

Original Research

Commission Structures, Fee Policy Changes, and Their Effects on Seller Entry, Pricing Strategies, and Retention in Platform-Based Retail

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Abstract

Platform-based retail increasingly relies on fee schedules that combine ad valorem commissions, per-transaction charges, subscription fees, and optional paid services such as advertising and fulfillment. These instruments are frequently revised as platforms search for revenue stability, category expansion, and perceived fairness across heterogeneous sellers. At the same time, sellers respond to fee policy changes by adjusting entry timing, pricing and promotion intensity, assortment breadth, and the choice to remain active or exit. This paper analyzes how commission structures and fee policy changes propagate through seller decision problems and market outcomes in platform-based retail. The approach integrates a structural model of seller entry, pricing under demand uncertainty, and dynamic retention with an empirical design that leverages discrete fee revisions and heterogeneous exposure across categories and seller types. The model clarifies how shifting from ad valorem to fixed fees changes marginal incentives, pass-through, and the composition of entrants, while fee increases in optional services can alter measured commissions indirectly by affecting effective marginal costs. The empirical component outlines identification strategies for isolating causal effects in the presence of concurrent platform interventions, including shipping policy updates, ranking algorithm adjustments, and seasonality. Counterfactual simulations quantify trade-offs between revenue, price levels, variety, and seller churn under alternative fee menus, emphasizing conditions under which platforms can reduce distortions without triggering large exit waves. The analysis highlights mechanisms linking fee design to long-run marketplace health through selection, learning, and the endogenous survival of sellers.

1. Introduction

Commission structures in platform-based retail are not merely accounting rules; they are core components of market design that shape who enters, how aggressively sellers price, and whether they persist through periods of low demand or high competition [1]. Platforms often begin with a relatively simple ad valorem commission on gross merchandise value because it is easy to implement and scales with transaction volume. Over time, however, the fee menu typically expands to include per-transaction charges, subscription plans that bundle services, category-specific commission rates, and add-on fees for advertising, premium placement, data tools, or fulfillment. These changes reflect platform objectives that include revenue diversification, balancing participation across categories with different margins and return rates, and internalizing operational costs. Sellers experience these policies as changes to marginal revenue retention, fixed costs of participation, and the volatility of profits [2]. Because seller decisions are forward-looking, fee revisions can affect not only contemporaneous prices and sales but also entry and exit patterns that determine long-run variety and competitive pressure.

A key challenge in understanding fee effects is that platforms adjust multiple levers simultaneously. A commission increase may coincide with a change in search ranking, a new promotion format, or a

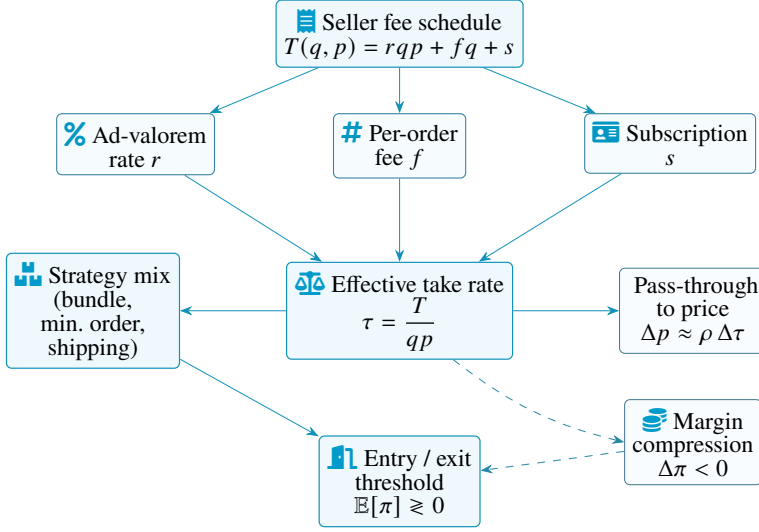


Figure 1: Decomposition of platform fees into ad-valorem, per-order, and subscription components and their aggregation into an effective take rate. The diagram highlights two dominant response channels: price pass-through (with elasticity ρ) and non-price strategy adjustments that shift seller order composition and entry thresholds.

change in shipping subsidies. Sellers may also respond endogenously by changing service usage, such as shifting to platform-managed fulfillment when the relative cost changes, which in turn affects delivery speed and conversion. The resulting equilibrium feedbacks complicate causal attribution [3]. A second challenge is heterogeneity: sellers differ in costs, product differentiation, capacity constraints, and multi-homing options. A fee that is small relative to revenue for a high-volume seller may be prohibitive for a small entrant. Similarly, a per-transaction fee can have very different incidence for low-priced versus high-priced goods, even if the ad valorem rate remains unchanged. A third challenge is dynamic selection. Fee changes affect who enters and who survives, changing the distribution of seller types and the competitive landscape [4]. Observed pricing responses can therefore conflate within-seller pass-through with composition effects.

This paper develops a technical framework that links commission structures and fee policy changes to seller entry, pricing strategies, and retention in platform-based retail. The framework is designed to be estimable using typical platform data, including seller-level listings, prices, sales, advertising usage, and account tenure. The model treats sellers as optimizing agents who face demand that depends on price, perceived quality, delivery attributes, and platform-provided exposure. Fees enter profits through both marginal and fixed components, and optional services create endogenous effective marginal costs [5]. Entry is modeled as a discrete choice with a sunk setup cost and uncertain future profits, while retention is modeled as a dynamic decision in which sellers update beliefs about demand and costs and can exit when continuation value falls below an outside option. The platform's fee policy is treated as an observed schedule that can change discretely over time, potentially with category-specific components.

The analysis aims to separate three channels through which fee policies affect outcomes. The marginal incentive channel captures how ad valorem commissions and per-transaction fees alter effective marginal costs and therefore optimal prices and promotion. The fixed-cost channel captures how subscription fees and compliance costs affect entry thresholds and survival, often through liquidity constraints and risk [?]. The selection channel captures how fee changes alter the composition of sellers, which feeds back into competition and consumer choice. The paper also formalizes how sellers may substitute across fee-bearing services, such as advertising, and how such substitution can attenuate or amplify the direct effect of headline commission changes.

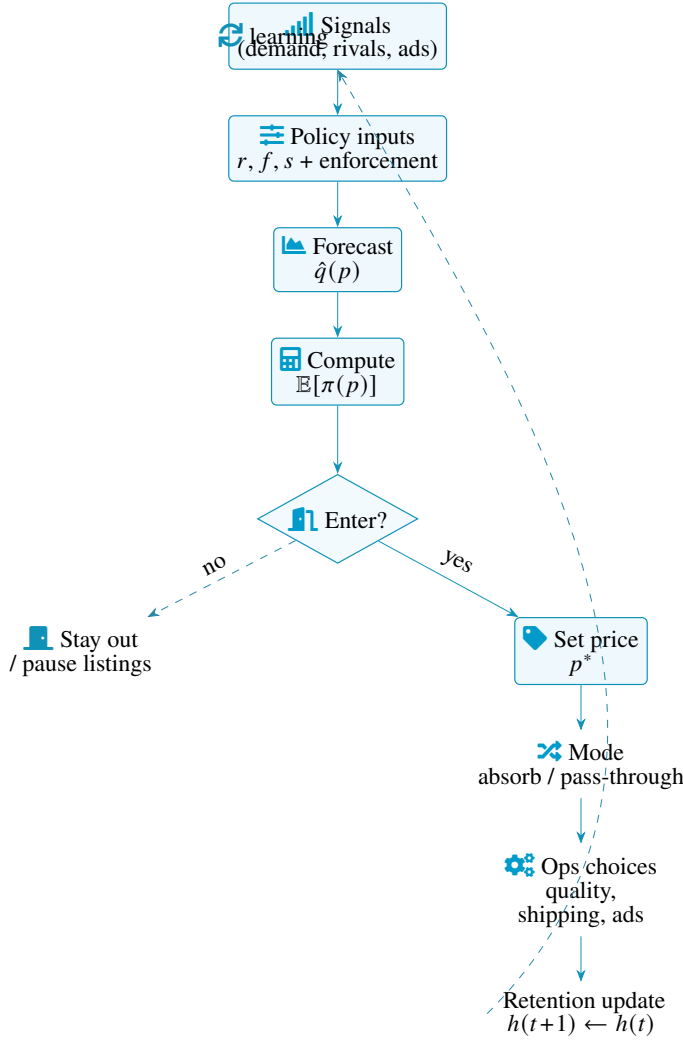


Figure 2: Seller decision pipeline under changing platform fees: sellers forecast demand, evaluate expected profit under the current schedule, decide on entry/listing, and choose a pricing mode (absorbing fees vs passing them through) alongside operational adjustments. Retention evolves through a learning loop as realized performance updates future expectations.

The empirical portion outlines an identification strategy built around discrete policy revisions, category-level differential exposure, and seller-specific predicted treatment intensity derived from pre-change behavior. The design emphasizes event-time variation and careful controls for concurrent platform changes [6]. Where feasible, the approach combines reduced-form estimates of entry and exit elasticities with structural estimation of demand and seller costs. Counterfactual experiments evaluate alternative fee menus, including revenue-neutral swaps between ad valorem and fixed fees, and assess implications for price indices, seller churn, platform revenue volatility, and consumer surplus measures derived from estimated demand.

The contribution is methodological rather than rhetorical: it provides a coherent mapping from fee design to equilibrium outcomes with explicit dynamic selection, and it provides an empirical blueprint for isolating causal effects in environments where platform policies are frequent and multifaceted. The

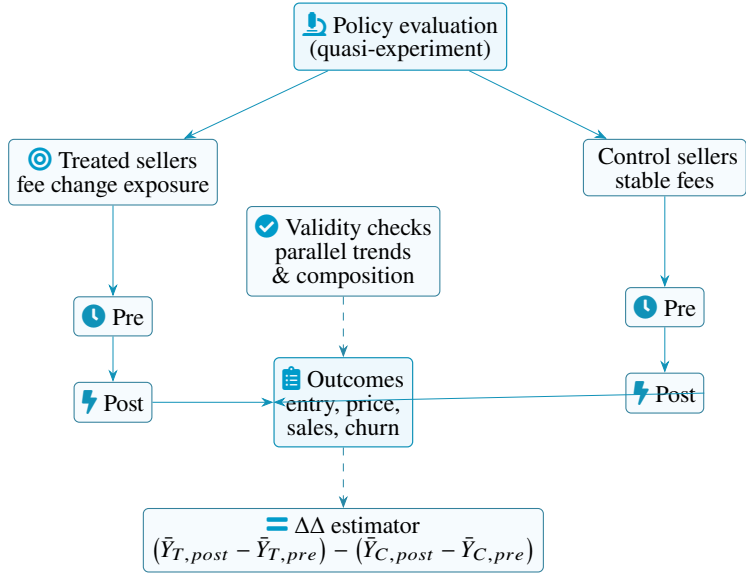


Figure 3: A compact identification schematic for measuring fee policy impacts using treated versus control sellers across pre/post windows. Outcomes span seller entry, pricing, sales, and retention, with a difference-in-differences contrast supported by parallel-trends and composition diagnostics.

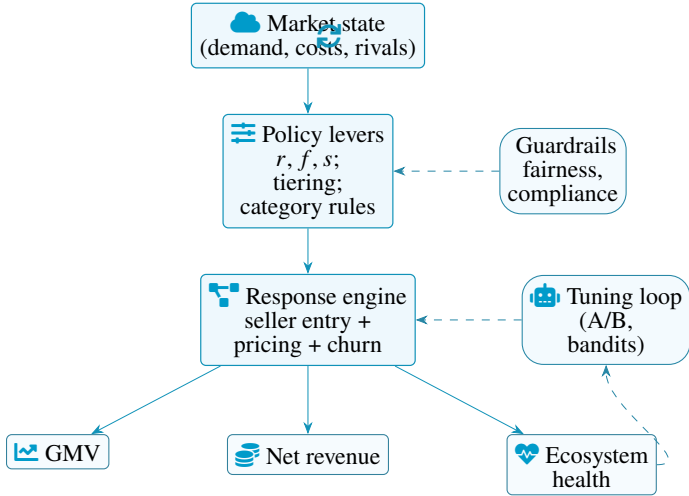


Figure 4: Platform-level control view: policy levers (commission, fixed fees, tiering) interact with market conditions to induce seller entry, pricing, and churn responses that jointly determine GMV, net revenue, and ecosystem health. Guardrails constrain feasible policies while an experimentation loop tunes parameters under feedback from health metrics.

results generated by this framework are intended to inform platform governance and seller strategy without assuming a particular normative objective beyond clarity about trade-offs.

2. Commission and Fee Policy Environment in Platform Retail

Platform fee menus typically include an ad valorem commission rate applied to transaction revenue, sometimes net of shipping and taxes and sometimes gross, depending on the platform [7]. Additional

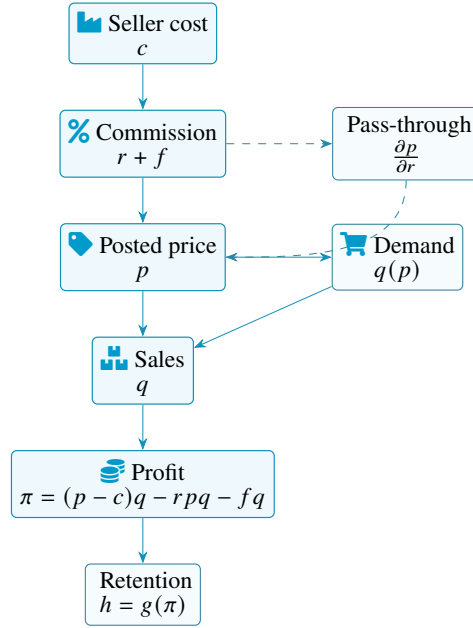


Figure 5: Compact equilibrium pathway: fee changes shift the effective marginal wedge, inducing price adjustments (pass-through), demand changes, and profit impacts that update retention incentives. The structure separates the mechanical effect of the wedge from behavioral pricing responses captured by the pass-through sensitivity.

Plan type	Commission rate (%)	Fixed listing fee (\$)	Other fees (%)
Basic	5.0	0.00	0.0
Standard	10.0	0.10	0.5 (payment)
Premium	15.0	0.25	1.0 (promotion)
Enterprise	12.5	0.00	0.8 (services)

Table 1: Commission schemes and fee components offered by the platform.

components often include a per-order fee, payment processing fees that behave like a combination of fixed and variable charges, and optional services such as fulfillment, advertising, and premium analytics. Platforms also use category-specific rate cards, sometimes with tiered schedules that change at revenue thresholds or by product price bands. From the seller's perspective, this implies that the marginal revenue from a sale is not simply price minus cost; it is price net of a revenue share, net of per-transaction fees, and net of any endogenous service fees that may be required to be competitive. Because exposure and conversion can depend on service adoption, a fee change in one instrument can propagate into effective costs through induced changes in service usage.

Policy changes take several forms [8]. A platform can change the headline ad valorem rate for a category, introduce a new tier that reduces commissions above a volume threshold, add a per-item fee to fund customer support, or modify subscription plans that bundle listing limits and discounts on variable fees. Separately, the platform can change the pricing of optional services such as sponsored listings, which often operate as auctions and thus translate into an endogenous cost per click that varies across sellers. Fulfillment fees can also change with dimensional weight rules, seasonal surcharges, or storage fees, which are partly fixed and partly volume-related. Importantly, sellers may perceive some of these fees as more salient than others. A salient commission increase can trigger immediate repricing, while a more complex fulfillment fee change may generate gradual adjustment as sellers learn its incidence

Period	Policy change	Avg commission (%)	Avg fixed fee (\$)
Pre-2018	Baseline schedule	9.8	0.04
2018Q1–2018Q4	Higher fees for low-price items	11.2	0.09
2019Q1–2019Q4	Volume discounts	10.5	0.06
2020Q1–2020Q4	Promotional credit cap	10.8	0.05
2021Q1–2021Q4	New premium tier	11.6	0.08
2022Q1–2022Q4	Simplified fee menu	10.1	0.03

Table 2: Timeline of major fee policy changes on the platform.

Commission tier	New sellers per month	Avg listing price (\$)	Share of promo usage (%)
≤ 7%	1,420	18.3	22.1
7%–10%	1,010	21.7	28.4
10%–13%	760	24.9	35.2
> 13%	430	27.1	41.7

Table 3: Seller entry and initial pricing by commission tier.

Specification	Commission coefficient	Std. error	R^2
(1) OLS, no controls	−0.85	0.14	0.18
(2) + category fixed effects	−0.62	0.11	0.34
(3) + seller fixed effects	−0.54	0.09	0.47
(4) + time × category FE	−0.49	0.08	0.53
(5) IV, policy-induced variation	−0.71	0.19	0.29

Table 4: Effect of commission rates on the log number of entering sellers.

Specification	Commission coefficient	Std. error	Pass-through (%)
(1) Baseline	0.31	0.05	62.0
(2) + seller FE	0.24	0.04	48.0
(3) + demand controls	0.21	0.04	42.0
(4) High-competition subsample	0.15	0.06	30.0
(5) Low-competition subsample	0.39	0.07	78.0

Table 5: Estimated pass-through of commission changes into listing prices.

[9]. Salience matters because it affects how quickly equilibrium moves and whether short-run estimates capture long-run effects.

Commission structures also interact with return policies and fraud risk. If a commission is charged on gross revenue and later refunded upon return, then commission incidence depends on return rates and timing. Sellers with high return categories face additional working capital risk, especially when commission refunds are delayed. A commission increase in such categories can therefore disproportionately reduce entry and increase exit even if average margins remain positive [10]. Similarly, fee schedules

Seller segment	Pre-change 12m retention (%)	Post-change 12m retention (%)	Change (pp)
Bottom quartile (sales)	41.3	36.8	-4.5
Second quartile	58.9	54.2	-4.7
Third quartile	71.5	69.8	-1.7
Top quartile	84.1	83.4	-0.7

Table 6: Seller retention before and after a platform-wide commission increase.

Price response band	Share of sellers (%)	Avg price change (%)	Avg quantity change (%)
Decrease > 5%	18.7	-8.4	9.6
Decrease $\leq$ 5%	22.3	-3.1	4.2
No change ($\pm 1\%$)	29.5	-0.2	0.3
Increase $\leq$ 5%	17.1	2.7	-3.4
Increase > 5%	12.4	7.9	-7.8

Table 7: Distribution of seller price adjustments following a fee policy change.

Revenue component	Pre-change share (%)	Post-change share (%)	Change (pp)
Commission on sales	63.2	69.5	6.3
Fixed and listing fees	11.8	8.9	-2.9
Advertising and promo	17.4	15.1	-2.3
Payment services	7.6	6.5	-1.1

Table 8: Decomposition of platform revenue before and after fee schedule reform.

Sample / outcome	Commission coefficient	<i>p</i> -value	Observations
Main sample, entry rate	-0.54	0.001	9,600
Excl. top 1% sellers	-0.51	0.003	9,130
New categories only	-0.63	0.012	3,420
High-frequency sellers	-0.49	0.008	4,050
Alt. fee definition (net)	-0.58	0.004	9,600

Table 9: Robustness of commission effects on seller entry across samples and definitions.

can include penalties for late shipment or customer complaints, creating a nonlinear mapping from operational performance to effective costs. These performance-contingent fees can change selection by favoring sellers with better logistics and process control, thereby affecting retention and the distribution of quality.

The platform's ranking and recommendation systems create an additional layer. If ranking rewards competitive prices, fast delivery, and high conversion, then fee changes that increase marginal costs can reduce ranking, lowering demand, which further reduces the ability to cover fixed fees. This complementarity implies that fee changes can have amplified effects on low-scale sellers who are near viability thresholds [11]. Conversely, if the platform smooths exposure for small sellers to encourage variety, then some fee increases may be absorbed through reduced platform take on ancillary services or through

promotional subsidies. Empirically, these compensatory adjustments can confound naive before-after comparisons unless the analyst models the full menu and measures changes in exposure.

A useful organizing concept is the seller's effective take rate, defined as the ratio of total platform payments to gross merchandise value. Even if the headline commission is unchanged, changes in advertising costs, fulfillment fees, and subscription uptake can shift effective take rates [12]. Policy changes can therefore be reinterpreted as shocks to the mapping from seller actions to effective take rates. The empirical task is to isolate variation that shifts this mapping in a known way and to separate mechanical accounting effects from behavioral responses. For instance, if the platform reduces the ad valorem rate but increases per-transaction fees, low-price items may face a higher effective take rate while high-price items face a lower one. Aggregated outcomes can mask this redistribution, making it necessary to analyze incidence by price level, margin, and seller scale.

Fee policy changes also affect seller strategy through inventory and assortment [13]. Sellers choose which products to list and how to allocate limited attention across listing optimization, customer service, and advertising. When variable fees increase, sellers may drop low-margin variants, raising average prices and potentially improving measured conversion if unprofitable traffic is avoided. When fixed fees increase, sellers may consolidate into fewer, higher-volume listings to amortize the fixed cost, which can reduce variety. A platform that relies on long-tail variety may therefore prefer variable fees to fixed fees, even if fixed fees stabilize revenue. The framework in the next section formalizes these trade-offs by embedding fee instruments into a seller profit function and a dynamic participation problem [?].

3. A Model of Seller Entry, Pricing, and Retention Under Fee Menus

Consider a platform marketplace with a continuum of sellers indexed by i and a set of product categories indexed by k . Time is discrete, $t = 0, 1, 2, \dots$. Each seller can choose whether to be active on the platform in a category, list products, set prices, and choose optional services such as advertising intensity and fulfillment mode. Let the platform fee menu in category k at time t be summarized by $\Phi_{kt} = (\tau_{kt}, f_{kt}, F_{kt}, \psi_{kt})$, where $\tau_{kt} \in [0, 1]$ is the ad valorem commission rate, $f_{kt} \geq 0$ is a per-transaction fee, $F_{kt} \geq 0$ is a per-period fixed fee (subscription or mandatory compliance cost), and ψ_{kt} denotes parameters governing optional service pricing, including the cost of advertising and fulfillment. A seller's type θ_i captures persistent differences in marginal cost, product quality, and operational capability. Sellers also face idiosyncratic shocks ε_{ikt} that shift demand or costs each period.

Demand for seller i 's representative product in category k is modeled as a function of price and service attributes [14]. Let p_{ikt} be the posted price, and let s_{ikt} be a service vector that includes delivery speed, fulfillment choice, and advertising intensity. A reduced-form demand function is $q_{ikt} = D_k(p_{ikt}, s_{ikt}, x_{ikt}, m_{kt}, \xi_{ikt})$, where x_{ikt} are observed listing characteristics, m_{kt} captures market-level conditions such as category traffic and competitor prices, and ξ_{ikt} is an unobserved demand shifter. To connect to pricing incentives, assume that for interior solutions demand is differentiable in price with elasticity $\epsilon_{ikt} = -\frac{\partial q_{ikt}}{\partial p_{ikt}} \frac{p_{ikt}}{q_{ikt}} > 1$. Seller marginal cost is $c_{ikt} = c_k(\theta_i, z_{ikt}) + u_{ikt}$, where z_{ikt} are observed cost shifters and u_{ikt} is an unobserved cost shock.

Given the fee menu, per-period operating profit for an active seller can be expressed as

$$\pi_{ikt} = (1 - \tau_{kt})p_{ikt}q_{ikt} - c_{ikt}q_{ikt} - f_{kt}q_{ikt} - C_k(s_{ikt}; \psi_{kt}) - F_{kt} + \varepsilon_{ikt}^\pi, \quad (3.1)$$

$$= ((1 - \tau_{kt})p_{ikt} - c_{ikt} - f_{kt})q_{ikt} - C_k(s_{ikt}; \psi_{kt}) - F_{kt} + \varepsilon_{ikt}^\pi, \quad (3.2)$$

where $C_k(s_{ikt}; \psi_{kt})$ captures optional service costs, which may include an advertising spend component and a fulfillment fee component that can depend on quantity and product dimensions, and ε_{ikt}^π aggregates residual profit shocks. The key feature is that ad valorem and per-transaction fees reduce the seller's marginal return from sales, while fixed fees shift the intercept of the profit function and therefore affect entry and exit thresholds.

Conditional on demand primitives, the seller's static pricing problem in period t chooses p_{ikt} to maximize π_{ikt} holding s_{ikt} fixed. Using the envelope condition for q_{ikt} , the first-order condition for

price is

$$\frac{\partial \pi_{ikt}}{\partial p_{ikt}} = (1 - \tau_{kt})q_{ikt} + ((1 - \tau_{kt})p_{ikt} - c_{ikt} - f_{kt}) \frac{\partial q_{ikt}}{\partial p_{ikt}} = 0. \quad (3.3)$$

Rearranging yields a Lerner-style condition with an effective marginal cost:

$$\frac{(1 - \tau_{kt})p_{ikt} - (c_{ikt} + f_{kt})}{(1 - \tau_{kt})p_{ikt}} = \frac{1}{\epsilon_{ikt}}, \quad (3.4)$$

$$p_{ikt} = \frac{c_{ikt} + f_{kt}}{(1 - \tau_{kt})} \frac{\epsilon_{ikt}}{\epsilon_{ikt} - 1}. \quad (3.5)$$

This expression clarifies incidence. An increase in τ_{kt} scales up the effective marginal cost by a factor $\frac{1}{1 - \tau_{kt}}$, amplifying the markup even if the elasticity is unchanged. A per-transaction fee f_{kt} enters as an additive marginal cost, which has stronger proportional effects on low-priced items and can induce discontinuous assortment changes when f_{kt} exceeds gross margin for some products. If the seller can adjust service choices s_{ikt} , then the commission can also affect the optimal intensity of advertising and fulfillment. For instance, if advertising increases demand but is paid per click, higher commissions reduce the marginal profit per conversion and can reduce optimal ad bids, which can lower demand and further alter optimal prices through changes in elasticity and exposure [15].

To incorporate entry and retention, sellers face a dynamic participation problem. Let $a_{ikt} \in \{0, 1\}$ indicate whether seller i is active in category k at time t . If inactive, the seller may enter by paying a sunk setup cost K_{ik} , which can include listing creation, compliance, and initial inventory positioning. If active, the seller may exit and receive an outside value V_{ik}^0 that can reflect sales on alternative channels or liquidation. Let the seller discount factor be $\beta \in (0, 1)$. The value function for a potential seller can be written as

$$V_{ik}(x_{ikt}, \Phi_{kt}, \eta_{ikt}) = \max \{V_{ik}^{\text{in}}(x_{ikt}, \Phi_{kt}, \eta_{ikt}), V_{ik}^{\text{out}}(x_{ikt}, \Phi_{kt}, \eta_{ikt})\}, \quad (3.6)$$

where η_{ikt} collects the state variables relevant for demand and costs, including beliefs about ξ_{ikt} and u_{ikt} if these are partially observed. The outside option can be normalized as [16]

$$V_{ik}^{\text{out}} = V_{ik}^0 + \beta \mathbb{E} [V_{ik}(x_{ik,t+1}, \Phi_{k,t+1}, \eta_{ik,t+1}) \mid a_{ikt} = 0]. \quad (3.7)$$

If the seller enters or remains active, per-period profit is earned net of fixed fees, and the seller chooses price and services. The in-platform value is

$$V_{ik}^{\text{in}} = -1\{a_{ik,t-1} = 0\}K_{ik} + \max_{p_{ikt}, s_{ikt}} \{\pi_{ikt}(p_{ikt}, s_{ikt}; \Phi_{kt}) + \beta \mathbb{E} [V_{ik}(x_{ik,t+1}, \Phi_{k,t+1}, \eta_{ik,t+1}) \mid a_{ikt} = 1]\}. \quad (3.8)$$

Retention emerges from the comparison between V_{ik}^{in} and V_{ik}^{out} . A fee increase that raises F_{kt} reduces V_{ik}^{in} one-for-one each period, potentially inducing exit for sellers with low continuation value. An increase in τ_{kt} or f_{kt} reduces V_{ik}^{in} through lower static profits and also through induced changes in s_{ikt} and therefore future demand. Selection arises because sellers with different θ_i have different cost levels and elasticities, and therefore different profit sensitivity to fees.

To capture learning and gradual adjustment, suppose sellers do not observe their persistent demand shifter ξ_i perfectly at entry. Instead, each period they observe sales realizations that update beliefs [?]. Let μ_{it} denote the posterior mean of ξ_i and σ_{it}^2 its posterior variance. Then the state includes $(\mu_{it}, \sigma_{it}^2)$, and retention decisions depend on the option value of learning. Fee increases that raise fixed costs can truncate learning by inducing early exit, reducing the platform's ability to discover high-quality sellers among noisy early signals. This mechanism implies that short-run exit responses can be amplified in the

long run through reduced survival of potentially good sellers, particularly in categories with high initial uncertainty.

Competition can be incorporated by allowing demand to depend on the distribution of prices and qualities in the category. Let M_{kt} be the set of active sellers, and define an aggregate price index P_{kt} and quality index Q_{kt} that enter consumer choice. A tractable approach is to use a logit demand structure at the product level, where the share of seller i in category k is

$$s_{ikt} = \frac{\exp(\delta_{ikt} - \alpha_k p_{ikt})}{1 + \sum_{j \in M_{kt}} \exp(\delta_{jkt} - \alpha_k p_{jkt})}, \quad \delta_{ikt} = \gamma_k^\top x_{ikt} + \lambda_k^\top s_{ikt} + \xi_{ikt}. \quad (3.9)$$

Quantity is $q_{ikt} = s_{ikt} \cdot \mathcal{D}_{kt}$ where $\mathcal{D}_{kt}$ is category traffic. Under this structure, a seller's price elasticity depends on its share and the diversion to outside options and competitors [17]. Fee-induced repricing by many sellers changes shares and elasticities, producing general equilibrium effects. A commission increase that raises prices across the board can reduce total category demand, potentially lowering platform revenue even if take rates rise, depending on the demand elasticity at the category level and the extent of substitution to offline or other platforms.

Optional service choice can be modeled as an investment that shifts δ_{ikt} or $\mathcal{D}_{kt}$. For example, advertising can increase exposure, effectively increasing δ_{ikt} , but at a cost that depends on auction competition. Let advertising intensity be A_{ikt} and its cost be $g_k(A_{ikt}; \psi_{kt})$, with marginal cost increasing in A_{ikt} . If advertising increases perceived quality or exposure linearly, $\delta_{ikt} = \bar{\delta}_{ikt} + \rho_k A_{ikt}$, then optimal advertising satisfies

$$\frac{\partial \pi_{ikt}}{\partial A_{ikt}} = ((1 - \tau_{kt})p_{ikt} - c_{ikt} - f_{kt}) \frac{\partial q_{ikt}}{\partial A_{ikt}} - \frac{\partial g_k(A_{ikt}; \psi_{kt})}{\partial A_{ikt}} = 0. \quad (3.10)$$

Higher τ_{kt} reduces the marginal profit per incremental sale and therefore reduces optimal A_{ikt} , which can lower q_{ikt} and change the slope of demand with respect to price. This interaction implies that pass-through estimates that ignore advertising adjustment may be biased, because the observed price response includes indirect demand shifts from changed advertising.

The platform's fee design problem can be expressed, without committing to a specific welfare criterion, as choosing Φ_{kt} to maximize an objective that includes platform revenue and potentially a function of marketplace health. Platform revenue in category k is

$$R_{kt} = \sum_{i \in M_{kt}} (\tau_{kt} p_{ikt} q_{ikt} + f_{kt} q_{ikt} + F_{kt} + r_k(s_{ikt}; \psi_{kt})), \quad (3.11)$$

where r_k captures revenue from optional services, such as advertising fees [18]. Because M_{kt} depends on retention and entry, and because p_{ikt} and s_{ikt} depend on Φ_{kt} , the platform faces a dynamic mechanism design problem with selection. The analysis in subsequent sections treats fee changes as exogenous or policy-driven shocks for identification, while acknowledging that platforms may time changes in response to market conditions. This motivates empirical designs that exploit differential exposure across categories or sellers that is predetermined relative to the timing of changes.

4. Identification and Estimation of Fee Effects in the Presence of Endogenous Exposure

Empirical analysis of commission and fee policy changes must confront several sources of confounding. Platforms rarely change only one parameter at a time; sellers and competitors respond strategically; and platform exposure mechanisms can shift contemporaneously. A workable identification strategy therefore uses variation that is plausibly exogenous to individual sellers' contemporaneous shocks and that generates heterogeneous treatment intensity [?]. The setting often provides three such sources: category-specific rate changes, threshold-based fee schedules, and seller-specific exposure to per-transaction fees determined by pre-change price and quantity distributions.

Suppose a platform changes τ_{kt} for a subset of categories at date T_0 , leaving other categories unchanged, and suppose categories are otherwise comparable after controlling for time-varying category demand. A difference-in-differences framework can estimate average effects on prices and quantities, but the model indicates that composition changes can contaminate price estimates if entrants and exits differ by treatment status. A more robust approach tracks a balanced panel of incumbent sellers around the change to estimate within-seller price responses while separately modeling entry and exit. Let y_{ikt} denote an outcome such as log price, log quantity, or an indicator for activity. A basic event-time specification for incumbents is

$$y_{ikt} = \sum_{\ell \neq -1} \beta_\ell 1\{t - T_0 = \ell\} \cdot \text{Treat}_k + \alpha_i + \delta_t + \kappa_k + \varepsilon_{ikt}, \quad (4.1)$$

where α_i are seller fixed effects, δ_t are time fixed effects, κ_k are category fixed effects, and Treat_k indicates categories with a fee change. The coefficients β_ℓ trace dynamic adjustment and allow pre-trend assessment. However, even among incumbents, treatment can affect exposure via ranking and advertising [19]. If exposure shifts are correlated with unobserved shocks, then ε_{ikt} may be correlated with treatment in event time.

To address endogenous exposure, one can incorporate direct measures of impressions, search rank, or platform traffic, and treat them as mediators rather than controls depending on the estimand. If the goal is the total effect of fee changes on outcomes, controlling for exposure may block part of the causal pathway. If the goal is the direct pricing response holding exposure fixed, then controlling for exposure is appropriate but requires credible measurement and timing. A pragmatic approach estimates both total and conditional effects: one specification without exposure controls, interpreting coefficients as reduced-form equilibrium responses, and another with exposure controls, interpreting coefficients as partial equilibrium pass-through conditional on platform-provided visibility [20].

Treatment intensity can be refined using predicted changes in effective marginal cost. From the pricing condition, the effective marginal cost component affected by fees is $\tilde{c}_{ikt} = \frac{c_{ikt} + f_{kt}}{1 - \tau_{kt}}$. A small change in (τ_{kt}, f_{kt}) implies

$$d\tilde{c}_{ikt} = \frac{1}{1 - \tau_{kt}} df_{kt} + \frac{c_{ikt} + f_{kt}}{(1 - \tau_{kt})^2} d\tau_{kt}. \quad (4.2)$$

If seller-level marginal costs are unobserved, one can approximate c_{ikt} using pre-change gross margins or using cost proxies such as wholesale prices for standardized goods. Alternatively, one can use predicted exposure based on pre-change price level and category-level averages. The idea is to construct an instrument-like shifter Z_{ik} that captures the mechanical incidence of the fee change absent behavioral adjustment. For example, if the platform introduces a per-transaction fee increase Δf_k , the implied proportional change in effective marginal cost is larger for low-priced items. A pre-change average price $\bar{p}_{ik,\text{pre}}$ can therefore predict intensity as $\Delta f_k / \bar{p}_{ik,\text{pre}}$. This allows a continuous-treatment event study:

$$y_{ikt} = \sum_{\ell \neq -1} \beta_\ell 1\{t - T_0 = \ell\} \cdot Z_{ik} + \alpha_i + \delta_t + \kappa_k + \varepsilon_{ikt}. \quad (4.3)$$

Because Z_{ik} is computed from pre-change outcomes, it is predetermined with respect to post-change shocks, although it can still correlate with unobserved seller traits. Seller fixed effects mitigate this concern for incumbent analysis.

Entry and retention require separate treatment because the set of observed sellers changes endogenously [21]. Entry can be measured as the count of new sellers listing in a category per period, potentially normalized by category traffic. A Poisson or negative binomial model with category and time fixed effects can estimate semi-elasticities with respect to fee changes:

$$\mathbb{E}[\text{Entry}_{kt} \mid \cdot] = \exp(\omega_k + \delta_t + \theta \Delta \tau_{kt} + \phi \Delta f_{kt} + \nu \Delta F_{kt} + \Gamma^\top W_{kt}), \quad (4.4)$$

where W_{kt} includes controls for category demand and competition. Identification relies on the assumption that absent the fee change, entry trends would have been similar after conditioning on W_{kt} . Because entry is forward-looking, anticipation effects are plausible; event-time leads can detect pre-change adjustments, and one can redefine treatment timing as announcement date rather than implementation date when available.

Retention can be modeled using a discrete-time hazard framework where the probability of exit depends on profitability proxies and fees. Let $Exit_{i,t+1}$ indicate that seller i is inactive at $t + 1$ given active at t . A logit hazard can be written as [22]

$$\Pr(Exit_{i,t+1} = 1 \mid a_{it} = 1, \cdot) = \Lambda(\chi_i + \delta_t + \zeta_k + \lambda_1 \tau_{kt} + \lambda_2 f_{kt} + \lambda_3 F_{kt} + \lambda_4 \hat{\pi}_{ikt} + \lambda_5 \text{Exposure}_{ikt}), \quad (4.5)$$

where $\Lambda(\cdot)$ is the logistic function and $\hat{\pi}_{ikt}$ is a profitability proxy such as contribution margin net of fees and shipping. Interpreting $\lambda_1, \lambda_2, \lambda_3$ causally requires that unobserved shocks affecting exit are not simultaneously driving fee changes, which motivates category-level treatment variation and rich time controls. One can also exploit within-category heterogeneity in intensity using pre-change price distributions, as above, to identify how fee incidence drives exit. Importantly, the hazard model must accommodate left truncation and tenure dependence, as newer sellers may have different baseline exit rates.

To connect reduced-form estimates to the structural model, demand estimation is necessary to interpret price changes as pass-through versus changes in market power or composition. If product-level panel data are available, a demand system such as a logit with product fixed effects can be estimated using instruments for price that exploit cost shifters or fee changes that are plausibly orthogonal to unobserved demand [23]. Fee changes provide a natural instrument because they shift marginal incentives, but only if they are not correlated with demand shocks. Category-specific fee changes that are announced according to a predetermined calendar can strengthen this assumption. With estimated price sensitivity α_k and mean utilities δ_{ikt} , one can infer implied markups and assess whether fee changes alter competitive conduct or simply shift costs.

A practical estimation sequence proceeds by first estimating within-incumbent price responses to fee changes using event-time and intensity variation, then estimating entry and exit responses using category-level counts and hazard models, and finally estimating demand to translate observed price changes into welfare and revenue implications. Structural estimation can then calibrate the dynamic participation model by matching moments such as the distribution of tenure, the response of exit hazards to profitability, and the entry elasticity to fixed fees. The resulting model can simulate long-run steady states under alternative fee menus, capturing selection and learning effects [24].

A central empirical nuance is that sellers can change their service adoption in response to fees, which alters both costs and demand. If fulfillment or advertising adoption is observed, one can model it as an endogenous choice with its own first-order condition or discrete choice structure. In reduced form, one can treat service adoption as an intermediate outcome and estimate how fees shift adoption and how adoption mediates sales and exit. In structural form, one can include service choice directly in π_{ikt} and estimate its effect on demand. Either way, ignoring service substitution risks misattributing changes in sales to direct fee effects when they occur via reduced advertising or slower shipping [25].

5. Counterfactual Fee Design, Market Outcomes, and Retention Dynamics

Counterfactual analysis evaluates how alternative commission structures would change equilibrium outcomes, including prices, variety, seller churn, and platform revenue stability. The structural model provides a mapping from a fee menu Φ_{kt} to seller pricing, service intensity, and participation decisions. Given estimated demand parameters and calibrated cost and exit processes, one can simulate market trajectories under candidate fee policies. The central trade-off is between marginal distortion and fixed-cost screening. Ad valorem commissions raise effective marginal costs and therefore tend to increase

prices and reduce quantities, which can reduce consumer surplus and potentially total platform revenue if demand is elastic. Fixed fees, by contrast, do not distort marginal pricing directly but can deter entry and accelerate exit among low-volume sellers, reducing variety and potentially raising concentration [26].

A revenue-neutral swap illustrates these trade-offs. Consider reducing τ_{kt} by $\Delta\tau < 0$ while increasing F_{kt} by $\Delta F > 0$ to keep expected platform revenue unchanged under baseline behavior. In partial equilibrium holding seller sets fixed, lower τ_{kt} reduces effective marginal cost and lowers prices via the pricing condition. In general equilibrium, lower prices can increase category demand and shift shares. However, higher F_{kt} reduces the value of participation, inducing exit among marginal sellers and reducing entry. The net effect on prices depends on the balance between lower marginal distortion and reduced competition from fewer sellers. If demand is highly substitutable across sellers, fewer sellers can increase market power and attenuate price reductions. If products are differentiated and competition is limited, the price effect may be dominated by the marginal-cost channel and still be negative [27].

These competing forces can be expressed in comparative statics. Let $\bar{p}_{kt}$ be an aggregate price index, and let N_{kt} be the number of active sellers. A reduced-form approximation is

$$d \log \bar{p}_{kt} \approx \underbrace{\omega_1 d \log \tilde{c}_{kt}}_{\text{marginal incentive}} + \underbrace{\omega_2 d \log N_{kt}}_{\text{competition and variety}} + \underbrace{\omega_3 d \log E_{kt}}_{\text{exposure and services}}, \quad (5.1)$$

where $\tilde{c}_{kt}$ is an average effective marginal cost induced by fees, E_{kt} captures exposure and service quality, and $\omega_1, \omega_2, \omega_3$ are elasticities implied by the demand system. A policy that reduces $\tilde{c}_{kt}$ but also reduces N_{kt} has an ambiguous net effect. Structural simulation resolves this by jointly determining N_{kt} through entry and exit and E_{kt} through service choice.

Retention dynamics add an intertemporal dimension. If fixed fees increase, marginal sellers may exit earlier, which reduces future competition and can change incumbents' profitability. This can generate a positive feedback loop: exit reduces competition, which increases incumbents' profits, potentially stabilizing retention among remaining sellers [?]. At the same time, reduced entry can lower innovation and variety, potentially reducing consumer demand and harming incumbents. The net effect depends on how consumers value variety and on how platform search and recommendation allocate traffic when variety declines. In a demand system where the outside option becomes more attractive when variety shrinks, reduced variety can lower total category demand, offsetting increased margins for incumbents.

Policy changes in per-transaction fees provide a different set of counterfactual implications because they disproportionately affect low-priced items. A per-transaction fee increase can induce sellers to raise prices to restore contribution margins, potentially causing bunching at price points where consumers are less sensitive or where platform fee thresholds change [28]. If the platform has tiered commissions by price band, a per-transaction fee can interact with these tiers to create kinks in optimal pricing. Sellers might increase prices to move into a band with lower ad valorem rates or to increase absolute margin per transaction. Such behavior can change the distribution of prices in ways that affect consumer search and platform ranking if ranking rewards lower prices. The model can incorporate these kinks by allowing $\tau_{kt}(p)$ to be piecewise constant or by including thresholds based on revenue. Equilibrium can exhibit price clustering near thresholds, which is informative for identifying the role of fee salience and optimization frictions.

Optional service fees, particularly advertising, raise questions about the distinction between commissions and marketing costs [29]. If the platform increases advertising auction reserve prices or changes relevance scoring that increases average cost per click, sellers may reduce advertising intensity, lowering demand and potentially raising prices if elasticity decreases for remaining buyers. Conversely, some sellers may increase advertising to defend share, treating it as a strategic complement to pricing. Counterfactuals that cap advertising fees or provide advertising credits can therefore indirectly affect prices and retention. In the model, advertising shifts δ_{ikt} and therefore shares, and its optimality condition depends on the margin net of fees. A lower commission rate increases margin and can increase optimal

advertising, which can further increase demand and improve seller survival probabilities, especially for new entrants who rely on paid visibility to overcome cold-start problems [30]. This interaction implies that fee reductions can have multiplicative effects on seller growth and retention when they relax the constraint on customer acquisition spending.

From the platform perspective, revenue volatility matters. Ad valorem commissions scale with sales and therefore are pro-cyclical, while fixed fees provide a stabilizing revenue component. A platform may prefer a mix that balances revenue stability with marketplace growth. The model can quantify revenue volatility by simulating demand shocks at the category level and computing the variance of platform revenue under different fee mixes [31]. A fee menu with higher fixed components reduces revenue variance conditional on participation, but it may increase variance by making participation more sensitive to shocks, causing discrete exit waves during downturns. This endogenous participation volatility can dominate mechanical stabilization, leading to higher long-run volatility in seller counts and possibly in consumer demand. Counterfactual evaluation should therefore track both revenue variance and the variance of active sellers and listings.

Seller welfare and marketplace health can be proxied by the distribution of seller profits and the churn rate. A fee increase that raises platform revenue can still reduce long-run revenue if it increases churn and reduces demand [32]. The dynamic model captures this via the effect of fees on continuation values and learning. If early sales are noisy and informative, then policies that increase early-period fixed costs can prevent sellers from reaching the scale where their type is revealed and where they become profitable. Counterfactuals that reduce fixed fees for new sellers, such as introductory discounts or graduated fee schedules, can increase entry and improve selection by allowing more experimentation. However, such policies can also attract low-quality entrants and increase consumer risk if quality screening is weak. The model can incorporate this by allowing seller type to affect complaint rates or return rates, which enter platform costs and potentially fee penalties [33]. Under such an extension, the platform can use fee design as an indirect screening mechanism, trading off experimentation against quality control.

Pricing strategies under fee changes also include pass-through heterogeneity and strategic absorption. Sellers with strong differentiation or brand loyalty may pass through more of a commission increase, while sellers in commodity segments may absorb fees to maintain rank and conversion. The logit demand structure implies that pass-through depends on own-share and substitution patterns. In categories with high diversion to outside options, pass-through is lower because price increases lead to large quantity losses [34]. In categories with high within-platform substitution, pass-through may be higher because the seller can rely on loyal segments or because competitors also raise prices, reducing the penalty for increasing price. Counterfactual simulations can separate within-seller pricing changes from market-level price indices and can quantify how much of a fee change is borne by consumers versus sellers.

Retention implications can be summarized by simulating the hazard path for cohorts of entrants under each fee menu. One can compute survival curves and compare median tenure, as well as the distribution of cumulative sales per entrant [35]. Fee policies that reduce early churn but allow later exit of persistently unprofitable sellers can increase efficiency by improving the match between seller type and platform fit. Policies that increase early churn may reduce platform congestion but can also reduce discovery of high-quality sellers. Because these effects depend on the variance of demand shocks and the informativeness of early sales, the counterfactual results are sensitive to assumptions about learning and noise. Sensitivity analysis can vary the signal-to-noise ratio in early demand and assess robustness of conclusions about the desirability of fixed-fee increases.

The counterfactual section also highlights implementation constraints [36]. Platforms may face regulatory or reputational limits on fee discrimination across sellers, and they may need to keep fee schedules simple for salience and trust. A theoretically optimal nonlinear tariff might be infeasible. Therefore, counterfactuals should focus on plausible menus, such as modest category-level adjustments, tiering by verified volume, or time-limited entry subsidies. The model can evaluate these menus while acknowledging that enforcement and compliance costs can rise with complexity, effectively increasing F_{kt} . Incorporating an administrative cost term into platform objectives can rationalize why platforms sometimes prefer blunt commission changes over finely targeted menus.

6. Conclusion

Commission structures and fee policy changes in platform-based retail affect seller entry, pricing strategies, and retention through interconnected marginal, fixed-cost, and selection channels [37]. Ad valorem commissions and per-transaction fees alter effective marginal costs and therefore shift optimal pricing and marketing intensity, while subscription-like fees and compliance costs reshape participation thresholds and amplify the role of liquidity and risk. Because seller participation is dynamic and subject to learning, fee changes influence not only contemporaneous outcomes but also the long-run composition of sellers and the evolution of competition and variety. Optional services such as advertising and fulfillment further complicate incidence by creating endogenous service adoption that can mediate both demand and costs.

The modeling framework in this paper integrates static pricing under commissions with a dynamic participation problem that captures entry, exit, and learning. The resulting structure clarifies how changes in fee instruments propagate through seller decision rules and how equilibrium feedbacks can amplify or dampen direct effects [38]. The empirical design discussed here emphasizes discrete policy changes with heterogeneous exposure, event-time dynamics, and separation of incumbent pricing responses from entry and exit adjustments. Constructing treatment intensity from predetermined pre-change behavior provides a practical way to measure mechanical incidence and to diagnose heterogeneous pass-through and churn effects.

Counterfactual analysis illustrates that revenue-neutral shifts among fee instruments can have materially different implications for prices, seller churn, and variety. Fixed fees can reduce marginal distortions but may deter entry and accelerate exit, potentially reducing variety and changing competitive pressure. Variable fees can preserve entry incentives but may raise prices and reduce demand, with additional effects through reduced optimal advertising and service quality [39]. The long-run consequences depend on demand elasticity, the value consumers place on variety and service attributes, and the informativeness of early sales for learning about seller type. Evaluating fee policy therefore benefits from a joint view of pricing, service choice, and dynamic selection rather than isolated analysis of commission pass-through.

The framework does not prescribe a single optimal fee schedule, since platform objectives and constraints differ, but it provides a technically explicit way to evaluate trade-offs using data commonly available to platforms and, in some cases, to external analysts. Future extensions can incorporate richer multi-product assortment decisions, endogenous multi-homing across platforms, and platform-side costs tied to returns, fraud, and customer service. Within the scope considered here, the central implication is that fee design influences marketplace outcomes as much through who participates and survives as through how individual sellers adjust posted prices, and credible measurement of these mechanisms is essential for interpreting observed effects of fee policy changes [40].

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