

Article

Research on Data Product Operation Strategies Considering Dynamic Data Updates Under Different Power Structures

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Abstract

As data product transactions become increasingly standardized, the operational strategies of data product manufacturers and service providers play a pivotal role in shaping market outcomes. This study develops a game-theoretic framework that incorporates dynamic data updates under alternative power structures to examine the equilibrium performance of pricing, demand, technological investment, update rates, and promotional effort. The results indicate that optimal prices under Stackelberg leadership exceed those in the Nash game, whereas demand, technological investment, update frequency, and promotion are consistently higher in the Nash setting. The effects of these decisions are moderated by end-user preference heterogeneity: when users exhibit stronger promotion preferences, service-provider leadership generates superior outcomes, while stronger quality preferences favor manufacturer leadership. Demand preferences and cost coefficients significantly influence profitability—enhanced preferences improve the leader's returns, whereas high technological and promotional costs suppress profits for both parties. Cost savings in dynamic updates and increases in perceived value exert strong positive effects on market competitiveness, while higher update investment and data acquisition costs exert negative effects. Overall, this study deepens the theoretical understanding of how power structures interact with dynamic updating and user preferences, providing analytical insights and decision support for optimizing operational strategies in data product markets.



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MSC: 91A10

1. Introduction

With the rapid advancement of cloud computing, the Internet of Things (IoT), and artificial intelligence, data has become a strategic production factor that reshapes productivity and production relations, forming a key foundation of China's new-quality productive forces. Recognizing its economic value, China has launched a systematic reform agenda to promote the market-oriented allocation of data elements. A series of institutional measures—such as the Opinions on Building a Data Infrastructure System to Better Leverage Data Elements, the establishment of the National Data Administration, and the Data Element × Three-Year Action Plan (2024–2026)—have accelerated the development of a standardized data product transaction system [1]. In practice, China's emerging

data product market operates through platform-mediated exchanges—such as the Shanghai Data Exchange and JD Wanxiang—that connect data product manufacturers, service providers, and end users. Data product transactions are essential because they constitute the core mechanism for transforming raw data resources into measurable economic value and driving the data-element economy forward [1]. However, according to the National Data Resources Survey Report (2023), the transaction rate of data products remains only 17.9%, and the supply–demand matching rate is still low, revealing persistent challenges in market activation and transaction efficiency.

Within the widely adopted “data product manufacturer–data product service provider–data product end user” transaction architecture, the operational decisions of manufacturers and service providers play a central role in determining market performance [2,3]. Data product manufacturers must invest in technological improvement to enhance accuracy, completeness, and usability, and, due to the strong timeliness and rapid depreciation of data products, dynamic updating is essential for maintaining product effectiveness [4]. For data product service providers, promotional activities remain the primary channel for increasing user awareness and lowering adoption barriers, especially given the still limited public understanding and participation in data product usage in China [5]. These operational strategies—technological investment, dynamic updating, and promotion—are inherently interdependent, and coordinated decision-making is crucial for improving transaction efficiency. Moreover, prior research shows that such strategies are strongly shaped by the underlying market power structure [6,7]. In practice, bargaining power between data product manufacturers and service providers is often asymmetric. Data product manufacturers with higher product quality, broader application scenarios, or larger market scale typically hold stronger bargaining positions, as seen in cases where digital-native firms such as Alibaba dominate negotiations with smaller service providers. Conversely, small-scale or lower-quality manufacturers tend to operate in subordinate positions. As a result, heterogeneous power structures arise and exert substantial influence on pricing, quality improvement, updating, and promotional effort. Although earlier studies have explored the impact of power structures in traditional product markets [8–12], the virtual, time-sensitive, non-rival, and non-exclusive characteristics of data products differentiate them fundamentally from conventional goods and generate decision-making mechanisms unique to data product markets.

A distinctive characteristic of data product transactions is the pronounced information asymmetry embedded in such exchanges. End users are unable to fully evaluate a data product before purchase, giving rise to the well-known “information paradox” highlighted in prior studies [1,6]. On the one hand, users lack access to complete product information *ex ante*, making it difficult to accurately assess expected utility or judge whether the price is reasonable. On the other hand, if users could obtain full knowledge of a data product’s content and quality beforehand, their marginal expected utility would be nearly exhausted, thereby weakening the incentive to purchase. This paradox illustrates the unique nature of information asymmetry in data product markets and may further amplify existing transaction barriers [7]. The resulting uncertainty regarding expected utility forms the core of end users’ perceived value uncertainty. Under such conditions, users cannot determine in advance whether a data product will meet their needs [13], which reduces purchase intention, suppresses demand, and complicates the design of effective operational strategies.

Beyond these empirical challenges, the existing research on data product operations provides an important theoretical foundation. A central view in the literature is that the value of data products is not inherent but is generated through continuous investments in acquisition, processing, analysis, and updating [3]. Boyd et al. [14] emphasize the systemic

and asymmetric nature of data investment, particularly in relation to provenance and control, while Grunes et al. [15] argue that sustained data investment is essential for firms seeking long-term competitive advantages. Li et al. [16] further show that disclosures about data-collection breadth and user heterogeneity can influence optimal investment decisions. Although this line of work clarifies the “investment–value realization” logic, it focuses primarily on acquisition and processing, offering limited insight into how dynamic updating affects product quality and market outcomes. Another stream of literature investigates data product transactions and pricing mechanisms [17–19]. Yu et al. [20] incorporate uncertain data demand and user risk preferences into a pricing model, while Jing [21] shows that data advantages enable platforms to conduct differentiated pricing under different competitive regimes. Wang et al. [22] distinguish between public and commercial data to derive pricing strategies suited to their respective attributes. While these studies deepen our understanding of pricing behavior, they typically examine pricing in isolation and rarely integrate it with other strategic decisions such as technological investment, updating, and promotion. Despite these contributions, three major gaps remain. First, existing studies often analyze technological optimization, dynamic updating, and promotional activities separately, lacking an integrated framework that captures their complementarities and trade-offs. Second, prior analyses of market structure rely heavily on traditional product-market settings and do not fully reflect how asymmetric bargaining power between manufacturers and service providers shapes strategic behavior in data product markets. Third, the pervasive perceived value uncertainty faced by end users is insufficiently incorporated into existing models, leaving unclear how it influences demand formation and the joint decision-making of manufacturers and service providers.

Motivated by these gaps, this study incorporates the dynamic updating characteristics of data products and the perceived value uncertainty faced by end users. It develops three game-theoretic frameworks—a balanced power scenario, a data product manufacturer–led scenario, and a data product service provider–led scenario—to investigate the following research questions: (1) Under different power structures, how should data product manufacturers and service providers determine pricing, technological improvement levels, updating frequency, and promotional effort to maximize profits? (2) In light of the “information paradox,” how can firms integrate end users’ perceived value uncertainty into their operational strategies to improve the efficiency of data product transactions? (3) What factors fundamentally shape data product operational strategies, through what mechanisms do they exert influence, and how do their effects evolve in magnitude over time?

Beyond addressing gaps in existing research, this study offers substantial theoretical and practical value by uncovering the core mechanisms underlying data product operational strategies from a multidimensional and interdependent perspective. First, we develop an integrated framework that jointly considers technological investment, dynamic updating, and market promotion, thereby clarifying their strategic complementarities and trade-offs. This contributes to establishing a more unified theoretical foundation for understanding data product operations. Second, we incorporate end users’ perceived value uncertainty directly into the demand function and demonstrate how such uncertainty influences demand formation and, in turn, shapes the strategic decisions of manufacturers and service providers. This offers a new analytical perspective for studying data product markets. Third, we systematically compare optimal decisions under three power structures and show how asymmetric bargaining power reshapes the interaction among pricing, investment, updating, and promotion strategies, providing novel insights into strategy formation under bilateral cooperation. From a practical perspective, the findings help data product firms design more effective operational strategies under uncertain demand and limited user awareness. The study also provides theoretical guidance for policymakers in

improving transaction mechanisms, strengthening market governance, and unlocking the economic potential of data elements.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 presents the problem description and formulates the reasonable assumptions for model construction. Section 4 develops and solves the game models under three different power structures. Section 5 compares and analyzes the equilibrium solutions under various scenarios. Section 6 uses numerical simulations to quantify the results of the model's equilibrium solutions and the impact of parameters, validating the correctness of the conclusions. Section 7 concludes the paper and offers targeted recommendations.

2. Literature Review

As market-oriented reforms in the allocation of data elements continue to advance, the literature has evolved into three principal strands. The first investigates the value attributes of data and the theoretical principles that guide data pricing. The second examines the circulation of data products from the standpoint of data-related supply chains and game-theoretic structures. The third focuses on user preferences, privacy concerns, and the design of transaction mechanisms.

Regarding the attributes of data value and the foundations of pricing, early studies primarily focused on developing methods to measure data value across different application scenarios and to translate these assessments into actionable pricing rules. Shen et al. [23] proposed a pricing model for personal big-data environments that incorporates privacy sensitivity into the utility function, arguing that pricing should reflect users' subjective evaluations of privacy risk. Yu et al. [24] advanced a pricing approach grounded in data-quality considerations, demonstrating that quality grades and service levels jointly determine prices and that data quality plays a central role in shaping willingness to pay and demand elasticity. Jia et al. [25] subsequently situated the pricing problem within a machine-learning framework and formulated a model-based pricing mechanism informed by model contribution, accuracy disparities, and the substitutability of data. In parallel, Zhao et al. [26] developed a dynamic pricing model grounded in credit-based game theory. By incorporating repeated interactions and credit metrics, their framework seeks to correct pricing distortions that arise when platforms possess unilateral pricing power or when market participants lack sufficient creditworthiness. Building on this work, Lu et al. [27] integrated compressed sensing with game-theoretic reasoning under the GHMP framework to propose an adjustable-precision, pay-as-needed pricing mechanism. Liao et al. [28] adopted a platform-individual co-creation perspective on data property rights and constructed a bidirectional pricing model that jointly embeds privacy computation, user decision-making, and platform revenue considerations. Hendershott et al. [29] conceptualized data as a proprietary output of trading platforms and examined how data product sales interact with and complement trading activity in securities markets. Taken together, this stream of research has progressed from static attribute-based pricing toward a richer value framework encompassing task relevance, credit mechanisms, and precision-on-demand. Nevertheless, much of the literature continues to treat data as a one-off deliverable, devoting limited attention to the dynamic costs associated with updating, maintenance, and incremental improvement. Moreover, the role of promotional activities in shaping demand formation remains insufficiently explored.

In examining data supply chains and game-theoretic structures, the literature typically conceptualizes data products as composite outputs jointly produced by multiple stakeholders and models the strategic interactions among data owners, platforms, service providers, and end users using game-theoretic frameworks. Mei et al. [30] developed a Stackelberg-based pricing model for IoT information services and analyzed how data owners determine

service prices and quality levels when positioned as leaders. Liu et al. [31] incorporated data-purchasing prices, subscription fees, and device heterogeneity into a supply-chain game within a blockchain-enabled IoT environment, highlighting the combined effects of data quality, network topology, and incentive mechanisms. Xu et al. [32] applied blockchain mechanisms to vehicular networking scenarios and evaluated the efficiency implications of on-chain versus off-chain pricing and trading strategies. Zhang et al. [33] designed a data-trading mechanism for federated learning that integrates blockchain and game theory, enhancing aggregation quality through credit-based weighting and ensuring traceability and auditability via blockchain infrastructure. Abbasi et al. [34] proposed a blockchain-enabled industrial data-trading architecture that demonstrates how decentralized storage, fine-grained access control, and traceability strengthen transaction security and trust in industrial IoT systems. In the mechanism-design literature, Cao et al. [35] modeled price formation under bilateral and iterative auction settings and examined how social welfare and transaction efficiency can be simultaneously optimized in markets featuring multiple data owners and heterogeneous demand. Collectively, this research advances our understanding of pricing structures and revenue-allocation mechanisms in multi-agent data markets. However, much of the literature abstracts the supply side into a single platform or a simple data owner–platform dyad. Only a limited number of studies adopt the more realistic structure involving both a data product manufacturer and a data product service provider, and systematic comparisons of pricing, updating investment, and promotional strategies across different power configurations—such as manufacturer dominance, service-provider dominance, and balanced bargaining power—remain largely absent.

In the domain of user preferences, privacy protection, and transaction-mechanism design, Jung et al. [36] developed a privacy–price negotiation mechanism under a differential privacy framework and demonstrated that higher privacy sensitivity substantially increases users’ required compensation, thereby shifting market-equilibrium prices. Within a co-created data-property-rights setting, Liao et al. [28] modeled the utility differences associated with users’ choices to buy, sell, or remain inactive, introduced a privacy-computation term to capture individuals’ trade-offs between privacy risk and monetary compensation, and established a two-sided pricing model that links platform decisions with user behavior. Liu et al. [37] examined the role of government subsidies by developing three scenarios—no subsidy, manufacturer-subsidy, and service-provider-subsidy—and analyzed how alternative subsidy regimes redistribute profits in data product markets. Although this line of research enriches the behavioral foundations of data product pricing by integrating privacy, preference, and institutional considerations, several limitations persist. First, many existing models assume deterministic user utility and do not capture the perceived value uncertainty arising from the virtual, context-dependent, and experience-lagged characteristics of data products. Second, although recent studies have begun to account for government subsidies or platform incentives, they have yet to incorporate the interconnected dynamics among quality investment, promotional expenditure, dynamic updating, and market-power configurations. Third, the literature remains focused on transaction occurrence and mechanism design, while devoting limited attention to how firms adjust quality-based and promotion-based operational strategies in response to evolving market structures and shifts in user perceptions.

A careful examination of the core literature reveals that the existing research exhibits three notable deficiencies:

- (1) Although prior studies on data product pricing have proposed a variety of pricing models based on static quality attributes, privacy considerations, and model contribution, they largely conceptualize data products as static, one-off, or stage-based deliverables and offer limited systematic analysis of dynamic updating behaviors or

lifecycle-based cost structures. While a few studies incorporate dynamic assessment or credit-based game-theoretic approaches [26], these efforts continue to focus primarily on price adjustments rather than on the interplay among updating activities, quality investment, and promotional decisions. Promotional expenditure is often subsumed under broader platform operations and seldom treated as an explicit strategic variable in formal models. By contrast, the present study explicitly incorporates updating investment, quality investment, and promotional investment as strategic variables for both data product manufacturers and data product service providers, and examines—within a unified analytical framework—how these decisions jointly shape demand, pricing outcomes, and profit distributions. This approach helps address the literature’s insufficient treatment of the integrated and interdependent nature of operational decision-making.

- (2) Although supply-chain and platform game studies frequently employ Stackelberg and Nash frameworks to analyze pricing behavior [30,31,38], they often assume a single dominant supplier or simplify the supply side into a data owner–platform dyad, thereby overlooking the bargaining-power disparities that characterize real interactions between data product manufacturers and data product service providers. Existing analyses of power structures typically rely on coarse distinctions between upstream and downstream dominance and rarely incorporate the distinctive attributes of data products—such as updating costs and joint quality–promotion investments—into systematic comparative analyses. This study differentiates among three canonical power configurations: a Nash setting with balanced power between the data product manufacturer and the data product service provider, a manufacturer-led Stackelberg structure, and a service-provider-led Stackelberg structure. It then examines how optimal pricing and investment decisions shift as the underlying power structure changes. Through this comparative approach, the analysis demonstrates how differing power configurations reshape operational strategies and market outcomes for data products, thereby filling an important gap in the existing literature.
- (3) Studies on privacy preferences and incentive mechanisms demonstrate that users’ subjective trade-offs between privacy risks and economic compensation play a critical role in determining their willingness to participate in data transactions [27,28,36]. However, because data products are virtual, time-sensitive, and highly context dependent, end users generally cannot accurately evaluate their true utility prior to purchase, creating systematic gaps between perceived and actual value. Existing models typically treat user utility and preference parameters as fixed, an assumption that obscures the inherent “value uncertainty” of data products and leaves unexamined the complex interactions among quality-perception bias, promotional persuasion, and pricing effects. To address this limitation, the present study introduces an explicit parameter for perceived value uncertainty into the end-user utility formulation. It further distinguishes user preferences for quality and promotion and embeds these preferences as core determinants of data product demand. The analysis then investigates how data product manufacturers and service providers—under different power structures—strategically adjust quality and promotional investments to counteract perception bias and improve market outcomes. This approach expands the behavioral foundation of existing pricing models and enhances their applicability to more realistic market environments.

3. Model Description and Assumptions

3.1. Model Description

Following the approach of Hu et al. [39] and Wang et al. [40], this study examines a data product transaction system composed of data product manufacturers, service providers, and end users. In China's mainstream data product markets, the transaction process proceeds as follows: data product manufacturers collect and organize raw data, process it through de-identification, and convert it into clearly defined and potentially valuable data products, which are then sold to service providers at a given price. Service providers are responsible for product promotion and post-sale support, selling the data products to end users to generate revenue. End users—including individuals, enterprises, and governments—decide whether to purchase based on product quality, promotional intensity, and their own needs.

Given the strong time sensitivity and rapid value depreciation of data products, manufacturers must engage in continuous data collection and dynamic updating to improve applicability and timeliness, extend product lifecycles, and maintain market competitiveness. Specifically, after end users consume the product, manufacturers pay a certain price to acquire user-generated data (e.g., interaction data, incremental data, or feedback information). Such data serves as an input for remanufacturing, enabling updates to existing products and further optimization of content and quality. In this process, manufacturers must consider both the value and cost of data collection to determine the optimal update rate that maximizes profit while ensuring the timeliness and quality necessary to meet market demand. Because manufacturers and service providers occupy different positions in the transaction process, the power structure between them exerts a significant influence on optimal strategic decisions. Accordingly, this study develops three game-theoretic models under alternative power configurations—balanced power between manufacturers and service providers, manufacturer dominance, and service-provider dominance—based on the characteristics of data product demand. The specific decision-making sequence is illustrated in Figure 1.

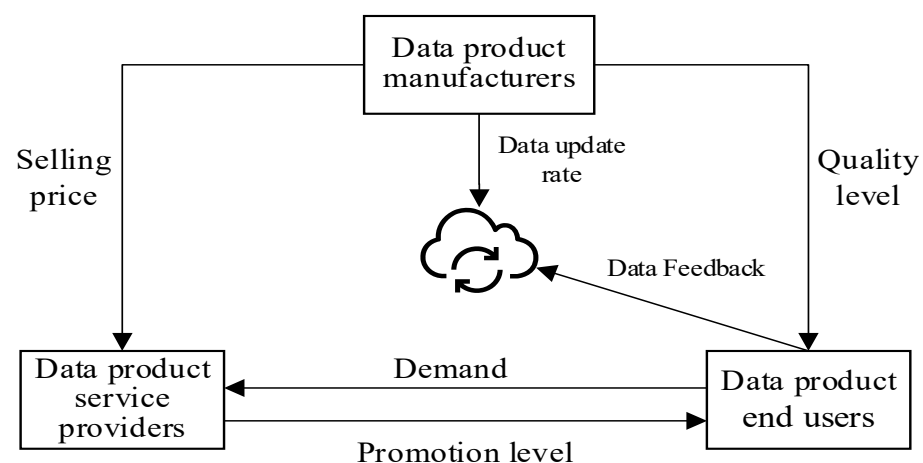


Figure 1. Decision-Making Interaction Diagram Considering Data Updates.

3.2. Model Assumptions and Parameter Setup

Building on the preceding analysis and in accordance with the requirements of the modeling framework, the following basic assumptions are introduced.

Assumption 1. According to Lin et al. [41], the quality of data products not only reflects the underlying production processes and cost structures but also serves as a key determinant of end users' willingness to pay. Consequently, the technological investment made by data product

manufacturers is of considerable importance. Moreover, given the limited public awareness and low participation levels in data product usage in China [5], data product service providers play a central role in promoting these products. Therefore, this paper assumes that k_1 represents the technological investment level made by data product manufacturers in the production of data products, and k_2 represents the promotional investment level made by data product service providers for the data products. Based on the principle of increasing marginal costs for firms and referring to widely used cost models in academia [42], it is assumed that the technological investment cost for data product manufacturers is $\frac{1}{2}\lambda_1 k_1^2$ and the promotional investment cost for data product service providers is $\frac{1}{2}\lambda_2 k_2^2$, where $\lambda_1 (\lambda_1 > 0)$ is the cost coefficient for the technological investment of data product manufacturers, and $\lambda_2 (\lambda_2 > 0)$ is the cost coefficient for the promotional investment of data product service providers.

Assumption 2. In addition to technological investment costs, data product manufacturers must also incur updating costs to address the timeliness of data products. This paper assumes that the data update cost is $\frac{1}{2}\delta\tau^2$, where $\tau (0 \leq \tau \leq 1)$ represents the update rate of data product manufacturers, and $\delta (\delta > 0)$ represents the update cost coefficient of data product manufacturers.

Assumption 3. Assume the market size for data product end users is $a (a > 0)$, and their willingness to purchase, denoted as θ , follows a uniform distribution in the range $(0, a)$; end users have a preference for data product quality represented by $d_1 (d_1 > 0)$ and promotion represented by $d_2 (d_2 > 0)$; the price sensitivity coefficient for data product end users is $\beta (\beta > 0)$, and their perceived value of the product is $\mu (\mu > 0)$, where a higher μ indicates lower perceived value uncertainty, making end users more likely to purchase the product. Therefore, the utility function for data product end users can be expressed as $U = \theta\mu - \beta p + d_1 k_1 + d_2 k_2$ [37]. Further analysis reveals that data product end users will only purchase the product when their utility is non-negative. Specifically, when $U = 0$, the indifference point for end users, denoted as $\theta^* = \frac{\beta p - d_1 k_1 - d_2 k_2}{\mu}$, can be derived. From this, the final data product demand function can be obtained as:

$$Q = a - \frac{\beta p + d_1 k_1 + d_2 k_2}{\mu} \quad (1)$$

Assumption 4. Data product manufacturers initially incur substantial expenditures to build the data infrastructure required for producing data products. Once completed, this infrastructure investment becomes a sunk cost and therefore does not affect subsequent pricing decisions [24]. Moreover, the replication cost of data products is exceedingly low [43]. Therefore, this paper ignores the costs associated with initial infrastructure construction and replication, and only considers the actual cost c incurred by data product manufacturers in the initial production of data products.

Assumption 5. In the process of considering data product updates, it is assumed that data product manufacturers collect the necessary data for updating the data products from end users at a price R , and the reprocessing cost for data product updates is c_r . Furthermore, to ensure that the data product updates are both meaningful and profitable, data product manufacturers must satisfy $\Delta = c - c_r > 0$ and $\Delta - R > 0$, where Δ represents the cost savings in the data product update process.

Assumption 6. To ensure the computability of the parameters in this paper, the following conditions must be satisfied: $2\beta\mu\lambda_1 - d_1^2 > 0$, $a\mu - \beta c > 0$, and $2d_2^2\delta\lambda_1 + d_1^2\delta\lambda_2 + \beta\lambda_1\lambda_2[\beta(R - \Delta)^2 - 4\delta\mu] < 0$.

The parameters used in the model constructed in this paper are shown in Table 1, where w, p, k_1, k_2 and τ are decision variables, while the others are basic variables.

Table 1. Parameter Design and Description.

Parameter Symbol	Parameter Description
w	Selling Price of Data Product Manufacturers
p	Pricing of Data Product Service Providers
k_1	Technological Investment Level of Data Product Manufacturers
k_2	Promotional Investment Level of Data Product Service Providers
τ	Update Rate of Data Products
a	Market Size of Data Products
β	Price Sensitivity Coefficient of Data Products End Users
c	Initial Cost of Data Products
c_r	Update Cost of Data Products
Δ	Cost Savings During the Update Process of Data Products
δ	Update Investment Cost Coefficient of Data Product Manufacturers
R	Data Acquisition Price
λ_1	Technological Investment Cost Coefficient of Data Product Manufacturers
λ_2	Promotional Investment Cost Coefficient of Data Product Service Providers
d_1	Quality Preference Factor of End Users of Data Products
d_2	Promotion Preference Factor of End Users of Data Products
μ	Perceived Value of End Users of Data Products
m	Marginal Profit of Data Product Service Providers
Q	Demand for Data Products
π_m	Profit of Data Product Manufacturers
π_s	Profit of Data Product Service Providers

4. Solution and Analysis of the Model

When data product manufacturers consider data updates, they determine the price w , the technological investment level k_1 , and the update rate τ of data products by maximizing profits. Data product service providers maximize their revenue by determining the data product price p and the level of market promotion investment k_2 . Data product end users decide whether to purchase the product based on its price p , their perceived value r , and their demand preferences d_1 and d_2 . Therefore, the objective function for the data product manufacturer is:

$$\pi_m = (w - c)Q + (c - c_r - R)Q\tau - \frac{1}{2}\lambda_1 k_1^2 - \frac{1}{2}\delta\tau^2 \quad (2)$$

The objective function for the data product service providers is:

$$\pi_s = (p - w)Q - \frac{1}{2}\lambda_2 k_2^2 \quad (3)$$

4.1. Nash Game Under Power Equilibrium

When data product manufacturers and service providers are of comparable strength, both parties follow a Nash equilibrium, as seen in the case of large data product manufacturers such as Alibaba and strong data product service providers such as the Shanghai Data Exchange. In this case, the decision-making process follows a simultaneous decision-making pattern where both data product manufacturers and service providers independently determine their optimal strategies. The optimal price w_1^* , optimal technological investment level k_{11}^* , and optimal update rate τ_1^* for the data product manufacturer, and the optimal price p_1^* and optimal promotion investment level k_{21}^* for the data product service provider are as follows:

$$w_1^* = \frac{a\lambda_1\lambda_2\mu[\beta(R - \Delta)^2 - \delta\mu] + c\delta[d_2^2\lambda_1 + \lambda_2(d_1^2 - 2\beta\lambda_1\mu)]}{d_2^2\delta\lambda_1 + d_1^2\delta\lambda_2 + \beta\lambda_1\lambda_2[\beta(R - \Delta)^2 - 3\delta\mu]} \quad (4)$$

$$k_{11}^* = \frac{d_1 \delta \lambda_2 (c\beta - a\mu)}{d_2^2 \delta \lambda_1 + d_1^2 \delta \lambda_2 + \beta \lambda_1 \lambda_2 [\beta(R - \Delta)^2 - 3\delta\mu]} \quad (5)$$

$$\tau_1^* = \frac{\beta(\Delta - R)\lambda_1 \lambda_2 (c\beta - a\mu)}{d_2^2 \delta \lambda_1 + d_1^2 \delta \lambda_2 + \beta \lambda_1 \lambda_2 [\beta(R - \Delta)^2 - 3\delta\mu]} \quad (6)$$

$$p_1^* = \frac{a\lambda_1 \lambda_2 \mu [\beta(R - \Delta)^2 - 2\delta\mu] + c\delta [d_2^2 \lambda_1 + \lambda_2 (d_1^2 - \beta \lambda_1 \mu)]}{d_2^2 \delta \lambda_1 + d_1^2 \delta \lambda_2 + \beta \lambda_1 \lambda_2 [\beta(R - \Delta)^2 - 3\delta\mu]} \quad (7)$$

$$k_{21}^* = \frac{d_2 \delta \lambda_1 (c\beta - a\mu)}{d_2^2 \delta \lambda_1 + d_1^2 \delta \lambda_2 + \beta \lambda_1 \lambda_2 [\beta(R - \Delta)^2 - 3\delta\mu]} \quad (8)$$

By substituting Equations (4)–(8) into Equations (1)–(3), the optimal demand Q_1^* for the data product, the optimal profit π_{m1}^* for the data product manufacturer, and the optimal profit π_{s1}^* for the service provider under the Nash equilibrium are as follows:

$$Q_1^* = \frac{\beta \delta \lambda_1 \lambda_2 (c\beta - a\mu)}{d_2^2 \delta \lambda_1 + d_1^2 \delta \lambda_2 + \beta \lambda_1 \lambda_2 [\beta(R - \Delta)^2 - 3\delta\mu]} \quad (9)$$

$$\pi_{m1}^* = \frac{\delta \lambda_1 \lambda_2^2 (c\beta - a\mu)^2 \left\{ \beta \lambda_1 [2\delta\mu - \beta(R - \Delta)^2] - d_1^2 \delta \right\}}{2 \left\{ d_2^2 \delta \lambda_1 + d_1^2 \delta \lambda_2 + \beta \lambda_1 \lambda_2 [\beta(R - \Delta)^2 - 3\delta\mu] \right\}^2} \quad (10)$$

$$\pi_{s1}^* = \frac{\delta^2 \lambda_1^2 \lambda_2 (c\beta - a\mu)^2 (2\beta \lambda_2 \mu - d_2^2)}{2 \left\{ d_2^2 \delta \lambda_1 + d_1^2 \delta \lambda_2 + \beta \lambda_1 \lambda_2 [\beta(R - \Delta)^2 - 3\delta\mu] \right\}^2} \quad (11)$$

4.2. Stackelberg Game Led by Data Product Manufacturers

When large data product manufacturers such as Alibaba and ByteDance collaborate with weaker data product service providers, they gain market dominance through their superior data quality and scale. In this case, the market follows a Stackelberg game dominated by the data product manufacturer. According to the basic assumptions, when the data product manufacturer leads the market, the decision-making sequence is as follows: the data product manufacturer first decides the price w_2^* , the technological investment level k_{12}^* , and the update rate τ_2^* ; then the data product service provider decides the data product price p_2^* and the promotion investment level k_{22}^* . The specific optimal decisions are as follows:

$$w_2^* = \frac{a\lambda_1 \mu \left\{ d_2^2 \delta + \beta \lambda_2 [\beta(R - \Delta)^2 - 2\delta\mu] \right\} + c\beta \delta [d_2^2 \lambda_1 + \lambda_2 (d_1^2 - 2\beta \lambda_1 \mu)]}{\beta \left\{ 2d_2^2 \delta \lambda_1 + d_1^2 \delta \lambda_2 + \beta \lambda_1 \lambda_2 [\beta(R - \Delta)^2 - 4\delta\mu] \right\}} \quad (12)$$

$$k_{12}^* = \frac{d_1 \delta \lambda_2 (c\beta - a\mu)}{2d_2^2 \delta \lambda_1 + d_1^2 \delta \lambda_2 + \beta \lambda_1 \lambda_2 [\beta(R - \Delta)^2 - 4\delta\mu]} \quad (13)$$

$$\tau_2^* = \frac{\beta(\Delta - R)\lambda_1 \lambda_2 (c\beta - a\mu)}{2d_2^2 \delta \lambda_1 + d_1^2 \delta \lambda_2 + \beta \lambda_1 \lambda_2 [\beta(R - \Delta)^2 - 4\delta\mu]} \quad (14)$$

$$p_2^* = \frac{a\lambda_1 \mu \left\{ d_2^2 \delta + \beta \lambda_2 [\beta(R - \Delta)^2 - 3\delta\mu] \right\} + c\beta \delta [d_2^2 \lambda_1 + \lambda_2 (d_1^2 - \beta \lambda_1 \mu)]}{\beta \left\{ 2d_2^2 \delta \lambda_1 + d_1^2 \delta \lambda_2 + \beta \lambda_1 \lambda_2 [\beta(R - \Delta)^2 - 4\delta\mu] \right\}} \quad (15)$$

$$k_{22}^* = \frac{d_2 \delta \lambda_1 (c\beta - a\mu)}{2d_2^2 \delta \lambda_1 + d_1^2 \delta \lambda_2 + \beta \lambda_1 \lambda_2 [\beta(R - \Delta)^2 - 4\delta\mu]} \quad (16)$$

By substituting Equations (12)–(16) into Equations (1)–(3), the optimal demand Q_2^* for the data product, the optimal profit π_{m2}^* for the data product manufacturer, and the optimal profit π_{s2}^* for the service provider under the Stackelberg game dominated by the data product manufacturer are as follows:

$$Q_2^* = \frac{\beta\delta\lambda_1\lambda_2(c\beta - a\mu)}{2d_2^2\delta\lambda_1 + d_1^2\delta\lambda_2 + \beta\lambda_1\lambda_2[\beta(R - \Delta)^2 - 4\delta\mu]} \quad (17)$$

$$\pi_{m2}^* = \frac{\delta\lambda_1\lambda_2(c\beta - a\mu)^2}{2\{\beta\lambda_1\lambda_2[4\delta\mu - \beta(R - \Delta)^2] - 2d_2^2\delta\lambda_1 - d_1^2\delta\lambda_2\}} \quad (18)$$

$$\pi_{s2}^* = \frac{\delta^2\lambda_1^2\lambda_2(c\beta - a\mu)^2(2\beta\lambda_2\mu - d_2^2)}{2\{2d_2^2\delta\lambda_1 + d_1^2\delta\lambda_2 + \beta\lambda_1\lambda_2[\beta(R - \Delta)^2 - 4\delta\mu]\}^2} \quad (19)$$

4.3. Stackelberg Game Led by Data Product Service Providers

When powerful data product service providers, such as the Shanghai Data Exchange, collaborate with weaker data product manufacturers, the service provider gains market dominance due to its strong capabilities. In this case, the market follows a Stackelberg game led by the data product service provider. According to the basic assumptions, when the data product service provider leads the market, the decision-making sequence is as follows: the data product service provider first decides the price p_3^* and the promotion investment level k_{23}^* ; then the data product manufacturer determines the price w_3^* , the technological investment level k_{13}^* , and the update rate τ_3^* . The specific optimal decisions are as follows:

$$p_3^* = \frac{a\lambda_2\mu[d_1^2\delta + \beta\lambda_1(2\beta(R - \Delta)^2 - 3\delta\mu)] + c\beta\delta[d_2^2\lambda_1 + \lambda_2(d_1^2 - \beta\lambda_1\mu)]}{\beta\{d_2^2\delta\lambda_1 + 2\lambda_2\{d_1^2\delta + \beta\lambda_1[\beta(R - \Delta)^2 - 2\delta\mu]\}\}} \quad (20)$$

$$k_{23}^* = \frac{d_2\delta\lambda_1(c\beta - a\mu)}{d_2^2\delta\lambda_1 + 2\lambda_2\{d_1^2\delta + \beta\lambda_1[\beta(R - \Delta)^2 - 2\delta\mu]\}} \quad (21)$$

$$w_3^* = \frac{c\{\beta\lambda_1\lambda_2[3\delta\mu - \beta(R - \Delta)^2] - d_2^2\delta\lambda_1 - 2d_1^2\delta\lambda_2\} - a\lambda_1\lambda_2\mu[\beta(R - \Delta)^2 - \delta\mu]}{d_2^2\delta\lambda_1 + 2\lambda_2\{d_1^2\delta + \beta\lambda_1[\beta(R - \Delta)^2 - 2\delta\mu]\}} \quad (22)$$

$$k_{13}^* = \frac{d_1\delta\lambda_2(c\beta - a\mu)}{d_2^2\delta\lambda_1 + 2\lambda_2\{d_1^2\delta + \beta\lambda_1[\beta(R - \Delta)^2 - 2\delta\mu]\}} \quad (23)$$

$$\tau_3^* = \frac{\beta(\Delta - R)\lambda_1\lambda_2(c\beta - a\mu)}{d_2^2\delta\lambda_1 + 2\lambda_2\{d_1^2\delta + \beta\lambda_1[\beta(R - \Delta)^2 - 2\delta\mu]\}} \quad (24)$$

By substituting Equations (20)–(24) into Equations (1)–(3), the optimal demand Q_3^* for the data product, the optimal profit π_{m3}^* for the data product manufacturer, and the optimal profit π_{s3}^* for the service provider under the Stackelberg game led by the data product service provider are as follows:

$$Q_3^* = \frac{\beta\delta\lambda_1\lambda_2(c\beta - a\mu)}{d_2^2\delta\lambda_1 + 2\lambda_2\{d_1^2\delta + \beta\lambda_1[\beta(R - \Delta)^2 - 2\delta\mu]\}} \quad (25)$$

$$\pi_{m3}^* = \frac{\delta\lambda_1\lambda_2^2(c\beta - a\mu)^2\{\beta\lambda_1[2\delta\mu - \beta(R - \Delta)^2] - d_1^2\delta\}}{2\{d_2^2\delta\lambda_1 + 2\lambda_2\{d_1^2\delta + \beta\lambda_1[\beta(R - \Delta)^2 - 2\delta\mu]\}\}^2} \quad (26)$$

$$\pi_{s3}^* = \frac{\delta\lambda_1\lambda_2(c\beta - a\mu)^2}{4\lambda_2\{\beta\lambda_1[2\delta\mu - \beta(R - \Delta)^2] - d_1^2\delta\} - 2d_2^2\delta\lambda_1} \quad (27)$$

5. Properties and Comparative Analysis of Equilibrium Results

This section conducts a qualitative and comparative analysis of the equilibrium results of the above model. First, the influence of each parameter on the optimal decisions is analyzed, followed by a comparison of the optimal decisions under different power structures. Finally, the following proposition is derived.

5.1. Analysis of the Properties of Equilibrium Solutions

Proposition 1. $\frac{\partial w_i^*}{\partial \beta} < 0$, $\frac{\partial k_{1i}^*}{\partial \beta} < 0$, $\frac{\partial k_{2i}^*}{\partial \beta} < 0$, $\frac{\partial \tau_i^*}{\partial \beta} < 0$, $\frac{\partial p_i^*}{\partial \beta} < 0$, $\frac{\partial Q_i^*}{\partial \beta} < 0$, $\frac{\partial \pi_{mi}^*}{\partial \beta} < 0$, $\frac{\partial \pi_{si}^*}{\partial \beta} < 0$, implying that under the three power structures, w , k_1 , k_2 , τ , p , Q , π_m , and π_s are all negatively correlated with β ; where $i = 1, 2, 3$.

Proposition 1 indicates that higher price sensitivity among end users amplifies their response to price adjustments, depresses overall market demand, and triggers a sequence of adjustments in the optimal decisions of both the data product manufacturer and the data product service provider. The reduction in demand diminishes the marginal returns to high-quality data products and markedly weakens the incentives for data product manufacturers to pursue continued quality improvement or sustain a high rate of dynamic updating. Because technological investment and dynamic updating exhibit increasing costs, the weakened demand makes cost recovery more difficult, prompting data product manufacturers to scale back quality investment, reduce updating frequency, and lower wholesale prices in order to stem additional demand loss. For data product service providers, shrinking demand similarly reduces the marginal payoff to promotion, making a reduction in promotional expenditure optimal and necessitating lower retail prices to preserve user volume and revenue. While these adjustments may ease short-term demand pressure, the concurrent decline in quality investment, updating intensity, and promotional effort erodes product quality and market visibility, accelerates demand deterioration, and results in a joint decline in profits for both firms. The findings suggest that price sensitivity imposes a powerful dual constraint on data product markets. It directly suppresses demand and indirectly undermines long-run competitiveness by discouraging firms from investing in quality enhancement and market development. Therefore, across all power configurations, both the data product manufacturer and the data product service provider must strike a dynamic balance between cost containment and demand preservation to prevent a downward spiral in which reduced investment further weakens demand and erodes profitability.

Proposition 2. $\frac{\partial w_i^*}{\partial c} > 0$, $\frac{\partial k_{1i}^*}{\partial c} < 0$, $\frac{\partial k_{2i}^*}{\partial c} < 0$, $\frac{\partial \tau_i^*}{\partial c} < 0$, $\frac{\partial p_i^*}{\partial c} > 0$, $\frac{\partial Q_i^*}{\partial c} < 0$, $\frac{\partial \pi_{mi}^*}{\partial c} < 0$, $\frac{\partial \pi_{si}^*}{\partial c} < 0$, meaning that under the three power structures, k_1 , k_2 , τ , Q , π_m , and π_s are negatively correlated with c , while w and p are positively correlated with c .

Proposition 2 shows that with end users' quality and promotion preferences fixed, rising initial costs exert a systematic squeezing effect on the profits of both the data product manufacturer and the data product service provider, cascading through their strategic adjustments and reshaping market outcomes. Rising initial costs substantially raise the data product manufacturer's fixed spending in data collection, preprocessing, and product development, reducing the marginal payoff to additional quality investment and dynamic updating. Faced with rising costs, the data product manufacturer seeks to alleviate pressure by increasing wholesale prices to shift costs downstream and by scaling back quality

investment and updating frequency to contain discretionary expenses. As the downstream party, the data product service provider likewise encounters profit erosion when initial costs rise. In response to the manufacturer's higher wholesale price, the service provider raises retail prices to transfer costs and trims promotional spending to reduce its own operating burden. Although such adjustments may cushion the immediate impact of rising costs, they jointly push prices upward and reduce investment in quality and promotion, eroding product quality, user experience, and market visibility. These effects ultimately diminish end-user purchase intentions and contract market demand. The resulting contraction in demand further depresses the sales revenues of both firms, making the profit displacement effect of rising initial costs even more pronounced.

Proposition 3. $\frac{\partial w_i^*}{\partial d_j} > 0$, $\frac{\partial k_{1i}^*}{\partial d_j} > 0$, $\frac{\partial k_{2i}^*}{\partial d_j} > 0$, $\frac{\partial \tau_i^*}{\partial d_j} > 0$, $\frac{\partial p_i^*}{\partial d_j} > 0$, $\frac{\partial Q_i^*}{\partial d_j} > 0$, $\frac{\partial \pi_{mi}^*}{\partial d_j} > 0$, $\frac{\partial \pi_{si}^*}{\partial d_j} > 0$, meaning that under the three power structures, w , k_1 , k_2 , τ , p , Q , π_m , and π_s are all positively correlated with d_j ; where $j = 1, 2$.

Proposition 3 indicates that stronger user preferences for quality and promotion fundamentally reshape demand formation, leading users to favor data products with superior quality and more extensive promotional information. Heightened preferences increase users' sensitivity to perceived utility, amplifying the marginal demand effects of both technological enhancement and promotional effort. In response, the data product manufacturer increases quality investment and accelerates updating to improve accuracy, completeness, and timeliness, enhancing both functional performance and adaptive capability to meet rising user expectations. Similarly, the data product service provider expands promotional activities by strengthening scenario presentation, disseminating application cases, and deepening market penetration, raising product visibility and translating promotional preferences into higher purchase rates. Since enhancing quality and promotion increases costs, both the data product manufacturer and the data product service provider raise prices to preserve profit margins. Yet with stronger user preferences, the dampening effect of higher prices is substantially attenuated and offset by gains in product quality and visibility. As a result, both demand and prices rise together, producing higher profits.

Proposition 4. $\frac{\partial w_i^*}{\partial \lambda_j} < 0$, $\frac{\partial k_{1i}^*}{\partial \lambda_j} < 0$, $\frac{\partial k_{2i}^*}{\partial \lambda_j} < 0$, $\frac{\partial \tau_i^*}{\partial \lambda_j} < 0$, $\frac{\partial p_i^*}{\partial \lambda_j} < 0$, $\frac{\partial Q_i^*}{\partial \lambda_j} < 0$, $\frac{\partial \pi_{mi}^*}{\partial \lambda_j} < 0$, $\frac{\partial \pi_{si}^*}{\partial \lambda_j} < 0$, meaning that under the three power structures, w , k_1 , k_2 , τ , p , Q , π_m and π_s are all negatively correlated with λ_j .

Proposition 4 shows that increases in the manufacturer's technological cost coefficient and the service provider's promotional cost coefficient raise the marginal costs of technological improvement and promotion at the same time, thereby deteriorating their cost-benefit ratios. Given unchanged prices and demand, the incremental revenue from additional quality or promotional effort becomes insufficient to offset rising costs, leading both firms to curtail discretionary investments to protect profitability. The data product manufacturer reduces technological investment and slows updating to contain production costs, whereas the data product service provider lowers promotional spending to reduce operating costs. Such reductions in investment inevitably diminish product quality and market visibility, lowering technological performance, slowing updating, and weakening market exposure. Because user preferences for quality and promotion are unchanged, weaker product quality and diminished promotional effectiveness directly erode user recognition, further contracting demand. The combined effect of weaker demand and reduced investment further undermines the market competitiveness of data products. To counter additional demand losses, both firms typically reduce prices to ease the burden on

users and attempt to stabilize sales volumes. Yet the concurrence of declining demand and lower prices intensifies revenue compression, further reducing the profits of both the data product manufacturer and the data product service provider.

Proposition 5. $\frac{\partial w_i^*}{\partial \delta} > 0$, $\frac{\partial k_{1i}^*}{\partial \delta} < 0$, $\frac{\partial k_{2i}^*}{\partial \delta} < 0$, $\frac{\partial \tau_i^*}{\partial \delta} < 0$, $\frac{\partial p_i^*}{\partial \delta} > 0$, $\frac{\partial Q_i^*}{\partial \delta} < 0$, $\frac{\partial \pi_{mi}^*}{\partial \delta} < 0$, $\frac{\partial \pi_{si}^*}{\partial \delta} < 0$, meaning that under the three power structures, k_1 , k_2 , τ , Q , π_m and π_s are negatively correlated with δ , while w and p are positively correlated with δ .

Proposition 5 shows that an increase in the updating-cost coefficient sharply raises the marginal cost of updating, making it more costly for the data product manufacturer to sustain a high updating frequency. As rising updating costs diminish the marginal profit contribution of updates, the data product manufacturer responds by increasing its price to shift part of the burden downstream and by reducing quality investment and updating frequency to preserve profitability. Faced with higher upstream prices, the data product service provider similarly raises its retail price and cuts promotional expenditure to manage its operating costs. Together, these responses lead to higher prices, reduced quality investment, slower updating, and diminished promotional effort, eroding the product's technological quality, timeliness, and market exposure. Given stable user preferences for quality and promotion, deteriorating quality and weaker promotion directly diminish product appeal, and higher prices further depress demand. The resulting contraction in demand further erodes the profitability of both firms, intensifying the profit squeeze they face in a high updating-cost environment.

Proposition 6. $\frac{\partial w_i^*}{\partial \Delta} < 0$, $\frac{\partial k_{1i}^*}{\partial \Delta} > 0$, $\frac{\partial k_{2i}^*}{\partial \Delta} > 0$, $\frac{\partial \tau_i^*}{\partial \Delta} > 0$, $\frac{\partial p_i^*}{\partial \Delta} < 0$, $\frac{\partial Q_i^*}{\partial \Delta} > 0$, $\frac{\partial \pi_{mi}^*}{\partial \Delta} > 0$, $\frac{\partial \pi_{si}^*}{\partial \Delta} > 0$, meaning that under the three power structures, k_1 , k_2 , τ , Q , π_m , and π_s are positively correlated with Δ , while w and p are negatively correlated with Δ .

Proposition 6 shows that greater cost savings in the updating stage raise the marginal benefit of updating, reshaping the optimal operational strategies of both the data product manufacturer and the data product service provider. For the data product manufacturer, reduced updating costs improve the cost-effectiveness of quality investment and updating, encouraging deeper investment in technological enhancement and data renewal to strengthen accuracy, completeness, and timeliness. As the product becomes more competitive, the data product service provider enjoys higher marginal returns to promotion and correspondingly increases promotional effort to broaden market visibility and user reach. With user preferences held constant, stronger quality investment and enhanced promotion raise product attractiveness, boost user purchase intentions, and expand market demand. The confluence of cost savings, heightened investment, and expanding demand improves product quality, strengthens promotional performance, and elevates market competitiveness, generating substantial profit gains for both firms. These results underscore the pivotal leverage role that cost savings play in shaping data product operational strategies.

Proposition 7. $\frac{\partial w_i^*}{\partial \mu} > 0$, $\frac{\partial k_{1i}^*}{\partial \mu} > 0$, $\frac{\partial k_{2i}^*}{\partial \mu} > 0$, $\frac{\partial \tau_i^*}{\partial \mu} > 0$, $\frac{\partial p_i^*}{\partial \mu} > 0$, $\frac{\partial Q_i^*}{\partial \mu} > 0$, $\frac{\partial \pi_{mi}^*}{\partial \mu} > 0$, $\frac{\partial \pi_{si}^*}{\partial \mu} > 0$, meaning that under the three power structures, w , k_1 , k_2 , τ , p , Q , π_m , and π_s are positively correlated with μ .

Proposition 7 shows that higher perceived value enables end users to form clearer expectations about product content, functionality, and performance, thereby reducing pre-purchase uncertainty and improving the certainty with which they evaluate product benefits. As perceived value increases, users form more stable utility assessments and become more willing to purchase. With demand conditions improving, the data product

manufacturer deepens quality investment and accelerates updating to enhance accuracy, completeness, and timeliness, strengthening the product's quality-based competitiveness. The data product service provider, meanwhile, expands promotional efforts—improving visibility, user guidance, and scenario presentation—to strengthen user awareness and broaden market reach. Enhanced technological performance and stronger promotional effectiveness together deepen user reliance, thereby expanding market demand. As demand rises, both firms experience improved pricing power and higher product acceptance. When the growth in investment exceeds the additional cost pressure induced by higher demand, the optimal price level rises. The joint forces of greater demand and higher prices substantially lift the profits of both the data product manufacturer and the data product service provider.

5.2. Comparative Analysis of Equilibrium Solutions

Proposition 8. $w_2^* > w_1^* > w_3^*$; $p_2^* > p_1^*, p_3^* > p_1^*$, and when $\beta^2(R - \Delta)^2 + \frac{d_1^2}{\lambda_1}\delta - \frac{d_2^2}{\lambda_2} > 0$, $p_2^* > p_3^*$; when $\beta^2(R - \Delta)^2 + \frac{d_1^2}{\lambda_1}\delta - \frac{d_2^2}{\lambda_2} < 0$, $p_2^* < p_3^*$; and when $\beta^2(R - \Delta)^2 + \frac{d_1^2}{\lambda_1}\delta - \frac{d_2^2}{\lambda_2} = 0$, $p_2^* = p_3^*$.

Proposition 9. $k_{11}^* > k_{12}^*, k_{11}^* > k_{13}^*, k_{21}^* > k_{22}^*, k_{21}^* > k_{23}^*, \tau_1^* > \tau_2^*, \tau_1^* > \tau_3^*, Q_1^* > Q_2^*, Q_1^* > Q_3^*$; and when $\beta^2(R - \Delta)^2 + \frac{d_1^2}{\lambda_1}\delta - \frac{d_2^2}{\lambda_2} > 0$, $k_{12}^* < k_{13}^*, k_{22}^* < k_{23}^*, \tau_2^* < \tau_3^*, Q_2^* < Q_3^*$; when $\beta^2(R - \Delta)^2 + \frac{d_1^2}{\lambda_1}\delta - \frac{d_2^2}{\lambda_2} < 0$, $k_{12}^* > k_{13}^*, k_{22}^* > k_{23}^*, \tau_2^* > \tau_3^*, Q_2^* > Q_3^*$; and when $\beta^2(R - \Delta)^2 + \frac{d_1^2}{\lambda_1}\delta - \frac{d_2^2}{\lambda_2} = 0$, $k_{12}^* = k_{13}^*, k_{22}^* = k_{23}^*, \tau_2^* = \tau_3^*, Q_2^* = Q_3^*$.

Proposition 10. $\pi_{m2}^* > \pi_{m1}^* > \pi_{m3}^*, \pi_{s3}^* > \pi_{s1}^* > \pi_{s2}^*$.

Propositions 8–10 indicate that profits differ systematically across market power structures, largely because first movers benefit from strategic advantages inherent in the game's sequencing. In a manufacturer-led Stackelberg structure, the data product manufacturer moves first and sets price, quality investment, and updating rate to its advantage, limiting the service provider's feasible responses and forcing it to optimize within the manufacturer's strategic constraints. The strategic-commitment effect allows the manufacturer to choose a more advantageous quality–cost configuration, yielding the highest profit, whereas the service provider earns the lowest profit due to limited bargaining power and strategic discretion. Conversely, in a service-provider-led Stackelberg setting, the service provider first sets retail price and promotional intensity, imposing its strategic structure on the manufacturer, resulting in the manufacturer earning the lowest profit and the service provider the highest. Under a Nash equilibrium, simultaneous decision-making prevents either party from exploiting first-mover advantage, placing both profits between those observed in the two Stackelberg regimes. These results imply that both firms are incentivized to secure market leadership—by expanding market scale, deepening product dependence, or establishing ecosystem control—since occupying the Stackelberg leader position substantially boosts individual profitability and alters the market's overall distribution of payoffs.

From the above propositions, it can be observed that in the comparison of the three different power structures, when data product manufacturers and service providers are in a Nash equilibrium, the levels of technological investment, promotional investment, update rates, and demand are higher compared to the Stackelberg game, with data product prices being lower than in the Stackelberg scenario. The reason is that in the Stackelberg game, the dominant player uses its leadership position to alter decision-making behaviors to increase its own profit. However, whether the data product manufacturer or service

provider becomes the market leader, their decision-making behavior will ultimately lead to higher data product prices, which in turn reduces the demand for data products. A decline in demand for data products directly impacts the profits of both data product manufacturers and service providers. To maintain demand, they will reduce cost investments, which in turn leads to lower levels of technological investment, update rates, and promotional investment in the Stackelberg game compared to the Nash equilibrium.

Furthermore, in the Stackelberg game, the magnitude of the above factors primarily depends on the sign of $\beta^2(R - \Delta)^2 + \frac{d_1^2}{\lambda_1}\delta - \frac{d_2^2}{\lambda_2}$. When $\beta^2(R - \Delta)^2 + \frac{d_1^2}{\lambda_1}\delta - \frac{d_2^2}{\lambda_2} > 0$, this indicates that the strength of data product quality exceeds that of promotion, which results in higher demand, technological investment levels, update rates, and promotional investment levels in the service provider-led Stackelberg game compared to the manufacturer-led Stackelberg game, and vice versa. The reason is that when quality effects outweigh promotional effects, end users become more responsive to quality improvements, heightening the marginal demand impact of technological investment and updating. Under this preference pattern, additional quality investment yields a stronger improvement in product appeal. However, when the data product manufacturer occupies the Stackelberg leadership position, it can move first and exploit users' strong preference for quality by moderately cutting quality investment and updating while preserving essential product attractiveness, thereby reducing costs and enhancing profits. This first-mover-driven cost optimization causes the manufacturer, when dominant, to respond to stronger quality preferences not by expanding investment aggressively but by adopting more conservative levels of quality investment and updating. Thus, when quality effects dominate, a service-provider-led structure better incentivizes the manufacturer to sustain higher quality investment and updating, while a manufacturer-led structure, driven by profit maximization, leads to comparatively lower investment levels.

6. Numerical Simulation

6.1. Parameter Setup

In the previous section, we compared and analyzed the impact of different power structures on the optimal decisions of data product manufacturers and service providers. This section considers the validation and analytical explanation of all equilibrium solutions and key conclusions from the models through a set of numerical values, aiming to gain further managerial insights. The corresponding parameter values, based on related literature [39,44], are shown in Table 2.

Table 2. Parameter Settings.

Parameter	a	β	c	d_1	d_2	λ_1	λ_2	μ	Δ	δ	R
Values	2	1.8	0.3	1.2	0.8	2.2	1.8	0.8	0.15	1	0.05

6.2. Sensitivity Analysis

The values of the research parameters are adjusted by 10% and 20%, respectively, to further analyze the impact of different parameters on the decision variables and profit equilibrium solutions. Since this paper involves three models under different power structures, for simplicity, sensitivity analysis is conducted using the decision variables and profit equilibrium solutions under Nash equilibrium, as shown in Table A1 of Appendix C.

The results indicate that the direction of change in the influencing factors of decision variables and profit equilibrium solutions is consistent with the previous conclusions. Therefore, the positive and negative directions of influence of each parameter on the decision variables and profit equilibrium solutions are not repeated here. In terms of the

degree of impact of each parameter, the price sensitivity coefficient β has the greatest influence on the optimal decision variables of both data product manufacturers and service providers. This is because, despite the data product end users' preferences for quality, promotion, and other factors, price remains the most important issue for them. In addition, the optimal profit of data product manufacturers and service providers is influenced by the market size a , followed by the price sensitivity coefficient β . Further analysis shows that both the demand and price of data products jointly determine profits, but demand is the more critical factor. The behavior and pricing decisions of data product manufacturers and service providers are more dependent on demand fluctuations, while market size is the most crucial factor affecting data product demand. Therefore, it is evident that the development of the potential market for data products is the most important area for data product manufacturers and service providers to focus on.

The changes in the perceived value μ of data products by end users have a significant impact on the optimization of the equilibrium solution. As shown in Table A1, as the uncertainty in perceived value decreases, the behavioral decisions of data product manufacturers and service providers become more optimized. Specifically, data product manufacturers can significantly enhance product quality, extend product lifecycle, and increase market competitiveness by increasing technological investment, improving update efficiency, and enhancing product information transparency. Data product service providers can effectively reduce end users' perceived uncertainty and further stimulate market demand by strengthening market promotion strategies, providing value-added services, and establishing data security guarantees. This dual effect not only facilitates the circulation and market acceptance of data products but also promotes the healthy development of the data industry, laying the foundation for the multiplier effect of data elements. These measures provide strong support for the continuous growth of the digital economy and the long-term development of the social economy.

As shown in Table A1, the changes in the cost savings Δ , the update investment cost coefficient δ of data product manufacturers, and the data collection price R have a profound impact on the key equilibrium solutions and the decision-making of game participants in the data product market. Specifically, when Δ increases, the cost savings in the update process significantly reduce the economic burden of the update stage for data product manufacturers, enabling them to increase technological investment and update rates, further enhancing product quality and market competitiveness. This also promotes the growth of market demand and strengthens the market promotion efforts of data product service providers, resulting in a dual increase in profits for both manufacturers and service providers. In contrast, an increase in δ intensifies the cost pressure on data product manufacturers in the update process, forcing them to reduce the update rate and technological investment to control total costs. This not only weakens product quality and market appeal but also dampens the promotion efforts of service providers and their market input, leading to a decrease in overall market demand and a reduction in profits for both parties. The change in R primarily affects the efficiency and cost management of the data collection stage. When R increases, the rise in data collection costs directly increases the cost burden on data product manufacturers. To alleviate this pressure, they typically choose to increase product prices and reduce technological investment and update rates to control costs. However, this strategy negatively impacts product quality and market demand, further limiting improvements in market transaction efficiency and optimizing profits for both parties. Therefore, properly reducing δ and R , and optimizing Δ to enhance cost-saving potential, is not only an important direction for data product manufacturers and service providers to develop efficient operational strategies, but also a key path to achieving sustainable development in the data product market.

6.3. Impact of Parameters on Data Product Pricing

Based on the parameter settings in Table 2, the impact of each parameter on data product pricing is illustrated in Figure 2.

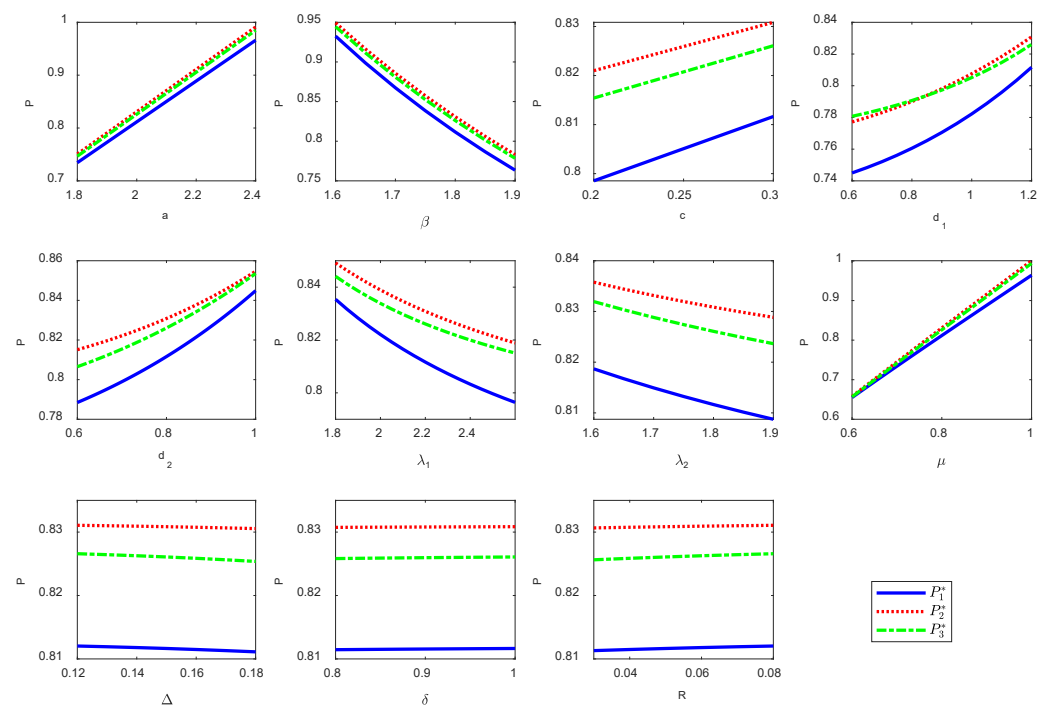


Figure 2. The Impact of Various Parameters on Data Product Prices p .

As shown in Figure 2, the impact of various key parameters on the final price of data products exhibits significant differences and dynamics, reflecting the complex relationship between data product manufacturers and service providers in formulating operational strategies under different power structures. Overall, the expansion of market size significantly increases the final price level of data products. A larger market size means broader user coverage, which not only drives market demand growth but also provides data product manufacturers and service providers with greater profit space, thereby supporting higher pricing. In contrast, an increase in the price sensitivity coefficient of data products negatively impacts the final price. As data product end users become more sensitive to prices, the elasticity of market demand increases, forcing data product manufacturers and service providers to lower prices in order to maintain market competitiveness and stabilize demand. Meanwhile, an increase in the initial development cost of data products also significantly negatively affects the final pricing. High development costs not only limit manufacturers' flexibility in technological investment and update rates but also increase the promotional pressure on service providers, leading to a decline in market demand and thus suppressing the increase in data product prices.

Moreover, the impact of data product end users' quality preferences and promotion preferences on data product pricing is also crucial. d_1 is jointly determined by the data product manufacturer's technological investment and update rate. Its increase significantly enhances the quality of data products, which increases market demand and drives up the final pricing. However, the combined effect of d_1 and d_2 is also moderated by the positive or negative value of the equation $\beta^2(R - \Delta)^2 + \frac{d_1^2}{\lambda_1}\delta - \frac{d_2^2}{\lambda_2}$. When the formula value is greater than 0, the effect of quality preferences becomes more significant, leading to higher pricing power in the Stackelberg game led by data product manufacturers; When the formula value is less than 0, promotion preferences dominate, with data product service

providers increasing promotion efforts to boost market demand, leading to a stronger pricing advantage in the Stackelberg game led by the service provider. An increase in the technological cost investment coefficient λ_1 and the promotion cost investment coefficient λ_2 will suppress the technological optimization and promotional efforts of data product manufacturers and service providers, thereby reducing the pricing level of data products. At the same time, the cost savings in the data product update process Δ also have a positive effect on pricing. An increase in t reduces the update costs for data product manufacturers and enhances their technological investment capacity, thus driving up the pricing level. In contrast, an increase in the update investment cost coefficient δ and the data collection price R significantly limits the technological optimization of data product manufacturers and the promotional efforts of service providers, ultimately leading to a decrease in the pricing level. This indicates that rationally optimizing the update cost structure is key to enhancing market competitiveness.

Based on the above results, data product manufacturers and service providers should flexibly adjust their operational strategies according to market demand and cost structure. Data product manufacturers should increase technological investment, optimize data product update mechanisms, and especially focus on the dynamic balance between quality preferences and promotion preferences. By enhancing the positive effects of $\beta^2(R - \Delta)^2 + \frac{d_1^2}{\lambda_1}\delta - \frac{d_2^2}{\lambda_2}$, they can ensure an advantage in quality-driven markets. At the same time, data product service providers should stimulate market demand through diversified promotional strategies and strengthen collaborative efforts with manufacturers. They should reasonably allocate technological and promotional resources to ensure they can leverage their advantages in promotion-driven markets. This collaborative optimization not only maximizes profits but also promotes the healthy development of the data product market, providing support for the sustainable development of the digital economy.

6.4. Impact of Parameters on the Update Rate of Data Products

Based on the parameter settings in Table 2, the impact of each parameter on the data product update rate is plotted as shown in Figure 3.

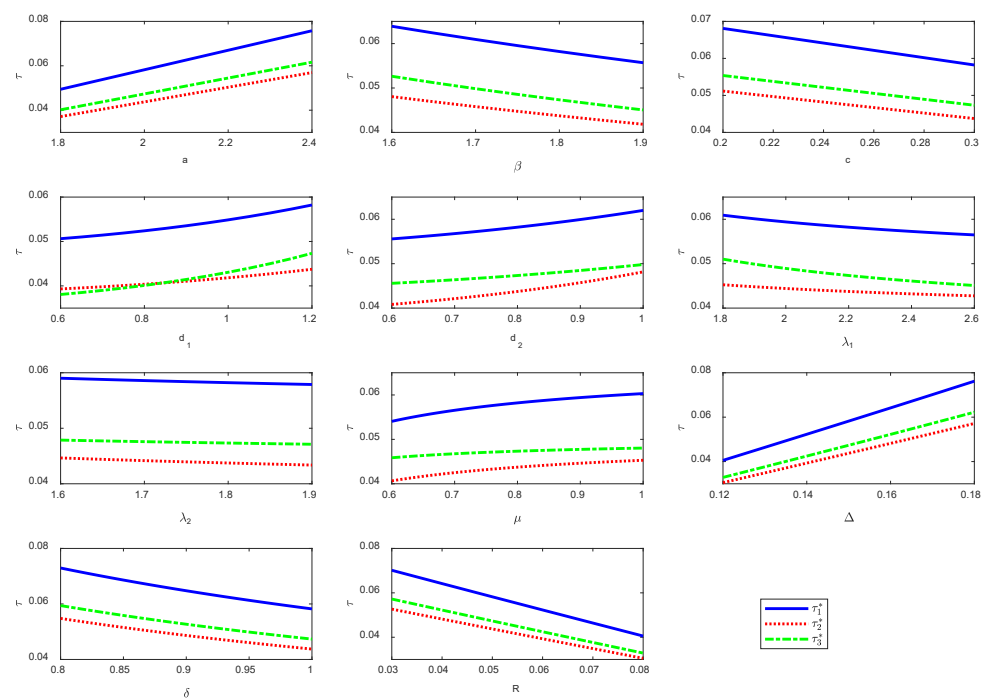


Figure 3. The Impact of Various Parameters on Data Product Update Rate τ .

As shown in Figure 3, the impact of different parameters on the update rate of data products exhibits significant variation. The expansion of market size significantly increases the update rate, primarily because a larger market implies higher demand, which drives data product manufacturers to increase the frequency of data updates to meet the dynamic needs of end users. Conversely, when the price sensitivity coefficient increases, market demand becomes more sensitive to price, leading data product manufacturers to reduce update investments in order to lower costs. Meanwhile, the increase in initial development costs further compresses the financial flexibility of data product manufacturers in terms of updates, limiting their ability to maintain high-frequency updates.

Furthermore, the impact of end users' quality and promotion preferences on the update rate of data products is equally crucial. Quality preference is directly dependent on the technological investment and update strategies of data product manufacturers, and an increase in quality preference drives manufacturers to enhance the update frequency to meet end users' demand for high-quality data. On the other hand, the rise in promotion preference indirectly stimulates the update investments of data product manufacturers through the marketing efforts of data product service providers, thus driving the overall increase in update rates. However, this effect is also constrained by the sign of the formula $\beta^2(R - \Delta)^2 + \frac{d_1^2}{\lambda_1}\delta - \frac{d_2^2}{\lambda_2}$. When the formula value is positive, the influence of quality preference becomes more pronounced, with data product manufacturers taking a dominant position in quality-driven markets; When the formula value is negative, promotion preference becomes the primary driver, and data product service providers, by expanding market coverage, indirectly increase the update frequency. Moreover, an increase in the technical cost coefficient and promotion cost coefficient intensifies the resource allocation pressure on data product manufacturers and service providers, thereby suppressing the update rate. Further analysis of Figure 3 shows that the update cost structure largely determines the potential for optimizing the update rate. The cost savings during the data product update process have a remarkably positive effect on the update rate. By saving costs, data product manufacturers free up more resources, enabling them to more efficiently support update activities. Conversely, the rise in update investment cost coefficients and data acquisition prices significantly hampers the update rate, leading to a substantial increase in the operational costs of data product manufacturers and subsequently a decrease in the update rate.

Therefore, data product manufacturers and service providers must flexibly respond to the impact of different parameters in actual operations. Data product manufacturers should prioritize optimizing the update cost structure, for instance, by increasing Δ to reduce the cost burden, while simultaneously reducing expenditures on the update cost coefficient δ and data acquisition price R , in order to enhance the update capability of data products. Moreover, data product manufacturers should adjust the scale of technological investment according to end users' quality preferences, increasing the update frequency in quality-driven markets; In promotion-driven markets, they need to strengthen cooperation with data product service providers to maximize promotional benefits. Data product service providers should expand market demand through differentiated promotional strategies, providing greater update incentives for data product manufacturers. Through collaboration and optimization, both parties can jointly enhance the market competitiveness of data products and achieve sustainable growth while meeting the demands of data product end users.

6.5. Impact of Parameters on the Profits of Data Product Manufacturers and Service Providers

Based on the parameter settings in Table 2, the graph in Figure 4 illustrates the impact of data product end users' demand preferences on the profits of data product

manufacturers and service providers. The graph in Figure 5 shows the impact of the data product technology investment cost coefficient and promotion cost coefficient on the profits. The graphs in Figures 6 and 7 show the influence of other parameters.

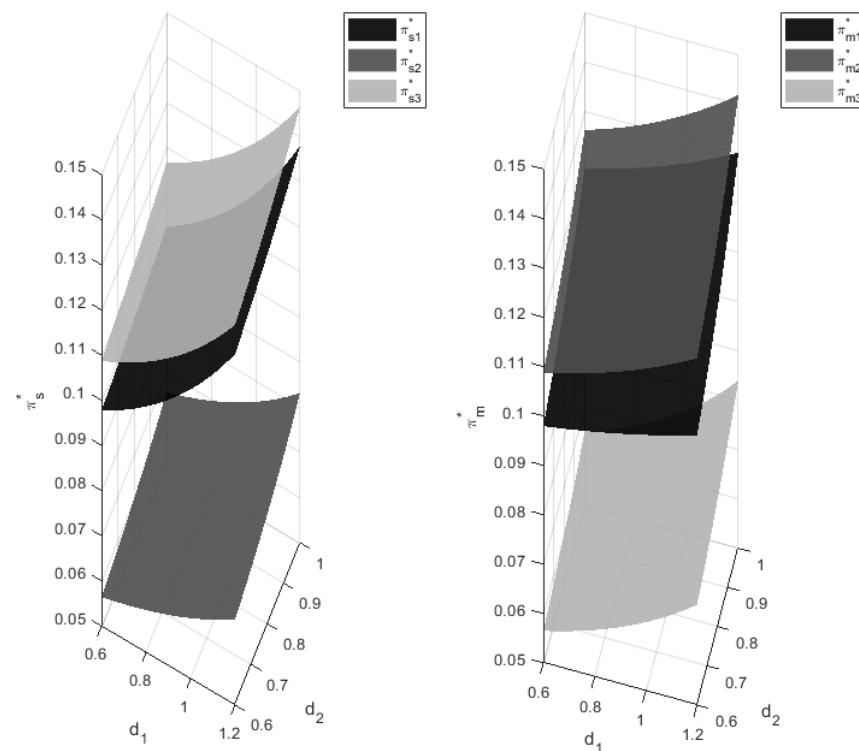


Figure 4. Impact of End-User Demand Preferences on Profits of Data Product Manufacturers and Service Providers.

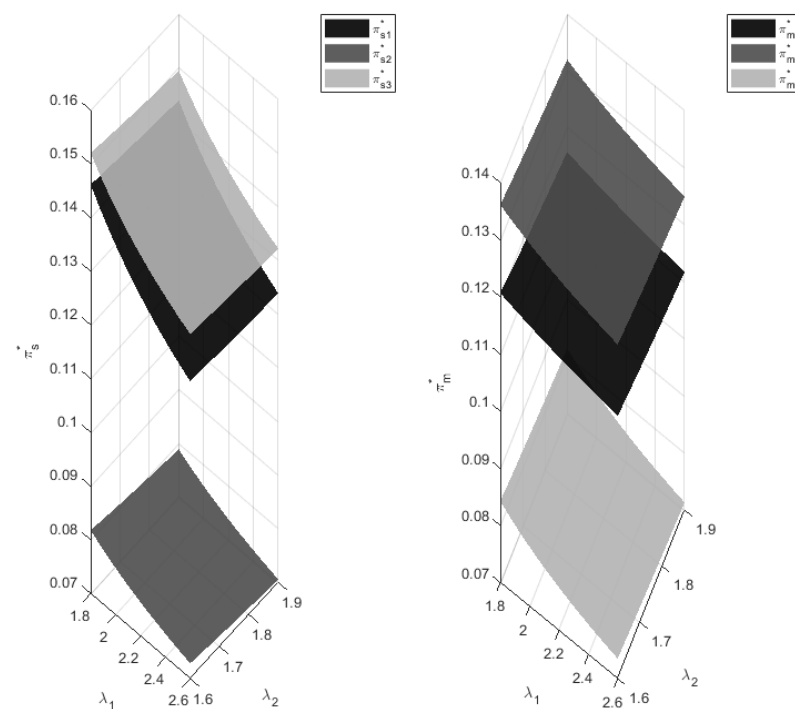


Figure 5. Impact of Technology and Promotion Input Cost Coefficients on Profits of Data Product Manufacturers and Service Providers.

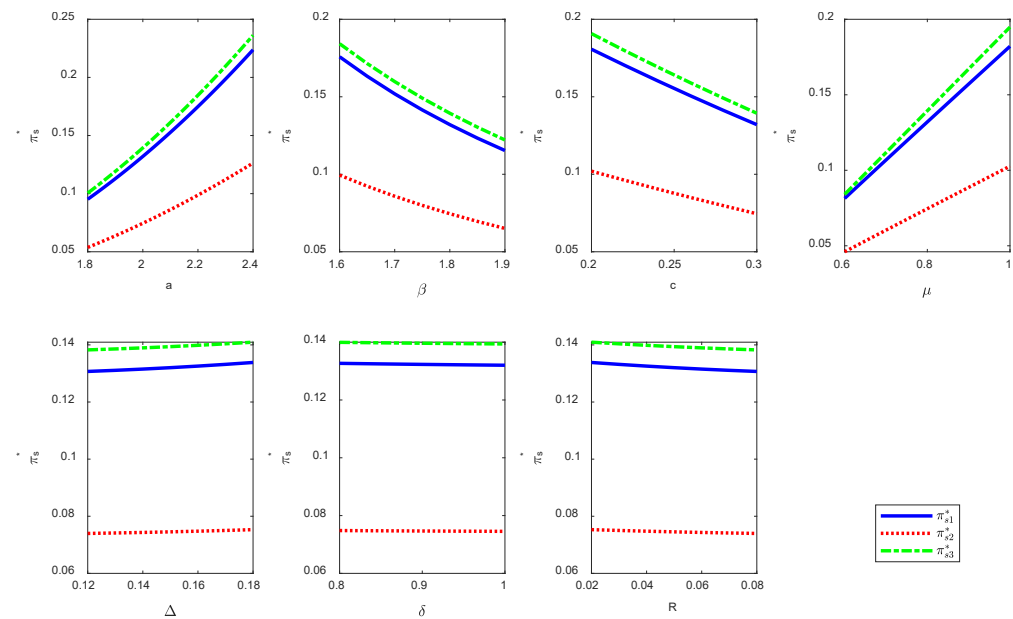


Figure 6. Impact of Other Parameters on the Profits of Data Product Service Providers.

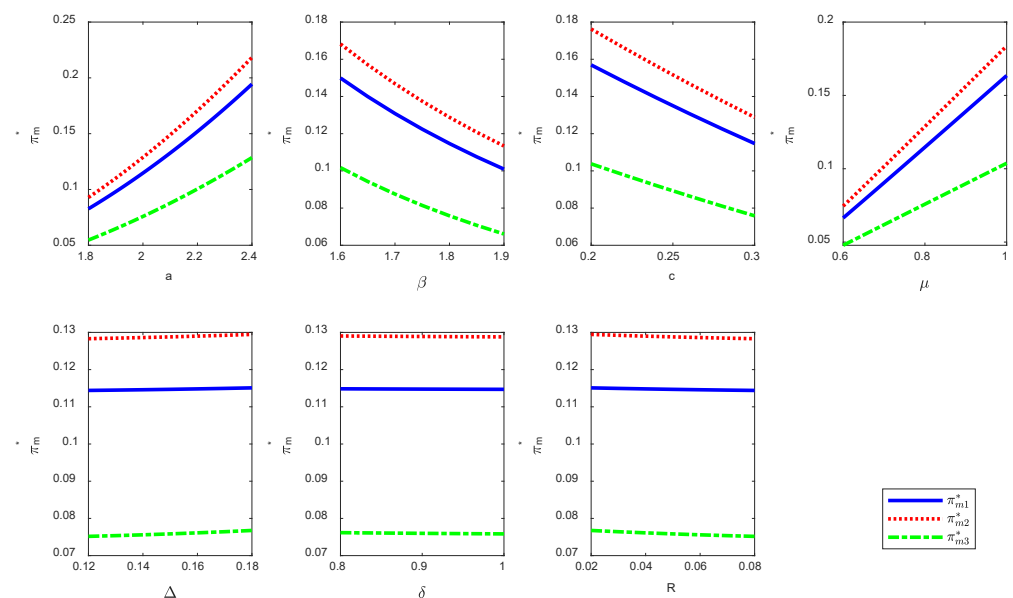


Figure 7. Impact of Other Parameters on the Profits of Data Product Manufacturers.

As shown in Figure 4, the quality preference d_1 and promotion preference d_2 of end users have a significant positive impact on the profits of both data product manufacturers and service providers. In a scenario where both quality and promotion preferences are enhanced, the profits of data product manufacturers and service providers both show an upward trend. This trend indicates that the demand preferences of data product end users are the key drivers of market activity and profit growth. Specifically, an increase in the quality preference of data product end users encourages manufacturers to increase their technological investment and update frequency, thereby enhancing the market competitiveness of the data product. Meanwhile, an increase in promotion preference drives data product service providers to intensify market promotion efforts and expand market coverage. The positive impact of these two demand preferences on the market cannot be overlooked.

Moreover, Figure 4 also shows that different power structures significantly affect the distribution of profits between data product manufacturers and service providers. In the

Stackelberg game where data product manufacturers lead, manufacturers leverage their first-mover advantage to dominate the market by maximizing technological investment and optimizing the data update frequency, resulting in significantly higher profits than those of service providers. In this scenario, data product service providers are in a followership position during promotional activities and cannot exert effective influence on market pricing or technological strategies, leading to relatively lower profits. In contrast, in the Stackelberg game, where data product service providers lead, service providers maximize market demand and increase their profits by utilizing their market promotion resources and first-mover advantage, while data product manufacturers, lacking market power, face limitations in technological investment and update strategies, resulting in lower profits. This indicates that the distribution of market power not only determines the decision-making priorities of data product manufacturers and service providers but also directly impacts the dynamic changes in their profits. In the Nash equilibrium, data product manufacturers and service providers reach a relatively balanced state through simultaneous decision-making, with their profits lying between those in the manufacturer-led and service provider-led Stackelberg games. This further illustrates that adjustments in market power structure can significantly alter the profit distribution pattern, and data product manufacturers and service providers need to develop corresponding strategies based on their position to gain a competitive advantage. Further analysis of Figure 4 reveals that the combined impact of quality and promotion preferences is also subject to the dynamic adjustment of market demand. When data product end users have a higher quality preference, data product manufacturers are more proactive in technological investment and update strategies, with a significantly higher profit growth rate compared to service providers. In contrast, when promotion preference is the dominant factor, service providers experience faster profit growth and exert a more substantial impact on the expansion of market demand.

From a practical application perspective, data product manufacturers and service providers should develop targeted operational strategies within the context of different power structures and demand preferences. Data product manufacturers should focus on market contexts with higher quality preferences, enhancing their competitiveness by increasing technological investment and optimizing data update mechanisms to further boost profits. At the same time, in markets with stronger promotion preferences, data product manufacturers should strengthen collaboration with service providers, leveraging their marketing networks to improve market penetration. Data product service providers should, in promotion-driven markets, flexibly utilize market demand and attract more end users through differentiated promotion strategies, thereby increasing profits. Moreover, both parties need to find a balance in the power structure, optimize resource allocation, and work together to maximize market demand. This collaborative strategy not only enhances profits for both parties but also promotes the healthy development of the data product market, laying a foundation for the sustainable growth of the digital economy.

As shown in Figure 5, the data product technology investment cost coefficient λ_1 and the promotion investment cost coefficient λ_2 have a significant constraining effect on the profits of both data product manufacturers and service providers. As the data product technology investment costs and promotion investment cost coefficients increase, the profits of both data product manufacturers and service providers show a declining trend. This indicates that high technology and promotion costs have a particularly pronounced overall suppressive effect on the market. A higher technology investment cost coefficient limits the flexibility of data product manufacturers in technology optimization and update investment, thereby reducing their market competitiveness and profit levels. Meanwhile, a higher data product promotion investment cost coefficient directly reduces the service

provider's promotional budget, leading to a significant shrinkage in the effective market coverage and a marked decline in profits.

Further analysis of Figure 5 reveals significant differences in the profit distribution of data product manufacturers and service providers under cost constraints, depending on the market power structure. In the Stackelberg game dominated by data product manufacturers, manufacturers adjust the scale of their technology investments through early decision-making, partially offsetting the adverse effects of the rising technology investment cost coefficient, resulting in a relatively smaller decline in profits. However, data product service providers, lacking decision-making priority, experience a more pronounced suppressive effect on their profits from high promotion costs, showing a clear passivity. In contrast, in the Stackelberg game dominated by data product service providers, they can alleviate the negative effects of the promotion investment cost coefficient to some extent by optimizing marketing strategies, resulting in a relatively lower decline in profits. On the other hand, data product manufacturers, due to their lack of market dominance, experience an amplified negative impact of technology costs on profits, leading to a faster decline in profits. In the Nash equilibrium scenario, the profit levels of data product manufacturers and service providers lie between the two Stackelberg games, reflecting a balanced state, where both parties must compromise on resource allocation to stabilize profits. Moreover, Figure 5 also reveals the impact of the synergistic effect between data product technology costs and promotion costs at different cost levels. When both the technology investment cost coefficient and the promotion investment cost coefficient are high, the profits of both data product manufacturers and service providers are at their lowest levels. This dual suppression effect indicates that the combination of high technology and promotion costs severely weakens market competitiveness, leading to a significant decline in profit levels. When technology costs are low but promotion costs are high, data product manufacturers benefit from lower technology investment pressures, leading to a relatively smaller decline in profits. Meanwhile, data product service providers face a greater risk of profit decline due to the increase in promotion costs. Similarly, when promotion costs are low and technology costs are high, data product service providers stabilize their profits through efficient promotional activities, whereas data product manufacturers experience a faster decline in profits due to the pressure of technology costs.

From a practical application perspective, data product manufacturers and service providers should formulate targeted operational strategies under different power structures and cost conditions. Data product manufacturers should focus on market scenarios with high technology costs by improving technological research and development efficiency, optimizing the updating mechanism, and reducing unit technology costs to ensure the enhancement of product quality and the maintenance of market competitiveness. Meanwhile, in environments with high promotion costs, data product manufacturers should strengthen collaboration with service providers, expanding market coverage by supporting promotional activities, thereby alleviating the suppressive effect of promotion costs on market demand. Data product service providers should optimize the allocation of promotional resources, reduce the marginal cost of promotional activities, and enhance market penetration and the coverage of end-users through differentiated promotional strategies. Furthermore, both parties should allocate resources based on the power structure, ensuring effective synergy between technology and promotional strategies to maximize profits and enhance market competitiveness.

From Figures 6 and 7, it can be observed that the profits of data product service providers and manufacturers are significantly influenced by various parameters such as market size a , end-user perceived value μ , price sensitivity coefficient β , development cost c , and update cost Δ . Moreover, the profit changes in both parties show certain similarities and

differences under varying parameter conditions. In the case of an expanding market size, the profits of both data product service providers and manufacturers increase significantly. This reflects that a larger market size provides more demand opportunities for both parties, with data product service providers increasing promotional revenue by expanding market coverage, and manufacturers obtaining higher profits by increasing technological input and update frequency. However, the increase in the price sensitivity coefficient negatively affects the profits of both data product service providers and manufacturers. The increase in end-users' price sensitivity leads to a rise in market demand elasticity, forcing both parties to adjust pricing or reduce investment to cope with market changes, thereby compressing profit margins.

Additionally, the increase in end-user perceived value μ has a positive impact on the profits of both data product service providers and manufacturers. A higher perceived value reduces user uncertainty, enhances market acceptance of data products, and thereby expands the market demand. This change enhances the promotional effectiveness of data product service providers and the technological optimization capabilities of manufacturers, contributing to the growth of profits for both parties. Furthermore, an increase in development costs significantly suppresses the profits of both parties. High development costs increase the cost-sharing pressure for data product service providers in promotional activities, while also limiting the flexibility of data product manufacturers in technological research and update frequency, leading to a decline in profits for both parties under high development cost conditions.

From the perspective of data product updates, the cost savings Δ during the update process have a positive impact on the profits of both data product service providers and manufacturers. Data product manufacturers can optimize resource allocation and further enhance technological investment and product update capabilities by saving update costs. Data product service providers indirectly benefit from the optimization of costs by manufacturers, gaining more promotional resources and improving market demand responsiveness. In contrast, increases in the data product update cost coefficient δ and data collection price R significantly suppress the profits of both parties. This indicates that high update costs not only directly limit the technological optimization capabilities of data product manufacturers but also indirectly weaken the promotional flexibility and market coverage abilities of data product service providers.

Further analysis reveals that different power structures significantly moderate the profit changes in data product service providers and manufacturers. In the Stackelberg game led by data product manufacturers, manufacturers effectively mitigate profit pressure under high-cost conditions through their first-mover advantage, with their profit levels significantly higher than those of service providers in most scenarios. In contrast, in the Stackelberg game led by data product service providers, service providers maintain a higher profit level by optimizing promotional strategies, while the profits of data product manufacturers are constrained by the market dominance of service providers, leading to a more significant decline under high-cost or high-price sensitivity conditions. In the Nash equilibrium scenario, both parties' profits are in a relatively balanced state, reflecting the balance of resource allocation and returns under conditions of equal power.

The practical significance behind the above conclusions lies in the need for data product service providers and manufacturers to flexibly adjust their operational strategies according to market conditions and cost constraints, in order to maximize profits and enhance market competitiveness. In situations with a larger market size or higher user perceived value, data product manufacturers should increase investment in technology research and development, optimize data update mechanisms, and enhance product quality to meet the expansion of market demand. Data product service providers should leverage

market potential by implementing targeted promotional strategies to expand user coverage, thereby increasing revenue. Under conditions of high price sensitivity or high costs, both parties need to collaborate to reduce cost pressures. Data product manufacturers should optimize update costs, while service providers need to streamline promotional resource allocation and enhance promotional efficiency. Under different power structures, data product manufacturers and service providers need to adopt differentiated strategies. In markets led by data product manufacturers, they should strengthen their technological advantages, while data product service providers should align with technology-driven market promotion. In markets led by data product service providers, they should drive demand growth through flexible promotional strategies, while data product manufacturers need to adapt to a promotion-driven market environment.

7. Conclusions and Managerial Insights

7.1. Conclusions

This paper is set against the backdrop of different market power structures in data product transactions, considering the dynamic updating characteristics of data products. It constructs a game theory model for data product manufacturers and service providers, analyzing in depth the performance of data product pricing, technology investment, update rates, and promotional efforts under different power structures, and explores the impact of dynamic updates and perceived value. Through model derivations and numerical simulations, the following main conclusions are drawn:

- (1) The optimal pricing of data products is higher in the Stackelberg game than in the Nash game, while in the Nash game, the demand for data products, the optimal technology investment level of data product manufacturers, the optimal update rate, and the optimal promotional efforts of data product service providers are all higher than in the Stackelberg game. In both Stackelberg game scenarios, the magnitude of data product demand, technology investment levels, update rates, and promotional efforts are also influenced by the sign of the formula $\beta^2(R - \Delta)^2 + \frac{d_1^2}{\lambda_1}\delta - \frac{d_2^2}{\lambda_2}$. When the formula value is greater than 0, in the Stackelberg game led by data product service providers, the demand for data products, technology investment levels, update rates, and promotional efforts are all greater than in the Stackelberg game led by data product manufacturers; When the formula value is less than 0, the above variables perform better in the Stackelberg game led by data product manufacturers.
- (2) The demand preferences and cost coefficients have a significant impact on the profits of data product manufacturers and service providers under different market power structures. An increase in the quality preference and promotion preference of data product end-users has enhanced the profits of both data product manufacturers and service providers, particularly in Stackelberg games, where these preferences have a more significant driving effect on the profits of the leading player. The increase in the technology cost coefficient of data product manufacturers and the promotion cost coefficient of service providers negatively impacts the profits of both parties. In markets led by data product manufacturers, the profits of data product service providers decrease more significantly due to the pressure from promotion costs; Whereas in markets led by data product service providers, the limited technology investment by data product manufacturers results in a larger decrease in their profits.
- (3) The dynamic updates of data products and the perceived value by end-users play a key role in the operational strategies and profit levels of data product manufacturers and service providers. The cost savings during the dynamic update process of data products significantly reduce the update pressure on manufacturers, further enhancing their technical optimization capacity, while indirectly improving the promotional

capability and profit levels of data product service providers through cost savings. The increase in perceived value by end-users effectively reduces their uncertainty, enhances market acceptance, and drives demand expansion, thereby providing a driving force for profit growth of both data product manufacturers and service providers. In contrast, the increase in the data product update input cost coefficient and data collection prices not only suppresses the technological investment and update strategies of data product manufacturers but also limits the flexibility of data product service providers in market promotion, ultimately imposing a significant constraint on the profits of both parties.

7.2. Managerial Insights

Based on the research findings presented above, this paper provides the following management implications:

- (1) For the data product manufacturer, sustained improvements in technological optimization and dynamic updating efficiency are critical for strengthening quality advantages and consolidating market competitiveness. Within a manufacturer-led market structure, the manufacturer should optimize the allocation of quality investment by enhancing accuracy, coverage, and updating frequency to meet users' demand for high-quality and timely data, thereby strengthening its bargaining position. The manufacturer should also refine its cost structure by identifying cost-saving opportunities in the updating process—for example, through automated data collection and cleaning or more efficient data feedback mechanisms—to reduce updating-cost coefficients and data acquisition expenses. This alleviates cost pressures and frees resources for continued R&D and market expansion. In a service provider-led market structure, the manufacturer should adapt to promotion-oriented dynamics by collaborating closely with the service provider to establish joint product-iteration mechanisms, allowing quality investment and promotional effort to become complementary and improving the product's responsiveness to user preferences and market demand elasticity.
- (2) For the data product service provider, careful refinement of promotional strategies and efficient allocation of promotional resources are essential for strengthening demand formation and market penetration. In a service provider-led market structure, the service provider should exploit its strengths in channel coverage, user access, and scenario building by optimizing promotional allocation, improving content quality, and expanding potential user reach to effectively stimulate demand. When users exhibit strong promotion preferences, the service provider should appropriately intensify promotional efforts through case demonstrations, trial access, and scenario-based presentations to strengthen user awareness. In highly price-sensitive markets, the service provider should employ differentiated promotional strategies and refined operations to reduce marginal promotional costs and preserve the cost–benefit efficiency of promotional spending. The service provider should also strengthen product interpretability during promotion to reduce users' perceived value uncertainty, thereby improving market acceptance and expanding demand. In a manufacturer-led structure, the service provider must align promotional activities with the manufacturer's technological enhancement strategies and strengthen coordination to improve the technology–promotion fit, thereby jointly enhancing market competitiveness and transaction efficiency.
- (3) At the policy level, regulators should strengthen the functioning of data product markets along three dimensions: market governance, cost-relief mechanisms, and improvements in user cognition. First, regulators should develop clear standards for data product quality, updating frequency, and data-processing transparency. By

setting minimum quality thresholds, periodic updating requirements, and disclosure rules, policymakers can enhance transparency, reduce perceived value uncertainty, and support demand formation. Second, by investing in public data infrastructures, shared computing capacity, and unified governance tools, the government can reduce updating costs for data product manufacturers and mitigate the profit squeeze associated with higher updating-cost coefficients and data-acquisition expenses. In addition, fiscal subsidies, tax incentives, and pilot programs that support promotional activities can meaningfully reduce promotional costs for data product service providers and accelerate demand formation. Moreover, the government should introduce certification systems, risk-assessment frameworks, and credit-based regulatory mechanisms to improve market trust and strengthen transaction efficiency. Collectively, these institutional interventions help optimize market cost structures, strengthen user trust and understanding, and establish the institutional foundations necessary for the sound development of data-factor markets.

7.3. Limitations and Prospects

Although the theoretical analysis in this study leads to several insightful conclusions, important questions remain open for future research. First, as China's data product market remains nascent, micro-level datasets and representative cases are limited, which constrains access to reliable information on the real decision-making behaviors of firms and users. Future work may thus integrate industry surveys with case-based analyses by observing firm behavior in concrete data product settings, modeling user preferences, and assessing policy impacts. Such efforts will help accumulate data suitable for parameter estimation and enhance the explanatory strength of analytical models. Second, the dynamic updating mechanism developed in this study abstracts from institutional constraints related to privacy protection, data authorization, and regulatory compliance. Introducing elements such as privacy costs, regulatory penalties, or platform governance mechanisms would markedly expand the decision space and render analytical solutions intractable, which justifies the abstraction used here. Future studies may systematically embed privacy risks, compliance costs, and regulatory incentives into the game-theoretic framework to explore the optimization of data product operational strategies within institutional environments, thereby aligning the model more closely with actual data-factor markets. In addition, the model relies on static user preferences and a static market equilibrium to maintain analytical tractability, which presents limitations in fast-evolving data markets. Future research may extend the framework to a dynamic setting—such as allowing preferences to evolve over time or incorporating multi-period decisions—to better reflect real market dynamics.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Appendix A.1. Nash Game Under Power Equilibrium

When the data product manufacturer and the service provider have comparable bargaining power, both parties follow a Nash game, which can be solved using the backward induction method. Let $p = m + w$, and substitute it into Equations (1)–(3).

For Equation (2), take the Hessian matrix with respect to w, k_1, τ , denoted as $H(w, k_1, \tau) = \begin{bmatrix} -\frac{2\beta}{\mu} & \frac{d_1}{\mu} & \frac{\beta(R-\Delta)}{\mu} \\ \frac{d_1}{\mu} & -\lambda_2 & \frac{d_1(\Delta-R)}{\mu} \\ \frac{\beta(R-\Delta)}{\mu} & \frac{d_1(\Delta-R)}{\mu} & -\delta \end{bmatrix}$. It can be easily verified that $-\frac{2\beta}{\mu} < 0$ and $\frac{2\beta\lambda_1\mu-d_1^2}{\mu^2} > 0$; therefore, when $\frac{d_1^2\delta+\beta\lambda_1[\beta(R-\Delta)^2-2\delta\mu]}{\mu^2} < 0$, $H(w, k_1, \tau)$ is negative definite, implying that Equation (2) admits a unique optimal solution.

Similarly, for Equation (3), take the Hessian matrix with respect to m, k_2 , denoted as $H(m, k_2) = \begin{bmatrix} -\frac{2\beta}{\mu} & \frac{d_2}{\mu} \\ \frac{d_2}{\mu} & -\lambda_2 \end{bmatrix}$. It can be verified that $-\frac{2\beta}{\mu} < 0$ and $\frac{2\beta\lambda_2\mu-d_2^2}{\mu^2} > 0$, indicating that $H(m, k_2)$ is negative definite and Equation (3) also admits a unique optimal solution. Next, take the first-order derivatives of Equation (2) with respect to w, k_1, τ , and the first-order derivatives of Equation (3) with respect to m, k_2 , and set them equal to zero, i.e., $\frac{\partial \pi_m}{\partial w} = 0$, $\frac{\partial \pi_m}{\partial k_2} = 0$, $\frac{\partial \pi_m}{\partial \tau} = 0$, $\frac{\partial \pi_s}{\partial m} = 0$, $\frac{\partial \pi_s}{\partial k_2} = 0$. Combining these with $p = m + w$, we can obtain the Nash equilibrium solutions: the manufacturer's optimal selling price w_1^* , optimal technology investment level k_{11}^* , and optimal data update rate τ_1^* ; as well as the service provider's optimal pricing p_1^* and optimal promotion investment level k_{21}^* .

Appendix A.2. Stackelberg Game Led by DPM

When the data product manufacturer acts as the leader, the interaction between the manufacturer and the data product service provider forms a Stackelberg game, which can also be solved by backward induction. Let $p = m + w$ and substitute it into Equations (1)–(3).

First, consider the decision-making problem of the data product service provider. The Hessian matrix of Equation (3) with respect to m, k_2 is denoted as $H(m, k_2) = \begin{bmatrix} -\frac{2\beta}{\mu} & \frac{d_2}{\mu} \\ \frac{d_2}{\mu} & -\lambda_2 \end{bmatrix}$. Since $-\frac{2\beta}{\mu} < 0$ and $\frac{2\beta\lambda_2\mu-d_2^2}{\mu^2} > 0$, the matrix $H(m, k_2)$ is negative definite, implying that Equation (3) has a unique optimal solution. By taking the first-order derivatives of Equation (3) with respect to m, k_2 and setting them equal to zero, i.e., $\frac{\partial \pi_s}{\partial m} = 0$, $\frac{\partial \pi_s}{\partial k_2} = 0$, we can jointly solve for $m = \frac{\lambda_2\mu(d_1k_1-w\beta+a\mu)}{2\beta\lambda_2\mu-d_2^2}$ and $k_2 = -\frac{d_2(d_1k_1-w\beta+a\mu)}{d_2^2-2\beta\lambda_2\mu}$.

Next, analyze the decision-making problem of the data product manufacturer. Substituting m, k_2 into Equation (2), the Hessian matrix of Equation (2) with respect

to w, k_1, τ is denoted as $H(w, k_1, \tau) = \begin{bmatrix} -\frac{2\beta^2\lambda_2}{d_2^2-2\beta\lambda_2\mu} & -\frac{d_1\beta\lambda_2}{d_2^2-2\beta\lambda_2\mu} & \frac{\beta^2\lambda_2(\Delta-R)}{d_2^2-2\beta\lambda_2\mu} \\ -\frac{d_1\beta\lambda_2}{d_2^2-2\beta\lambda_2\mu} & -\lambda_1 & \frac{d_1\beta\lambda_2(R-\Delta)}{d_2^2-2\beta\lambda_2\mu} \\ \frac{\beta^2\lambda_2(\Delta-R)}{d_2^2-2\beta\lambda_2\mu} & \frac{d_1\beta\lambda_2(R-\Delta)}{d_2^2-2\beta\lambda_2\mu} & -\delta \end{bmatrix}$. As $-\frac{2\beta^2\lambda_2}{d_2^2-2\beta\lambda_2\mu} < 0$ and $\frac{\beta^2\lambda_2(4\beta\lambda_1\lambda_2\mu-2d_2^2\lambda_1-d_1^2\lambda_2)}{(d_2^2-2\beta\lambda_2\mu)^2} > 0$, $H(w, k_1, \tau)$ is negative definite when $\frac{\beta^2\lambda_2\{2d_2^2\delta\lambda_1+d_1^2\delta\lambda_2+\beta\lambda_1\lambda_2[\beta(R-\Delta)^2-4\delta\mu]\}}{(d_2^2-2\beta\lambda_2\mu)^2} < 0$, indicating that Equation (2) admits a unique optimal solution.

Taking the first-order derivatives of Equation (2) with respect to w, k_1, τ and setting them to zero, i.e., $\frac{\partial \pi_m}{\partial w} = 0$, $\frac{\partial \pi_m}{\partial k_2} = 0$, $\frac{\partial \pi_m}{\partial \tau} = 0$, allows us to obtain the manufacturer's optimal decisions under the manufacturer-led Stackelberg game, including the optimal selling price w_2^* , the optimal technology investment level k_{12}^* , and the optimal update rate τ_2^* .

Substituting these results into m, k_2 and $p = m + w$ yields the optimal data product pricing p_2^* and promotion investment level k_{22}^* for the manufacturer-led Stackelberg equilibrium.

The proof in Section 4.3 is similar to that in Appendix A.2. and is therefore omitted here for brevity.

Appendix B

Proof of Propositions 1–7. The proofs of Propositions 1–7 are all derived by taking the partial derivatives of the equilibrium solutions with respect to the corresponding parameters and are therefore omitted for brevity. $\square$

Proof of Proposition 8. According to the assumptions and relevant constraints of the study, the following relationships exist:

$$w_2^* - w_1^* = \frac{\delta^2 \lambda_1 (a\mu - c\beta) (\beta \lambda_2 \mu - d_2^2) [\lambda_2 (2\beta \lambda_1 \mu - d_1^2) - d_2^2 \lambda_1]}{\beta \left\{ 2d_2^2 \delta \lambda_1 + d_1^2 \delta \lambda_2 + \beta \lambda_1 \lambda_2 [\beta (R - \Delta)^2 - 4\delta \mu] \right\} \left\{ d_2^2 \delta \lambda_1 + d_1^2 \delta \lambda_2 + \beta \lambda_1 \lambda_2 [\beta (R - \Delta)^2 - 3\delta \mu] \right\}} > 0$$

$$w_3^* - w_1^* = - \frac{\lambda_1 \lambda_2^2 (a\mu - c\beta) [\beta (R - \Delta)^2 - \delta \mu] \left\{ d_1^2 \delta + \beta \lambda_1 [\beta (R - \Delta)^2 - \delta \mu] \right\}}{\left\{ d_2^2 \delta \lambda_1 + d_1^2 \delta \lambda_2 + \beta \lambda_1 \lambda_2 [\beta (R - \Delta)^2 - 3\delta \mu] \right\} \left\{ d_2^2 \delta \lambda_1 + 2\lambda_2 \left\{ d_1^2 \delta + \beta \lambda_1 [\beta (R - \Delta)^2 - 2\delta \mu] \right\} \right\}} < 0$$

Therefore, the relationship $w_2^* > w_1^* > w_3^*$ holds.

$$p_2^* - p_1^* = \frac{\delta^2 \lambda_1 (a\mu - c\beta) (d_2^2 - \beta \lambda_2 \mu) [d_2^2 \lambda_1 + \lambda_2 (d_1^2 - \beta \lambda_1 \mu)]}{\beta \left\{ 2d_2^2 \delta \lambda_1 + d_1^2 \delta \lambda_2 + \beta \lambda_1 \lambda_2 [\beta (R - \Delta)^2 - 4\delta \mu] \right\} \left\{ d_2^2 \delta \lambda_1 + d_1^2 \delta \lambda_2 + \beta \lambda_1 \lambda_2 [\beta (R - \Delta)^2 - 3\delta \mu] \right\}} > 0$$

$$p_3^* - p_1^* = \frac{\delta \lambda_2 (c\beta - a\mu) (\beta \lambda_1 \lambda_2 \mu - d_2^2 \lambda_1 - d_1^2 \lambda_2) \left\{ d_1^2 \delta + \beta \lambda_1 [\beta (R - \Delta)^2 - \delta \mu] \right\}}{\beta \left\{ d_2^2 \delta \lambda_1 + d_1^2 \delta \lambda_2 + \beta \lambda_1 \lambda_2 [\beta (R - \Delta)^2 - 3\delta \mu] \right\} \left\{ d_2^2 \delta \lambda_1 + 2\lambda_2 \left\{ d_1^2 \delta + \beta \lambda_1 [\beta (R - \Delta)^2 - 2\delta \mu] \right\} \right\}} > 0$$

Therefore, the relationship $p_2^* > p_1^*, p_3^* > p_1^*$ holds.

$$p_2^* - p_3^* = \left[\beta^2 (R - \Delta)^2 + \frac{d_1^2}{\lambda_1} \delta - \frac{d_2^2}{\lambda_2} \right] \times \frac{(a\mu - c\beta) (\beta \lambda_1 \lambda_2 \mu - d_2^2 \lambda_1 - d_1^2 \lambda_2)}{\beta \left\{ 2d_2^2 \delta \lambda_1 + d_1^2 \delta \lambda_2 + \beta \lambda_1 \lambda_2 [\beta (R - \Delta)^2 - 4\delta \mu] \right\} \left\{ d_2^2 \delta \lambda_1 + 2\lambda_2 \left\{ d_1^2 \delta + \beta \lambda_1 [\beta (R - \Delta)^2 - 2\delta \mu] \right\} \right\}},$$

Since

$$\frac{(a\mu - c\beta) (\beta \lambda_1 \lambda_2 \mu - d_2^2 \lambda_1 - d_1^2 \lambda_2)}{\beta \left\{ 2d_2^2 \delta \lambda_1 + d_1^2 \delta \lambda_2 + \beta \lambda_1 \lambda_2 [\beta (R - \Delta)^2 - 4\delta \mu] \right\} \left\{ d_2^2 \delta \lambda_1 + 2\lambda_2 \left\{ d_1^2 \delta + \beta \lambda_1 [\beta (R - \Delta)^2 - 2\delta \mu] \right\} \right\}} > 0,$$

it follows that when $\beta^2 (R - \Delta)^2 + \frac{d_1^2}{\lambda_1} \delta - \frac{d_2^2}{\lambda_2} > 0$, $p_2^* > p_3^*$ holds; when $\beta^2 (R - \Delta)^2 + \frac{d_1^2}{\lambda_1} \delta - \frac{d_2^2}{\lambda_2} < 0$, $p_2^* < p_3^*$ holds; when $\beta^2 (R - \Delta)^2 + \frac{d_1^2}{\lambda_1} \delta - \frac{d_2^2}{\lambda_2} = 0$, $p_2^* = p_3^*$ holds. $\square$

The proof procedures for Propositions 9–10 are analogous to that of Proposition 8 and are therefore omitted.

Appendix C

Table A1. Sensitivity Analysis for the Nash Equilibrium Game.

Parameter	Change Rate	Equilibrium Solution							
		w_1^*	p_1^*	k_{11}^*	k_{21}^*	Q_1^*	τ_{m1}^*	π_{m1}^*	π_{s1}^*
a	−20%	0.4766	0.6572	0.1232	0.1003	0.4064	0.0406	0.0559	0.0643
	−10%	0.5147	0.7344	0.1498	0.1220	0.4943	0.0494	0.0827	0.0952
	0	0.5529	0.8116	0.1764	0.1437	0.5822	0.0582	0.1147	0.1320
	+10%	0.5911	0.8889	0.2030	0.1654	0.6700	0.0670	0.1519	0.1749
	+20%	0.6293	0.9661	0.2297	0.1871	0.7579	0.0758	0.1944	0.2238
β	−20%	0.6784	1.0637	0.2627	0.2141	0.6935	0.0694	0.1889	0.2260
	−10%	0.6062	0.9187	0.2131	0.1736	0.6329	0.0633	0.1458	0.1706
	0	0.5529	0.8116	0.1764	0.1437	0.5822	0.0582	0.1147	0.1320
	+10%	0.5120	0.7293	0.1482	0.1208	0.5380	0.0538	0.0913	0.1038
	+20%	0.4795	0.6641	0.1258	0.1025	0.4982	0.0498	0.0733	0.0825
c	−20%	0.5187	0.8038	0.1944	0.1584	0.6415	0.0641	0.1393	0.1603
	−10%	0.5358	0.8077	0.1854	0.1511	0.6118	0.0612	0.1267	0.1458
	0	0.5529	0.8116	0.1764	0.1437	0.5822	0.0582	0.1147	0.1320
	+10%	0.5700	0.8156	0.1674	0.1364	0.5525	0.0552	0.1033	0.1189
	+20%	0.5871	0.8195	0.1584	0.1291	0.5228	0.0523	0.0925	0.1065
d_1	−20%	0.5359	0.7773	0.1317	0.1341	0.5431	0.0543	0.1106	0.1149
	−10%	0.5437	0.7929	0.1530	0.1385	0.5609	0.0561	0.1125	0.1226
	0	0.5529	0.8116	0.1764	0.1437	0.5822	0.0582	0.1147	0.1320
	+10%	0.5640	0.8340	0.2025	0.1500	0.6076	0.0608	0.1171	0.1438
	+20%	0.5773	0.8609	0.2321	0.1576	0.6382	0.0638	0.1198	0.1587
d_2	−20%	0.5434	0.7924	0.1698	0.1107	0.5603	0.0560	0.1062	0.1285
	−10%	0.5478	0.8013	0.1728	0.1268	0.5704	0.0570	0.1101	0.1301
	0	0.5529	0.8116	0.1764	0.1437	0.5822	0.0582	0.1147	0.1320
	+10%	0.5588	0.8236	0.1805	0.1618	0.5957	0.0596	0.1201	0.1342
	+20%	0.5656	0.8373	0.1853	0.1811	0.6113	0.0611	0.1265	0.1366
λ_1	−20%	0.5662	0.8385	0.2321	0.1513	0.6127	0.0613	0.1176	0.1463
	−10%	0.5587	0.8233	0.2005	0.1470	0.5954	0.0595	0.1160	0.1381
	0	0.5529	0.8116	0.1764	0.1437	0.5822	0.0582	0.1147	0.1320
	+10%	0.5484	0.8025	0.1575	0.1412	0.5718	0.0572	0.1136	0.1274
	+20%	0.5448	0.7952	0.1423	0.1391	0.5634	0.0563	0.1128	0.1237
λ_2	−20%	0.5600	0.8259	0.1813	0.1847	0.5984	0.0598	0.1212	0.1346
	−10%	0.5560	0.8179	0.1786	0.1617	0.5893	0.0589	0.1175	0.1332
	0	0.5529	0.8116	0.1764	0.1437	0.5822	0.0582	0.1147	0.1320
	+10%	0.5504	0.8067	0.1747	0.1294	0.5765	0.0576	0.1125	0.1311
	+20%	0.5484	0.8026	0.1733	0.1177	0.5718	0.0572	0.1107	0.1304
μ	−20%	0.4907	0.6869	0.1672	0.1363	0.5519	0.0552	0.0760	0.0916
	−10%	0.5220	0.7498	0.1725	0.1406	0.5693	0.0569	0.0953	0.1119
	0	0.5529	0.8116	0.1764	0.1437	0.5822	0.0582	0.1147	0.1320
	+10%	0.5835	0.8729	0.1794	0.1462	0.5920	0.0592	0.1342	0.1521
	+20%	0.6139	0.9338	0.1818	0.1481	0.5998	0.0600	0.1537	0.1721
Δ	−20%	0.5546	0.8120	0.1755	0.1430	0.5792	0.0405	0.1144	0.1307
	−10%	0.5538	0.8119	0.1759	0.1433	0.5806	0.0493	0.1145	0.1313
	0	0.5529	0.8116	0.1764	0.1437	0.5822	0.0582	0.1147	0.1320
	+10%	0.5518	0.8114	0.1770	0.1442	0.5840	0.0672	0.1149	0.1329
	+20%	0.5506	0.8111	0.1776	0.1447	0.5861	0.0762	0.1151	0.1338

Table A1. Cont.

Parameter	Change Rate	Equilibrium Solution							
		w_1^*	p_1^*	k_{11}^*	k_{21}^*	Q_1^*	τ_{m1}^*	π_{m1}^*	π_{s1}^*
δ	−20%	0.5521	0.8115	0.1768	0.1441	0.5836	0.0729	0.1148	0.1327
	−10%	0.5525	0.8116	0.1766	0.1439	0.5828	0.0648	0.1148	0.1323
	0	0.5529	0.8116	0.1764	0.1437	0.5822	0.0582	0.1147	0.1320
	+10%	0.5532	0.8117	0.1763	0.1436	0.5816	0.0529	0.1146	0.1318
	+20%	0.5535	0.8118	0.1761	0.1435	0.5812	0.0484	0.1146	0.1316
R	−20%	0.5522	0.8115	0.1768	0.1440	0.5834	0.0642	0.1148	0.1326
	−10%	0.5526	0.8116	0.1766	0.1439	0.5827	0.0612	0.1148	0.1323
	0	0.5529	0.8116	0.1764	0.1437	0.5822	0.0582	0.1147	0.1320
	+10%	0.5532	0.8117	0.1762	0.1436	0.5816	0.0553	0.1146	0.1318
	+20%	0.5535	0.8118	0.1761	0.1435	0.5811	0.0523	0.1146	0.1315

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