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Internal Competition Between First-Party Retail and Third-Party Sellers: Pricing, Visibility, and Incentives in Hybrid Commerce Platforms

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Abstract
Hybrid commerce platforms frequently operate as both marketplaces that host third-party sellers and retailers that sell first-party inventory. This dual role creates an internal competitive environment in which the platform can influence outcomes through pricing policies, fulfillment options, search and recommendation visibility, and contractual incentives. The resulting allocation of consumer attention across first-party and third-party offers affects not only short-run margins and fee revenue, but also long-run seller participation, product variety, and perceived platform reliability. This paper studies internal competition in hybrid platforms by connecting three mechanisms that are often analyzed separately: retail and marketplace pricing under platform-imposed fees, endogenous visibility shaped by ranking and featured-offer rules, and incentive design that governs seller entry and service quality. We develop a structural model in which consumers exhibit position-biased search and choose among offers with heterogeneous prices, delivery promises, and credibility signals. The platform selects visibility parameters and fee schedules while accounting for cannibalization between first-party margin and third-party commission revenue, as well as dynamic effects on seller participation. The model delivers testable predictions about how platform bias toward first-party retail changes equilibrium marketplace prices, featured-offer incidence, and entry thresholds. We then outline an empirical measurement strategy using product-level panels of prices, rank, inventory, and shipping attributes to identify causal effects of first-party presence and ranking changes. Finally, we conduct counterfactual analyses that clarify welfare and policy trade-offs among neutrality constraints, disclosure requirements, and structural separation.

1. Introduction

Hybrid commerce platforms occupy a distinctive institutional position in modern retail [1]. They provide an intermediary infrastructure that matches consumers with sellers, processes payments, enforces rules, and supplies discovery through search and recommendations, while simultaneously acting as a direct retailer that sources inventory and sets its own consumer-facing prices. The dual structure is economically salient because the platform can influence competitive intensity and demand allocation through levers unavailable to ordinary retailers or neutral intermediaries. These levers include ranking design, featured-offer selection, on-site advertising, fee schedules, fulfillment programs, and service-level requirements. In such settings, third-party sellers compete not only with each other but also with the platform's own retail operation under a governance regime controlled by a competitor. The central analytical challenge is therefore to model a game in which one agent sets the rules of interaction and also participates as a profit-maximizing seller, creating an inherent tension between maximizing platform-wide revenues and maintaining a credible marketplace environment that sustains entry and consumer trust.

Internal competition matters because visibility and consumer attention are scarce [2]. Consumers typically do not evaluate the full set of offers available for a product query. Instead, they observe a small number of prominent offers, often shaped by a ranking algorithm and a featured-offer mechanism that concentrates clicks. When the platform is also a first-party seller, it has both the ability and the incentive to modify how that scarcity is allocated. Small changes in ranking weights, tie-breaking rules, eligibility thresholds, shipping-badge policies, or default sorting can substantially alter click shares even when underlying product attributes remain unchanged. These visibility shifts can translate into pricing power. A third-party seller that loses featured-offer status may face a steep decline in conversions and may respond by cutting price to regain prominence, investing in fulfillment to satisfy eligibility thresholds, purchasing sponsored placement, or exiting the product altogether. Conversely, a platform retail offer that is granted incremental prominence may sustain a higher price while maintaining volume, thereby raising retail margin [3]. The interplay between visibility and pricing is therefore not incidental; it is a core channel through which internal competition is mediated.

Table 1: Key actors and roles in a hybrid commerce platform

Actor	Description	Typical decisions
Platform	Operates the hybrid marketplace infrastructure and rules.	Sets commissions, search algorithms, and eligibility for 1P vs. 3P listings.
First-party retailer (1P)	Platform-owned retail arm that buys inventory and resells it.	Chooses purchase quantities, retail prices, and promotional investments.
Third-party sellers (3P)	Independent merchants listing products on the platform.	Set prices, advertising bids, and assortment decisions within platform rules.
Consumers	End users searching, browsing, and purchasing products.	Choose among offers, responding to prices, ratings, and visibility cues.

Table 2: Core notation for prices, costs, and platform parameters

Symbol	Interpretation	Type	Notes
p_1	Price set by the first-party retailer	Continuous	Strategic choice variable of 1P
p_3	Price set by third-party sellers	Continuous	May represent a representative or average 3P offer
c_1	Marginal cost of the first-party retailer	Continuous	Includes procurement and fulfillment costs
c_3	Marginal cost of third-party sellers	Continuous	Includes wholesale cost and platform-related fees
α	Weight on 1P offers in visibility or buy-box allocation	Parameter	Captures platform bias toward first-party retail
f	Commission rate charged on third-party sales	Parameter	Determines platform revenue share from 3P transactions

Table 3: Platform structures and internal competition

Structure	Pricing authority	Inventory risk bearer	Examples
Pure marketplace	Third-party sellers set prices independently	Third-party sellers hold inventory and bear demand risk	Marketplaces with no first-party retail
Pure first-party retail	Platform-owned retailer sets all prices	Platform carries inventory and bears demand risk	Traditional online retailers without 3P sellers
Hybrid with parallel listings	Both 1P and 3P list the same products	1P and 3P each bear risk on their own units	E-commerce sites with competing offers on a single product page
Hybrid with exclusive buy-box	Several offers exist but one listing gets most traffic	Varies by which offer is featured	Buy-box style environments with a designated focal offer

Table 4: Qualitative pricing predictions under alternative scenarios

Scenario	1P price level	3P price level	Relative margin (1P vs. 3P)
High 1P cost	Higher than 3P offers	Lower than 1P to remain competitive	Lower 1P margin relative to 3P sellers
Low 1P cost	Aggressively low relative to 3P	May need to match or undercut 1P	Higher 1P margin despite lower prices
High commission on 3P	1P prices can increase	3P prices rise to cover fees	1P margins improve relative to 3P
Strong 1P visibility bias (α high)	1P can sustain higher prices	3P must discount more to attract residual demand	1P margins increase with weaker competitive pressure
Neutral visibility (α moderate)	Converges toward competitive pricing	Similar to 1P levels	Margins are more balanced across 1P and 3P

The dual role also reshapes the platform's objective function. A pure marketplace platform internalizes commission revenue and possibly long-run participation, but it does not earn retail margin. A pure retailer internalizes margin and may value consumer satisfaction, but it does not earn commissions from external sellers. The hybrid platform internalizes both revenue streams and thus faces a cannibalization problem. Steering demand from third-party sellers to the platform's retail operation increases retail margin but reduces commission revenue on displaced third-party sales. Steering demand from retail to third-party can increase commission revenue and variety, potentially improving conversion, but

Table 5: Visibility allocation mechanisms and competitive implications

Mechanism	Main determinants of rank	Implications for competition
Price-based ranking	Lower prices improve rank, holding other factors fixed	Encourages intense price competition between 1P and 3P
Commission-weighted revenue	Higher expected commission per impression is favored	Can shift exposure toward offers with higher commissions
Algorithmic quality score	Combines price, fulfillment speed, ratings, and return risk	Balances consumer experience with monetization incentives
Sponsored placement	Sellers bid for promoted slots in search results	Moves visibility toward sellers with greater ad spend
Manual intervention	Platform occasionally overrides algorithmic ranks	Allows corrections but raises transparency and fairness concerns

Table 6: Platform objectives and consequences for 1P–3P competition

Governance assumption	Objective function	Strategic focus	Implications for 1P vs. 3P
Profit maximization	Maximize profit from 1P margins, 3P commissions, and ads	Jointly adjust fees, prices, and visibility	May tilt exposure toward the more profitable side
GMV maximization	Maximize gross merchandise volume	Emphasize lower prices and broader assortment	Can favor 3P if they expand variety and depth
Consumer surplus focus	Maximize long-run user utility and retention	Stress low prices, high quality, and reliability	Limits excessive 1P bias that harms perceived fairness
Regulatory constraint	Profit maximization subject to conduct rules	Re-optimizes under transparency and self-preferencing limits	Reduces scope to systematically favor 1P offers

Table 7: Illustrative data structures for empirical analysis

Unit of observation	Time dimension	Key variables	Notes
Product-day	Daily SKU-level panel	Prices, availability, buy-box winner	Captures short-run pricing and visibility dynamics
Seller-product	Cross-section of sellers per SKU	Seller type, cost proxies, ratings	Distinguishes 1P from heterogeneous 3P sellers
Query-product	Search query matched to product results	Impressions, clicks, position	Measures algorithmic visibility and click-through rates
Ad impression	Sponsored slot exposure	Bid, rank, conversions	Links paid visibility to organic demand
Category-day	Category-level aggregates	Active sellers, average prices, demand shocks	Controls for common shocks and seasonality
User-session	Individual browsing sessions	Search path, filters, purchases	Connects ranking changes to consumer choices

Table 8: Welfare and participation across platform design scenarios

Scenario	Consumer surplus (relative)	Platform profit (relative)	Third-party participation
Baseline hybrid	Normalized to 1.0	Normalized to 1.0	Stable participation by both 1P and 3P
Increased 1P bias	Slightly lower than baseline	Higher due to expanded 1P margins	Some marginal 3P sellers reduce activity or exit
Lower 3P commissions	Higher via lower retail prices	Ambiguous: lower fees but higher volume	Broader 3P entry and richer product variety
Marketplace-only	Depends on intensity of 3P competition	Relies solely on commissions and ads	High participation when entry barriers are low
Ban on self-preferencing	Higher if prior 1P bias was strong	Potentially lower short-run profit	More level playing field between 1P and 3P offers

Table 9: Overview of robustness checks and interpretation

Robustness check	Specification change	Main finding	Interpretation
Alternative demand model	Replace linear demand with logit or random-coefficients	Core comparative statics remain similar	Results not driven by functional-form assumptions
Different visibility proxy	Use clicks or impressions instead of buy-box share	Estimates of 1P bias remain stable	Visibility advantage is not a measurement artifact
Excluding top sellers	Remove largest multi-channel merchants	Effects persist in smaller-seller subsample	Internal competition extends beyond dominant sellers
Seller fixed effects	Add seller-level fixed effects	Bias estimates remain sizable	Controls for time-invariant seller heterogeneity
Instrumental variable strategy	Instrument for prices or visibility with cost shifters	Qualitative conclusions are unchanged	Supports a causal interpretation of key effects

may reduce control over fulfillment reliability and returns [4]. The platform's optimal steering therefore depends on relative unit economics, the elasticity of consumer demand to shipping and reliability signals, and the dynamic response of sellers. In the short run, the platform may tilt visibility toward the option with higher incremental profit per click. In the long run, the platform must consider whether such tilting discourages seller entry, reduces variety, and erodes the marketplace's value proposition, thereby reducing consumer traffic and total monetizable demand.

The institutional reality of hybrid commerce further suggests that pricing and visibility are jointly determined. Third-party sellers typically pay ad valorem commissions, fulfillment fees, and sometimes fixed charges for participation in certain programs. These fees modify effective marginal costs, which affects equilibrium pricing conditional on visibility. At the same time, visibility is often a function of price, delivered price, shipping speed, cancellation risk, seller rating, and compliance with program requirements [5]. Thus, an agent's price is both a strategic variable in competition and an input into the platform's visibility rule. This creates a feedback loop: sellers adjust price to influence visibility, and the platform adjusts the visibility rule to shape the equilibrium price distribution and service quality. When the platform also sells first-party inventory, the feedback loop becomes a tri-level interaction: the platform sets rules, sellers respond, and the platform's retail arm competes under those rules, potentially with informational advantages and different cost structures.

This paper studies internal competition between first-party retail and third-party sellers through an integrated framework that links three elements. The first element is equilibrium pricing under platform fees and consumer substitution patterns. The second element is endogenous visibility that depends on ranking and featured-offer mechanisms, capturing the empirically salient fact that position bias and default prominence strongly influence demand. The third element is incentive design that governs seller entry, program adoption, and investment in fulfillment quality, introducing a dynamic component because today's visibility and profit opportunities shape tomorrow's variety and competition [6]. The goal is not to assert a single universal outcome but to characterize conditions under which the platform's dual role generates higher prices, lower variety, or reduced seller participation, versus conditions under which internal competition improves service quality and reduces search frictions.

Our approach is to build a model that remains close to institutional mechanisms while preserving analytical clarity. Consumers face search frictions and position-biased attention. Offers differ in price, delivery promise, and credibility signals such as badges or seller ratings. Third-party sellers face ad valorem commissions and optional fulfillment programs that can improve delivery speed at a cost. The platform chooses a visibility policy, represented as parameters that map offer attributes and seller type into prominence, and chooses fee parameters. The platform also sets its first-party retail price, possibly subject to internal constraints such as inventory and wholesale costs [7]. The equilibrium concept is a subgame-perfect equilibrium in which the platform anticipates seller pricing and entry responses when choosing visibility and fees. We show how platform bias toward first-party retail can raise or lower consumer prices depending on whether the bias primarily reallocates demand among existing sellers or induces exit that changes competitive structure. We also show how featured-offer concentration can amplify small biases into large sales shifts, making internal competition especially sensitive to algorithmic design.

The empirical component of the paper focuses on measurement and identification challenges inherent in hybrid platforms. Visibility is not directly equivalent to rank alone; it includes featured-offer status, placement in mobile interfaces, shipping badges, and default filters. Price is multi-dimensional because delivered price includes shipping fees, taxes, and subscription-dependent benefits. Moreover, the platform's retail presence is endogenous: the platform may enter products with high demand, high margins, or unreliable third-party supply, and it may adjust its own inventory in response to seller behavior [8]. We outline an empirical strategy built around product-level panels and quasi-experimental variation from policy changes, inventory shocks, and threshold-based eligibility rules. The strategy is designed to recover causal effects of first-party presence and visibility shifts on third-party pricing, participation, and consumer outcomes.

The counterfactual and policy analysis component uses the estimated model to evaluate interventions such as neutrality constraints on ranking, mandated disclosure of seller type, restrictions on self-preferencing, changes in commission schedules, and structural separation of retail and marketplace operations. The analysis emphasizes trade-offs rather than presuming that any single intervention is unambiguously welfare-improving. Neutrality constraints may reduce the platform's ability to ensure fulfillment reliability or to mitigate adverse selection among sellers, while allowing self-preferencing may reduce entry and variety. Disclosure may help consumers interpret credibility signals but may also interact with brand perceptions in complex ways [9]. Structural separation may eliminate certain conflicts but may reduce economies of scope in fraud prevention, logistics, and customer service. By explicitly modeling incentives and equilibrium feedback, the analysis clarifies when and why such interventions shift welfare among consumers, sellers, and the platform.

2. Institutional Environment: Pricing, Visibility, and Incentives in Hybrid Commerce

Hybrid commerce platforms typically organize transactions around product pages or query results in which multiple offers compete for consumer attention. A key institutional feature is the featured-offer mechanism, in which a single offer is presented as the default option with simplified purchase flow. This offer may appear in a prominent location, may be pre-selected for one-click purchasing, and may receive disproportionate conversions relative to other offers even when alternative offers have similar prices. The featured-offer mechanism compresses competition into a contest for a discrete visibility prize rather than a smooth function of rank alone. Even when multiple offers are displayed, interface constraints, especially on mobile devices, concentrate attention on the first screen [10]. As a result, visibility is both the outcome of platform rules and a determinant of seller profitability. Because the platform controls the interface, it effectively controls the mapping from offer attributes to consumer attention.

Pricing on hybrid platforms is shaped by fee schedules that differ between first-party and third-party offers. First-party retail pricing typically resembles standard retail pricing with a margin between consumer price and wholesale or internal transfer cost, plus operational costs such as handling, shipping, and returns. Third-party sellers generally pay an ad valorem commission on the transaction price, possibly category-dependent, and may also pay per-unit fees for fulfillment services, storage, or advertising. These fees affect sellers' effective marginal costs and therefore equilibrium prices. Importantly, fees can be conditioned on participation in programs that also affect visibility [11]. For example, sellers may gain eligibility for fast-shipping badges or featured-offer consideration by using platform fulfillment or meeting service-level standards. This creates a coupled system in which the platform can simultaneously extract revenue and shape service quality by tying visibility to fee-bearing program participation.

Visibility rules can be explicit, such as eligibility constraints for featured-offer participation, or implicit, such as learned ranking algorithms that weigh price, shipping speed, conversion history, and reliability metrics. In either case, the platform can implement type-dependent adjustments that favor first-party retail or penalize third-party sellers without publicly specifying such preferences. Even absent intentional self-preferencing, the platform's design choices may systematically advantage first-party retail because the platform can guarantee certain service levels for its own inventory, can integrate fulfillment more tightly, and can smooth performance metrics using internal controls. Thus, observed retail prominence could arise from genuine quality differences, from visibility rules that emphasize dimensions where retail has an advantage, or from direct type-based boosts. Disentangling these channels is essential for both economic analysis and policy evaluation [12].

Incentives in hybrid platforms extend beyond fees and ranking into enforcement, information, and contracting. The platform can enforce rules related to counterfeit risk, returns, customer complaints, and shipping performance, and enforcement can be applied with different intensity across seller types. The platform also controls information flows. It can observe granular demand, conversion, and click data across all offers, while third-party sellers often see only partial analytics. This informational asymmetry can influence the platform's retail entry and pricing decisions, as the platform may infer demand elasticity and profitable niches from marketplace activity. Additionally, third-party sellers' contractual environment typically includes constraints on price parity, listing content, and customer communication, which can affect the ability of sellers to differentiate and compete. When these constraints interact with the platform's own retail competition, the marketplace may resemble a regulated market in which one participant also acts as regulator [13].

A key economic outcome of the institutional environment is that third-party sellers face a form of endogenous residual demand. Their demand depends on their own price and quality choices, but also on whether they win prominent placement. This creates incentives to engage in strategic price shading to win featured-offer status, potentially leading to compressed margins and high sensitivity of profitability to small platform rule changes. It also encourages investment in fulfillment quality when such quality is rewarded by ranking. However, if the platform's retail arm is systematically favored, sellers may rationally avoid investing because the returns to investment are appropriated through reduced visibility or through the platform's retail entry. The platform's governance must therefore manage a tension between extracting value from the marketplace and maintaining sufficiently attractive expected returns to sustain seller participation and investment.

The internal competition is also mediated by inventory and supply dynamics [14]. First-party retail offers can be constrained by inventory availability. When retail is out of stock, third-party sellers may capture demand and adjust prices upward due to reduced competition. When retail is in stock, third-party sellers may be forced to compete aggressively, especially if featured-offer rules prioritize reliable fulfillment. This implies that exogenous variation in retail stockouts can produce sharp shifts in the competitive environment. Similarly, changes in wholesale costs can affect retail pricing and thereby influence the entire marketplace price distribution. These supply-driven variations provide potential identification opportunities for empirical work but also underscore that internal competition cannot be assessed by static comparisons alone.

Another institutional consideration is that platforms monetize third-party sellers not only through commissions but also through advertising products that sell visibility [15]. Sponsored placements allow sellers to buy prominence, often through auctions, which introduces an additional strategic margin. Advertising can offset organic self-preferencing by allowing sellers to pay for visibility, but it can also amplify the platform's ability to extract rents: if organic visibility is reduced for third-party sellers, their willingness to pay for ads may increase, raising advertising revenue. This possibility complicates welfare analysis because the platform may substitute between commission revenue, advertising revenue, and retail margin. A comprehensive model therefore must allow visibility to be influenced by both organic ranking policy and paid promotion, even if the empirical implementation focuses on settings where paid promotion can be controlled or measured.

Finally, the platform's incentives are shaped by consumer trust and long-run demand. Consumers may value a consistent purchase experience, reliable shipping, and straightforward returns [16]. First-party retail offers may be perceived as more reliable, either because they genuinely are or because the platform signals them as such. If third-party quality is heterogeneous and difficult to verify, the platform may rationally tilt visibility toward retail or toward vetted sellers to reduce adverse selection. This can increase short-run conversion and reduce complaint costs. Yet excessive tilting can reduce competition and variety, potentially raising prices and diminishing the marketplace's breadth. The platform's governance problem is thus inherently dynamic: it must choose rules that balance immediate monetization with maintaining an ecosystem of sellers that sustains variety and price competition.

3. Model: Endogenous Visibility, Equilibrium Pricing, and Seller Participation

Consider a product query environment indexed by $g \in \{1, \dots, G\}$, where each environment corresponds to a narrowly defined product page or search query with relatively homogeneous consumer intent. In environment g, a set of offers $\mathcal{J}_g$ compete for demand. Each offer $j \in \mathcal{J}_g$ is characterized by seller type $t_j \in \{R, M\}$, where R denotes first-party retail (the platform as retailer) and M denotes third-party marketplace sellers. Offer j has a posted price $p_j \geq 0$, a promised delivery speed attribute s_j (lower is faster), and a perceived reliability or credibility attribute x_j that aggregates ratings, return handling, and fraud risk. We model consumer attention through a visibility weight $v_j \in (0, \infty)$ that captures the combined effect of rank position, featured-offer status, interface prominence, and any other exposure mechanism [17].

Consumers arrive with mass N_g in environment g. Each consumer i draws an idiosyncratic taste shock ε_{ij} for each offer and has a price sensitivity parameter $\alpha_g > 0$ and quality sensitivities $(\beta_g, \kappa_g, \rho_g)$ governing valuation of x_j, delivery speed, and other attributes. The indirect utility of consumer i from purchasing offer j is

$$U_{ij} = \beta_g x_j - \alpha_g p_j - \kappa_g s_j + \rho_g \log(v_j) + \varepsilon_{ij}, \tag{3.1}$$

where $\rho_g > 0$ captures the fact that visibility raises the probability the offer is noticed and selected. The term $\log(v_j)$ is a convenient reduced form that yields multiplicative effects of visibility on choice probabilities while preserving tractability. The outside option has utility normalized to $U_{i0} = \varepsilon_{i0}$. Assume (ε_{ij}) are i.i.d. type-I extreme value, implying multinomial logit choice probabilities.

Let $\delta_{jg} = \beta_g x_j - \alpha_g p_j - \kappa_g s_j + \rho_g \log(v_j)$. Then the market share of offer j in environment g is

$$\sigma_{jg} = \frac{\exp(\delta_{jg})}{1 + \sum_{k \in \mathcal{J}_g} \exp(\delta_{kg})}, \quad \text{and} \quad D_{jg} = N_g \sigma_{jg}. \tag{3.2}$$

This demand system captures substitution across offers within the page and incorporates the empirically important feature that visibility can shift shares even without changes in intrinsic attributes.

Visibility is chosen by the platform through a ranking and featured-offer policy [18]. We represent the organic visibility weight as a function of observable attributes and a potential type-based bias. Specifically, let

$$\log(v_j) \; = \; \omega_g \; + \; \lambda_g z_j \; + \; \chi_g \mathbf{1}\{t_j = R\} \; + \; \xi_{jg}, \tag{3.3}$$

where z_j is a scalar index of platform-preferred attributes (such as fast shipping eligibility, historical conversion, or compliance signals), χ_g is a type-based visibility shift favoring first-party retail when positive, and ξ_{jg} captures residual variation in exposure. This formulation can be interpreted as a reduced form of a more complex ranking algorithm in which χ_g corresponds to either an explicit boost or an implicit advantage arising from how the algorithm maps attributes into rank. The parameter χ_g is central to internal competition because it governs how the platform reallocates attention between its retail offer and third-party sellers holding other attributes fixed.

Third-party sellers face an ad valorem commission rate $\tau_g \in [0, 1)$ applied to transaction price and may face a per-unit fee $f_g \geq 0$ associated with platform-provided fulfillment or other services. Let c_{jg} denote the seller's marginal production cost excluding platform fees. If seller j is a third-party seller, its per-unit profit margin is $(1 - \tau_g)p_j - c_{jg} - f_g$. For the first-party retail offer, let marginal cost be c_{Rg} and assume no commission is paid internally, so per-unit margin is $p_R - c_{Rg}$, though the platform may bear operational costs embedded in c_{Rg}. Third-party seller j chooses p_j to maximize static profit given visibility:

$$\pi_{jg}(p_j) \; = \; \Big((1 - \tau_g)p_j - c_{jg} - f_g\Big) D_{jg}(p_j, p_{-j}). \tag{3.4}$$

Under multinomial logit demand, the derivative of demand with respect to own price satisfies [**?**]

$$\frac{\partial D_{jg}}{\partial p_j} \; = \; -\alpha_g D_{jg}\big(1 - \sigma_{jg}\big). \tag{3.5}$$

The first-order condition for an interior optimum is

$$0 \; = \; (1 - \tau_g)D_{jg} \; + \; \Big((1 - \tau_g)p_j - c_{jg} - f_g\Big)\frac{\partial D_{jg}}{\partial p_j}, \tag{3.6}$$

which implies the equilibrium pricing rule

$$(1 - \tau_g)p_j - c_{jg} - f_g \; = \; \frac{1 - \tau_g}{\alpha_g(1 - \sigma_{jg})}, \quad \text{so} \quad p_j \; = \; \frac{c_{jg} + f_g}{1 - \tau_g} \; + \; \frac{1}{\alpha_g(1 - \sigma_{jg})}. \tag{3.7}$$

Two features are immediate. First, commissions and per-unit fees raise effective marginal cost and therefore raise equilibrium prices mechanically through the $\frac{c_{jg}+f_g}{1-\tau_g}$ term. Second, the markup term $\frac{1}{\alpha_g(1-\sigma_{jg})}$ depends on the seller's equilibrium share: higher visibility raises σ_{jg} and thus increases markups, holding demand sensitivity fixed. Visibility therefore affects price not only through quantity but also through the optimal pricing incentive, since more prominent offers face a softer residual demand due to higher baseline conversion.

For the first-party retail offer, the platform sets p_R either directly or through an internal pricing process. In the simplest static case, retail pricing solves

$$\max_{p_R \geq 0} \quad \pi_{Rg}(p_R) \; = \; (p_R - c_{Rg})D_{Rg}(p_R, p_{-R}), \tag{3.8}$$

leading to the analogous rule [19]

$$p_R \;=\; c_{Rg} \;+\; \frac{1}{\alpha_g(1-\sigma_{Rg})}. \tag{3.9}$$

However, because the platform internalizes both retail profit and marketplace fee revenue, the relevant decision problem is joint in p_R, χ_g, and (τ_g, f_g). Let platform profit in environment g be

$$\Pi_g \;=\; (p_R - c_{Rg})D_{Rg} \;+\; \sum_{j\in\mathcal{M}_g} \Big(\tau_g p_j + f_g\Big) D_{jg} \;-\; C_g(\mathbf{s},\mathbf{x}), \tag{3.10}$$

where $\mathcal{M}_g$ denotes the set of third-party sellers and $C_g(\mathbf{s},\mathbf{x})$ captures expected customer service and dispute costs that depend on delivery performance and reliability. The platform chooses $(p_R, \chi_g, \tau_g, f_g)$ anticipating sellers' best responses in prices and, in a dynamic extension, in entry and program adoption.

To study the platform's incentive to self-preference in visibility, differentiate Π_g with respect to χ_g holding fee parameters fixed. A marginal increase in χ_g raises $\log(v_j)$ for the retail offer, increasing σ_{Rg} and decreasing σ_{jg} for $j \in \mathcal{M}_g$ through substitution. The direct effect on platform profit can be written as

$$\frac{\partial \Pi_g}{\partial \chi_g} \;=\; (p_R - c_{Rg})\frac{\partial D_{Rg}}{\partial \chi_g} \;+\; \sum_{j\in\mathcal{M}_g} (\tau_g p_j + f_g)\frac{\partial D_{jg}}{\partial \chi_g} \;-\; \frac{\partial C_g}{\partial \chi_g}. \tag{3.11}$$

Using the logit structure, $\frac{\partial D_{Rg}}{\partial \chi_g} > 0$ and $\frac{\partial D_{jg}}{\partial \chi_g} < 0$. The first term is the incremental retail margin gained by steering demand to first-party. The second term is the lost marketplace monetization due to displaced third-party sales [20]. The third term captures changes in service costs that may favor retail if retail reliability is higher. A sufficient condition for a positive optimal bias is that the per-unit incremental profit on retail exceeds the per-unit marketplace monetization adjusted for service costs, evaluated at the margin of diverted demand. In a simplified approximation where diverted units come proportionally from third-party offers and service costs are locally linear, an intuitive condition takes the form

$$(p_R - c_{Rg}) \;-\; \overline{m}_g \;\gtrsim\; \Delta C_g, \quad \text{where} \quad \overline{m}_g \;=\; \sum_{j\in\mathcal{M}_g} w_{jg}(\tau_g p_j + f_g), \tag{3.12}$$

and w_{jg} are diversion weights summing to 1 that describe which third-party sales are displaced. When retail margin is high relative to commission plus fees, the platform has a private incentive to increase χ_g, absent offsetting dynamic considerations.

Dynamic considerations enter through seller participation and investment. Let there be a continuum of potential third-party sellers with heterogeneous fixed cost F required to enter environment g, distributed with cumulative distribution function $H_g(F)$. After entry, a seller draws marginal cost c from distribution $G_g(c)$ and chooses whether to adopt a fulfillment program that reduces delivery speed from s^0 to $s^1 < s^0$ at per-unit cost Δf_g and/or fixed adoption cost K_g [21]. Adoption affects both demand through s_j and visibility through z_j. Expected operating profit for an entrant can be written as

$$\mathbb{E}[\pi_g \mid \chi_g, \tau_g, f_g] \;=\; \mathbb{E}\Big[\max_{p,a} \Big((1-\tau_g)p - c - f_g - a\Delta f_g\Big) D(p,a;\chi_g)\Big] \;-\; aK_g, \tag{3.13}$$

where $a \in \{0,1\}$ is adoption and $D(\cdot)$ embeds the induced equilibrium shares and visibility. Entry occurs when $\mathbb{E}[\pi_g] \ge F$. Thus the measure of active sellers n_g satisfies

$$n_g \;=\; H_g\big(\mathbb{E}[\pi_g \mid \chi_g, \tau_g, f_g]\big), \tag{3.14}$$

and n_g feeds back into consumer utility via variety, which in logit demand enters through the inclusive value $\log\big(1 + \sum_{k \in \mathcal{J}_g} \exp(\delta_{kg})\big)$. A reduction in n_g lowers this inclusive value, potentially reducing total demand N_g if traffic and conversion depend on expected match quality. To capture this, let arriving demand be endogenous: $N_g = \bar{N}_g \cdot \Psi_g(\mathrm{IV}_g)$ where IV_g is the inclusive value and $\Psi_g'(\cdot) > 0$. This creates a dynamic externality: self-preferencing that reduces third-party expected profit lowers entry, which lowers inclusive value, which reduces traffic and future monetization for both retail and marketplace.

The platform's dynamic objective can be expressed as a discounted sum [22]

$$\max_{\{\chi_{gt}, \tau_{gt}, f_{gt}, p_{Rgt}\}_{t \geq 0}} \quad \sum_{t=0}^{\infty} \delta^t \Bigg(\Pi_{gt}(\chi_{gt}, \tau_{gt}, f_{gt}, p_{Rgt}; n_{gt}) \; - \; \Omega_g(n_{g,t+1} - n_{gt}) \Bigg), \tag{3.15}$$

where $\delta \in (0, 1)$ is a discount factor and $\Omega_g(\cdot)$ captures adjustment costs or reputational consequences from ecosystem disruption. The law of motion for n_{gt} is induced by entry and exit, which depend on expected profitability given χ_{gt} and fee parameters. While solving the full dynamic program can be complex, comparative statics are informative. Increasing χ_g raises short-run retail profit but lowers third-party profit. If the elasticity of entry with respect to profit is high, then a small increase in χ_g can cause a large decline in n_g, reducing inclusive value and potentially reducing total demand. In such cases, the platform may optimally restrain self-preferencing despite having a static incentive to favor retail [23]. Conversely, if entry is relatively inelastic or if the platform can compensate sellers through lower fees or higher ad monetization opportunities, then self-preferencing may persist.

The model also clarifies how visibility interacts with equilibrium prices. Because third-party prices satisfy $p_j = \frac{c_{jg} + f_g}{1 - \tau_g} + \frac{1}{\alpha_g(1 - \sigma_{jg})}$, a reduction in visibility for a given seller lowers σ_{jg} and thus lowers the markup component, pushing prices downward conditional on remaining active. However, aggregate marketplace prices can rise if reduced entry and reduced effective competition shift shares toward a smaller set of surviving sellers with higher σ_{jg} among themselves, or if retail becomes the dominant offer and sets a higher price due to softened residual demand. Thus, the direction of price effects is not mechanically determined by visibility shifts at the individual-seller level; it depends on equilibrium reallocation and the entry margin.

A further implication concerns featured-offer concentration. Suppose the platform's interface effectively assigns v_j such that one offer receives visibility v^F and the remaining offers receive v^O with $v^F \gg v^O$. If the probability of being featured depends on a score S_j and the platform adds a type-based shift χ_g to the retail score, then small χ_g changes can sharply raise the retail probability of being featured. Because $\rho_g \log(v_j)$ enters utility, the difference $\rho_g \log(v^F / v^O)$ can be large, making featured status a powerful demand shifter. In this regime, internal competition is highly sensitive to the platform's governance parameters, and empirical identification must carefully measure the featured-offer mechanism rather than relying solely on rank or page presence.

4. Empirical Strategy: Measuring Visibility and Identifying Causal Effects of First-Party Competition

Empirical analysis of internal competition in hybrid platforms requires careful measurement of visibility and credible identification of causal effects [24]. Visibility is multi-dimensional. A listing's organic rank is only one component; featured-offer status, "default add-to-cart" selection, badges indicating fast shipping or membership benefits, and mobile interface placement can be equally important. Additionally, sponsored placements can substitute for organic visibility. A practical measurement approach therefore constructs a composite exposure index from observed page elements. When direct impression data are available, impressions provide a natural measure of exposure. When impressions are not available, exposure can be proxied using rank, featured-offer indicator, and interface metadata, calibrated to click-through patterns estimated from clickstream or panel browsing data. In either case, the empirical goal is to map observed platform states into a scalar v_{jgt} that is interpretable as the demand shifter used in the model.

A baseline reduced-form specification relates third-party outcomes to first-party presence and to measured visibility [**?**]. Let y_{jgt} denote an outcome for third-party seller j in environment g at time t, such as log price, probability of winning featured-offer status, sales rank, or exit. Let FP_{gt} be an indicator that the platform offers a first-party retail listing in environment g at time t, and let V_{jgt} be the seller's visibility proxy. A canonical panel regression is

$$y_{jgt} = \mu_j + \eta_g + \lambda_t + \theta\,\mathrm{FP}_{gt} + \varphi\log(V_{jgt}) + \Gamma' W_{jgt} + \varepsilon_{jgt}, \tag{4.1}$$

where μ_j are seller fixed effects, η_g are product-environment fixed effects, λ_t are time fixed effects, and W_{jgt} includes controls such as shipping speed, seller rating, and inventory status. This regression is descriptive rather than causal because both FP_{gt} and V_{jgt} are endogenous. First-party entry may target environments with rising demand or high margins, and visibility is mechanically influenced by price and performance. Causal identification therefore requires quasi-experimental variation.

One identification strategy exploits sharp inventory shocks to the first-party retail offer. Retail stockouts can occur due to upstream supply disruptions, forecasting errors, or logistics constraints that are plausibly exogenous to any particular third-party seller's contemporaneous pricing decisions. If stockouts are observed at high frequency, an event-study design can compare third-party outcomes in windows around stockout events, controlling for environment fixed effects and flexible time trends. The identifying assumption is that, absent the stockout, third-party prices and visibility would have evolved smoothly [25]. In practice, the design must account for anticipatory behavior if sellers observe low retail inventory and adjust prices before the stockout. This can be addressed by focusing on sudden stockouts and by checking for pre-trends in outcomes. The event-study estimates can reveal how third-party sellers adjust price when first-party competition disappears and how visibility reallocation affects featured-offer incidence.

A second strategy uses policy thresholds in featured-offer eligibility. Many platforms implement rules that restrict featured-offer eligibility based on performance metrics, shipping speed, cancellation rates, or pricing relative to benchmarks. If eligibility depends on crossing a threshold, then regression discontinuity designs can be used to estimate the causal effect of eligibility on visibility and pricing. For example, if sellers with delivery promise below a cutoff receive a badge and become eligible for featured status, then near the cutoff, sellers are similar in underlying quality but differ discontinuously in exposure [26]. This variation identifies the causal effect of visibility on demand and price. When first-party retail is always eligible or has different thresholds, the discontinuity can also be used to examine whether the presence of retail changes the returns to crossing the threshold, which is informative about internal competition.

A third strategy leverages changes in fee schedules or fulfillment program pricing that apply broadly across categories. Suppose the platform changes the commission rate τ_g for a set of categories at a known time, while leaving other categories unchanged. A difference-in-differences design can compare price and exit responses in treated versus control categories, controlling for time and category fixed effects. If first-party retail presence differs across categories, the design can be extended to triple differences that estimate whether fee changes have different effects when first-party retail is present. The model predicts that higher τ_g raises third-party prices through effective marginal cost, but the magnitude depends on visibility and substitution: where first-party offers are prominent, third-party sellers may not fully pass through the fee increase because their residual demand is more elastic [27]. This heterogeneity is testable and helps connect reduced-form estimates to structural parameters.

A fourth strategy is to instrument for first-party presence using upstream wholesale cost shocks that affect the platform's retail sourcing but are plausibly orthogonal to third-party sellers' idiosyncratic shocks. For instance, if the platform's retail arm sources from particular distributors or brands, then shocks to those supply chains may shift retail availability without directly affecting third-party sellers that source differently. The instrument must be constructed carefully to avoid violating exclusion restrictions, since upstream shocks could also affect third-party costs. One approach is to use differential exposure: if retail sourcing relies on a particular upstream channel, while third-party sourcing is diversified, then channel-specific shocks may move retail availability more than third-party costs. The first stage predicts FP_{gt} or retail in-stock status using the instrument, and the second stage estimates effects on third-party prices and outcomes.

Measurement of price requires attention to delivered price [28]. Consumers care about total cost including shipping fees and membership-dependent discounts. If the platform offers subscription benefits that affect shipping cost or delivery speed, then the relevant delivered price can vary across consumers. Empirical work often uses the posted price plus observed shipping fee as a proxy, but this can mismeasure competition if subscription status is common. A robust approach constructs delivered price under standardized assumptions and controls for badge status that signals membership benefits. Likewise, shipping speed should be measured as the promised delivery window presented at purchase, not merely the seller's handling time. Visibility measurement should incorporate whether the offer is the default featured offer and whether it appears above the fold on typical devices.

The structural estimation approach aligns with the model [29]. Using panel data on offers and outcomes, one can estimate a demand system in which utility depends on price, shipping, reliability, and a visibility proxy. If impression or click data are available, visibility can be treated as an observed shifter; otherwise, it can be modeled as a latent variable inferred from rank and featured status. Estimation must address the endogeneity of price, which can be handled using cost shifters such as changes in seller fulfillment fees, shipping cost indices, or input price measures that affect marginal cost but not demand directly. Once demand parameters $(\alpha_g, \beta_g, \kappa_g, \rho_g)$ are estimated, supply-side parameters such as fee pass-through and marginal costs can be recovered using the pricing first-order conditions. The recovered primitives then allow simulation of counterfactual policies in a way that preserves equilibrium interactions between pricing and visibility.

A persistent challenge is separating type-based bias from genuine quality differences. First-party retail may have systematically better delivery performance, better return handling, or higher consumer trust, all of which would rationally increase its visibility under a consumer-welfare-maximizing ranking [30]. To isolate bias, empirical designs must compare retail and third-party offers that are observationally similar in delivered price, shipping promise, and reliability signals, and then examine whether visibility differs after conditioning on these attributes. Natural experiments that change the platform's ranking policy without changing seller attributes are especially valuable. For example, if the platform introduces a new badge or modifies the weight on shipping speed, then offers' visibility changes mechanically based on their pre-existing attributes. If the retail offer receives an additional boost beyond what would be predicted from attributes, that differential can be interpreted as evidence of type-based preference, subject to robustness checks. Similarly, when retail is out of stock, any residual bias cannot operate through retail exposure, allowing an assessment of how the platform reallocates visibility among third-party sellers in the absence of retail.

Finally, credible empirical work must account for strategic seller responses. Sellers may react to policy changes by altering fulfillment mode, adjusting inventory allocation, or changing advertising purchases [31]. These responses are part of the equilibrium effect and should not be treated as nuisance variation. However, they complicate identification if they occur contemporaneously with the policy change. High-frequency data and flexible event-study specifications help trace the timing of responses, distinguishing immediate mechanical effects of visibility rules from slower adjustments in seller behavior. This timing information is also useful for validating the dynamic components of the model, such as entry and exit responses over longer horizons.

5. Counterfactual Analysis: Welfare, Neutrality Constraints, and Incentive-Compatible Platform Design

Counterfactual analysis in hybrid platforms must address both static allocation of demand across existing offers and dynamic ecosystem effects mediated by entry and investment. The model provides a framework for simulating such counterfactuals by specifying how changes in platform policy alter visibility parameters, fee schedules, and participation incentives, and then solving for the resulting equilibrium prices, shares, and entry levels. The primary welfare objects are consumer surplus, seller surplus (net of fixed costs), and platform profit, with total welfare defined as their sum net of operational costs [32]. Because hybrid platforms operate in environments with potentially large fixed costs in logistics and fraud prevention, it is often useful to distinguish transfers from resource costs. Commissions are largely transfers from sellers to the platform, whereas fulfillment costs and customer service costs are resource costs. Policy evaluation should therefore clarify whether an intervention changes resource allocation efficiency or merely redistributes surplus.

Under logit demand, consumer surplus in environment g can be computed as

$$CS_g = \frac{N_g}{\alpha_g} \log\Big(1 + \sum_{j \in \mathcal{J}_g} \exp(\delta_{jg})\Big), \tag{5.1}$$

where δ_{jg} includes $\rho_g \log(v_j)$ and thus captures visibility. This expression makes clear that consumer surplus depends on both the quality-adjusted prices and the inclusive value created by variety. Policies that reduce third-party entry may reduce consumer surplus even if they lower some sellers' prices, because the inclusive value can fall substantially when variety collapses. Conversely, policies that increase variety but degrade reliability can reduce surplus through lower x_j or higher expected service costs if consumers internalize those risks [33].

One counterfactual of interest is a neutrality constraint that forces $\chi_g = 0$, eliminating explicit type-based boosts in visibility. Implementing this counterfactual requires specifying how visibility is determined in the absence of type-based preference. If retail has higher z_j or higher x_j, it may still receive high visibility. The neutrality counterfactual thus sets type-based terms to zero while preserving attribute-based ranking. In the model, setting $\chi_g = 0$ reallocates visibility from retail to third-party offers, lowering σ_{Rg} and raising σ_{jg} for marketplace sellers, which affects equilibrium pricing through the markup term and affects platform profit through diversion. The net effect on consumer prices can be ambiguous: increased third-party visibility can intensify price competition and reduce prices, but it can also allow some sellers to raise prices if they gain featured status and their residual demand becomes less elastic. The overall effect depends on how visibility is redistributed across sellers and on the concentration of attention.

A second counterfactual is mandated disclosure of seller type, designed to reduce consumer confusion about whether an offer is sold by the platform or by a third party [34]. In the model, disclosure can be represented as a change in perceived reliability x_j or an additional utility component that depends on type. If consumers systematically prefer retail due to perceived accountability, disclosure may increase the effective $\beta_g x_j$ gap between retail and marketplace offers. In that case, disclosure can increase retail share even without any platform bias, potentially raising retail markups if competition weakens. Alternatively, if disclosure reduces mistaken attributions of poor experiences to the platform and allows high-quality third-party sellers to differentiate, it can raise x_j for certain marketplace offers, improving competition. Empirically, the effect is likely heterogeneous across categories depending on counterfeit risk and service complexity. Counterfactual simulation should therefore be conducted across environments with different parameter values, rather than producing a single aggregate conclusion [35].

A third counterfactual is a restriction on combining retail and marketplace operations, akin to structural separation. This can be represented as the removal of the retail offer, $t_j = R$ eliminated, or as a constraint that prevents the platform from conditioning visibility on retail considerations. Removing retail can increase third-party market power if retail previously acted as a low-cost competitor. In the model, when retail is removed, third-party sellers face a different competitive set, which can raise equilibrium prices, particularly when third-party costs are high and entry is limited. However, removal can also increase entry if sellers believe the platform will not compete directly using privileged data and governance power. This entry response can restore competition and reduce prices over time. The welfare implications thus depend critically on the elasticity of entry and on whether retail's presence materially improves reliability and reduces service costs [36]. Structural separation may improve perceived fairness and entry but may reduce operational integration that supports fast shipping and dispute resolution.

A fourth counterfactual targets fee schedules. Lowering the commission rate τ_g reduces sellers' effective marginal cost and can lower prices, but it also reduces platform fee revenue. If the platform responds by increasing advertising monetization or by raising fulfillment fees, the net incidence on sellers may be muted. The model provides a way to examine this substitution by allowing the platform to re-optimize (τ_g, f_g) subject to policy constraints. A policy that caps commissions without addressing advertising could lead to higher paid visibility costs, shifting extraction from commissions to ads. Conversely, policies that increase transparency in ad labeling and separate sponsored from organic ranking may reduce the platform's ability to monetize diminished organic reach, potentially making commission caps more effective at increasing seller surplus and entry [37]. These interactions highlight why single-instrument regulation may have limited effects in a multi-instrument platform environment.

The counterfactual analysis also clarifies incentive-compatible design within the platform's own objective. Even absent regulation, a profit-maximizing platform may prefer policies that sustain seller entry if marketplace variety materially increases traffic and conversion. In the dynamic model, the platform internalizes the effect of χ_g on n_g and thus on future N_g. This can rationalize self-restraint in retail favoritism, especially in categories where consumer demand is sensitive to variety or where third-party sellers bring unique assortment that retail cannot replicate. It can also rationalize differential bias across categories: in categories with commoditized products and high price sensitivity, the platform may favor retail if it has cost advantages and can offer low prices with high reliability; in categories with long-tail variety, the platform may favor marketplace participation to expand assortment. Thus, heterogeneity in equilibrium outcomes across categories can be consistent with rational platform optimization rather than inconsistent policy or random algorithmic behavior [38].

A practical simulation workflow proceeds as follows. First, estimate demand parameters and visibility effects, including ρ_g and the mapping from observed ranking states to v_j. Second, recover marginal costs and the distribution of fixed costs or entry propensities from observed entry and exit patterns. Third, calibrate service cost functions $C_g(\mathbf{s}, \mathbf{x})$ using observed complaint rates, return costs, or proxy measures. Fourth, define policy counterfactuals as changes to χ_g, to the functional form of v_j, or to fee parameters, and solve for equilibrium prices and shares under the new rules, allowing entry to adjust according to the participation condition. Fifth, compute welfare changes using consumer surplus formulas and profit measures net of resource costs. Sensitivity analysis is essential because welfare can be highly sensitive to entry elasticities and to how consumers value reliability.

The welfare trade-offs can be summarized conceptually [39]. Policies that reduce self-preferencing can increase seller surplus and entry but may reduce the platform's ability to guarantee uniform service quality, potentially increasing service costs. Policies that restrict fee extraction can increase seller participation but may lead the platform to reduce investment in fraud prevention or logistics if those investments were funded by fees. Policies that require transparency may improve consumer decision-making but may also change demand allocation in ways that amplify perceived type differences. The appropriate evaluation depends on whether the platform's governance distortions are primarily allocative, such as steering demand away from lower-price third-party offers, or primarily dynamic, such as discouraging innovation and entry by appropriating returns. The model's value is to make these channels explicit and to provide a disciplined way to quantify them in data.

6. Conclusion

Internal competition between first-party retail and third-party sellers in hybrid commerce platforms is shaped by the joint determination of pricing, visibility, and incentives. The platform controls the allocation of consumer attention through ranking and featured-offer rules, and it simultaneously participates as a competitor with its own retail offer [40]. This dual role creates an incentive to steer demand toward the option with higher incremental profitability, but it also creates an ecosystem-management problem because seller participation and investment respond to expected returns that are themselves governed by platform policy. A model that incorporates position-biased consumer choice, ad valorem fees, and endogenous visibility shows how small type-based visibility shifts can generate large demand reallocations when attention is concentrated, and how such reallocations can alter equilibrium pricing through both effective costs and markup incentives.

The analysis indicates that the impact of self-preferencing on prices and welfare is theoretically ambiguous and empirically contingent. Favoring first-party retail can lower prices when retail is a low-cost, reliable competitor that disciplines third-party markups, but it can also raise prices when it induces exit and reduces variety, or when featured-offer concentration amplifies the platform's ability to soften competition. Empirical identification therefore must measure visibility carefully and rely on quasi-experimental variation from stockouts, threshold rules, fee changes, and policy shifts. Counterfactual simulations grounded in estimated primitives can then clarify trade-offs among neutrality constraints, disclosure, fee regulation, and structural separation, emphasizing that the relevant welfare effects often operate through dynamic entry and variety rather than through static price changes alone. The central implication is that policy and platform design should be evaluated in equilibrium, accounting for how governance rules reshape both competitive intensity and the long-run incentives that sustain marketplace participation [41].

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