Pricing Decisions in Live Streaming E-Commerce Supply Chains Under the Scarcity Effect

Xinyi Liu *, Xiaofang Zhong

School of Economics and Management, Nanjing University of Science and Technology, Nanjing, China

* Corresponding Author Email: 17754091340@163.com

Abstract. Despite being a prevalent scarcity marketing strategy in live streaming e-commerce, limited-release sales still lack rigorous theoretical elucidation regarding their underlying supply chain coordination and pricing mechanisms. This paper constructs a three-echelon supply chain game model comprising a brand, a live streamer (either an in-house employee or an external influencer), and a live streaming platform to systematically analyze the impacts of scarcity strategies (supply ratio control) and traffic empowerment on operation mode selection. We identify three channel structures: the pure in-house streaming model (Model R), the pure influencer streaming model (Model A), and the dual-channel streaming model (Model D). Our findings reveal that the scarcity strategy affects the equilibrium through a dual pathway of "willingness-to-pay amplification" and "physical supply restriction." The centralization of pricing power with the influencer streamer mitigates coordination failure but exacerbates double marginalization, prompting the brand to implement aggressive supply rationing as a hedging mechanism. When dual channels coexist, a subtle trade-off emerges between the inter-channel demand spillover effect and the self-cannibalization effect, leading to pricing suppression and asymmetric scarcity allocation. Furthermore, platform traffic allocation exhibits a strong scarcity preference, creating a positive feedback loop with brand supply restrictions. The theoretical analysis provides a systematic decision-making framework for understanding operation mode selection in live streaming e-commerce.

Keywords: Live streaming e-commerce; Supply chain management; Scarcity strategy; Traffic empowerment; Stackelberg game.

1. Introduction

Live streaming e-commerce has emerged as a globally significant retail paradigm, fundamentally altering distribution channel structures. By the end of 2023, the Gross Merchandise Volume (GMV) of live streaming e-commerce in China surpassed 4.9 trillion RMB, with rapid expansion also observed in overseas platforms like TikTok Shop. Within this ecosystem, supply chain operations are driven by the deep interactions among brands, streamers, and platforms. Notably, streamers are generally categorized into influencer streamers, who leverage personal influence and fan loyalty, and in-house streamers, who are brand employees focusing on professional product explanations. These two modes differ fundamentally in decision-making dominance, cost structures, and incentive compatibility, thereby posing distinct challenges for supply chain coordination.

Despite the prevalence of live streaming commerce, several theoretical gaps persist in understanding its supply chain dynamics. First, existing literature predominantly focuses on consumer behavior or the influence mechanisms of a single streamer type, neglecting the heterogeneity between in-house and influencer streaming modes and the inter-channel competition in dual-channel scenarios. Second, while scarcity strategies (limiting supply ratios) are widely employed to stimulate demand, prior research largely treats the scarcity effect as an exogenous marketing variable, failing to internalize it as a strategic inventory and pricing mechanism that creates a "potential demand amplification" and "actual sales limitation" trade-off. Third, platforms act not merely as passive commission collectors but as traffic providers and rule-makers; however, the prerequisite role of platform traffic support in enabling the efficacy of scarcity strategies remains underexplored.

To address these gaps, this paper constructs a three-echelon supply chain game model comprising a single brand, a streamer, and a live streaming platform. We internalize the scarcity effect by allowing the brand to strategically set an inventory supply ratio, and we investigate three game structures: pure in-house streaming (Model R), pure influencer streaming (Model A), and dual-channel streaming (Model D). Specifically, we capture the multiplier amplification effect of scarcity on demand and the substitution competition between channels.

This paper makes three primary contributions to the literature. First, we systematically compare pricing, quality, marketing, and scarcity strategies across in-house, influencer, and dual-channel streaming models, correcting the mis-specification of the game sequence in the influencer streaming model found in prior studies. Second, we endogenize the scarcity effect into the supply chain decision framework, revealing the internal mechanism of how strategically limiting the supply ratio restructures the profit landscape of all entities. Third, we elucidate the synergistic logic between platform traffic empowerment and brand scarcity creation, demonstrating how the platform's technical service fee rate and traffic acquisition cost moderate the efficacy of scarcity strategies.

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the problem and establishes the model assumptions. Section 4 derives the equilibrium results. Section 5 conducts comparative static analysis and model comparisons. Section 6 provides numerical analysis. Section 7 presents conclusions and managerial implications.

2. Literature Review

The literature pertinent to this study primarily intersects two research streams: live streaming e-commerce supply chain operations and scarcity strategies in operations management.

2.1. Live Streaming E-commerce Supply Chain Operations

The emergence of live streaming e-commerce has reshaped traditional distribution channel structures and decision-making logic. Existing research primarily focuses on channel structure selection, pricing strategies, and supply chain coordination mechanisms within this novel ecosystem. Regarding channel dominance and mode selection, studies have systematically compared the efficiency boundaries of different structures. Wang et al. [1] find that manufacturers' sales mode decisions are significantly affected by the proportion of live streaming viewers and platform commission rates. Liang et al. [2] compare the efficiency of online direct sales, distribution, and agency sales. Recently, scholars have focused on dual-channel live streaming where brands simultaneously operate brand-owned and influencer streaming. Dong et al. [3] analyze channel conflict and coordination mechanisms under dual-channel live streaming, finding that reasonable price differentiation can alleviate demand stealing effects. Bai et al. [4] study the impact of different channel power structures on pricing, pointing out that high commission rates shift traffic toward brand-owned channels. In the context of pricing and coordination mechanisms, theoretical tools such as Stackelberg games and principal-agent models are widely applied. Wang and Wu [5] reveal the fundamental role of pricing power distribution in supply chain performance. Yu et al. [6] and Zennyo [7] confirm the coordination advantages of commission contracts in various channel structures. To further optimize performance, Peng et al. [8] analyze cost-sharing contracts, while Wang and Gong [9] design a composite "revenue-sharing + effort cost-sharing" contract. Additionally, platform governance constitutes a critical foundation; Zheng et al. [10]study the optimal commission ratio of live streaming platforms, and Huang et al. [11] emphasize the interaction among platform profit concerns, consumer surplus, and commission rates. However, while these studies provide valuable insights, existing literature predominantly focuses on single-channel optimization or treats dual-channel structures as exogenously given, leaving the systematic comparison and endogenous selection among heterogeneous modes underexplored.

2.2. Scarcity Strategies in Operations Management

Scarcity strategies, such as limited releases, have long been recognized as effective marketing tools. Early research on scarcity was rooted in consumer psychology, establishing that perceived value is inversely proportional to availability (Commodity Theory) [12], and that scarcity triggers needs for uniqueness [13] and psychological reactance [14] In the field of operations management, scholars have elevated scarcity from a psychological construct to a strategic operational tool. Stock and Balachander [15] demonstrate that limited availability can serve as a credible signal of high product quality. Cachon et al. [16] argue that "inventory does not always increase sales," suggesting that strategically restricting inventory can enhance sales velocity. With the rise of live streaming, the applicability of scarcity strategies presents new characteristics. Jiang et al. [17] find that real-time inventory displays in live streaming amplify perceived scarcity, stimulating urgency and impulse purchases. Li and Liu [18] point out that dynamic inventory display is key to strengthening scarcity perception, though excessive use triggers reactance. Recently, Cai et al. [19] incorporated the scarcity effect into game-theoretic models, finding it profoundly affects optimal live streaming mode choices and pricing rules. Nevertheless, most OM-focused studies treat the scarcity effect as an exogenous marketing variable that simply shifts the demand curve, overlooking the strategic proactiveness of platform traffic empowerment and its synergistic linkage with scarcity creation. This lack of endogenous integration leaves the critical trade-off between willingness-to-pay amplification and physical supply restriction underexplored, which motivates the current study.

3. Model Assumptions

We consider a three-tier live streaming e-commerce supply chain consisting of a single brand, a live streamer (either an in-house employee or an external influencer), and a live streaming platform. Within a single sales cycle, the brand can sell products through its own in-house streamer (Channel R), an independent influencer streamer (Channel A), or both simultaneously. Accordingly, we delineate three operational structures: the pure in-house streaming model (Model R), the pure influencer streaming model (Model A), and the dual-channel streaming model (Model D).

3.1. Demand Function Construction

To capture the synergistic effects of scarcity strategies and traffic empowerment on market demand, we construct the demand function from two dimensions. First, the potential demand is sensitive to price and effort levels.

The consumers' baseline willingness-to-pay is specified as: $V_0=\alpha+\lambda e_p+\nu q_m+\theta q_l$, where α represents the base market size, λ is the traffic sensitivity coefficient, ν is the quality sensitivity coefficient, and θ is the marketing effort sensitivity coefficient.

Second, market demand is concurrently constrained by the brand's scarcity strategy. The scarcity effect is internalized through the "supply ratio": the brand strategically sets the inventory supply ratio $g\in(0,1)$, making actual sales $\widehat{\mathrm{D}}=\mathrm{gD}$ strictly less than potential demand D. A scarcity amplification factor $k=1-\eta(1-g)$ is introduced, where $\eta\in(0,1)$ is the scarcity effect coefficient. A smaller supply ratio g yields a smaller k, amplifying the consumers' reservation price to $V=V_0/k$. Assuming consumers are heterogeneous, the potential market demand function for a single channel is derived as:

$$D_i=\frac{\alpha+\lambda e_{\mathrm{pi}}-\mathrm{p_i}+\nu q_{mi}+\theta q_{li}}{k_i}, i\in\{R,A\} \tag{1}$$

This formulation captures the multiplier amplification effect of scarcity on demand and the market base expansion effect of platform traffic support e_{p}. When dual channels coexist (Model D), we introduce a cross-price sensitivity coefficient

$\beta \in (0,1)$ to characterize the substitution competition between channels. The dual-channel potential demand functions are:

$$D_R = \frac{\alpha + \lambda e_{\mathrm{pR}} - p_{\mathrm{R}} + v q_{\mathrm{m}} + \theta q_{IR}}{k_R} + \beta p_A \tag{2}$$

$$D_{\mathrm{A}} = \frac{\alpha + \lambda e_{\mathrm{pA}} - p_A + v q_{\mathrm{m}} + \theta q_{\mathrm{IA}}}{k_A} + \beta p_{\mathrm{R}} \tag{3}$$

Note that the revenue accounting of the supply chain is entirely based on actual sales $\widehat{D}_{\mathrm{i}} = g_{\mathrm{i}} D_{\mathrm{i}}$, reflecting the physical supply restriction.

3.2. Cost and Profit Functions

Regarding the allocation of decision rights and cost structures, the brand determines the product quality effort q_{m} and the supply ratio g. In Channel R, the brand determines the retail price p_{R}; whereas in Channel A, the influencer streamer independently determines p_{A}. The streamer determines their marketing effort q_{I}, and the platform determines the traffic support e_{p}.

The cost structure includes the convex cost of quality effort $\frac{1}{2} e_1 q_m^2$, the convex cost of marketing effort $\frac{1}{2} e_2 q_{\mathrm{I}}^2$, and the convex cost of platform traffic support $\frac{1}{2} e_3 e_{\mathrm{p}}^2$, where $e_1, e_2, e_3 > 0$ are effort cost coefficients. To streamline the model and focus on the scarcity premium mechanism, we normalize the unit production cost to zero (i.e., $c=0$), which is a standard practice in live streaming operations modeling. For the contract parameters, both the platform and the streamers extract commissions based on actual transaction volume. The platform charges a technical service fee rate b. The in-house streaming commission rate is a_1 with a fixed base salary T_1, while the influencer streaming commission rate is a_2 ($a_2 > a_1$) with a slotting fee T_2 ($T_2 > T_1$).

The profit functions are constructed as follows:

1) In-house Streamer (Model R/D):

$$\Pi_{\mathrm{IR}} = \mathrm{a}_1 p_{\mathrm{R}} g_{\mathrm{R}} D_{\mathrm{R}} + T_1 - \frac{1}{2} e_2 q_{\mathrm{IR}}^2 \tag{4}$$

2) Influencer Streamer (Model A/D):

$$\Pi_{\mathrm{IA}} = \mathrm{a}_2 p_{\mathrm{A}} g_{\mathrm{A}} D_{\mathrm{A}} + T_2 - \frac{1}{2} e_2 q_{\mathrm{IA}}^2 \tag{5}$$

3) Brand:

$$\Pi_{\mathrm{m}} = \sum\nolimits_{i \in \{R,A\}} (1 - b - a_i) p_i g_i D_i - \frac{1}{2} e_1 q_{\mathrm{m}}^2 - \sum\nolimits_{i \in \{\mathrm{R,A}\}} T_i \tag{6}$$

4) Platform:

$$\Pi_{\mathrm{p}} = \sum\nolimits_{i \in \{\mathrm{R,A}\}} b p_i g_i D_i - \frac{1}{2} e_3 e_{pi}^2 \tag{7}$$

3.3. Model Specifications and Game Sequence

To ensure the mathematical tractability and economic rationality of the proposed model, we impose the following specifications. First, this paper does not impose a hard total traffic budget constraint on the platform; rather, the increasing marginal cost of traffic acquisition is endogenized through the quadratic traffic cost $\frac{1}{2} e_3 e_p^2$. This aligns with reality, as traffic is dynamically allocated based on the conversion efficiency of the live streaming rooms, acting as a soft constraint. Second, to ensure that the Hessian matrix of each decision maker's profit function is negative definite—thereby guaranteeing that the local equilibrium is the global maximum—we assume that the effort cost coefficients (e_1,e_2,e_3) are sufficiently large, and the base market size α is substantial enough to cover the potential effective demand.

Based on the aforementioned specifications, we construct a game-theoretic model to characterize the decision sequence. The game unfolds in two stages. In the first stage, the platform, acting as the leader, determines the traffic support level e_p. In the second stage, the brand and the streamers engage in a subgame: the brand determines the quality effort q_m, the supply ratio g, and the retail price for the channel it controls (if applicable); simultaneously, the streamer determines their marketing effort q_l and the retail price for the channel they control (if applicable). This two-stage structure aligns with the operational reality where platform traffic allocation precedes the real-time interactive decisions between the brand and the streamer during the live session. The model is solved using backward induction, and the subgame in the second stage is resolved via Nash equilibrium.

4. Model Solution and Equilibrium Analysis

This section solves the two-stage game equilibria under the three channel structures via backward induction and characterizes the optimal decisions.

4.1. Pure In-House Streaming Model (Model R)

Under Model R, the demand function simplifies to
$D_R = (\alpha + \lambda e_{pR} - p_R + \nu q_m + \theta q_{lR}) / k_R$, where k_R=1-η(1-g_R),The profit functions are:

$$\prod\nolimits_{\mathrm{E}}^{\mathrm{R}}(e_{\mathrm{pR}}) = b p_{\mathrm{R}} g_{\mathrm{R}} D_{\mathrm{R}} - \frac{1}{2} e_3 e_{\mathrm{pR}}^2 \tag{8}$$

$$\Pi_{\mathrm{M}}^{\mathrm{R}}(p_{\mathrm{R}}, q_{\mathrm{m}}, g_{\mathrm{R}}) = (1 - a_1 - b) p_{\mathrm{R}} g_{\mathrm{R}} D_{\mathrm{R}} - \frac{1}{2} e_1 q_{\mathrm{m}}^2 - T_1 \tag{9}$$

$$\Pi_{\mathrm{E}}^{\mathrm{R}}(q_{\mathrm{lR}}) = \mathrm{a}_1 p_{\mathrm{R}} g_{\mathrm{R}} D_{\mathrm{R}} - \frac{1}{2} e_2 q_{\mathrm{lR}}^2 + T_1 \tag{10}$$

Solving the game backward, we first examine the simultaneous subgame in the second stage. From the first-order condition $\partial \prod_E^R / \partial q_{lR}$ *the optimal marketing effort is obtained.*

Lemma 1: In the pure in-house streaming model, the in-house streamer's optimal marketing effort is $q_{\mathrm{lR}}^* = \frac{a_1 \theta g_{\mathrm{R}} p_{\mathrm{R}}}{e_2 k_{\mathrm{R}}}$, and the brand's optimal retail price satisfies:

$$p_{\mathrm{R}}^* = \frac{\alpha + \lambda e_{\mathrm{pR}} + \nu q_{\mathrm{m}}}{2\Lambda_{\mathrm{R}}} \tag{11}$$

Where $\Lambda_{\mathrm{R}} = 1 - \frac{a_1 \theta^2 g_{\mathrm{R}}}{e_2 k_{\mathrm{R}}}$. The optimal supply ratio g_{R}^* and quality effort q_{m}^* are implicitly determined by their respective first-order conditions.

The retail price in the in-house channel is indirectly moderated by the scarcity effect factor η. Since the in-house streamer's commission rate a_1 is relatively low, their marketing effort exhibits a positive dependence on the supply ratio g_{R}. Consequently, the brand can effectively incentivize the streamer's effort by increasing the supply ratio without bearing the high cost of conceding channel profits.

4.2. Pure Influencer Streaming Model (Model A)

Under Model A, the influencer streamer possesses autonomous pricing power. The demand function is
$D_A = (\alpha + \lambda e_{\mathrm{pA}} - p_{\mathrm{A}} + \nu q_{\mathrm{m}} + \theta q_{\mathrm{lA}}) / k_{\mathrm{A}}$, where k_A=1-η(1-g_A). The profit functions are:

$$\prod\nolimits_{\mathrm{P}}^{\mathrm{A}}(e_{\mathrm{pA}}) = bp_{\mathrm{A}}g_{\mathrm{A}}D_{\mathrm{A}} - \frac{1}{2}e_3e_{\mathrm{pA}}^2 \tag{12}$$

$$\Pi_{\mathrm{M}}^{\mathrm{A}}(q_{\mathrm{m}}, g_{\mathrm{A}}) = (1 - a_2 - b)p_{\mathrm{A}}g_{\mathrm{A}}D_{\mathrm{A}} - \frac{1}{2}e_1q_{\mathrm{m}}^2 - T_2 \tag{13}$$

$$\Pi_E^A(p_{\mathrm{A}}, q_{1\mathrm{A}}) = \mathrm{a}_2p_{\mathrm{A}}g_{\mathrm{A}}D_{\mathrm{A}} - \frac{1}{2}e_2q_{1\mathrm{A}}^2 + T_2 \tag{14}$$

In the second stage, the influencer streamer and the brand engage in a simultaneous subgame, where the streamer determines p_{A} and $q_{1\mathrm{A}}$.

Lemma 2: In the pure influencer streaming model, the influencer streamer's optimal marketing effort and retail price are respectively:

$$q_{1\mathrm{A}}^* = \frac{a_2\theta g_{\mathrm{A}}p_{\mathrm{A}}}{e_2k_{\mathrm{A}}}, p_{\mathrm{A}}^* = \frac{\alpha + \lambda e_{\mathrm{pA}} + \nu q_{\mathrm{m}}}{2\Delta_{\mathrm{A}}} \tag{15}$$

Where $\Delta_{\mathrm{A}} = 1 - \frac{a_2\theta^2 g_A}{2e_2k_A}$ denotes the adjusted margin coefficient reflecting the influencer's joint pricing-effort trade-off. The brand's optimal supply ratio g_{A}^* and quality effort q_{m}^* are determined by their respective first-order conditions.

The core difference from Model R lies in the denominator structure Δ_{A}. Because the influencer streamer simultaneously undertakes pricing and effort decisions, the quadratic effect of their effort cost creates an offset in the pricing margin, resulting in $\Delta_{\mathrm{A}}>\Lambda_{\mathrm{R}}$. The divisor $2e_2$ (compared to e_2 in Λ_{R}) captures the fact that the influencer internalizes the cost of their own effort when marking up the price. As consumer scarcity sensitivity η increases, k_{A} decreases, and the influencer tends to further raise the retail price to extract the scarcity premium, significantly compressing the brand's profit margin.

4.3. Dual-Channel Streaming Model (Model D)

Under Model D, the demand on each channel is affected by the cross-price effect β. The profit functions are:

$$\begin{aligned}\prod\nolimits_{\mathrm{P}}^{\mathrm{D}}(e_{\mathrm{pR}}, e_{\mathrm{pA}}) &= b(p_{\mathrm{R}}g_{\mathrm{R}}D_{\mathrm{R}} + p_{\mathrm{A}}g_{\mathrm{A}}D_{\mathrm{A}}) \\ &\quad - \frac{1}{2}e_3(e_{\mathrm{pR}}^2 + e_{\mathrm{pA}}^2)\end{aligned} \tag{16}$$

$$\begin{aligned}\prod\nolimits_{\mathrm{M}}^{\mathrm{D}}(p_{\mathrm{R}}, q_{\mathrm{m}}, g_{\mathrm{R}}, g_{\mathrm{A}}) &= (1 - \mathrm{a}_1 - b)p_{\mathrm{R}}g_{\mathrm{R}}D_{\mathrm{R}} \\ &\quad + (1 - \mathrm{a}_2 - b)p_{\mathrm{A}}g_{\mathrm{A}}D_{\mathrm{A}} - \frac{1}{2}e_1q_m^2 - T_1 - T_2\end{aligned} \tag{17}$$

$$\prod\nolimits_E^R(q_{1\mathrm{R}}) = a_1p_{\mathrm{R}}g_{\mathrm{R}}D_{\mathrm{R}} - \frac{1}{2}e_2q_{1\mathrm{R}}^2 + T_2 \tag{18}$$

$$\prod\nolimits_{\mathrm{E}}^{\mathrm{A}}(p_{\mathrm{A}}, q_{1\mathrm{A}}) = a_2p_{\mathrm{A}}g_{\mathrm{A}}D_{\mathrm{A}} - \frac{1}{2}e_2q_{1\mathrm{A}}^2 + T_2 \tag{19}$$

Lemma 3: In the dual-channel streaming model, the optimal marketing efforts are $q_{1\mathrm{R}}^* = \frac{a_1\theta g_{\mathrm{R}}p_{\mathrm{R}}}{e_2k_{\mathrm{R}}}$ and $q_{1\mathrm{A}}^* = \frac{a_1\theta g_{\mathrm{A}}p_{\mathrm{A}}}{e_2k_{\mathrm{A}}}$. The optimal channel retail prices satisfy:

$$
\begin{aligned}
p_{\mathrm{R}}^{*} &= \frac{2\Delta_{\mathrm{A}}(\alpha+\lambda e_{\mathrm{pR}}+\nu q_{\mathrm{m}})+\beta(\alpha+\lambda e_{\mathrm{pA}}+\nu q_{\mathrm{m}})}{4\Lambda_{R}\Delta_{A}-\beta^{2}} \\
p_{\mathrm{A}}^{*} &= \frac{2\Lambda_{R}(\alpha+\lambda e_{\mathrm{pA}}+\nu q_{\mathrm{m}})+\beta(\alpha+\lambda e_{\mathrm{pR}}+\nu q_{\mathrm{m}})}{4\Lambda_{R}\Delta_{A}-\beta^{2}}
\end{aligned}
\tag{20}
$$

Where $\Lambda_{\mathrm{R}}=1-\frac{a_1\theta^2 g_{\mathrm{R}}}{e_2 k_{\mathrm{R}}}$ and $\Delta_{\mathrm{A}}=1-\frac{a_2\theta^2 g_{\mathrm{A}}}{2e_2 k_A}$.

Unlike single-channel models, retail prices under the dual-channel structure are constrained by the cross-channel competition intensity β. When $\beta>0$, a price increase in one channel benefits the other through the demand spillover effect. However, this spillover is a double-edged sword: although it drives up equilibrium prices, it exacerbates the self-cannibalization effect regarding the brand's allocation of supply ratios, compelling the brand to conduct strict cross-channel profit-margin trade-offs when setting g_{R} and g_{A}.

5. Comparative Statics and Mode Selection Analysis

This section dissects the intrinsic mechanisms through which key parameters influence equilibrium decisions and delineates the boundary conditions governing mode selection.

5.1. Traffic-Scarcity Synergy and Endogenous Feedback

In live-streaming e-commerce, the brand's scarcity strategy and the platform's traffic empowerment exhibit profound strategic interactions.

Proposition 1: Across all three models, the platform's optimal traffic support level is negatively correlated with the brand's supply proportion, i.e., $\partial e_{\mathrm{p}}^{*}/\partial g_{\mathrm{i}}^{*}<0$ for $\mathrm{i}\in\{\mathrm{R},\mathrm{A}\}$ Furthermore, when $\eta>\bar{\eta}$, the platform's profit strictly increases with the scarcity effect coefficient η, i.e., $\partial\Pi_{\mathrm{p}}^{*}/\partial\eta>0$.

This occurs because, from the equilibrium expression $e_{\mathrm{p}}^{*}=\lambda bp^{*}g^{*}/(e_3k^{*})$, a reduction in g directly diminishes realized volume gD, but simultaneously reduces k, precipitating a sharp rise in latent demand D and price p. Within the effective scarcity interval ($\eta>\bar{\eta}$), the multiplier premium effect dominates, elevating the conversion value per unit of traffic (GMV). Consequently, the platform allocates greater traffic, revealing a positive feedback synergy of "platform traffic expansion–brand scarcity restriction."

5.2. Scarcity Hedging against Double Marginalization

The double marginalization stemming from the influencer's pricing power is the core pain point in Models A and D.

Proposition 2: In Model A, the brand's optimal supply ratio g_{A}^{*} strictly decreases as the influencer commission rate a_2 increases (i.e., $\partial g_{\mathrm{A}}^{*}/\partial a_2<0$), serving as a hedging mechanism against the erosion of marginal profit.

The logic behind this is that when the influencer demands a higher commission, the brand's marginal return per unit declines. Since the brand cannot profit by lowering prices—which would only allow the influencer to appropriate more surplus—it pivots to a more aggressive scarcity strategy by reducing g_{A}. This compels consumers to pay a higher price premium by creating an intense "undersupply" perception, acting as a rational response by the brand to reclaim residual claimancy via supply-side control when direct pricing power is ceded.

5.3. Pricing Suppression and Asymmetric Scarcity under Dual-Channel

In Model D, the cross-price elasticity effect β induces a coupling characteristic between pricing and scarcity decisions.

Proposition 3: In Model D: (a) The in-house channel price $p_{\mathrm{R}}^{\mathrm{D}^*}$ decreases as channel competition intensity β increases ($\partial p_{\mathrm{R}}^{\mathrm{D}^*} / \partial \beta < 0$); (b) When β exceeds a certain threshold $\mathring{\beta}$, the gap $g_{\mathrm{A}}^{\mathrm{D}^*} - g_{\mathrm{R}}^{\mathrm{D}^*}$ widens as β expands.

The in-house channel thus serves not merely as a sales conduit but as a strategic "anchor" to discipline influencer pricing. The brand intentionally suppresses p_{R}, which squeezes the influencer's markup space through cross-price effects, thereby mitigating double marginalization. Concurrently, to sustain the profit margin of the influencer channel amid fierce competition, the brand must manufacture extreme scarcity (an exceedingly low g_{A}) to stabilize the influencer's per-unit conversion price, preventing an all-out price war.

5.4. Mode Selection Boundaries

Under different parametric environments, the mode preferences of supply chain members diverge.

Proposition 4: There exist thresholds $\eta_1, \eta_2 (\eta_1 < \eta_2)$ and β^* such that: (a) When $\eta < \eta_1$, the pure in-house streaming model strictly dominates for the brand ($\Pi_{\mathrm{m}}^{\mathrm{R}*} > \Pi_{\mathrm{m}}^{\mathrm{A}*} > \Pi_{\mathrm{m}}^{\mathrm{D}*}$); (b) When $\eta \in [\eta_1, \eta_2)$ and $\beta < \beta^*$, the dual-channel model achieves Pareto improvement for both the brand and the platform; (c) When $\eta \geq \eta_2$, the pure influencer streaming model becomes the brand's optimal choice ($\Pi_{\mathrm{m}}^{\mathrm{A}*} > \Pi_{\mathrm{m}}^{\mathrm{D}*} > \Pi_{\mathrm{m}}^{\mathrm{R}*}$).

6. Numerical Analysis

While Section V establishes the directional mechanisms analytically, the exact thresholds and complex interactive effects remain intractable through closed-form solutions. This section conducts numerical simulations to quantify the mode selection boundaries and explore multi-parameter joint effects. Baseline parameters are set as: $\alpha=100, e_1=2, e_2=2, e_3=1.5, \lambda=5, v=4, \theta=3, a_1=0.05, a_2=0.2, b=0.05$.

6.1. Quantifying Scarcity Sensitivity Thresholds

While Proposition 4 proves the existence of mode transition thresholds, we numerically quantify these critical points and the curvature of brand profits.

Observation 1: As η increases within [0,1]: (a) The brand's profit under Model D, $\Pi_{\mathrm{m}}^{\mathrm{D}*}$, exhibits an inverted U-shaped pattern. (b) There exist two critical thresholds, $0<\hat{\eta}_1<\hat{\eta}_2<1$ (approx. 0.40 and 0.74 under baseline settings), partitioning the parameter space into in-house dominance, dual-channel synergy, and influencer dominance intervals.

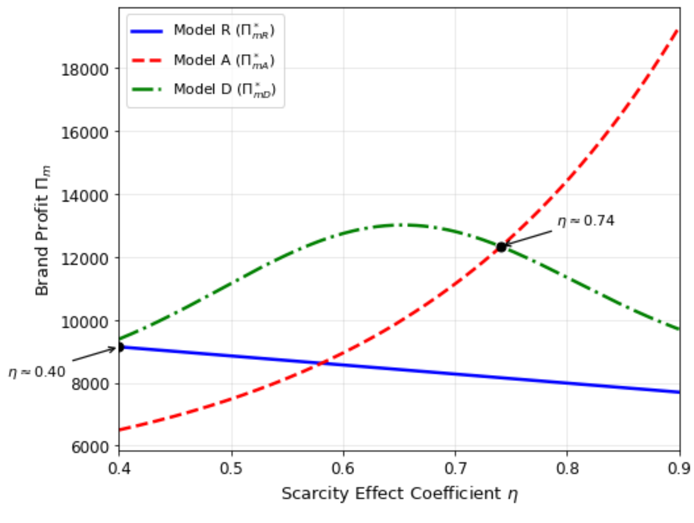

Figure 1. Brand Profit vs. η

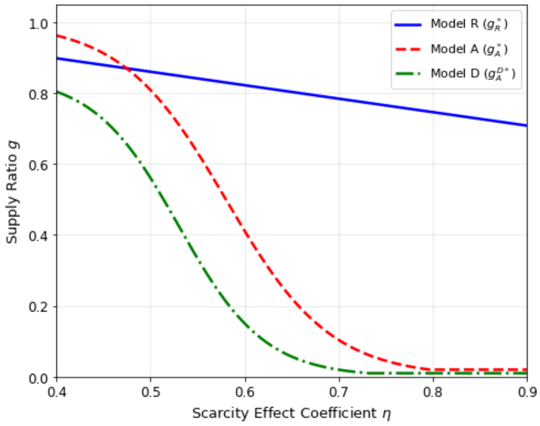

Figure 2. Supply Ratio vs. η

As depicted in Figure 2, the inverted U-shape of Π_m^{D*} reveals that the dual-channel synergy dividend is highly sensitive to scarcity sensitivity. When $\eta \geq \hat{\eta}_2$, extreme sensitivity amplifies the influencer's marketing leverage, causing the pure influencer model to surpass the dual-channel, confirming the analytical boundaries derived in Proposition 4(c).

6.2. Failure Boundary of the Dual-Channel Model

To visualize the joint impact of channel competition (β) and scarcity sensitivity (η) on mode selection, we plot the 2D profit dominance regions.

Observation 2: There exists a unique threshold $\hat{\beta} \approx 0.62$; the dual-channel dominates when $\beta < \hat{\beta}$, otherwise the pure in-house model is superior. Furthermore, the feasible region of the dual-channel model shrinks as β increases but expands as η increases.

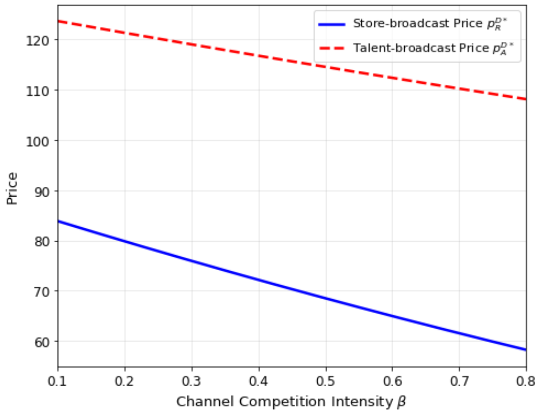

Figure 3. Pricing under Model D

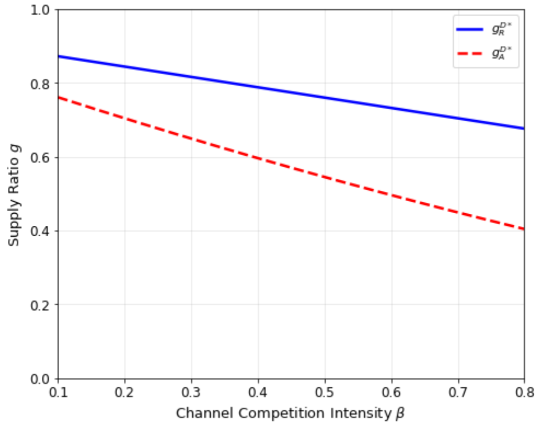

Figure 4. Supply Ratio under Model D

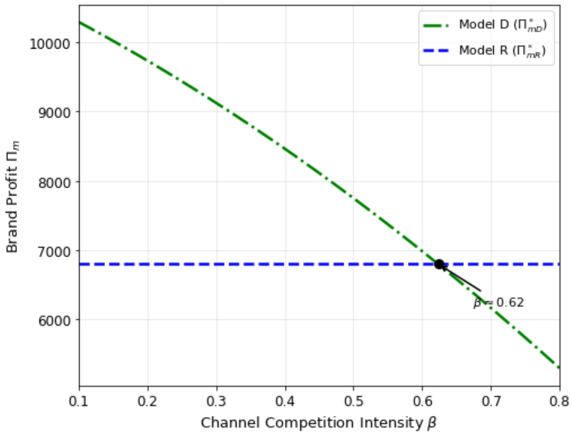

Figure 5. Dual-channel Failure Boundary

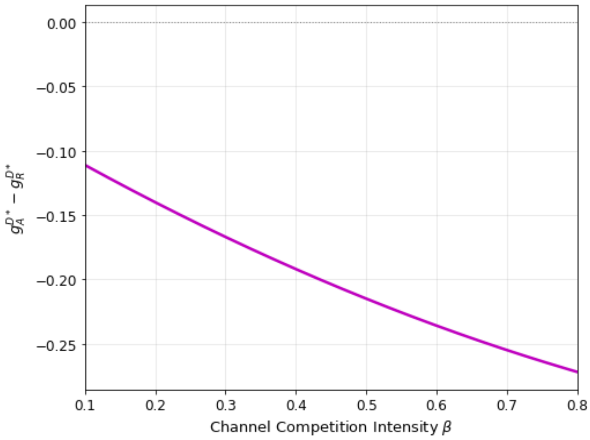

Figure 6. Asymmetric Scarcity Gap

Figures 3 through 6 collectively delineate the failure boundary of the dual-channel model, demonstrating that high channel substitutability ($\beta > \hat{\beta}$) eclipses the synergistic dividend through internal cannibalization. Notably, an increase in η can offset the negative impact of β to some extent, expanding the feasible region of Model D, which provides a novel insight unattainable through single-parameter comparative statics.

6.3. Traffic Allocation under Scarcity Strategies

Observation 3: At any given level of g, the platform's optimal traffic support consistently satisfies $e_p^{R*} > e_p^{A*}$. Moreover, the marginal traffic incentive (slope of e_p^* with respect to g) is steeper in Model R than in Model A.

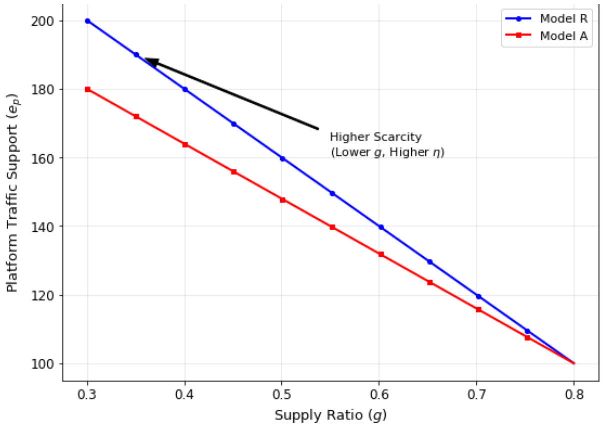

Figure 7. Traffic-Scarcity Synergy

Figure 7 depicts a strong scarcity preference in platform traffic allocation. Model R consistently lies above Model A because the in-house channel, devoid of double marginalization, possesses superior conversion efficiency, thereby securing higher traffic incentivization. This numerical finding extends Proposition 1 by showing that the conversion efficiency gap between channels amplifies the disparity in platform traffic empowerment.

7. Conclusion

This study develops a tripartite game-theoretic model to systematically analyze the impact of scarcity strategies and traffic empowerment on supply chain decisions and channel mode selection in live streaming e-commerce. By internalizing the supply ratio as a strategic decision, we uncover the dual trade-off mechanism of scarcity between willingness-to-pay amplification and physical supply restriction across pure in-house, pure influencer, and dual-channel streaming structures.

Our analysis yields several key insights. First, scarcity sensitivity acts as a pivotal endogenous driver; as consumer sensitivity intensifies, brands strategically reduce supply ratios, particularly in influencer channels, to hedge against double marginalization and reclaim channel power. Consequently, brand managers are advised to dynamically adjust their channel portfolios: prioritizing in-house channels in low scarcity environments, adopting a dual-channel synergy strategy in moderate regimes, and concentrating on top-tier influencers in high-scarcity environments. Second, channel competition delineates the feasibility boundary of the dual-channel model. While moderate competition stimulates synergistic complementarities, high intensity forces defensive pricing and triggers severe internal cannibalization. To mitigate this, brands should implement an asymmetric supply strategy—maintaining relatively lax supply in-house to serve as a pricing anchor while enforcing stringent inventory controls for influencers to compensate for commission erosion. If channel substitutability becomes excessively high, brands must promptly restructure pricing authority to avert destructive internal price wars. Third, platform traffic allocation exhibits a pronounced scarcity preference, where supply limitations induce a positive traffic feedback loop. The in-house channel consistently secures higher traffic empowerment due to its superior conversion efficiency. Therefore, platform operators should optimize traffic incentive mechanisms by incorporating merchant scarcity metrics (e.g., sell-through rates) into allocation algorithms to maximize aggregate ecosystem GMV, while allocating marginal traffic preference to high-quality self-operated content.

Our study has several limitations. First, this paper assumes a deterministic, linear demand function; future research could incorporate random demand distributions or stratified consumer typologies. Second, the present model is constrained to a single-period static analysis; subsequent investigations could extend the framework to a multi-period dynamic game to examine the intertemporal interplay between long-term reputation and scarcity sustainability. Third, beyond quantitative scarcity, temporal (flash sales) and access-based (member exclusivity) mechanisms warrant comparative analysis regarding their differential impacts on supply chain performance.

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