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Analysis and Improvement of Pricing Models for Bilateral Media Platforms

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Abstract: In the context of increasingly intense competition among digital platforms, the strategic pricing behavior of two-sided media platforms has attracted considerable academic attention. The pricing model for two-sided platforms proposed by Amaldoss et al. provides a theoretical foundation for understanding the interaction among consumer heterogeneity, multi-homing behavior, and advertising strategies. However, a series of idealized assumptions within the model present limitations when applied to real-world scenarios. This paper offers a systematic review and critical analysis of the model, identifying key issues in aspects such as consumer representation, advertiser behavior, platform strategy space, and market structure assumptions. Based on these insights, several extensions are proposed, including the introduction of continuous advertising aversion levels, endogenous attention allocation mechanisms, advertiser heterogeneity and budget constraints, asymmetric platform capabilities, and a dynamic game framework. Through structural modifications and mechanism enhancements, the model's behavioral realism and practical explanatory power are significantly improved, offering valuable references for the development of platform pricing theory and its practical implementation.

Keywords: Two-sided platform; Pricing game; Consumer heterogeneity; Multi-homing behavior; Advertising mechanism; Model extension.

1. Introduction

Embroidery Driven by the rapid expansion of digitalization, media platforms such as TikTok and YouTube have become increasingly influential in the modern economy. These platforms typically operate within a two-sided market structure, serving both consumers seeking content and advertisers seeking exposure. Designing effective pricing strategies that coordinate demand on both sides, maximize platform revenue, and preserve user experience has therefore become a central concern in both academic research and industry practice.

In the existing literature, the competitive media platform pricing model proposed by Amaldoss et al.[1] provides an important theoretical framework for understanding price competition and multihoming behavior in two-sided markets. The model characterizes how two symmetric platforms make strategic choices between uniform pricing and tiered pricing in the presence of heterogeneous consumer sensitivity to advertising and advertisers' valuation of user attention. It further shows how changes in the value of multihoming can lead to different equilibrium outcomes. Based on this framework, the authors derive several notable insights, including the possibility that symmetric platforms may adopt asymmetric strategies and the counterintuitive result that tiered pricing may reduce profits for both platforms in a prisoner's dilemma setting.

Despite its analytical rigor and logical coherence, several assumptions of the model remain highly stylized when confronted with the complexity of real-world platform markets. For instance, consumer advertising aversion is represented as a binary classification, advertisers are treated as homogeneous, and the allocation of attention among multihoming users is assumed to be fixed. While these simplifications enhance analytical tractability, they may also limit the model's explanatory power. This limitation becomes particularly salient in an environment characterized by increasing platform differentiation, more sophisticated advertising pricing mechanisms, and increasingly diverse patterns of user behavior. As a result, some key assumptions of the model may affect its ability to predict real-world platform strategies and the external validity of its policy implications.

Against this background, this study conducts a systematic critical analysis of the competitive media platform pricing model developed by Amaldoss et al. By revisiting the model's structure and core mechanisms and identifying its major limitations in both theoretical design and practical applicability, we propose several extensions to improve its realism and analytical scope. These include introducing advertiser heterogeneity, relaxing the assumption of fixed user attention allocation, expanding the range of pricing strategies, and incorporating platform asymmetry and dynamic game mechanisms. Through these extensions, this study aims to contribute to the further development of platform pricing theory while enhancing the model's relevance for real-world platform strategy.

2. Literature Review

Media platforms are typical examples of two-sided markets. The pricing issues of such platforms have attracted considerable attention since they were first proposed in economic theory. Scholars in academic circles have continuously explored the "two-sided market structure," "externalities of the network", "multihoming behavior" and "pricing strategies" to develop multi-dimensional models of these systems. Based on the framework proposed by Amaldoss et al., this model has been examined and further developed, offering significant representativeness.

(1) Two-Sided Market Pricing Theory

The theory of two-sided markets provides a systematic framework for analyzing platforms, with a focus on the pricing issue in the interaction between two user groups on such platforms. Rochet and Tirole[2] proposed a formal model in which platform pricing not only considers the platforms revenue and costs but also the value it provides to users. The platform adjusts the pricing to balance the interests of both sides through cross-subsidization, where one side's growth helps improve the other side's benefit, thus achieving overall network coordination and expansion.

Building on this foundation, Armstrong [3] introduced a user multihoming framework, constructing a model of two-sided platform competition. Armstrongs model highlights that when users can join multiple platforms simultaneously, the platform faces stronger competitive pressure on one side's subsidization strategy, which then influences market outcomes. Hagiu[4] and Evans[5] further extended the model by exploring the platforms structural complexity and the roles of participants in different contexts, reinforcing the importance of platform differentiation and strategy adaptation.

(2) Platform Competition and Advertising Mechanism in Media Markets

As digital content platforms increasingly come to dominate the landscape of information dissemination, advertising mechanisms have emerged as a critical link connecting user behavior, platform revenue, and advertiser objectives. Operating as quintessential two-sided markets, these platforms must strike a dynamic balance between attracting user traffic and monetizing through advertising. Their competitive advantage hinges largely on the coordinated design of ad load, content matching efficiency, and user experience.

Early research focused on the trade-off between ad density and user retention. In his analysis of newspaper advertising markets, Gentzkow[9] noted that while the volume of advertisements is positively correlated with short-term platform revenue, excessive commercialization may provoke user aversion, thereby undermining long-term platform value. Building on this foundation, Ambrus et al. developed a theoretical model incorporating a parameter for "ad aversion," revealing that heterogeneity in users tolerance for advertising plays a decisive role in shaping platform advertising strategies. In a related vein, Bergemann and Bonatti [10] explored the role of ad targeting mechanisms in enhancing the efficiency of information allocation, emphasizing that improved ad matching accuracy can alleviate competitive pressures arising from scarce user attention.

Within more context-specific research, scholars have also examined the evolutionary logic of advertising-driven platforms. Li [11], through the construction of a multi-agent game model, argued that platforms facing heterogeneous agents on both sides—advertisers and users—should strengthen their intermediary capabilities in algorithmic recommendation and content curation to enhance the synergy between ad conversion rates and user acceptance. Other studies have concentrated on the optimization of ad load strategies. For instance, Zhang et al. [12] demonstrated that by finely regulating ad duration and placement to control the level of intrusion, platforms can significantly improve user stickiness and engagement without compromising commercial returns.

In terms of competitive dynamics, advertising mechanisms are often shaped by differentiation strategies among platforms. Dellarocas et al. [13] developed a dynamic model based on the interplay between platform quality and user switching behavior, suggesting that the combination of ad load control and content uniqueness can jointly enhance user retention. Within this framework, further studies have pointed out that in a multi-platform environment, advertising mechanisms must accommodate the multihoming characteristics of users. By designing differentiated positioning and targeted delivery logics, platforms can carve out effective distinctions in an otherwise homogenized competitive landscape.

Taken together, advertising mechanisms constitute a vital pillar of platform business models. Their optimization must not only balance the interests of both sides of the market but also incorporate the interactive dynamics of user behavioral feedback and the evolution of algorithmic strategies. From static models of ad load equilibrium to the construction of dynamic user response mechanisms, current research has provided important theoretical support for platforms seeking to achieve the dual objectives of commercial revenue and user experience amid intense competition. It also opens up further avenues for the development of more intelligent and fine-grained advertising systems.

(3) Research on the original model

Amid the deepening research on platform economy and two-sided markets, the theoretical model proposed by Amaldoss et al. seeks to systematically examine how platforms strike a balance between the advertising side and the user side through pricing structure design. Rather than merely extending conventional platform pricing theory, this work places analytical emphasis on the strategic decision of whether platforms adopt a tiered pricing structure, thereby broadening the theoretical boundaries of the existing literature concerning platforms structural choices. In terms of theoretical lineage, the model builds upon the foundational two-sided market theory developed by Rochet and Tirole, while incorporating recent scholarly attention to platform competition and user multihoming behavior. In contrast to much of the literature that treats pricing structure as a given premise, Amaldoss et al. frame the platforms active choice between uniform and tiered pricing as a strategic decision, lending the study a stronger problem-driven orientation and bringing it closer to the actual business strategies observed in real-world platforms.

In terms of modeling approach, the authors incorporate a Hotelling spatial structure and user multihoming behavior, while distinguishing between ad-sensitive and ad-insensitive consumer types, endowing the model with both analytical tractability and explanatory power. Within this framework, the incremental utility δ generated by multihoming emerges as a core variable in the analysis, creating a tightly integrated feedback loop among platform strategy, consumer choice, and advertiser behavior. This dynamic interplay in a multi-agent game is relatively uncommon in related research and constitutes a distinctive feature of the model. Moreover, one of the most illuminating aspects of the model lies in its revelation of a "platform structure choice paradox": although platforms have the freedom to adopt tiered pricing, when both competing platforms choose this strategy, overall profits may decline. This finding challenges the intuitive assumption that strategic flexibility necessarily leads to higher profits, and offers a plausible explanation for why platforms in practice often exhibit caution in rolling out tiered pricing schemes.

To ensure theoretical rigor and clarity, the authors introduce several simplifying assumptions, such as platform symmetry, advertiser homogeneity, a binary classification of user types, and a static one-shot game structure. While these assumptions facilitate model solvability, they also constrain the models applicability to more complex real-world settings. Therefore, building on a thorough understanding of the original models logic, identifying its structural limitations, and extending it along dimensions such as behavioral heterogeneity and dynamic evolutionary paths will constitute the core directions for further analysis and refinement in the subsequent sections of this study.

Overall, the model stands at the intersection of two theoretical domains—platform structure strategy choice and multi-sided market interaction mechanisms—and offers not only considerable analytical depth but also a solid foundation for future extensions.

3. Overview of the Model Structure

To systematically analyze the pricing and advertising allocation decisions faced by platforms operating in two-sided markets, Amaldoss et al. construct a static complete information game model that examines how two competing platforms maximize their profits through uniform or tiered pricing strategies, in the presence of consumers with heterogeneous advertising aversion and advertisers engaging in budget allocation behavior. The model structure encompasses four core elements: consumer specification, advertiser specification, platform decision space, and the sequence of play. These are elaborated in the following subsections.

(1) Consumer Specification

The model assumes that consumers are uniformly distributed along the unit interval [0,1], representing their preference differences between the two platforms. Platform 1 is located at position 0, and Platform 2 at position 1, employing a Hotelling framework to capture location-based preferences. The utility function for consumers is given by:

$u_{k}^{\lambda}(\theta)$=u −t·|θ − lk|−Yλ·αk−pkλ

Among them:

u: Basic content utility (platforms are identical);

t: Position preference intensity;

lk: Position of platform k;

Yλ: Dislike degree of type λ users towards advertisements;

αk: Advertising intensity of platform k;

pkλ: Charging price of platform k for type λ users.

Consumers are divided into two types:

Low-sensitive type (L-type): Completely not disgusted by advertisements, YL = 0;

High-sensitive type (H-type): Have positive aversion to advertisements, YH > 0.

The platform can choose between two pricing models: a uniform pricing model, in which all users are exposed to advertisements, or a tiered pricing model, which allows highly ad-sensitive users to opt into a higher-priced, ad-free subscription. In addition, a subset of consumers may engage in multihoming, i.e., subscribing to both platforms simultaneously. Multihoming generates an additional utility δ for these users; however, they remain subject to the subscription fees charged by each platform and the ad nuisance associated with each platforms advertising policy.

(2) Advertiser Specification

Advertisers constitute the other side of the market, purchasing advertising impressions from platforms. Each advertiser is endowed with a unit budget, and platforms charge a per-impression advertising fee. The model assumes that all advertisers are homogeneous, valuing each advertising impression at v while deriving no marginal utility from repeated exposures (i.e., the value of a second exposure is zero). Advertisers are free to allocate their budgets across both platforms. Each consumer generates ak units of attention for a platform, depending on their usage intensity. A platforms advertising revenue is then determined by the product of the number of advertising slots purchased by advertisers and the unit price. Through a combination of user base size, advertising intensity α and pricing strategy, platforms collectively shape their value in the advertising market.

nuisance associated with each platforms advertising policy.

(3) Platform Behavior and Game Structure

The strategy space of the platform consists of two parts: pricing structure selection (uniform or hierarchical) and pricing level setting. In a uniform pricing structure, all users receive advertisements at the same price; in a hierarchical pricing structure, highly sensitive users can choose to pay PH to receive no advertisements, while low-sensitive users pay PL to receive advertisements.

The game sequence is as follows:

(1) The platform simultaneously selects the pricing structure and the price;

(2) Consumers observe the prices and the intensity of advertisements provided by the platform and choose to join Platform 1, Platform 2, or both;

(3) Advertisers observe the attention each platform receives and allocate their advertising budgets;

(4) Each platform obtains advertising revenue and user payment revenue. The platforms goal is to maximize profit:

Πk=R_{k}^{ads}+ R_{k}^{subs}− Ck

Among them,

R_{k}^{ads}represents advertising revenue

R_{k}^{subs}represent subscription revenue

Ck represents platform costs, which is set to zero in the basic model

4. Core mechanism and equilibrium conclusion

The main analysis of the model focuses on the equilibrium results of platform strategy combinations in different scenarios. Specifically, the authors introduce a key parameter: the multi-ownership incremental utility δ, whose magnitude determines whether users tend to choose both platforms, thereby influencing the overall market structure. Based on the value of δ, the model divides into three main scenarios.

(1) Multi-ownership incremental utility δ and the partition logic of market structure

The model assumes that consumers are uniformly distributed along the unit interval [0,1], representing their preference differences

The model assumes that when a user is multi-registered, that is, joins two platforms, the additional utility they obtain is δ, and the selection mechanism for user types is defined as follows:

If δ is small, the additional utility from multi-registration is insufficient to offset the repeated prices and advertising interference, and the user chooses to join one platform;

If δ is large enough, consumers are willing to choose multi-registration even if they have to pay twice the price and accept more advertisements;

In the middle area, there exists a mixed structure where multi-registered users and single-registered users coexist.

The model sets two critical values,δ^{*} and δ^{**}, and divides the market into three equilibrium structures:

$\delta<\delta^{*}$: bilateral complete differentiation equilibrium;

$\delta^{*}\leq\delta\leq\delta^{**}$: asymmetric differentiation equilibrium;

δ> δ** :non-differentiation equilibrium, all being multi-registered.

(2) Equilibrium Analysis in the Low-δ Scenario (δ < δ*)

When the marginal utility brought by multiple affiliations is relatively low, users tend to choose one of the two platforms to join. The platform strategy then presents a typical prisoners dilemma pattern. Both platforms adopt tiered pricing to obtain high-sensitivity users high-priced subscriptions and low-sensitivity users advertising income. However, this also leads to user diversion, advertisers dispersion, and a decrease in total advertising revenue. If either platform switches to a uniform pricing strategy, it will attract more advertisers to concentrate their placements and can compete for the attention of low-sensitivity users. However, it lacks a long-term stability mechanism and is prone to a non-cooperative outcome of "both losing". In this situation, the two-sided "tiered-tiered" structure is suboptimal but constitutes a Nash equilibrium.

(3) Equilibrium Analysis under High δ (δ > δ**)

When the multi-ownership utility is sufficiently high, most users choose to join two platforms, forming an attention superposition structure. Under this background, advertisers are more inclined to place advertisements separately on the two platforms, and the platform profit structure will be more dependent on advertising efficiency and attention weighting. The model indicates that when multi-ownership becomes the norm, the platforms will instead shift to uniform pricing to enhance the concentration of advertisers and user retention rates. More importantly, in this structure, an "asymmetric equilibrium" of platform strategies emerges: one platform chooses uniform pricing to attract advertisers and low-sensitivity users; the other platform chooses hierarchical pricing to target high-sensitivity users, avoiding direct conflicts. This differentiation can be regarded as an implicit market positioning collaboration between the platforms.

(4) The unexpected outcome of the consumer-level pricing mechanism

Although the original intention of the hierarchical pricing structure is to achieve price discrimination and improve efficiency, the model also reveals its potential side effects. On one hand, when the platform attempts to guide users to make their own choices, it may mistakenly set the price gap PH - PL, causing the critical point $Y* = \frac{P_H - P_L}{\alpha}$ to fall within the boundary area, thereby causing high-sensitive users to switch to another platform. On the other hand, if both platforms adopt the hierarchical strategy and raise PH at the same time, high-sensitive users may find themselves with no place to go, that is, neither of the two schemes can satisfy the condition of maximizing their utility, leading to a decline in overall market efficiency. This result indicates that although the price hierarchical strategy can optimize the revenue structure in the short term, in a competitive environment, it needs to precisely coordinate the diversion critical point; otherwise, it will trigger structural problems such as decreased user experience and blurred platform positioning.

5. Analysis of Model Limitations and Improvements

(1) Simplification in Consumer Modeling and Discrepancy from Reality

In the two-sided platform pricing model proposed by Amaldoss et al., the characterization of consumer behavior serves as the foundation for constructing the games equilibrium structure. However, to ensure analytical tractability and closed-form equilibrium solutions, the authors adopt several simplifying assumptions in their modeling of consumers, including a binary classification of user types, rigid allocation of attention resources, and mean-based treatment of multihoming utility. While these simplifications enhance mathematical solvability, they also limit the models ability to capture real-world user behavior in several respects, potentially constraining the generalizability of the equilibrium results.

The model categorizes consumers into two types: high ad-aversion types (H-type) and low ad-aversion types (L-type), with ad disutility parameters set as γH > 0 and γL = 0 , respectively. Although this binary distinction facilitates the identification of cutoff points for user segmentation under different pricing mechanisms, in reality, consumer tolerance for advertising is rarely so dichotomous. Rather, it tends to exhibit a continuous distribution. Users vary considerably in their perceptions of ad frequency, duration, placement, and even relevance. Setting γL = 0 effectively exaggerates the proportion of users for whom advertising imposes no disutility, leading the model to underestimate the extent to which ad nuisance erodes overall user experience and platform stickiness. Empirical research has shown that even users who are relatively tolerant of advertising exhibit a higher propensity to switch platforms when ad load increases or content interruptions become frequent. Consequently, the model s predictions regarding user acceptance under uniform pricing and platform advertising revenue may be systematically overestimated.

A more realistic extension would involve treating the ad aversion parameter γλ as a random variable drawn from a continuous distribution, such as γ ~ Uniform[a, b], or introducing more than two user types (e.g., high, medium, and low sensitivity). Such refinements would allow for greater flexibility in characterizing users strategic choices. This approach would not only more accurately capture marginal users responses to changes in platform pricing and advertising configurations, but also assist platforms in designing more finely differentiated tiered pricing strategies.

In the original model, each consumer is assumed to possess one unit of attention, which is split equally between the two platforms when they engage in multihoming, i.e., a1 =a2=0.5. While this assumption facilitates the calculation of advertising impressions and user value from the platforms perspective, it deviates significantly from the "primary platform—supplementary platform" usage pattern observed in reality. In actual usage scenarios, users tend to devote the vast majority of their time and interaction frequency to one platform, while the other serves only a marginal role, fulfilling specific functions or supplementing content. This imbalanced structure may be influenced by a variety of factors, including content appeal, interface preferences, algorithmic recommendation efficiency, and even device compatibility, and exhibits strong user-endogeneity. If the model consistently assumes an equal 0.5 split of attention, the advertising resources attributed to the secondary platform will be systematically overestimated in simulations, and the incentives for platforms to attract "secondary attention" users will be correspondingly understated.

A more reasonable modeling approach would be to treat attention allocation as an endogenous function driven by utility. Let the utilities derived by a user from Platform 1 and Platform 2 be denoted as U1 and U2, respectively. Attention allocation can then be expressed as:

$a1=\frac{U_1}{U_1+U_2}$, a2=1-a1

This modification not only captures the comprehensive competitiveness of platforms in terms of content quality, ad load, and price attractiveness, but also enhances the models ability to characterize platform strategies aimed at capturing dedicated user attention. It thus provides a stronger foundation for modeling the behavioral feedback effects of platform pricing and content decisions.

The model further assumes that all users who choose multihoming receive a fixed additional utility increment δ, reflecting the added value derived from content diversity, functional complementarity, and enhanced entertainment variety. However, treating δ as a constant overlooks the structural differences in platform content and the heterogeneity in users valuation of content diversity. In reality, the degree of content overlap, stylistic preferences, and algorithmic recommendation structures across platforms can lead to significantly different marginal values that users derive from a second platform. For instance, while Spotify and Apple Music partially overlap in their music libraries, algorithms, and subscription strategies, a platform like NetEase Cloud Music may offer greater content differentiation value due to its community-based commenting features and aggregation of original music. Different consumer types also exhibit varying sensitivities to content redundancy or differentiation—some users prefer deep engagement with a single category, while others are inclined toward broad exploration.

To enhance the models explanatory power regarding multihoming behavior, δ can be conceptualized as a function of content differentiation across platforms, users ex ploration preferences, and differences in recommendation systems:

δ = φ(content diversity,consumer type) or δλ

Here, φ can be constructed based on factors such as content category overlap, redundancy in viewing behavior, or the scope of personalized coverage. This formulation would render platforms investments in content strategy more strategically meaningful and provide a more granular analytical pathway for simulating users marginal multihoming choices across platforms.

In summary, while the simplifying assumptions in Amaldoss et al.s consumer modeling enhance the structural parsimony of the model and the transparency of equilibrium analysis, they introduce notable deviations from reality in three key areas: the characterization of ad aversion, the mechanism of attention allocation, and the structure of multihoming utility. By introducing continuous user heterogeneity, an endogenous attention allocation function, and differentiated modeling of δ, it is possible not only to improve the models fit w ith real-world market structures but also to expand the behavioral boundaries of platform strategy design in pricing and content decisions, thereby rendering the theoretical conclusions more practically instructive.

(2) Limitations of the Platform Strategy Space

In the model proposed by Amaldoss et al., the strategy space for two symmetric platforms is restricted to a binary choice between "uniform pricing" and "tiered pricing." Under the uniform pricing structure, platforms set a single price for all users accompanied by a uniform intensity of advertising. Under the tiered pricing structure, users can choose either a high-price ad-free experience PH or a low-price ad-supported version PL. Although this binary setup helps highlight the tension between user heterogeneity and platforms advertising monetization mechanisms, it exhibits three notable limitations when compared to the complexity of pricing strategies observed in real-world platform operations.

First, the model compresses platform pricing strategies into a simple dichotomy between uniform and tiered structures, overlooking the multidimensional nature of real-world pricing designs in terms of fee structures, service tiers, and feature bundling. Consider Spotify as an example: its pricing strategy not only distinguishes between ad-supported and ad-free versions but also encompasses multiple layers such as individual subscriptions, family plans, student discounts, and region-specific pricing. Similarly, YouTube offers not only its Premium service but also Music, Kids, and on-demand upgrade packages. In practice, platforms often achieve precise alignment with users heterogeneous willingness to pay, usage scenarios, and preference structures through service modularization and experience-based tiering. Such multidimensional hybrid pricing strategies significantly expand platforms flexibility in balancing revenue generation and user coverage. Restricting the strategic choice to whether or not to offer a tiered structure, as in the model, clearly fails to capture this real-world complexity.

Moreover, platform pricing designs are not solely centered on ad aversion; they frequently implement price discrimination strategies based on factors such as content depth, viewing permissions, and value-added features. Netflix, for instance, differentiates its subscription tiers by streaming quality, number of devices, and offline download capabilities, while Apple Music leverages device ecosystem integration and family account features to encourage locked-in renewals. Consequently, modeling platform strategic choices solely along the dimensions of price and advertising proves logically insufficient for capturing user segmentation mechanisms in complex consumption scenarios.

To better align with real-world business logic, a viable model extension would involve expanding the platforms strategy space from a "binary choice set" to a "multidimensional continuous combination space." Within this expanded framework, platforms could design their strategies along three key dimensions: first, the choice of revenue model (pure advertising, pure subscription, or hybrid); second, the number of service tiers offered (two-tier, three-tier, or continuous package structures); and third, the bundling of features and services (such as offering exclusive content, allowing ad skipping, or supporting multi-device access). Such an extension not only enhances the granularity of platform strategy modeling but also facilitates the analysis of how platforms achieve market differentiation through asymmetric strategies across various user segments.

Furthermore, the current model omits two extreme yet widely observed platform business models in practice: "pure advertising-supported free platforms" and "pure subscription-based ad-free platforms." The former, represented by platforms such as YouTube and Tubi TV, rely entirely on advertising revenue and do not charge users any fees. The latter, typified by Netflix, has long adhered to an ad-free model sustained solely by subscription revenues. In the original model, all platforms are implicitly assumed to operate under a "dual-sided revenue structure," simultaneously depending on both advertising income and user subscription fees. This assumption, to some extent, weakens the models explanatory power with respec t to "focused platform strategies" and "single-sided value creation mechanisms."

In the extended version of introducing extreme strategies, the platforms strategy options can include the following:

Pure advertising support: Set $p = 0$, $\alpha > 0$. The platform relies solely on the revenue from advertisers;

Pure subscription without ads: Set $\alpha = 0$, $p > 0$. The platform does not provide ad spaces and relies solely on user payments;

Hybrid structure: Keep $p > 0$ and $\alpha > 0$, which is the current model setting.

By incorporating these strategic structures into the analytical framework, the model can systematically explore which combinations of strategies are more conducive to profit optimization and market stability under varying advertiser budget structures, user ad sensitivity distributions, and platform content provision capabilities. This would further illuminate the strategic foundations underlying the observed divergence in ad load and pricing configurations across different platforms in practice.

Moreover, the model treats pricing structure as a one-time decision, overlooking platforms' ability to adjust strategies dynamically in response to user behavior, market feedback, and competitive moves. In reality, changes in pricing structures often unfold through gradual pilots, experimental rollouts, and data-driven iterations. YouTube, for instance, has adjusted its ad load based on regional skip-rate data, while Spotify has introduced mid-tier plans in selected markets to assess paid-user conversion potential. This pattern of rolling optimization is a routine feature of platform strategy in the digital economy, yet the static one-shot game in the original model fails to capture such dynamics.

This limitation can be addressed by introducing multi-stage or dynamic game structures, such as a two-stage framework (initial trial followed by adjustment) or an infinitely repeated game. In such setups, platforms would set an initial strategy combination in the first stage and then decide, based on market feedback, whether to maintain, fine-tune, or completely replace their current strategies. This approach not only better reflects the sequential logic of platform decision-making but also provides a richer structural basis for analyzing strategy stability, user retention, and the convergence paths of pricing strategies.

In summary, while the strategy space specification proposed by Amaldoss et al. offers theoretical clarity and analytical tractability, it exhibits notable limitations in three key areas: the diversity of strategic structures, the inclusiveness of extreme business models, and the mechanisms for dynamic adjustment. By introducing multidimensional strategy design, comparisons with extreme structures, and dynamic game frameworks, it is possible to enhance the model's fidelity to real-world platform behavior and to extend its applicability and predictive power across a broader range of market structures and behavioral patterns.

(3) Limitations and Improvements in Advertiser Modeling

In the two-sided platform competition model developed by Amaldoss et al., advertisers serve as a crucial source of platform revenue, and the specification of their behavior directly determines the strategic weight that platforms assign to pricing structure and advertising intensity decisions. However, to simplify the process of solving the game, the model adopts a highly stylized characterization of advertisers: all advertisers are treated as homogeneous agents with a fixed valuation per advertising impression, unlimited advertising capacity, and an assumed zero marginal utility for repeated exposures. While these assumptions help isolate the mechanism through which user segmentation affects advertising revenue, they also substantially compress the behavioral complexity and strategic heterogeneity inherent in real-world advertising markets. To enhance the models explanatory power, systematic extensions are needed along three dimensions: advertiser heterogeneity, budget constraints, and repetition utility.

The models assumption of advertiser homogene ity fails to capture structural differences in advertisers objectives, resources, and preferences. In actual markets, advertisers can be broadly categorized into two types based on their marketing goals: brand-oriented advertisers, who prioritize reach breadth and exposure frequency, and performance-oriented advertisers, who focus more on click-through rates and conversion behaviors. Moreover, advertisers exhibit differentiated preferences regarding platform audience composition. For instance, childrens b rands tend to favor platforms with stringent content review processes and well-defined user profiles for their advertising placements. The model lacks a mechanism for matching advertisers with platforms, which weakens the strategic role of platforms in competing for advertiser resources.

To better simulate advertiser choice behavior, the model could introduce a fit parameter μ_k that captures the alignment between an advertiser and a platform. Specifically, the value that advertiser i derives from placing an ad on platform k could be specified as:

$$v_{ik} = v_i \cdot \mu_k$$

where $\mu_k \in [0,1]$ represents the degree of congruence between the platforms user structure, content context, or ad delivery mechanism and the advertisers targeting objectives. This extension would introduce a dimension of "structured competition" into platform ad inventory sales, thereby enhancing the strategic flexibility of advertisers allocation decisions.

In addition, the original model does not impose budget constraints on advertisers, implicitly assuming that advertisers can advertise without limit across the two platforms. This assumption logically leads advertisers to always choose "full coverage" in order to maximize reach, leaving platforms to compete solely on the basis of ad display density. In reality, however, most advertisers must optimize their advertising portfolios within limited budgets, making rational allocations based on each platforms price f_k and advertising effectiveness θ_k.

To better reflect realistic budget constraints, we introduce a model in which advertisers determine their advertising volumes on platform 1 and platform 2, denoted as a_{i1} and a_{i2}, respectively. Each advertiser maximizes the following utility function:

$$\max v_i(\theta_1 a_{i1} + \theta_2 a_{i2}) - f_1 a_{i1} - f_2 a_{i2} \quad s.t. \; a_{i1} + a_{i2} \leq B_i$$

where B_i represents the total advertising budget of advertiser i, and θ_k denotes the advertising effectiveness or user coverage efficiency of platform k. This formulation introduces a "limited-resource game" mechanism, compelling platforms to not only optimize their advertising prices and user structures but also enhance their marginal return in advertisers resource allocation decisions. As a result, this enriches the strategic dimension of the advertising side and strengthens its competitive dynamics.

Third, the original models assumption of "zero utility" for repeated ad exposures is significantly biased. The authors assume that when a consumer receives the same advertisement on two platforms, the second exposure generates no incremental utility, i.e.:

Vtotal=v+0=v

While this assumption theoretically reinforces platforms incentives to capture "exclusive user attention," it contradicts a substantial body of empirical research in advertising and marketing. In reality, repeated ad exposures yield non-linear marginal utility—the first exposure captures attention, the second reinforces memory, and subsequent exposures build brand recognition. When frequency is properly managed, moderate repetition has a clear positive effect on conversion.

Accordingly, the marginal value of repeated exposures can be modeled as a discounted function:

$$V_{total}=v+\rho v=\rho(v+1) \quad \rho\in(0,1)$$

where ρ represents the marginal contribution of the second exposure, with empirical estimates typically ranging from 0.2 to 0.5. When an advertisement is shown on both platforms, the advertisers total utility should account for this repetition discount, thereby guiding budget allocation between two platforms with highly overlapping user bases to mitigate redundancy and the risk of ad overexposure. Platforms can also enhance the effectiveness of repeated exposures through ad duration limits, frequency capping mechanisms, and targeted recommendation systems, thereby increasing advertisers acceptance of multi -homed users.

Although the original model establishes a logical closed loop in advertiser modeling—namely, that the value of platform ad inventory is influenced by user multihoming—its behavioral assumptions remain relatively coarse. By introducing advertiser heterogeneity, budget constraints, and a marginal utility function for repeated exposures, the model can not only capture more nuanced advertiser-side strategic responses but also provide a theoretical foundation for platforms to design more flexible and tunable advertising mechanisms. These extensions would enhance the models explanatory power and offer a richer behavioral foundation for understanding how platforms, operating in two-sided markets, can simultaneously serve consumers and advertisers.

(4) Platform Symmetry and Structural Assumptions in Modeling

In the two-sided platform competition model developed by Amaldoss et al., the two participating platforms are analytically assumed to be perfectly symmetric: both share the same baseline content utility u, identical advertising capabilities, equivalent user reach potential, and comparable pricing power, differing only in their respective positions at the endpoints of the Hotelling line segment [0,1]. This symmetry assumption facilitates equilibrium solutions and enables a clear theoretical dissection of strategic interactions arising from variations in pricing structures and user allocation mechanisms. However, this symmetric treatment is empirically untenable and imposes significant structural constraints on the models capacity to explain heterogeneous competitive behavior, differentiated market positioning, and strategic divergence among platforms.

First, the model collapses platform heterogeneity solely into "locational differences" along the consumer preference space—namely, the Hotelling distance between the two endpoints—without endowing platforms with any substantive "capability asymmetries" or "product quality differences." Economically, this implies that the two platforms are indistinguishable in terms of service quality, content offering, and brand value, with competition driven exclusively by location and price. In reality, however, platform competition is frequently propelled by pronounced vertical differentiation. Netflix builds its content moat through original productions, exclusive premiere rights, and an ad-free experience; Spotify strengthens user stickiness through socially-aware recommendation algorithms and personalized playlists; whereas emerging platforms often rely on subsidies, low pricing, and ad-driven strategies to contest peripheral market segments. These behavioral variations stem from fundamental asymmetries among platforms in content capabilities, user bases, technological endowments, capital structures, and beyond—not merely differences in market location.

To enhance the models c apacity to capture platform heterogeneity, it is advisable to explicitly incorporate platform-specific content attractiveness parameters uk into the user utility function. The utility specification could thus be extended as:

$U_k^{\lambda}(\theta)=u_k - t\, dist_k(\theta) - \gamma\lambda\cdot\alpha_k - p_k\lambda$

where u1 > u2 captures the first-mover advantage of platform 1 in content quality, recommendation algorithms, or brand preference, while u2 > u1 reflects the potential for a late entrant to attract users through innovation or subsidized pricing strategies. This structural capability differential renders the strategic choices of platforms inherently asymmetric, laying the groundwork for modeling "asymmetric equilibria". For instance, one platform specializing in a high-subscription-fee strategy while the other pivots toward ad-driven, low-price expansion.

Second, the assumption of perfect symmetry between platforms obscures the prevalent "leader–follower" strategic landscape observed in reality. In most digital markets, first-mover platforms typically possess stronger brand recognition, higher user retention capabilities, and more established advertiser networks, thereby securing stable profit structures and pricing initiative. Late-entering platforms, by contrast, must build their user base through differentiation strategies such as price subsidies, advertising discounts, or content divergence. This realistic game structure aligns more closely with the "first-mover–follower" framework of a Stackelberg model than with the symmetric Nash equilibrium assumed in the original specification.

If the model allows for asymmetries in platforms' resource endowments, pricing flexibility, or advertising capabilities, it can further derive the following strategic phenomena:

The leading platform may choose to sustain a high-price strategy to stabilise its revenue structure and defend against marginal user churn through its content moat.

The follower platform is more likely to adopt aggressive tiered pricing, emphasise free advertising-supported plans, or enhance features such as short videos and social functionalities to expand user attention.

The strategic configuration of the two platforms exhibits a non-mirror-image "dominance-response" equilibrium, rather than a symmetric prisoner's-dilemma-type game.

Moreover, the model considers only bilateral competition between two platforms, neglecting the multi-platform market structure that is ubiquitous in reality. In industries such as streaming media, news, and social content, users typically face choices among three or more platforms, and the strategic interactions among platforms extend far beyond what a bilateral rivalry can capture. In the music platform market, for example, users may simultaneously switch among Spotify, Apple Music, and NetEase Cloud Music; in the video sector, YouTube, Netflix, Disney+, and Amazon Prime Video form a multipolar competitive landscape. In such an environment, platform strategies are devised not solely in response to a single "opponent" but are shaped around the overall market configuration, involving multiple dimensions such as price stabilisation, positioning differentiation, and management of user overlap.

Consequently, the model could be extended to a three-platform or even multi-platform structure, employing numerical simulations or incomplete-game methods to explore questions such as:

Do weaker platforms focus on the advertiser market while forgoing consumer-side pricing advantages?

Does an intermediate platform emerge that chooses a "hybrid strategy" to connect both sides of the market?

Under a multi-platform structure, does the equilibrium exhibit "strategic layering" rather than "structural symmetry"?

Although the symmetry assumption facilitates analytical tractability, it also compresses the complexity of platforms' capabilities, strategies, and structures observed in reality. By introducing heterogeneity in content capabilities, a leader-follower strategic configuration, and a multi-platform market structure, the model can attain stronger explanatory power and more accurately reveal the strategic diversity and evolutionary mechanisms of digital platforms under intense competition.

(5) Limitations of the Static Game Structure and Suggestions for Dynamic Extensions

The model developed by Amaldoss et al. employs a canonical static complete-information game framework. In this framework, platforms simultaneously set their pricing structures—whether uniform or tiered—along with their price levels and advertising intensities in a single round of play. Consumers and advertisers then respond once according to these established strategies, yielding determinate platform profits, equilibrium configurations, and welfare outcomes. While this static structure offers clarity and closure for theoretical deduction, its analytical limitations become evident when confronting the long-term interactions, strategic experimentation, and behavioral evolution characteristic of real-world platforms.

First, the static game structure implicitly rests on the premise of a one-shot choice of platform strategies: platforms make their pricing and advertising decisions at the outset and are not permitted to adjust or revise them in subsequent periods. This assumption disregards the prevalent logic of experimentation, feedback, and iteration observed in practice. In reality, numerous digital content platforms including Spotify, YouTube, and Hulu typically phase in revisions to their pricing strategies based on user conversion rates, retention data, and advertiser feedback after initial launch. Spotify, for instance, experiments with three-tier subscription plans in selected markets before rolling them out globally contingent on user response; YouTube has repeatedly adjusted its ad-skip mechanisms to balance user experience against advertising revenue. Such routine practices of strategic trial and error and rolling optimization cannot be captured within a static game, depriving the model of the capacity to depict strategic adjustment paths and temporal feedback mechanisms.

Theoretically, a natural extension is to transform the model into a two-stage or multi-stage game structure. In the first stage, platforms would announce initial pricing schemes and advertising configurations. In the second stage, based on feedback variables such as consumer affiliation rates and advertiser ad-spend densities, platforms would decide whether to retain, modify, or completely switch their original strategies. By introducing adjustment thresholds and modification costs, the model could further analyse platforms optimal path choices under the trade-off between delayed information feedback and switching costs. This extension would reveal why platforms in competitive environments exhibit gradual steady-state changes rather than frequent and drastic adjustments in behaviour.

Second, certain equilibrium results derived from the model—particularly the finding that simultaneous adoption of tiered pricing by both platforms leads to profit erosion—effectively constitute a classic prisoners -dilemma equilibrium. This structure demonstrates that under a one-shot static game, even though uniform pricing combinations could yield higher joint profits, platforms nevertheless resort to defensive tiered strategies for fear of being poached on marginal users and advertising budgets by rivals. However, this conclusion rests on the assumption of a one-shot non-cooperative game and does not account for the possibility of strategic coordination among platforms through long-term interaction, trust building, and punishment mechanisms in reality.

To more realistically simulate the pathways of strategic coordination among platforms, the model could be extended to an infinitely repeated game framework. By introducing a discount factor δ that lies in the interval from zero to one, the cumulative profit of a platform over periods t can be defined as:

$$\mathrm{Vk}=\sum_{t=1}^{\infty} \delta^{t-1}\Pi_k$$

Under this structure, the following issues can be examined: If the platform adopts a uniform pricing strategy at the initial stage to achieve a high-profit cooperative structure, when one party deviates and switches to a hierarchical strategy in a certain period in an attempt to increase short-term profits, will the other party retaliate through a "punitive rollback" strategy; whether there exists a stable cooperation interval above a certain discount rate δ; and whether the long-term cooperative structure is more strategically sustainable. This extension can not only explain why certain suboptimal structures are maintained in the long term, but also provide theoretical support for the formation of "hidden synergy" and "strategic tacit understanding" between platforms.

Moreover, the model assumes that the platform strategies are set synchronously and actions are taken simultaneously under complete information, that is, both parties make independent decisions at the same time point and fully understand each others parameters and action spaces. However, in real platform competition, the common structure is the "first mover - response" structure, where one party takes the lead in testing, and the other observes and responds. Netflix has long adhered to the "pure subscription, no ads" strategy, while Hulu and Disney have implemented a mixed model on this basis to compete for low-price users; Spotify has made corresponding adjustments after introducing new features or new pricing strategies on YouTube Music. Clearly, there is a causal sequence and observation feedback between the decisions of platforms, rather than simultaneous parallel games.

To reflect this structure, the model can be further transformed into a sequential game, where Platform 1 acts first, and Platform 2 observes its strategy and then makes the optimal response. This structure can be used to analyze mechanisms such as "first mover advantage", "strategic freeriding", and "information signal transmission", and to depict the strategic configuration logic of platforms in the face of incomplete information and opponent responses. Does the leading platform have the motivation to convey a "high content quality" positioning through a high-price signal, or does the lagging platform tend to adopt an aggressive strategy to disturb the equilibrium structure?

Therefore, the static game setting in Amaldoss et al.s model, although having theoretical simplicity and analytical closure, becomes increasingly evident in the face of the long-term evolutionary characteristics of real platform competition. Its lack of behavioral feedback mechanisms, repeated interaction paths, and sequential response capabilities becomes increasingly prominent. By introducing multi-stage structures, infinite repetition frameworks, and sequential decision-making mechanisms, the model can further reveal the strategic dynamics laws of platforms in the "trial - response - collaboration - evolution" process, providing a more profound theoretical basis for understanding the strategic stability and evolution direction of digital platforms.

6. Conclusion

This study focuses on the bilateral platform pricing model proposed by Amaldoss et al., conducting a systematic analysis of its theoretical structure and core mechanism. Based on a thorough identification of the models limitations, an attempt is made to propose more realistic extension ideas. In terms of consumer behavior setting, the model adopts an overly idealized binary classification, ignoring the continuous distribution of advertising sensitivity; in platform strategy design, it is limited to a binary choice between uniform and hierarchical pricing, which is difficult to reflect the rich and diverse service structure and pricing model of real platforms. Moreover, the models portrayal of the behavior of advertisers is relatively simplified, failing to reflect key elements such as budget constraints, repeated placement effects, and platform matching degree, and the platforms are set as completely symmetrical, which also weakens the strategic differences under the dominant and follower patterns in reality.

To enhance the models explanatory power for reality, this study introduces the continuous setting of advertising aversion and the endogenous user attention allocation mechanism, supplements the heterogeneity and resource limitations of advertisers, adds platform capability differences and strategic dimensions, and expands the static game framework into a dynamic evolutionary process. These adjustments not only enrich the behavioral structure of the model itself but also help to more realistically describe the strategic choices made by platforms when facing multi-ownership users, complex advertising markets, and long-term competition.

Future research can combine platform operation data to conduct empirical tests on the key parameters in the model, further explore the influence of recommendation algorithms, user social behaviors, etc. on the pricing game structure, and continuously expand the depth and applicability of platform economy research.

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