M^* = 0.1622$, $Q_1 = 0.2299$, and $Q_2 = 0.1533$.

The equilibrium results in Proposition 3 provide several economic insights. The manufacturer determines both the wholesale price and the level of carbon reduction by anticipating the retailer's pricing response and consumers' sensitivity to delivery time and environmental impact. When consumers place greater value on shorter delivery times or greener products, the manufacturer has stronger incentives to invest in carbon reduction and adjust wholesale pricing to stimulate demand. These results highlight how environmental preferences and delivery considerations jointly influence supply chain pricing and operational decisions.

4. Model with dynamic delivery time (DDT)

Motivated by the effectiveness of the dynamic pricing strategy, we developed a DDT quoting strategy to cope with consumers' strategic behavior. In this model, the retailer determines the delivery time and price in Period 1 and then revises them at the start of Period 2. The Stackelberg game structure of both models is the same. Fig. 2 presents the sequence of decision-making in the DDT model. In the DDT model, consumers' behavior is the same as the base model; however, because there are two different delivery times, their utility function is modified to:

$$u_1^{DDT} = v - p_1 - \gamma t_1 + \delta e \tag{13}$$

$$u_2^{DDT} = \varphi(v - p_2 - \gamma t_2 + \delta e) \tag{14}$$

Similar to the base model, the threshold utilities are calculated as $\widehat{v} = \frac{p_1 - \varphi p_2 + \gamma(t_1 - \varphi t_2) + \delta e(\varphi-1)}{1-\varphi}$ and $\widetilde{v} = p_2 + \gamma t_2 - \delta e$. With new $\widehat{v}$ and $\widetilde{v}$, the same procedure is needed to obtain the demand functions. So $q_1 = 1 - \widehat{v}$ and $q_2 = \widehat{v} - \widetilde{v}$.

Since the retailer decides delivery time in two different periods in the DDT model, the delivery system costs should be applied in both periods. There is a fixed investment cost part in the delivery cost function, r_0^2, which is independent of the delivery time and represents the initial cost of deploying a delivery system, so it is applied only in the first period. The dependent part of the cost function, $(r_1 t)^2 - 2r_0 r_1 t$, is considered the operational cost of the delivery system and is assumed to be also dependent on the timespan which is applied. Therefore, since the operational cost in the two periods is $(r_1 t)^2 - 2r_0 r_1 t$, the cost per period is $\left((r_1 t)^2 - 2r_0 r_1 t\right)/2$. Therefore, profit functions in the DDT model are as follows:

$$\pi_{R1}^{DDT} = (p_1 - w)q_1 - \left(r_0^2 + \frac{(r_1 t_1)^2 - 2r_0 r_1 t_1}{2}\right) \tag{15}$$

$$\pi_{R2}^{DDT} = (p_2 - w)q_2 + \left(\frac{2r_0 r_1 t_2 - (r_1 t_2)^2}{2}\right) \tag{16}$$

$$\pi_M^{DDT} = (w - c - \alpha(1-e))\,(q_1 + q_2) - ke^2/2 \tag{17}$$

All other descriptions and assumptions of the base model apply to the DDT model, except for Assumption 1, which changes as follows.

Assumption 5. In the DDT model, we assume $\gamma < r_1\sqrt{\frac{7-4\varphi-\sqrt{8\varphi+1}}{4}}$. Since r_1 is a cost factor and is usually greater than other parameters; the assumption holds for realistic parameter combinations.

Game-theoretic analysis is applied to the DDT model. We apply backward induction according to a Stackelberg game to derive the equilibrium solutions of the DDT case. Similar to the FDT model, we first find the retailer's optimum decision within Period 2.

Proposition 4. *In the DDT model, the retailer's best responses in the second period are:*

$$p_2^* = \frac{\gamma^2 w + r_1(\varphi-1)(r_1(p_1 + w + \gamma t_1) - \gamma r_0)}{2r_1^2(\varphi-1) + \gamma^2} \tag{18}$$

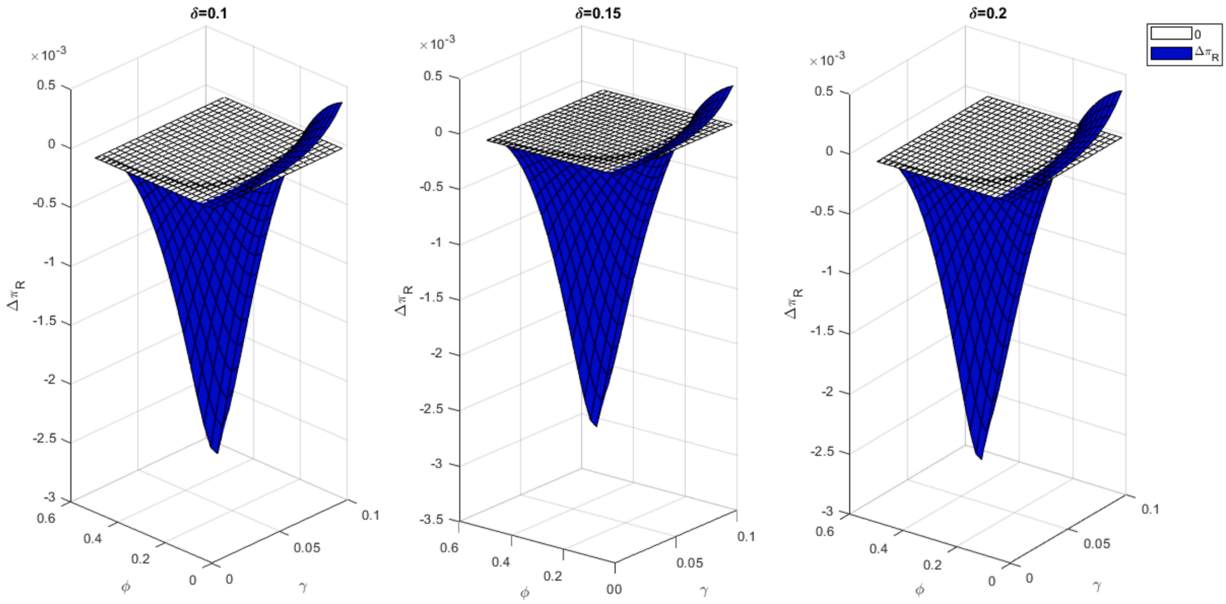

Fig. 3. Profit variations of retailer between the DDT model and FDT ($0 \le \varphi \le 0.5$).

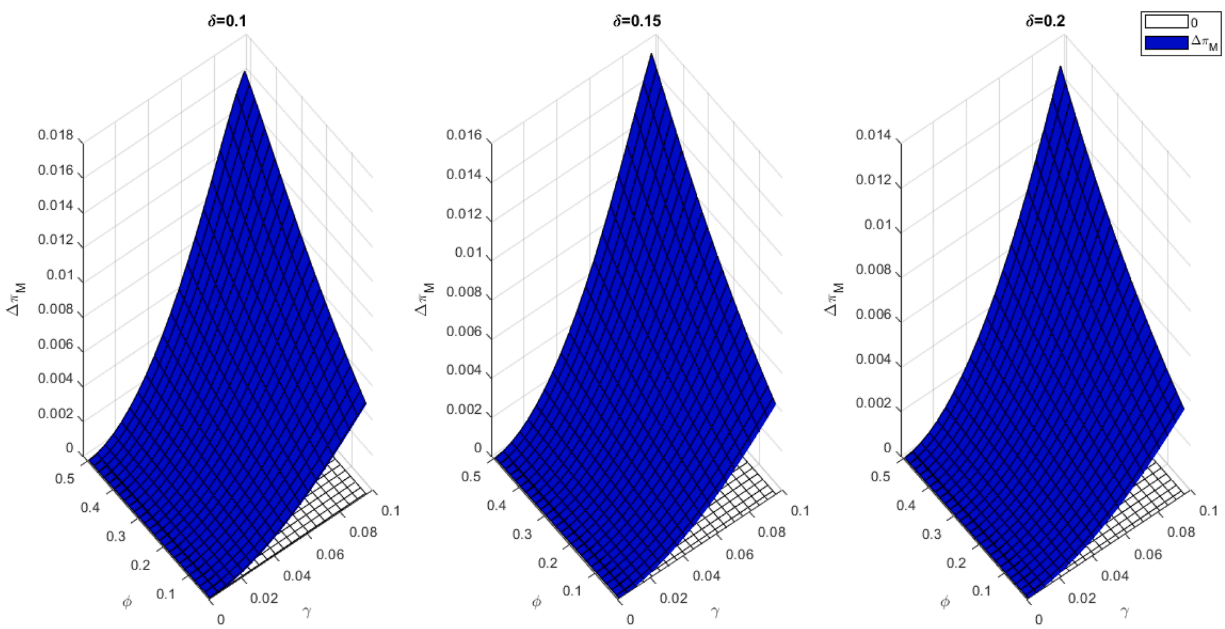

Fig. 4. Profit variations of the manufacturer between the DDT model and FDT ($0 \le \varphi \le 0.5$).

$$t_2^* = \frac{\gamma(\gamma t_1 + p_1 - w) + 2r_0 r_1(\varphi - 1)}{2r_1^2(\varphi - 1) + \gamma^2} \tag{19}$$

Proof. *See Appendix.*

Substituting these responses into the retailer's profit function in the first period, the solutions to the first-order optimality conditions are presented in *Proposition 5*.

Proposition 5. *In the DDT model, the retailer's best responses in the first period are:*

$$p_1^* = \frac{\left(r_1(r_1(1+\delta e) - \gamma r_0)A_4{}^2 + w\left(r_1^2(A_6 + A_5\gamma^2(\varphi - 4)) - \gamma^6\right)\right)}{A_5(\gamma^4 + 4r_1^4(1-\varphi) - \gamma^2 r_1^2(4-\varphi))} \tag{20}$$

$$t_1^* = \frac{(1+\delta e - w)\left(2\gamma r_1^2(1-\varphi) - \gamma^3\right) - 4r_0 r_1^3(1-\varphi) + \gamma^2 r_0 r_1(2+\varphi)}{\gamma^4 + 4r_1^4(1-\varphi) - \gamma^2 r_1^2(4-\varphi)} \tag{21}$$

After substituting the first period's best responses into the second period's optimal decisions and substituting both best responses of the retailer into the manufacturer's profit function, we can identify equilibrium values for decisions of the manufacturer, as presented in Proposition 6.

Proof. *See Appendix.*

Proposition 6. *In the DDT model, equilibrium values for manufacturer decisions are as follows:*

$$w^* = \frac{A_1A_7 + A_2A_8}{r_1((\alpha+\delta)^2A_7 + 2kA_8)} \tag{22}$$

$$e^* = \frac{A_7(\alpha + \delta)(r_1(\alpha + c - 1) + \gamma r_0)}{(\alpha+\delta)^2A_7 + 2kA_8} \tag{23}$$

Like the FDT model, the optimum decisions, profit, and demand are derived by substituting the equilibrium values into the related functions and best response values.

$$\begin{aligned}
p_1^* &= \frac{A_1A_9r_1^2\left(2r_1^4(\varphi^2 - 4\varphi + 3) + \gamma^2r_1^2(4\varphi - 7) + 2\gamma^4\right) + k(A_{10}r_1(\alpha + c) + A_{11}(r_1 - \gamma r_0))}{r_1(r_1^2(\varphi - 2) + \gamma^2)(\gamma^4 + 4r_1^2(1-\varphi)(r_1^2 - \gamma^2))(r_1(\alpha+\delta)^2A_7 + 2kA_8)} \\
p_2^* &= \frac{A_1\left(2r_1^6(\varphi^2 - 4\varphi + 3) + \gamma^2r_1^4(4\varphi - 7) + 2\gamma^4r_1^2\right) + k(A_{16}r_1(\alpha + c) + A_{17}(r_1 - \gamma r_0))}{r_1((\alpha+\delta)^2A_7 + 2kA_8)} \\
t_1^* &= \frac{A_{12} + \gamma r_1k(1 - \alpha - c)\left(2r_1^2(r_1^2(2 + \varphi^2 - 3\varphi) - \gamma^2(4 - 3\varphi)) + \gamma^4\right) + r_0r_1^2(\alpha+\delta)^2A_{13}}{(\alpha+\delta)^2A_7 + 2kA_8} \\
t_2^* &= \frac{k\left(\gamma r_1(1 - \alpha - c)\left(r_1^2\left(2r_1^3(1-\varphi) + \gamma^2(\varphi - 3)\right) + \gamma^4\right)A_{14} + r_0r_1^2(\alpha+\delta)^2A_{15}\right.}{r_1((\alpha+\delta)^2A_7 + 2kA_8)} \\
\pi_M^{DDT*} &= \frac{-k(r_1(\alpha + c - 1) + \gamma r_0)^2\left(2\gamma^4 + \gamma^2r_1^2(4\varphi - 7) + 2r_1^4(\varphi^2 - 4\varphi + 3)\right)}{2((\alpha+\delta)^2A_7 + 2kA_8)} \\
\pi_R^{(DDT*)} &= \left(-k^2(r_1(? + c - 1) + ?r_0)^2A_18\right)\Big/\left(2\left((? + ?)^2A_7 + 2kA_8\right)^2\right) \\
q_1^{DDT*} &= \frac{\left(kr_1(r_1(\alpha + c - 1) + \gamma r_0)\left(\gamma^4 + \gamma^2r_1^2(3\varphi - 4) + 2r_1^4(\varphi^2 - 3\varphi + 2)\right)\right)}{(\alpha+\delta)^2A_7 + 2kA_8} \\
q_2^{DDT*} &= \frac{\left(kr_1(r_1(\alpha + c - 1) + \gamma r_0)\left(\gamma^2 - 2r_1^2\right)\left(r_1^2(\varphi - 1) + \gamma^2\right)\right)}{(\alpha+\delta)^2A_7 + 2kA_8}
\end{aligned} \tag{24}$$

Proof. *See Appendix.*

Proposition 6 highlights how allowing delivery time to be adjusted dynamically alters the equilibrium decision structure. In particular, the retailer can respond more flexibly to consumer preferences by offering shorter delivery times when demand is high and relaxing delivery commitments when demand is lower. This flexibility reduces operational costs while maintaining consumer satisfaction, which explains why DDT strategies often improve overall supply chain performance relative to FDT policies.

5. Comparison of the DDT model with the FDT model

Because of the complexity of the equilibrium expressions in the two models, it is not possible to compare them explicitly. Therefore, we conduct a series of numerical experiments to compare the two models. In these experiments, the initial parameters are the same as those in the numerical example in Section 3.

The selection of parameter values in the numerical experiments is

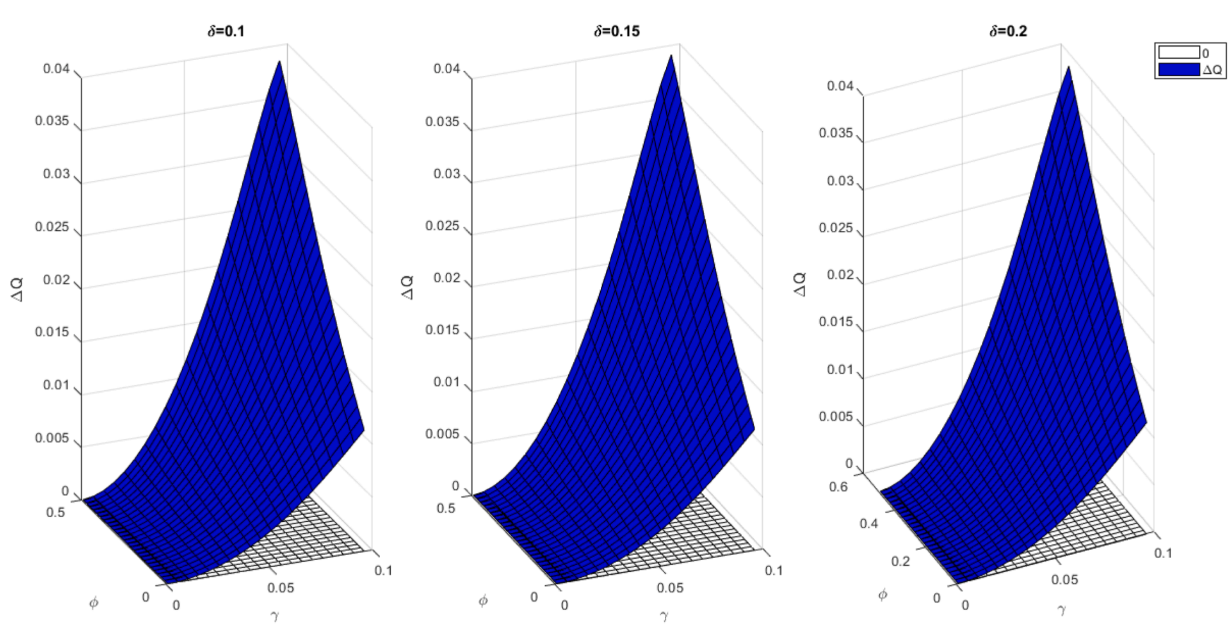

Fig. 5. Total demand variations between the DDT model and FDT ($0 \leq \varphi \leq 0.5$).

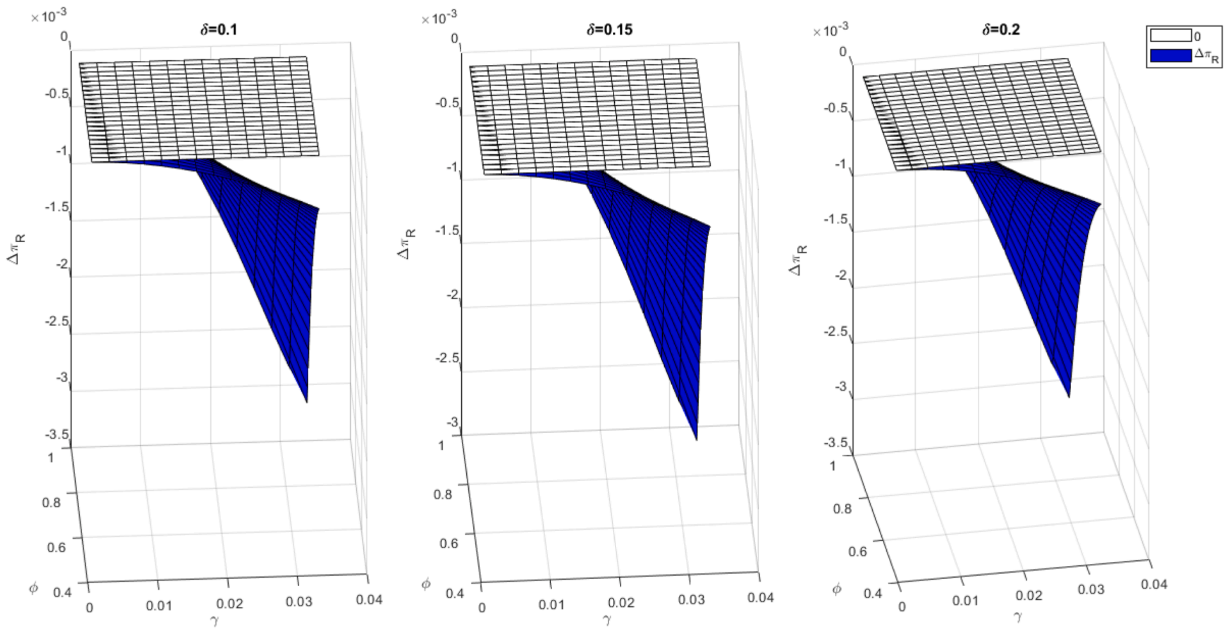

Fig. 6. Profit variations of retailer between the DDT model and FDT ($0.5 \leq \boldsymbol{\varphi} \leq 0.95$).

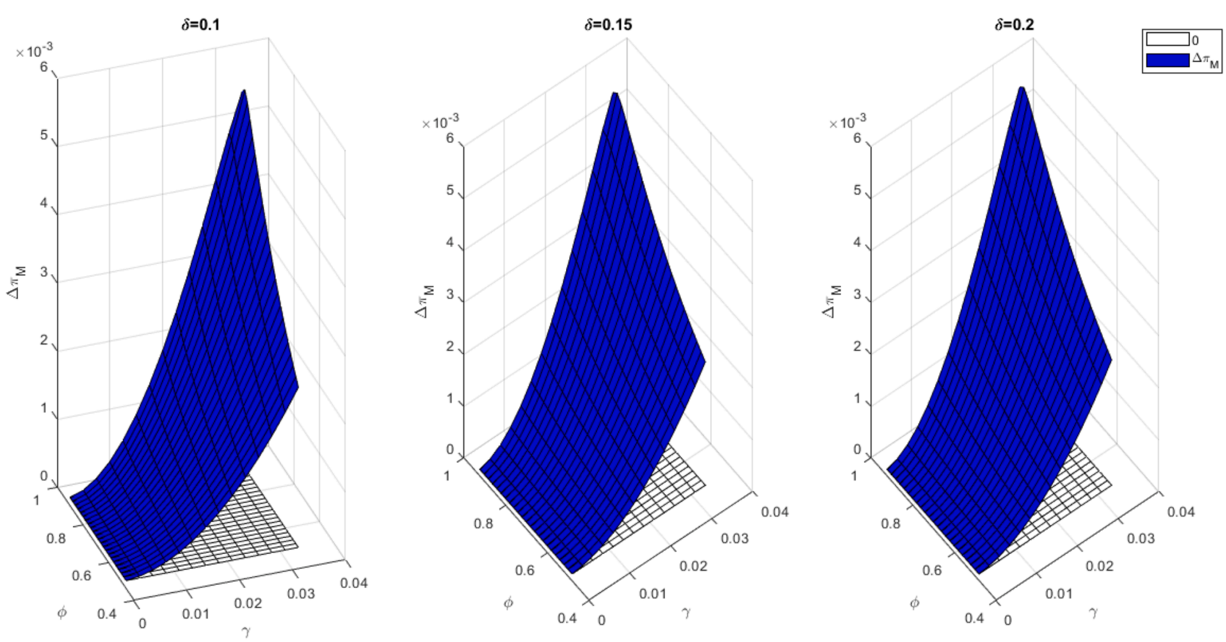

Fig. 7. Profit variations of the manufacturer between the DDT model and FDT ($0.5 \leq \boldsymbol{\varphi} \leq 0.95$).

guided by commonly adopted ranges in the supply chain and pricing literature. In particular, the delivery cost parameters and demand sensitivity coefficients are calibrated to be consistent with prior studies on pricing and delivery time decisions (e.g., [1,2,18]). The consumer sensitivity parameters, including sensitivity to delivery time, carbon emission reduction, and price, are chosen to reflect moderate-to-high responsiveness observed in online retail settings. Since closed-form analytical models often require normalized parameter ranges for tractability, the market size is set to unity, and cost parameters are scaled accordingly. These choices ensure that the numerical results remain economically meaningful while maintaining comparability with existing studies.

By changing consumers' sensitivity to delivery time (γ) and consumers' patience factor (φ), different scenarios are considered. It is worth mentioning that according to Assumption 5 in the DDT model, increasing the value of φ limits the acceptable range for γ. Therefore, we change φ in the interval [0, 0.5] while $0 < \gamma \leq 0.1$. Then, we change φ in the interval [0.5, 0.95] while $0 < \gamma \leq 0.035$ (In these ranges, we have omitted a small number of acceptable combinations of the parameters, which will not have an impact on the results.

The numerical experiments also provide insight into the economic mechanisms underlying the comparison between the FDT and DDT strategies. The critical parameter regions observed in the figures reflect the tradeoff between delivery system costs and consumers' sensitivity to delivery time. When consumers are highly sensitive to delivery time but relatively impatient, retailers benefit from dynamically adjusting delivery promises because shorter delivery times stimulate demand in the early period. Conversely, when consumers are highly patient, many

Table 3
Summary of numerical insights for FDT vs. DDT strategies.

Parameter conditions	Retailer profit (DDT vs FDT)	Manufacturer profit (DDT vs FDT)	Demand effect	Managerial insight
Low consumer patience (θ small), high delivery sensitivity (α large)	Higher	Higher	Increases significantly	DDT is highly effective; invest in fast delivery in the early period
Low consumer patience, low delivery sensitivity	Slightly higher or neutral	Higher	Moderate increase	Limited benefit from delivery improvements
High consumer patience (θ large), high delivery sensitivity	Lower	Higher	Increases	Retailer suffers; cost-sharing contract needed
High consumer patience, low delivery sensitivity	Lower	Higher	Slight increase	DDT is not attractive to retailers
All parameter combinations	Ambiguous for the retailer	Always higher	Always increases	The manufacturer always benefits from DDT

Table 4
Effects of cost-sharing contract (CSC).

Scenario	Retailer profit	Manufacturer profit	Feasibility condition	Insight
Without CSC	May decrease under DDT	Always increases	—	Misaligned incentives
With CSC (γ in feasible range)	Increases	Still higher than FDT	Conditions (28)–(29)	Coordination achieved
γ too small	Not effective	High	The retailer does not adopt DDT	Insufficient incentive
γ too large	Retailer benefits	Manufacturer loses	Violates condition (28)	Over-subsidization

customers delay their purchases, reducing the retailer's incentive to invest in faster delivery. In these cases, the FDT policy may be more profitable for the retailer, while the manufacturer continues to benefit from the demand expansion generated by the DDT strategy.

For each parameter combination, we calculate the profit difference between the two models for both the retailer and manufacturer. For the retailer's profit difference, we use the sum of profits over two periods. So, the difference is $\Delta\pi_R = \left(\pi_{R1}^{DDT} + \pi_{R2}^{DDT}\right) - \left(\pi_{R1}^{FDT} + \pi_{R2}^{FDT}\right)$. The profit difference for the manufacturer is $\Delta\pi_M = \pi_M^{DDT} - \pi_M^{FDT}$.

Beyond the direct effects of individual parameters, the numerical results reveal important interaction effects between consumer patience and delivery time sensitivity. In particular, the value of dynamic delivery time (DDT) strategies depends critically on the joint distribution of these parameters. When consumers are both highly patient and highly sensitive to delivery time, the retailer faces a strategic tradeoff between stimulating early demand and controlling delivery costs. This interaction may lead to situations in which improving service levels does not translate into higher profitability, highlighting the non-monotonic relationship between service investment and firm performance. Such findings underscore that optimal strategies cannot be determined based on single-parameter effects alone but require a joint consideration of behavioral and operational factors.

Figs. 3 and 4 show $\Delta\pi_R$ and $\Delta\pi_M$ for the first interval of φ, respectively. As depicted in Fig. 3, when φ is small ($\varphi < 0.5$) and γ is relatively large, the DDT policy leads to a larger profit for the retailer. This is because when consumers' patience is low, many of them purchase in the first period. In this case, since consumers have relatively high sensitivity to delivery time, the retailer can attract significant demand by investing enough capital in the delivery system and quoting a relatively low delivery time.

Under the DDT policy, the retailer can quote a longer delivery time in the second period, resulting in lower costs. Since there are fewer consumers in the second period, the online retailer's profit is not significantly affected. Therefore, the total profit of the retailer increases. In other words, in this case, the retailer does not need to have a short delivery time in the second period to be profitable, so quoting a longer delivery time can save costs and increase profit.

Fig. 4 shows that the manufacturer's profit always increases with the DDT policy. Applying the DDT strategy increases total demand; in this model, the delivery time is generally more responsive to consumer needs, so total demand will always increase across both periods. Fig. 5 shows the demand difference between the two models given by $\Delta q = \left(q_1^{DDT} + q_2^{DDT}\right) - \left(q_1^{FDT} + q_2^{FDT}\right)$. Therefore, since the manufacturer incurs no extra cost for this increase in demand, its profit increases.

Figs. 6 and 7 compare the two models when φ is in the interval [0.5, 0.95]. The results indicate that, all values of φ and γ result in the retailer's lower profit. However, as demand under the DDT policy increases, the manufacturer's profit rises, as shown in Fig. 7. Overall, these results illustrate how the interaction between consumer patience and delivery time sensitivity determines the relative profitability of fixed and DDT strategies.

To synthesize the insights obtained from the numerical analysis, Table 3 provides a structured summary of the comparative performance of the FDT and DDT strategies across different parameter regions. While Figs. 3–7 illustrate the detailed variations in profits and demand, the table highlights the key patterns by directly linking consumer characteristics, specifically the patience factor and sensitivity to delivery time, to the resulting profitability outcomes for supply chain members.

The results reveal that the effectiveness of the DDT strategy depends critically on the interaction between consumer patience and delivery time sensitivity. In particular, when consumers exhibit low patience and high sensitivity to delivery time, the retailer benefits significantly from dynamically adjusting delivery commitments, as early-period demand can be stimulated through faster delivery promises. In contrast, when consumers are highly patient, a larger proportion of demand shifts to the second period, reducing the retailer's incentive to invest in shorter delivery times and potentially making the DDT strategy less profitable.

Across all parameter configurations, the manufacturer consistently benefits from the DDT strategy due to the expansion of total demand. This divergence in incentives between the retailer and the manufacturer highlights coordination challenges within the supply chain, motivating the introduction of a cost-sharing contract mechanism. Overall, Table 3 complements the graphical analysis by providing a concise and decision-oriented representation of the main numerical findings.

Building on the above observations, Table 4 summarizes the effects of the cost-sharing contract (CSC) on supply chain coordination. The table highlights how introducing a cost-sharing mechanism modifies the profitability of both supply chain members and expands the parameter region in which the DDT strategy becomes mutually beneficial.

The results demonstrate that, in the absence of coordination, the retailer may be reluctant to adopt the DDT strategy despite its positive impact on total demand and manufacturer profit. By contrast, the cost-sharing contract allows the manufacturer to partially compensate the retailer for the additional delivery system costs associated with dynamic delivery decisions. As a result, the contract can align incentives and improve the profitability of both parties when the sharing parameter lies within a feasible range.

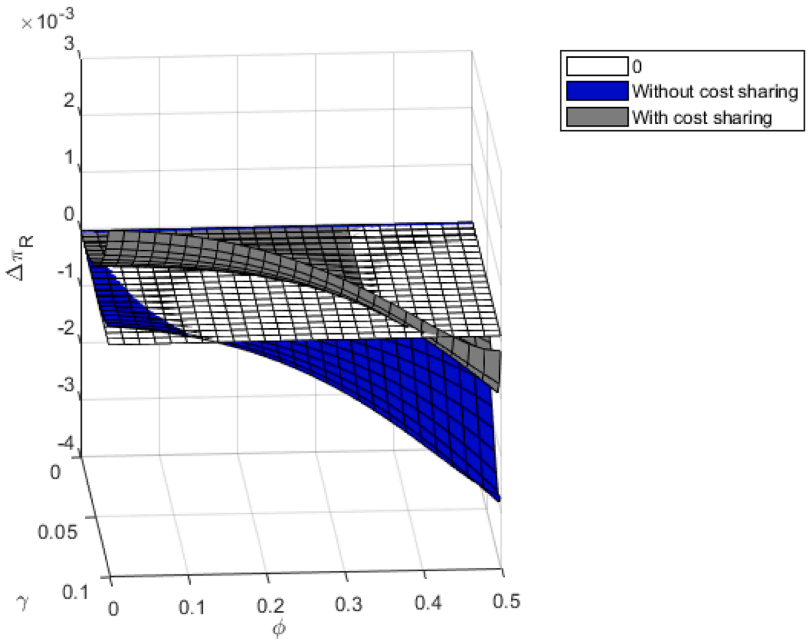

Fig. 8. Profit variations of retailer without and with CSC ($0 \leq \varphi \leq 0.5$).

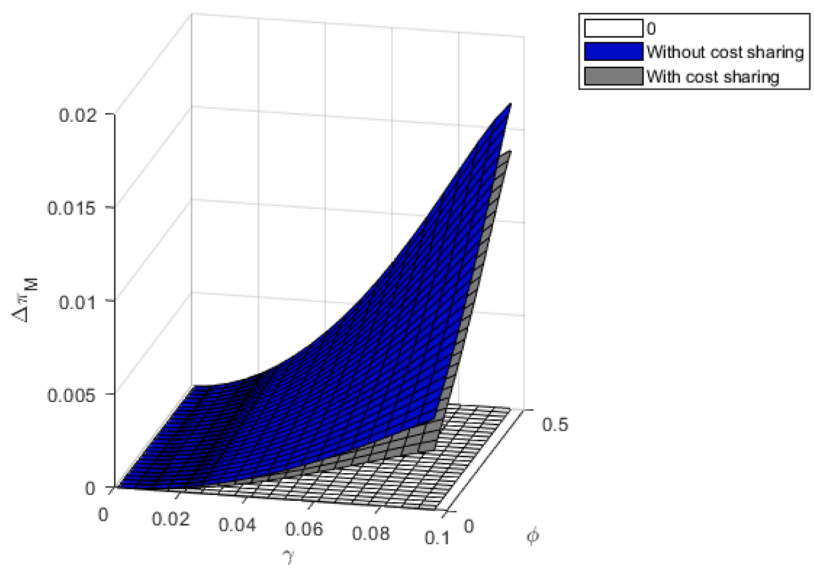

Fig. 9. Profit variations of the manufacturer without and with CSC ($0 \leq \varphi \leq 0.5$).

Across all parameter configurations, the manufacturer consistently benefits from the DDT strategy due to the expansion of total demand. This divergence in incentives between the retailer and the manufacturer highlights coordination challenges within the supply chain, motivating the introduction of a cost-sharing contract mechanism. Overall, Table 3 complements the graphical analysis by providing a concise and decision-oriented representation of the main numerical findings.

6. Cost-sharing contract

In the DDT case, we showed an increase in the manufacturer's profit from the FDT model. However, the profit of the retailer decreases when φ is large, and thus, the online retailer does not have an incentive to deploy the DDT. In this situation, the manufacturer can contribute to the retailer's delivery system costs so that the retailer's profit difference between the DDT and FDT models becomes positive. Let λ denote the fraction of the shared delivery system cost, then the profit functions of the SC members will change as shown below in the CSC:

$$\pi_{R1}^{CS} = q_1^*(p_1^* - w^*) - (1-\lambda)\left(r_0^2 - \frac{2r_0t_1^*r_1 - (t_1^*r_1)^2}{2}\right) \tag{25}$$

$$\pi_{R2}^{CS} = q_2^*(p_2^* - w^*) - (1-\lambda)\left(\frac{(r_1t_2^*)^2 - 2r_0r_1t_2^*}{2}\right) \tag{26}$$

$$\pi_M^{CS} = (w^* - c - \alpha(1-e^*))(q_1^* + q_2^*) - \frac{ke^{*2}}{2} - \lambda\left(r_0^2 - \frac{2r_0t_1^*r_1 - (t_1^*r_1)^2}{2} + \frac{2r_0r_1t_2^* - (t_2^*r_1)^2}{2}\right) \tag{27}$$

We consider the CSC based on the optimal decisions previously derived in the DDT model, i.e., the supply chain members determine

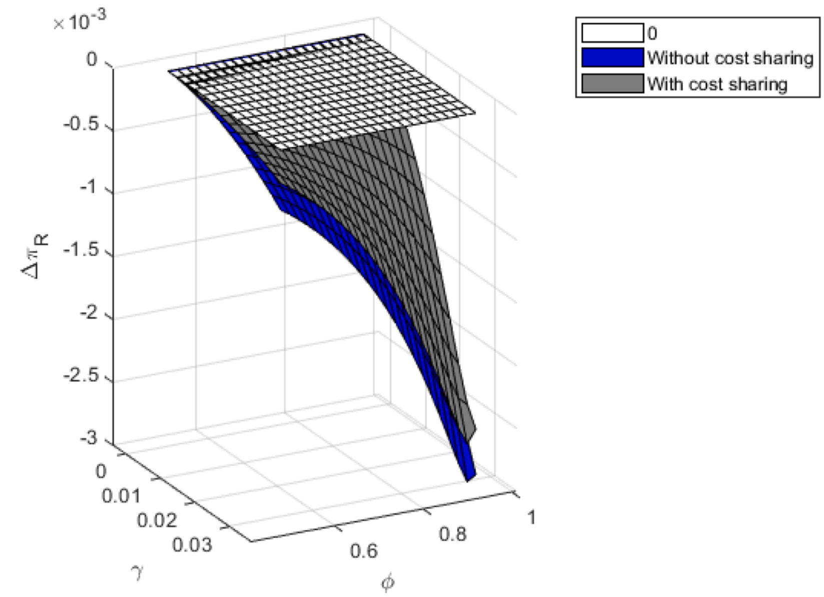

Fig. 10. Profit variations of the retailer without and with CSC ($0.5 \le \varphi \le 0.95$).

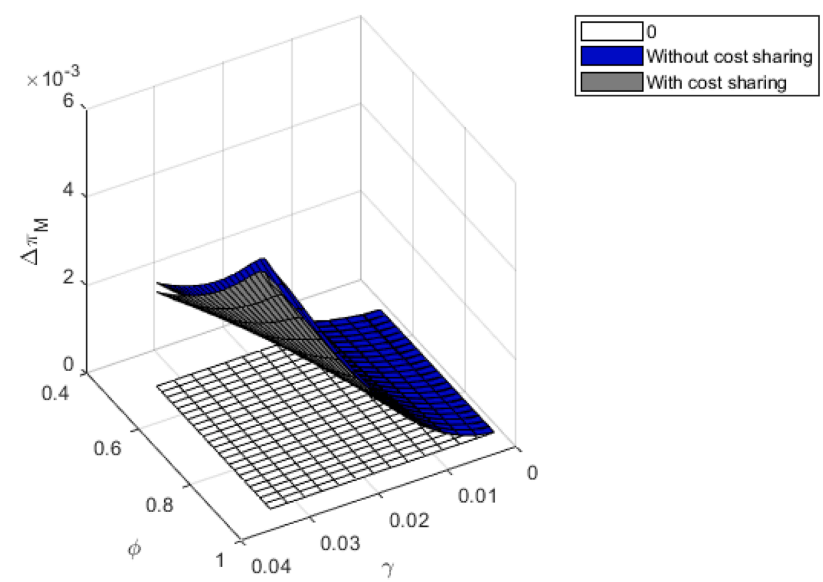

Fig. 11. Profit variations of the manufacturer without and with CSC ($0.5 \le \varphi \le 0.95$).

their decision, then they agree on λ. If the supply chain members determine their equilibrium decisions by maximizing the profit functions in Eqs. (25–27), the contract would not be effective since the extra costs incurred by the manufacturer cause him to increase the wholesale price, which means higher costs for the retailer. Therefore, the contract is effective when SC members base λ on the equilibrium decision of the DDT model.

The manufacturer incurs a reduction in profit by entering into the contract, thereby allowing the retailer's profit in the DDT to exceed that of the FDT model (as depicted in Fig. 3). The manufacturer agrees to the contract only if the manufacturer can achieve more profit in the DDT model than in the FDT model, i.e., $\pi_M^{CS} \ge \pi_M^{FDT}$ which, since $\pi_M^{CS} = \pi_M^{DDT} - \lambda\left(r_0^2 + \frac{(r_1 t_1^*)^2 - 2r_0 r_1 t_1^*}{2} + \frac{(r_1 t_2^*)^2 - 2r_0 r_1 t_2^*}{2}\right)$, leads to the condition:

$$\lambda_U < \frac{\pi^{*DDT}_M - \pi^{*FDT}_M}{r_0^2 + \frac{(r_1 t_1^*)^2 - 2r_0 r_1 t_1^*}{2} + \frac{(r_1 t_2^*)^2 - 2r_0 r_1 t_2^*}{2}} \tag{28}$$

The retailer will agree to the contract when their profit from the DDT model is more than that of the FDT model, i.e., $\pi_R^{CS} \ge \pi_R^{FDT}$, which means the online retailer will agree to the contract under the condition:

$$\lambda_L > \frac{\pi^{*FDT}_R - \pi^{*DDT}_R}{r_0^2 + \frac{(r_1 t_1^*)^2 - 2r_0 r_1 t_1^*}{2} + \frac{(r_1 t_2^*)^2 - 2r_0 r_1 t_2^*}{2}} \tag{29}$$

For any positive λ which meets conditions (28) and (29), i.e., $\lambda_L < \lambda < \lambda_U$, the retailer's and manufacturer's profits will be greater in the DDT model than in the FDT model.

In the following, we use the same parameters as in Section 3 to demonstrate the benefits of the cost-sharing contract. Likewise, we calculate the profit difference between the DDT and the FDT models in both situations, with and without a cost-sharing contract. First, we use a fixed value for λ, then we examine how λ affects the profits in the CSC. Here we use $\lambda = 0.1$. The $\Delta\pi_R$ with the cost-sharing contract is $\pi_R^{CS} - \pi_R^{DDT}$, and without the contract is $\pi_R^{DDT} - \pi_R^{FDT}$. The same explanations apply to the manufacturer's profit function. Figs. 8 and 9 show the results for $0 \le \varphi \le 0.5$. As shown in the figures, the cost-sharing contract

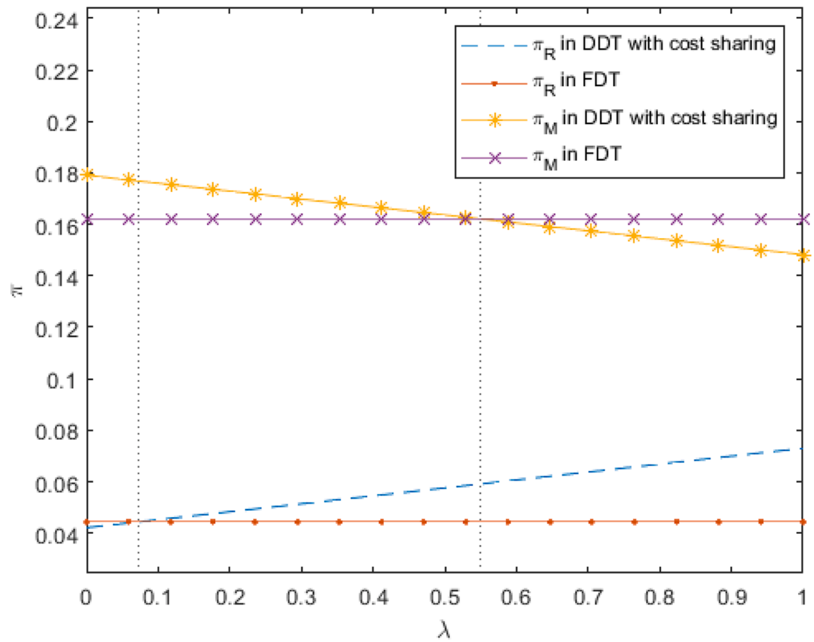

Fig. 12. Effect of λ on the profits with a cost-sharing contract, and the acceptable range for λ.

increases the parameter ranges for which the contract is viable for the retailer, while the manufacturer still makes more profit than in the FDT model. Figs. 10 and 11 show the results for $0.5 \leq \varphi \leq 0.95$. As shown, although the CSC brings more profit for the retailer and less for the manufacturer, the amount of shared costs is insufficient to make the DDT model profitable for the retailer, i.e., to exceed the threshold profit of FDT. For further analysis, we use the parameters in Section 3 to investigate how changing λ affects the decisions of SC members on whether to join the contract. Fig. 12 shows the results as λ is increased from 0 to 1. The first vertical line shows λ_L, above which the retailer will join the contract. Moreover, the manufacturer joins the contract if his profit exceeds that of the FDT model, so the manufacturer will agree to a contract where lambda is smaller than the threshold value lambda sub cap as depicted by the second vertical line in Fig. 12. In conclusion, in this example, it is profitable for both SC members to agree to a contract when λ is between the two vertical lines.

It is important to note that the cost-sharing contract proposed in this study does not fully coordinate the supply chain in the classical sense of achieving the centralized optimal solution. Instead, the contract serves as an incentive alignment mechanism, encouraging the retailer to adopt the DDT strategy when it benefits the overall supply chain, even if it reduces the retailer's profit under decentralized decision-making. In this setting, the manufacturer partially compensates the retailer for additional delivery system costs associated with the DDT strategy, thereby expanding the parameter region in which both parties benefit. Similar incentive-based coordination mechanisms have been widely discussed in the supply chain contract literature, where upstream firms provide financial support for downstream operational improvements that increase overall demand and system efficiency [66]. Future research could explore alternative contractual structures, such as revenue-sharing or two-part tariff contracts, that may achieve full supply chain coordination under DDT decisions. In practice, such arrangements may take the form of logistics-cost subsidies, shared investments in fulfillment infrastructure, or reimbursement schemes through which manufacturers support retailers' delivery-system improvements. The implementation of these contracts typically requires transparent cost information and mutually agreed-upon rules for determining the sharing parameter between supply chain partners.

An additional practical consideration concerns information asymmetry regarding retailers' delivery system costs. The proposed cost-sharing contract is developed under a complete-information setting in which the manufacturer and retailer have sufficient knowledge of the relevant cost structure to determine the sharing parameter. In practice, however, retailers' logistics and delivery-related costs may be partially proprietary or difficult for manufacturers to observe directly. Under such conditions, determining an appropriate cost-sharing parameter may require negotiated agreements, third-party auditing, or reliance on observable operational indicators, such as delivery performance and fulfillment expenditures. Nevertheless, cost-sharing arrangements remain commonly used in supply chain partnerships, particularly when manufacturers benefit from downstream service improvements that stimulate demand. Therefore, while information asymmetry may complicate implementation, it does not eliminate the feasibility of such contracts; rather, it highlights the importance of transparent coordination mechanisms and mutually agreed cost-verification procedures. Investigating contract design under incomplete or asymmetric information settings represents an important avenue for future research.

7. Sensitivity analysis and managerial insights

From a managerial perspective, the findings of this study provide actionable guidance for designing pricing and delivery strategies in sustainable supply chains. First, managers can leverage DDT strategies to align with consumer preferences better, particularly in markets where customers are sensitive to delivery speed yet exhibit limited strategic waiting behavior. Second, the results suggest that manufacturers should actively support downstream logistics investments through cost-sharing arrangements when such investments expand total demand but may not directly benefit retailers. Third, firms can align sustainability objectives with profitability by increasing carbon reduction efforts when consumers exhibit environmental sensitivity, as such investments can simultaneously enhance demand and firm performance. Overall, the study highlights the importance of jointly managing pricing, delivery time, and sustainability decisions rather than treating them as independent operational choices.

Although the analytical model demonstrates the economic benefits of DDT strategies under specific parameter conditions, their practical implementation requires operational capabilities and technological support. In practice, retailers must rely on advanced demand forecasting systems, real-time logistics monitoring, and flexible fulfillment networks

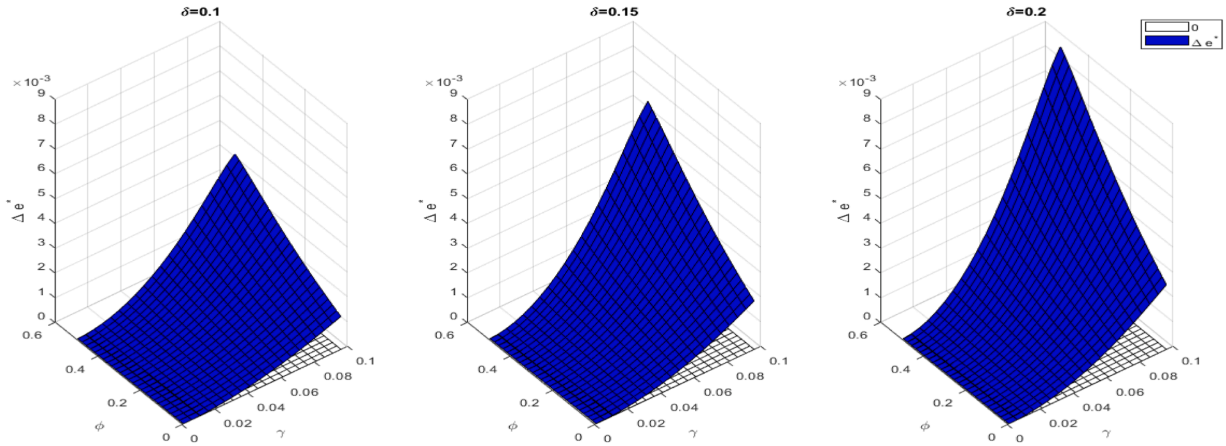

Fig. 13. Carbon emissions reduction difference between the DDT and FDT models ($0 \leq \varphi \leq 0.5$).

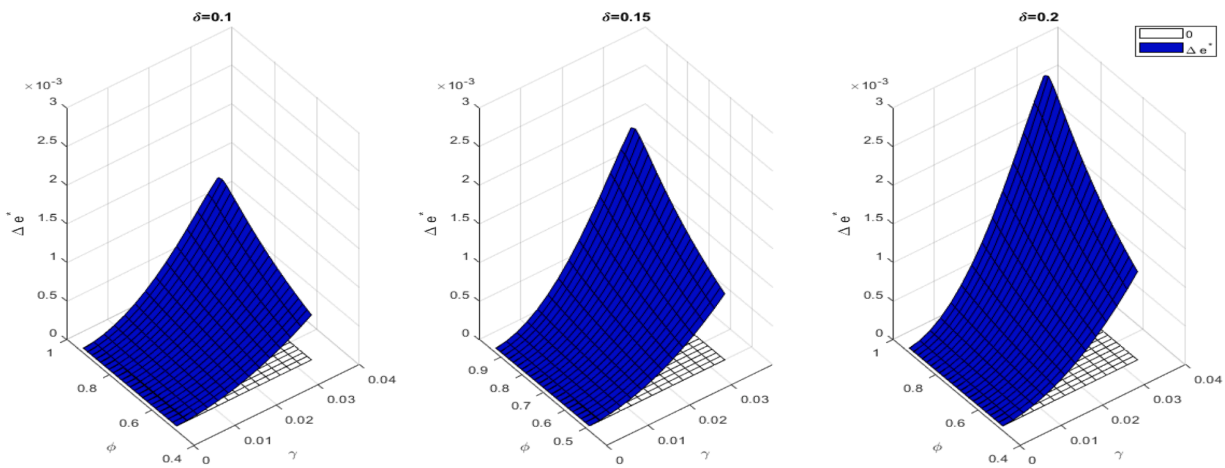

Fig. 14. Carbon emissions reduction difference between the DDT and FDT models ($0.5 \leq \varphi \leq 0.95$).

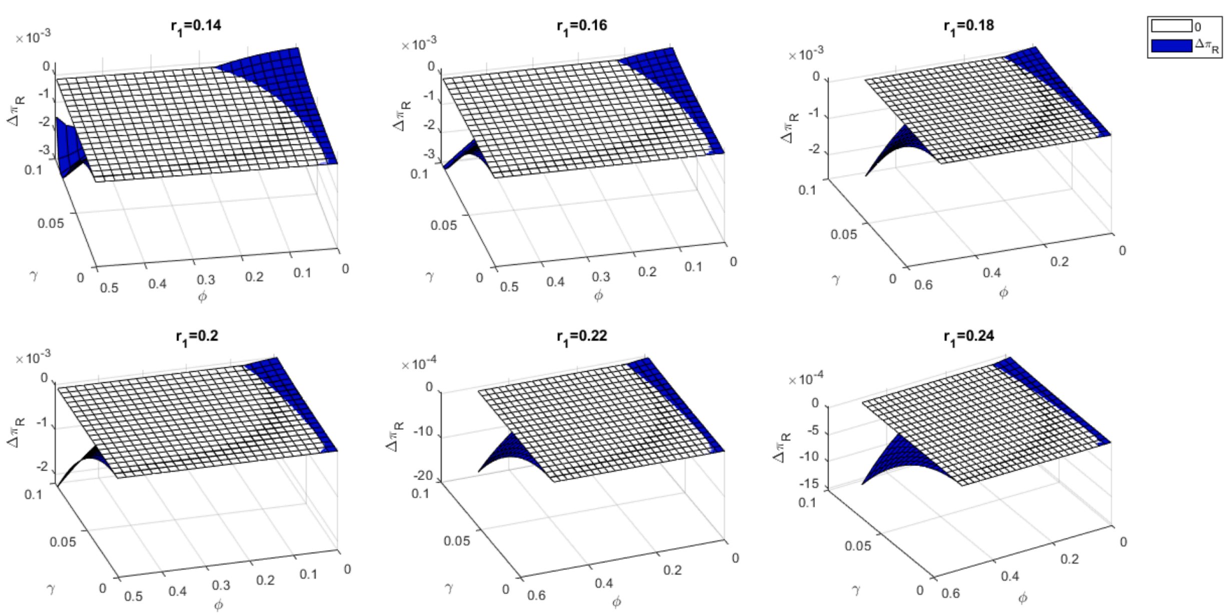

Fig. 15. Effect of operational cost of delivery system on the efficiency of the DDT model.

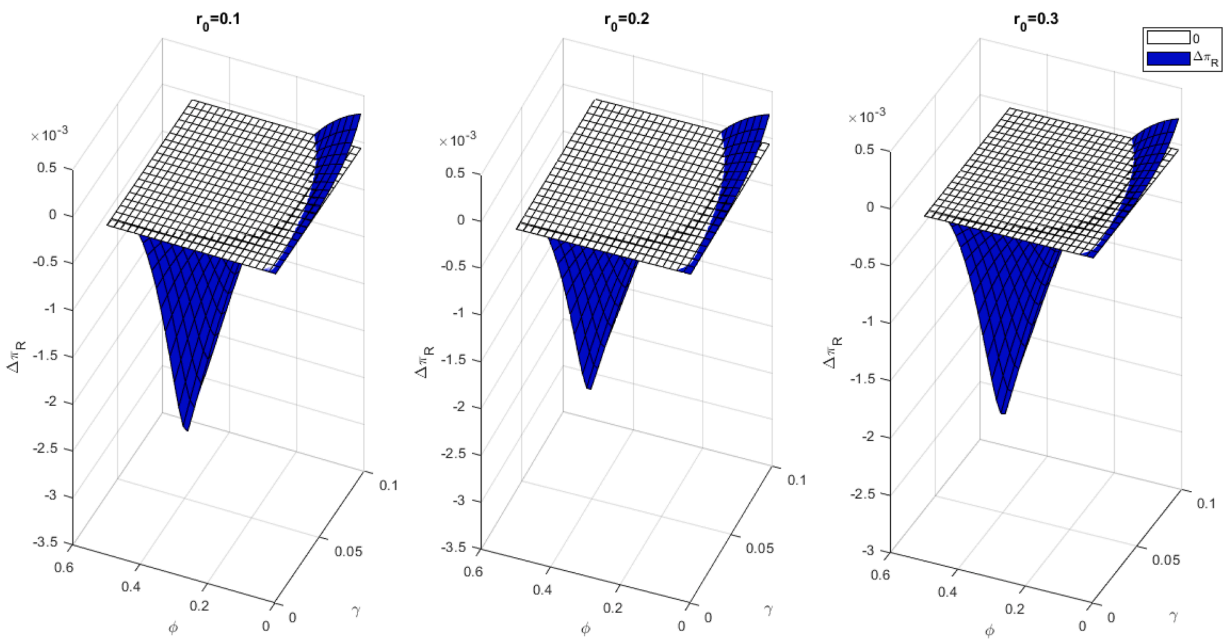

Fig. 16. Effect of fixed cost of delivery system on the efficiency of the DDT model.

to dynamically adjust delivery promises. Modern e-commerce platforms increasingly employ data-driven decision systems and dynamic order management technologies that enable firms to update delivery time estimates in response to demand fluctuations, warehouse capacity, and transportation availability. However, implementing such strategies may pose challenges, including increased coordination with logistics partners, investment in information systems, and potential consumer dissatisfaction if delivery promises are frequently revised. These operational considerations have been widely discussed in the logistics and last-mile delivery literature, which highlights the importance of flexible fulfillment infrastructure and real-time information systems in supporting dynamic delivery management [67]. Therefore, firms considering DDT strategies should carefully evaluate their operational flexibility, logistics infrastructure, and information capabilities before adopting such policies.

The findings of this study should also be interpreted within the scope of the modeling environment. Specifically, the proposed framework considers a single manufacturer and a single retailer operating within a decentralized supply chain. This structure allows the model to isolate and examine the core interactions among delivery-time decisions, strategic consumer behavior, pricing, and carbon-emission reduction while preserving analytical tractability. However, many contemporary online retail markets involve competition among multiple retailers, manufacturers, or platforms, which may introduce additional strategic dynamics, such as price competition, delivery-service rivalry, and competitive coordination. Consequently, while the present framework provides useful benchmark insights for decentralized e-commerce supply chains, caution should be exercised when generalizing the results to highly

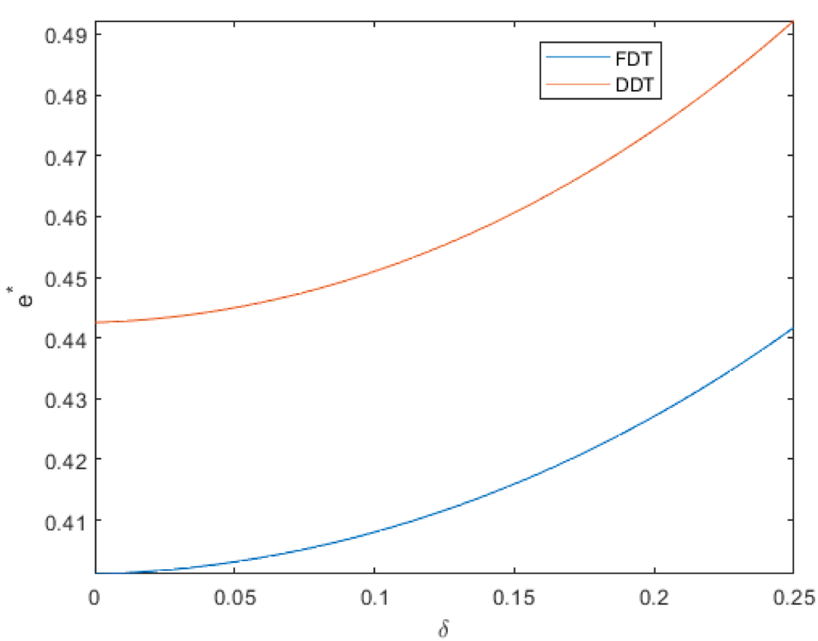

Fig. 17. Effects of changing δ on the carbon emission reduction.

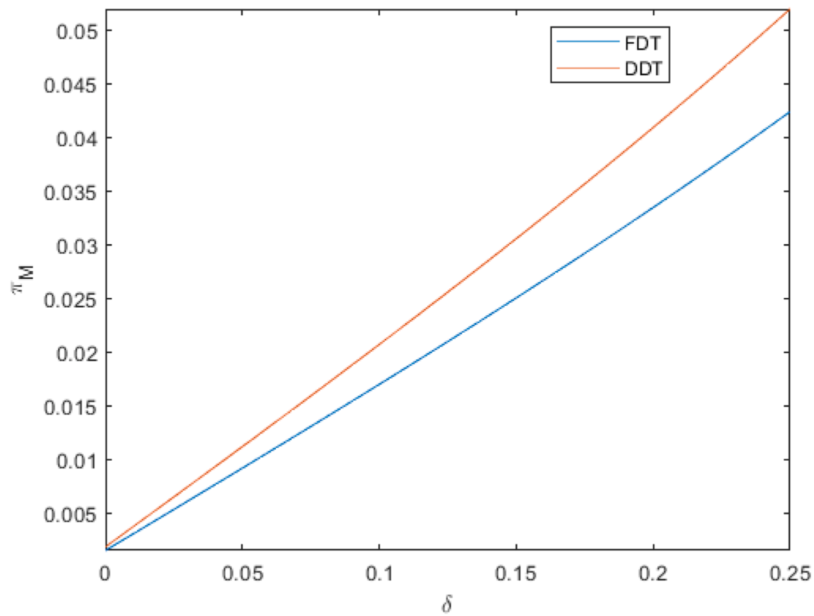

Fig. 18. Effects of changing δ on the manufacturer's profit.

competitive markets. Extending the model to competitive multi-agent settings represents an important avenue for future research.

7.1. Effects of the DDT strategy on the greenness of the SC

In Section 6, the DDT and FDT models were compared with respect to optimal profits; here, we compare their greenness. The equilibrium level of carbon emission reduction effort for each model is considered. Since explicit comparison is not possible due to the complexity of the expressions, we use the same numerical experiment as in Section 6. Figs. 13 and 14 show $\Delta e^* = e^{*DDT} - e^{*FDT}$. As both figures show, the carbon emission reduction in the DDT model is greater than in the FDT model. In other words, the DDT model is more environmentally friendly. Also, as δ increases, the difference in carbon reduction between the two models increases.

7.2. Effects of delivery costs

In Section 5, we compared FDT and DDT models for different combinations of γ and φ and showed the results for three different values of the δ. Here, we examine how the efficiency of the DDT model depends on the delivery cost factors, r_0 and r_1. Noting the initial value for r_1, we changed its value from 0.14 to 0.24 in 0.02 increments. We exclude the second range for the φ parameter, since the DDT model always yields less profit within those parameter ranges. Fig. 15 shows the results. As r_1 increases, smaller parameter combinations lead to larger profits in the DDT model. So, increasing r_1 has a negative effect on the DDT model. Next, we changed r_0 based on three values of 0.1, 0.2, and 0.3. The results are presented in Fig. 16, showing that changing r_0 does not significantly affect the efficiency of the DDT model.

7.3. Effects of consumer sensitivity on carbon emission

This sub-section examines the effects of changes in the sensitivity of consumers on CO_2 reduction (δ). These effects on the manufacturer's profit and the CO_2 reduction effort are described in *Propositions 7* and *8*.

Proposition 7. *In both the DDT and FDT models, as δ increases, the CO_2 reduction efforts of the manufacturer increase,* i.e., $\frac{\partial e^{*DDT}}{\partial \delta} > 0$, $\frac{\partial e^{*FDT}}{\partial \delta} > 0$.

Proof. *See Appendix.*

Proposition 8. *In both the DDT and FDT models, as δ increases, the profit of the manufacturer increases,* i.e., $\frac{\partial \pi_M^{DDT}}{\partial \delta} > 0$, $\frac{\partial \pi_M^{FDT}}{\partial \delta} > 0$.

Proof. *See Appendix.*

As shown in *Proposition 8*, this additional investment leads to increased demand and higher profits for the producer. Notably, the carbon tax does not affect the manufacturer's profit when consumers' sensitivity changes. From Appendix A, the signs of $\frac{\partial \pi_M^{DDT}}{\partial \delta}$ and $\frac{\partial \pi_M^{FDT}}{\partial \delta}$ are independent of the carbon tax parameter (α). The following numerical analyses illustrate the results. The parameter values in Section 3 are used while we change δ in the $[0,\ 0.25]$ interval. Figs. 17 and 18 show the results. Fig. 17 shows that when δ increases, the manufacturer increases its effort to reduce CO_2 emissions. As discussed earlier, the effort in the DDT model is higher than in the FDT model; however, as shown in Fig. 17, the patterns of increase are similar in both models. Fig. 18 demonstrates that an increase in δ leads to more profit for the manufacturer. Also, as δ increases, the difference between the two models increases.

This study employs a game theory framework to optimize a two-level SC comprising a manufacturer and a retailer. Customers are sensitive to price, delivery time, and carbon emissions associated with the manufacturing process, and they may behave strategically. By examining two models, one with FDT and the other with DDT, and performing sensitivity analyses, we derive the following managerial insights:

- Implementing DDT can increase the retailer's profits for only specific ranges of some parameters. However, DDT always increases the manufacturer's profit.
- Since the retailer is worse off with DDT for some parameter ranges, a cost-sharing contract where the manufacturer pays a part of the delivery time-related costs of the retailer can increase supply chain profit. Therefore, managers of both supply chain members can use the closed-form conditions and the numerical studies presented in this paper to develop suitable cost-sharing contracts and achieve higher profits.
- Under all conditions, the DDT model results in fewer carbon emissions. Thus, managers can consider this fact alongside the financial gains of the DDT model.

- As consumers get more sensitive to carbon emissions, manufacturers should increase their investment in carbon emissions reduction because their total profit increases. Therefore, if the manufacturer promotes environmental awareness, the manufacturer not only fulfills his social responsibility but also increases his profits.

8. Conclusion and directions for future research

This study developed a game-theoretic framework for a two-echelon supply chain comprising a manufacturer and an online retailer serving consumers who are sensitive to delivery time, retail price, and carbon emissions and who may also behave strategically. Two decision settings were examined: the FDT and DDT models under dynamic pricing. Equilibrium solutions were derived for retail pricing, delivery-time decisions, wholesale pricing, and carbon-emission reduction decisions.

The comparative analysis demonstrates that the effectiveness of DDT strategies depends strongly on consumer behavior. When consumers are less patient and highly sensitive to delivery time, DDT can improve retailer profitability. However, under other parameter conditions, the retailer may be disadvantaged despite increases in total demand. In contrast, the manufacturer consistently benefits from DDT due to increased demand. To address this incentive mismatch, a cost-sharing contract was proposed in which the manufacturer partially subsidizes the retailer's delivery-related costs. The results show that this mechanism enlarges the parameter region in which both supply chain members benefit and improves coordination under decentralized decision-making.

Sensitivity analyses further demonstrate that DDT strategies contribute to greater carbon-emission reduction and that stronger consumer sensitivity to environmental performance increases manufacturers' incentives to invest in carbon reduction. Overall, the findings highlight the importance of jointly managing pricing, delivery strategies, and sustainability decisions in modern e-commerce supply chains.

Ethics approval and consent to participate

Not Applicable

Consent for publication

All authors have agreed to this submission

Declaration of generative artificial intelligence use

Generative AI tools were used during the preparation of this manuscript solely to assist with language editing and improve readability. All content was reviewed and edited by the authors, who assume full responsibility for the accuracy and integrity of the manuscript.

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CRediT authorship contribution statement

Ata Allah Taleizadeh: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Hossein Choopani:** Writing – original draft, Validation, Methodology, Investigation, Formal analysis. **Madjid Tavana:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis. **Hamidreza Abedsoltan:** Writing – original draft, Validation, Investigation, Data curation.

Declaration of competing interest

The above 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.

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Not Applicable

Appendix

Proof for Lemma 1

When the customer with valuation v' buys an item within period 1, the utility of buying within Period 1 must be greater than buying in Period 2 or not buying at all (utility equal to zero). In other words*:*

$$v' - p_1 - \gamma t \geq max\{\varphi(v' - p_2 - \gamma t + \delta e), 0\}, \tag{30}$$

which means:

$$v' \geq max\left\{\frac{p_1 - \varphi p_2 + \gamma t(1-\varphi) + \delta e(\varphi - 1)}{1-\varphi}, p_1 + \gamma t - \delta e\right\} \tag{31}$$

Eq. (31) is true for every valuation v when $v > v'$.

Similarly, when the consumer with the valuation v' buys the product in Period 2, the utility of buying in Period 2 must be greater than buying in Period 1 or not buying, so we have*:*

$$\varphi(v' - p_2 - \gamma t + \delta e) \geq max\{v' - p_1 - \gamma t, 0\}, \tag{32}$$

which is equivalent to:

$$\varphi(p_2 + \gamma t - \delta e) \leq v' \leq \frac{p_1 - \varphi p_2 + \gamma t(1-\varphi) + \delta e(\varphi - 1)}{1-\varphi} \tag{33}$$

This means if a consumer's utility is positive, $\varphi(p_2 + \gamma t - \delta e) < v'$, then for every v lower than v' Eq. (33) is true.

It is obvious that the marginal valuations for both situations are the same and equal to $\frac{p_1 - \varphi p_2 + \gamma t(1-\varphi) + \delta e(\varphi-1)}{1-\varphi}$, which equals the valuation where $u_1^{FDT} =$

u_2^{FDT}.

Proof for Proposition 1

By calculating the second derivative for the profit function of the retailer in the second period, we have $\frac{\partial^2 \pi_{R2}^{FDT}}{\partial p_2{}^2} = \frac{-2+\varphi}{1-\varphi}$ which is negative since we have $0 \le \varphi < 1$. So, solving the first conditions, i.e., $\frac{\partial \pi_{R2}^{FDT}}{\partial p_2} = 0$, results in an optimal solution $p_2^* = \frac{p_{1+w}}{2}$.

Proof for Proposition 2

Calculating the second derivative for the profit function of the retailer within Period 1, we have $\frac{\partial^2 \pi_{R1}^{FDT}}{\partial p_1{}^2} = \frac{-2+\varphi}{1-\varphi}$, $\frac{\partial^2 \pi_{R1}^{FDT}}{\partial p_1 \partial t} = \frac{\partial^2 \pi_{R1}^{FDT}}{\partial t \partial p_1} = -\gamma$, and $\frac{d^2 \pi_{R1}^{FDT}}{dt^2} = -2r_1{}^2$. Knowing $\frac{\partial^2 \pi_{R1}^{FDT}}{\partial p_1{}^2} = \frac{-2+\varphi}{1-\varphi} < 0$, we calculate the Hessian matrix determinant as follows: $\begin{vmatrix} \frac{-2+\varphi}{1-\varphi} & -\gamma \\ -\gamma & -2r_1{}^2 \end{vmatrix} = \left(\frac{2-\varphi}{1-\varphi}\right)(2r_1{}^2) - \gamma^2$ which is always positive according to Assumption 1. Therefore, the Hessian matrix is definitely negative, and the profit function is concave. By solving the following equation system, $\begin{cases} \frac{\partial \pi_{R1}^{FDT}}{\partial p_1} = 0 \\ \frac{\partial \pi_{R1}^{FDT}}{\partial t_1} = 0 \end{cases}$ the optimal best responses, $p_1^* = \frac{2r_1^2(w - \varphi + 1 + \delta e(1-\varphi)) - (1-\varphi)(\gamma^2 w + 2\gamma r_0 r_1)}{2r_1^2(2-\varphi) - \gamma^2(1-\varphi)}$ and $t^* = \frac{2r_0 r_1(2-\varphi) - \gamma\ (1-\varphi)(1 - w + \delta e)}{2r_1^2(2-\varphi) - \gamma^2(1-\varphi)}$, are obtained.

Proof for Proposition 3

To prove the concavity of the profit function of the manufacturer, after substituting the best response of retailer into the manufacturer's profit function, we have the second partial derivatives as follows: $\frac{\partial^2 \pi_M^{FDT}}{\partial w^2} = \frac{2r_1^2(\varphi-3)}{\gamma^2(\varphi-1) + 2r_1^2(2-\varphi)}$, $\frac{\partial^2 \pi_M^{FDT}}{\partial w \partial e} = \frac{\partial^2 \pi_M^{FDT}}{\partial e \partial w} = \frac{r_1^2(\alpha - \delta)(\varphi - 3)}{\gamma^2(\varphi-1) + 2r_1^2(2-\varphi)}$, and $\frac{\partial^2 \pi_M^{FDT}}{\partial e^2} = \frac{k(\gamma^2(1-\varphi) + 2r_1^2(\varphi-2)) + 2\alpha\delta r_1^2(3-\varphi)}{\gamma^2(\varphi-1) + 2r_1^2(2-\varphi)}$. By Assumption 1, it is clear that $\frac{\partial^2 \pi_M^{FDT}}{\partial w^2} < 0$. Then we calculate the determinant of the Hessian matrix:

$$\begin{vmatrix} \frac{2r_1^2(\varphi-3)}{2r_1^2(2-\varphi) + \gamma^2(\varphi-1)} & \frac{r_1^2(\alpha - \delta)(\varphi - 3)}{2r_1^2(2-\varphi) + \gamma^2(\varphi-1)} \\ \frac{r_1^2(\alpha - \delta)(\varphi - 3)}{\gamma^2(\varphi-1) - 2r_1^2(\varphi-2)} & \frac{k(\gamma^2(1-\varphi) + 2r_1^2(\varphi-2)) + 2\alpha\delta r_1^2(3-\varphi)}{\gamma^2(\varphi-1) - 2r_1^2(\varphi-2)} \end{vmatrix} = \frac{r_1^2(\varphi-3)(\gamma^2 2k(1-\varphi) + r_1^2(4k(\varphi-2) + \alpha(3\alpha - \alpha\varphi + 2\delta(3-\varphi)) + \delta^2(3-\varphi)))}{(\gamma^2(\varphi-1) + 2r_1^2(2-\varphi))^2} \tag{34}$$

The denominator of Eq. (34) is always positive and for $k > \frac{(r_1^2(3-\varphi)(\alpha+\delta))^2}{2r_1^2(3-\varphi)(2r_1^2(2-\varphi) - \gamma^2(1-\varphi))}$ the numerator is positive, too. Since we assume k is significantly greater than other parameters, it is always true. So, the Hessian matrix is definitely negative, and the concavity of the function is easily proved. Thereafter we solve $\begin{cases} \frac{\partial \pi_M^{FDT}}{\partial w} = 0 \\ \frac{\partial \pi_M^{FDT}}{\partial e} = 0 \end{cases}$ to obtain the optimal decision values for the manufacturer:

$$w^* = \frac{(3-\varphi)A_1 - A_2(2r_1^2(2-\varphi) - \gamma^2(1-\varphi))}{r_1 A_3} \tag{35}$$

$$e^* = \frac{r_1(\alpha + \delta)(3 - \varphi)(r_1(\alpha + c - 1) + \gamma r_0)}{A_3} \tag{36}$$

Proof for Proposition 4

After calculating the second partial derivative of the retailer's profit function in Period 2, we have $\frac{\partial^2 \pi_{R2}^{DDT}}{\partial p_2{}^2} = \frac{-2}{1-\varphi}$, $\frac{\partial^2 \pi_{R2}^{DDT}}{\partial p_2 \partial t_2} = \frac{\partial^2 \pi_{R2}^{DDT}}{\partial t_2 \partial p_2} = \gamma\left(\frac{\varphi}{\varphi - 1} - 1\right)$, $\frac{\partial^2 \pi_{R1}^{DDT}}{\partial t^2} = -r_1{}^2$. We know $\frac{\partial^2 \pi_{R2}^{DDT}}{\partial p_2{}^2} = \frac{-2}{1-\varphi}$ is negative. The Hessian matrix determinant for the function is $\begin{vmatrix} \frac{-2}{1-\varphi} & \gamma\left(\frac{\varphi}{\varphi - 1} - 1\right) \\ \gamma\left(\frac{\varphi}{\varphi - 1} - 1\right) & -r_1{}^2 \end{vmatrix} = -\frac{2r_1^2(\varphi-1) + \gamma^2}{(\varphi - 1)^2}$, which is always positive under Assumption 5. Therefore, the function is concave, and by solving $\begin{cases} \frac{\partial \pi_{R2}^{DDT}}{\partial p_2} = 0 \\ \frac{\partial \pi_{R2}^{DDT}}{\partial t_2} = 0 \end{cases}$, the best responses are obtained:

$$p_2^* = \frac{\gamma^2 w + r_1^2(\varphi - 1)(p_1 + w + \gamma t_1) + \gamma r_0 r_1(1 - \varphi)}{2r_1^2(\varphi - 1) + \gamma^2} \tag{37}$$

$$t_2^* = \frac{\gamma(\gamma t_1 + p_1 - w) + 2r_0 r_1(\varphi - 1)}{2r_1^2(\varphi - 1) + \gamma^2} \tag{38}$$

Proof for Proposition 5

After substituting the retailer's best responses of the second period into their first-period profit function, we have partial derivatives $\frac{\partial^2 \pi_{R1}^{DDT}}{\partial {p_1}^2} = -\frac{2\left(r_1^2(\varphi-2)+\gamma^2\right)}{2r_1^2(\varphi-1)+\gamma^2}$, $\frac{\partial^2 \pi_{R1}^{DDT}}{\partial p_1 \partial t_1} = \frac{\partial^2 \pi_{R1}^{DDT}}{\partial t_1 \partial p_1} = -\frac{\gamma\left(r_1^2(\varphi-2)+\gamma^2\right)}{2r_1^2(\varphi-1)+\gamma^2}$, and $\frac{\partial^2 \pi_{R1}^{DDT}}{\partial t_1^2} = -{r_1}^2$. By Assumption 5, $\frac{\partial^2 \pi_{R1}^{DDT}}{\partial {p_1}^2} = -\frac{2\left(r_1^2(\varphi-2)+\gamma^2\right)}{2r_1^2(\varphi-1)+\gamma^2}$ is always negative. The determinant of the Hessian matrix of the profit function is $\frac{-\gamma^6+\gamma^4 2r_1^2(3-\varphi)+\gamma^2 r_1^4\left(-\varphi^2+10\varphi-12\right)+4r_1^6\left(\varphi^2-3\varphi+2\right)}{\left(2r_1^2(\varphi-1)+\gamma^2\right)^2}$. The denominator of the determinant is always positive. If we consider $\gamma^2 = x$, then the numerator is a cubic polynomial of x, which is denoted by $B_1(x) = -x^3 + x^2 2r_1^2(3-\varphi) + xr_1^4\left(-\varphi^2+10\varphi-12\right) + 4r_1^6\left(\varphi^2-3\varphi+2\right)$. By solving the third-degree equation, we can say B_1 is positive under one of the following conditions:

$$\begin{cases} r_1^2(2-\varphi) < x < r_1^2(2-\dfrac{\varphi-\sqrt{\varphi(\varphi+8)}}{2} \ (a) \\ \qquad\qquad or \\ \quad x < r_1^2\left(2-\dfrac{\varphi+\sqrt{\varphi(\varphi+8)}}{2}\right) \ (b) \end{cases} \tag{39}$$

We know Condition (39-a) violates Assumption 5; on the other hand, Condition (39-b) is always true under Assumption 5. So, by Assumption 5, the determinant is positive, and we can conclude that the retailer's profit function in the first period is concave. Therefore, by solving $\begin{cases} \dfrac{\partial \pi_{R1}^{DDT}}{\partial p_1} = 0 \\ \dfrac{\partial \pi_{R1}^{DDT}}{\partial t_1} = 0 \end{cases}$, the optimal best responses in the second period are obtained.

$$p_1^* = \frac{\left(r_1(r_1(1+\delta e)-\gamma r_0)A_4{}^2 + w\left(r_1^2(A_6+A_5\gamma^2(\varphi-4))-\gamma^6\right)\right)}{A_5(\gamma^4+4r_1^4(1-\varphi)-\gamma^2 r_1^2(4-\varphi))} \tag{40}$$

$$t_1^* = \frac{(1+\delta e-w)\left(2\gamma r_1^2(1-\varphi)-\gamma^3\right)-4r_0r_1^3(1-\varphi)+\gamma^2 r_0 r_1(2+\varphi)}{\gamma^4+4r_1^4(1-\varphi)-\gamma^2 r_1^2(4-\varphi)} \tag{41}$$

Proof of Proposition 6

To prove the concavity of the profit function of the manufacturer, first, the best responses of the retailer are substituted into the profit function of the manufacturer. Then, by calculating the second derivatives, we have:

$$\frac{\partial^2 \pi_M^{DDT}}{\partial w^2} = \frac{2r_1^2\left(2\gamma^4+\gamma^2 r_1^2(4\varphi-7)+2r_1^4(\varphi^2-4\varphi+3)\right)}{-B_1} \tag{42}$$

$$\frac{\partial^2 \pi_M^{DDT}}{\partial w \partial e} = \frac{\partial^2 \pi_M^{DDT}}{\partial e \partial w} = \frac{r_1^2(\alpha-\delta)\left(2\gamma^4+\gamma^2 r_1^2(4\varphi-7)+2r_1^4(\varphi^2-4\varphi+3)\right)}{-B_1} \tag{43}$$

$$\frac{\partial^2 \pi_M^{DDT}}{\partial e^2} = \frac{-\left(\gamma^6 k + r_1^2\left(4r_1^4(\varphi-1)(\alpha\delta(\varphi-3)-k(\varphi-2))+B_7\right)\right)}{-B_1} \tag{44}$$

$\frac{\partial^2 \pi_M^{DDT}}{\partial w^2}$ has the opposite sign of a quadratic polynomial, which is within itself and equals $B_2(x) = 2x^2 + xr_1^2(4\varphi-7) + 2r_1^4\left(\varphi^2-4\varphi+3\right)$, where $\gamma^2 = x$. $\frac{\partial^2 \pi_M^{DDT}}{\partial w^2}$ is negative when B_2 is positive under the conditions below:

$$\begin{cases} \gamma > r_1\sqrt{\dfrac{7-4\varphi+\sqrt{8\varphi+1}}{4}} \ (a) \\ \qquad or \\ \gamma < r_1\sqrt{\dfrac{7-4\varphi-\sqrt{8\varphi+1}}{4}} \ (b) \end{cases} \tag{45}$$

It is obvious that Condition (45-a) violates Assumption 5 while Condition (45-b) is the assumption itself. So, it is always true resulting in $\frac{\partial^2 \pi_M^{DDT}}{\partial w^2} < 0$. Thereafter, we have the determinant of the Hessian matrix $\frac{-B_2 r_1^2(B_3-2kB_1)}{B_1^2}$ where $B_3 = (r_1(\alpha+\delta))^2\left(2r_1^4(\varphi^2-4\varphi+3)+\gamma^2\left(2\gamma^2+r_1^2(4\varphi-7)\right)\right)$. The determinant is positive for $K > \frac{B_3}{2B_1}$, which is true since the k is sufficiently larger than the other parameters. Therefore, the profit function is concave because the Hessian matrix is negative definite. Solving $\begin{cases} \dfrac{\partial \pi_M^{DDT}}{\partial w} = 0 \\ \dfrac{\partial \pi_M^{DDT}}{\partial e} = 0 \end{cases}$ yields the optimal decisions:

$$w^* = \frac{A_1A_7 + A_2A_8}{r_1((\alpha+\delta)^2A_7 + 2kA_8)} \quad (46)$$

$$e^* = \frac{A_7(\alpha+\delta)(r_1(\alpha+c-1)+\gamma r_0)}{(\alpha+\delta)^2A_7 + 2kA_8} \quad (47)$$

Proof of Proposition 7

In the FDT model, the partial derivative of the equilibrium value of the carbon emissions reduction effort is:

$$\frac{\partial e^{*FDT}}{\partial\delta} = \frac{2r_1(3-\varphi)(r_1(1-\alpha-c)-\gamma r_0)\left(2r_1^2(2-\varphi)-\gamma^2(1-\varphi)\right)k + B_4}{{A_3}^2} \quad (48)$$

Based on Assumption 2, the sign of Eq. (48) depends on the coefficient$k$. Based on Assumptions 1 and 2, $2r_1(3-\varphi)(r_1(1-\alpha-c)-\gamma r_0)\left(2r_1^2(2-\varphi)-\gamma^2(1-\varphi)\right) > 0$ and we conclude $\frac{\partial e^{*FDT}}{\partial\delta} > 0$.

In the DDT model, we have:

$$\frac{\partial e^{*DDT}}{\partial\delta} = \frac{r_1B_2(r_1(1-\alpha-c)-\gamma r_0)((\alpha+\delta)^2A_7 + 2kB_1)}{(A_7(\alpha+\delta)^2 + 2kA_8)^2} \quad (49)$$

Similar to the FDT model, based on Assumption 2, and since we proved $B_1 > 0$ in *Proposition 5*, we conclude$\frac{\partial e^{*DDT}}{\partial\delta} > 0$.

Proof of Proposition 8

First, we calculate the partial derivative for the FDT model: $\frac{\partial\pi_M^{FDT}}{\partial\delta} = \frac{kr_1^2(\alpha+\delta)(3-\varphi)^2(r_1(1-\alpha-c)-\gamma r_0)^2}{{A_3}^2}$, which is positive.

For the DDT model, the partial derivative is $\frac{\partial\pi_M^{FDT}}{\partial\delta} = \frac{kB_2r_1^2(\alpha+\delta)(r_1(1-\alpha-c)-\gamma r_0)^2}{(A_7(\alpha+\delta)^2+2kA_8)^2}$, which, since we proved the $B_2 > 0$ in Proposition 6 is positive.

The following notations with their corresponding values are defined:

$$A_1 = (\alpha^2+\alpha\delta)(r_1-\gamma r_0) + r_1(c+\alpha)(\delta^2+\alpha\delta)$$

$$A_2 = k(r_1(1+\alpha+c) - \gamma r_0)$$

$$A_3 = 2\gamma^2k(1-\varphi) + r_1^2\left((\alpha+\delta)^2(3-\varphi) - 4k(2-\varphi)\right)$$

$$A_4 = 2r_1^2(1-\varphi) - \gamma^2$$

$$A_5 = r_1^2(2-\varphi) - \gamma^2$$

$$A_6 = (1-\varphi)\left(4r_1^4+\gamma^4\right)$$

$$A_7 = r_1^2\left(2r_1^4(\varphi-3)(\varphi-1) + \gamma^2r_1^2(4\varphi-7) + 2\gamma^4\right)$$

$$A_8 = \left(r_1^2\left(\gamma^2r_1^2(\varphi^2-10\varphi+12) + 2\gamma^4(\varphi-3) - 4r_1^4(\varphi-2)(\varphi-1)\right) + \gamma^6\right)$$

$$A_9 = \gamma^6 + 2\gamma^4r_1^2(\varphi-3) + \gamma^2r_1^4(\varphi^2-10\varphi+12) + 4r_1^6(-\varphi^2+3\varphi-2)$$

$$A_{10} = \gamma^6 - 4r_1^6(1-\varphi) + \gamma^4r_1^2(2\varphi-5) + \gamma^2r_1^3(\varphi^2-6\varphi+8)$$

$$A_{11} = 4r_1^6(-2\varphi^2+5\varphi-3) + \gamma^2r_1^4(\varphi^2-14\varphi+16) + \gamma^4r_1^2(2\varphi-7) + \gamma^6$$

$$A_{12} = kr_0r_1^2\left(8r_1^4(3\varphi-\varphi^2-2) + 2\gamma^2r_1^2(10-7\varphi) - \gamma^4(8-\varphi)\right)$$

$$A_{13} = 2r_1^2\left(r_1^2(\varphi^2-4\varphi+3) - (7-4\varphi)\right) + 2\gamma^4$$

$$A_{14} = kr_0r_1^2\left(8r_1^4(-\varphi^2+3\varphi-2) + 2\gamma^2r_1^2(\varphi^2-9\varphi+11) + 3\gamma^4(\varphi-3)\right) + \gamma^6r_0)$$

$$A_{15} = 2r_1^4(\varphi^2-4\varphi+3) + \gamma^2r_1^2(4\varphi-7) + 2\gamma^4$$

$$A_{16} = 2r_1^6(-\varphi^2+4\varphi-3) + \gamma^2r_1^4(3-2\varphi) + \gamma^4r_1^2(\varphi-5) + \gamma^6$$

$$A_{17} = 2r_1^6(-3\varphi^2+8\varphi-5) + \gamma^2r_1^4(2\varphi^2-14\varphi+15) + \gamma^4kr_1^2(3\varphi-7) + \gamma^6$$

$$A_{18} = (2\gamma^{10} + 8r_1^{10}(-2\varphi^4+11\varphi^3-21\varphi^2+17\varphi-5) + 4\gamma^2r_1^8(\varphi^4-18\varphi^3-60\varphi^2+70\varphi-27) + 2\gamma^4r_1^6(7\varphi^3-7\varphi^2+109\varphi-59) + \gamma^6r_1^4(18\varphi^2-76\varphi+65) + 2\gamma^8r_1^2(5\varphi-9)$$

$$B_1 = -\gamma^6 + \gamma^4 2r_1^2(3-\varphi) + \gamma^2r_1^4(-\varphi^2+10\varphi-12) + 4r_1^6(\varphi^2-3\varphi+2)$$

$$B_2 = 2\gamma^4 + \gamma^2 r_1^2(4\varphi - 7) + 2r_1^4(\varphi^2 - 4\varphi + 3)$$

$$B_3 = (r_1(\alpha+\delta))^2\left(2r_1^4(\varphi^2 - 4\varphi + 3) + \gamma^2(2\gamma^2 + r_1^2(4\varphi - 7))\right)$$

$$B_4 = -r_1^3(3-\varphi)^2(r_1(\alpha + c - 1) + \gamma r_0)(\alpha+\delta)^2$$

Data availability

The authors will make the data supporting this study's findings available upon reasonable request.

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