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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
Digital markets increasingly organize exchange through intermediated platforms that coordinate search, matching, payments, reputation, and post-transaction services. In many new digital categories, early fragmentation is followed by rapid concentration, and a single intermediary (or a small set) becomes the default locus of liquidity. This paper studies how network effects, expectation formation, and endogenous platform design jointly shape market tipping and the emergence of dominant intermediated markets. The analysis emphasizes that dominance is not mechanically implied by increasing returns; rather, tipping arises from a coupled system in which cross-side participation, perceived match quality, and governance-induced trust form complementary state variables. A dynamic model links adoption decisions to both contemporaneous participation and forward-looking beliefs about future liquidity, while allowing frictions such as multi-homing costs, switching costs, congestion, and platform learning. The framework clarifies the conditions under which multiple equilibria exist, when an unstable interior fixed point generates critical-mass dynamics, and how design levers such as ranking, subsidy allocation, and identity verification shift the basin of attraction toward a dominant equilibrium. The paper further characterizes dominance in categories where intermediation itself improves product definition, reduces measurement error in quality, and internalizes externalities through rules and enforcement. Empirical implications are developed for identifying network effects and tipping using observational data, highlighting pitfalls from reflection, simultaneity, and endogenous platform policy. Overall, the paper provides a technical account of why dominance is common but not inevitable in new digital categories.

1. Introduction

Intermediated digital markets differ from traditional pipelines because they do not merely distribute a product; they construct an environment in which heterogeneous participants can find each other, assess trustworthiness, negotiate terms, and complete transactions with low friction [1]. In many categories, this environment is itself the product, and its quality is inseparable from participation levels. A buyer's willingness to search depends on the expected density of relevant sellers, while sellers' incentives to list depend on expected buyer traffic, conversion probability, and the platform's ability to adjudicate disputes. These interdependencies create feedback loops often summarized as network effects, yet the term covers several distinct mechanisms: direct participation externalities, cross-side liquidity effects, learning-driven improvements in matching or ranking, and belief-mediated coordination. Understanding market tipping requires separating these mechanisms, specifying how they enter participant payoffs, and analyzing the resulting dynamics under realistic frictions such as multi-homing, capacity constraints, and endogenous governance choices [2].

New digital categories frequently begin with uncertainty about product boundaries, quality metrics, and the appropriate contractual form. Intermediation can reduce this uncertainty by standardizing listings, implementing identity or payment verification, and enforcing rules that transform a set of bilateral

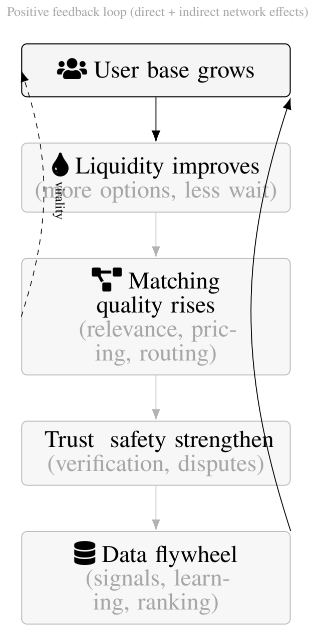

Figure 1: A compact flywheel linking growth in participants to higher liquidity, better matching, stronger trust, and data-driven optimization—creating self-reinforcing network effects that can accelerate adoption in new digital categories.

interactions into a coherent market. This implies that the platform's design choices shape not only transaction costs but also the effective substitutability among sellers and the variance of buyer experiences, both of which feed back into adoption. Dominance may emerge because a single intermediary internalizes coordination benefits, but the same feedback can also generate fragility: small shocks to trust, policy, or perceived fairness can redirect flows when participants can switch or multi-home [3].

This paper develops a unified, technical account of network effects and tipping in intermediated markets, with emphasis on how dominance emerges in new digital categories. The argument proceeds in three layers. The first layer formalizes participation complementarities and distinguishes between contemporaneous network effects and belief-based strategic complementarities. The second layer introduces a dynamic adoption model with heterogeneous agents, learning, congestion, and platform policy as endogenous control variables [4]. The third layer connects the model to observable implications and identification challenges, including the reflection problem, endogenous sorting, and policy endogeneity.

The key objective is not to claim that tipping is universal, but to characterize when it is likely and what forms it can take. Dominance can arise as a stable equilibrium in which one platform aggregates liquidity, but it can also appear as a transient state produced by aggressive subsidy schedules, by algorithmic ranking that temporarily concentrates attention, or by category-specific trust innovations that later diffuse. Intermediated markets thus require a view of competition that integrates dynamic expectations, market design, and governance, rather than relying solely on static price competition.

2. Network Effects and Intermediation as State-Dependent Quality

Consider a category in which participants must expend search effort and bear risk about quality or counterparty behavior [5]. An intermediary can reduce these costs by organizing information, providing standardized contracts, and enforcing rules. A central feature is that the value of the intermediary is endogenous to participation. Let B denote the measure of buyers and S the measure of sellers active on a platform. A minimal reduced-form representation of expected match value to a buyer is increasing in

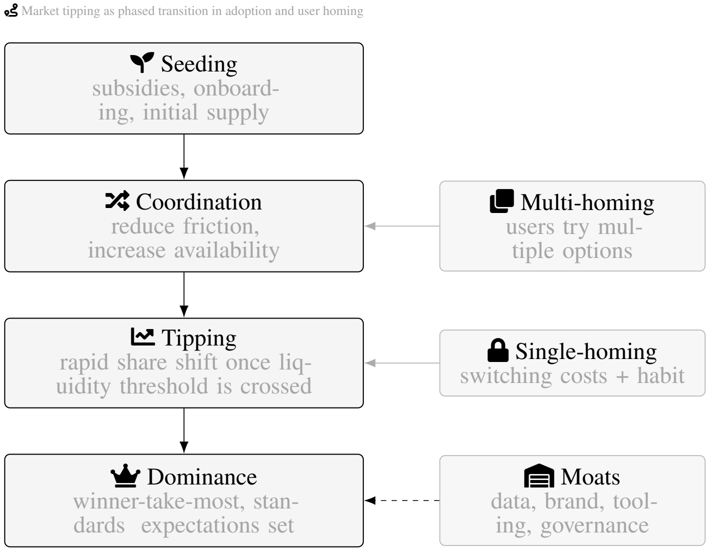

Figure 2: A phased view of market tipping: early seeding and coordination build enough liquidity to trigger a rapid share shift, after which single-homing and accumulated moats support a dominant intermediated market structure.

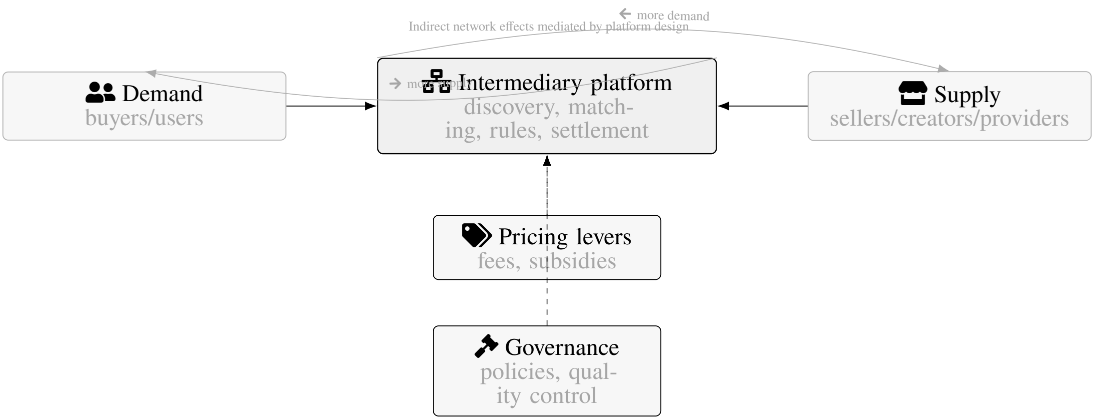

Figure 3: A two-sided intermediated market: a central platform coordinates demand and supply while shaping cross-side effects via pricing and governance, enabling rapid scale when participation and quality reinforce each other.

S, and expected sales to a seller is increasing in B [6]. However, in intermediated markets the strength of these effects is mediated by design choices that determine how efficiently the platform maps participants into successful matches. Ranking, recommendation, query matching, and anti-fraud systems determine the conversion rate from participation to transactions, making the effective network effect a function of both scale and policy.

A useful conceptual distinction is between participation externalities that operate through contemporaneous liquidity and strategic complementarities that operate through beliefs. A participant deciding whether to join today may care about current B and S, but also about expected future participation because switching and onboarding costs make joining partially irreversible [7]. If future liquidity is expected to be high, joining early may be optimal even when current liquidity is low. This creates a coordination component that can generate multiple equilibria: one in which everyone expects the platform to become liquid and thus joins, and another in which everyone expects it to remain illiquid and thus

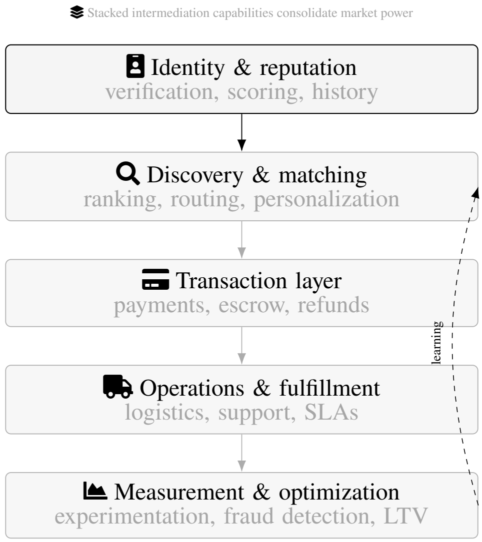

Figure 4: A layered intermediation stack: as platforms internalize identity, discovery, settlement, and operations, they reduce uncertainty and friction—making the intermediary the default coordination point for a new digital category.

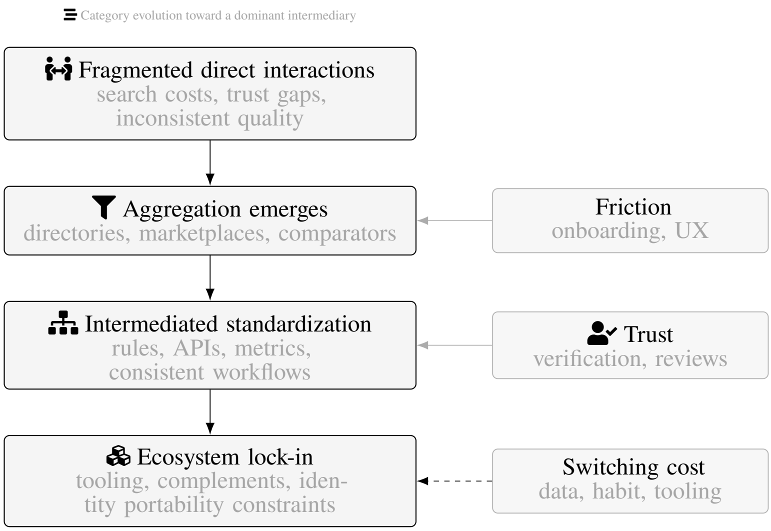

Figure 5: A progression from fragmented bilateral exchange to a standardized, intermediated market: aggregation reduces search and coordination costs, then governance and tooling can consolidate activity into a dominant ecosystem.

stays away. The fact that intermediated markets often subsidize early participation can be interpreted as an attempt to move the system across an unstable threshold separating these basins of attraction.

Intermediation also changes the variance of outcomes. In decentralized exchange, buyers may face a high variance of quality due to incomplete information and weak enforcement [8]. A platform can reduce variance by screening, reputation, and dispute resolution, increasing risk-adjusted utility even if mean quality is unchanged. Importantly, the effectiveness of these mechanisms often scales with participation because more transactions generate more data, improving screening and ranking, and because larger platforms can amortize fixed governance costs. This creates a data feedback loop, which is a form of

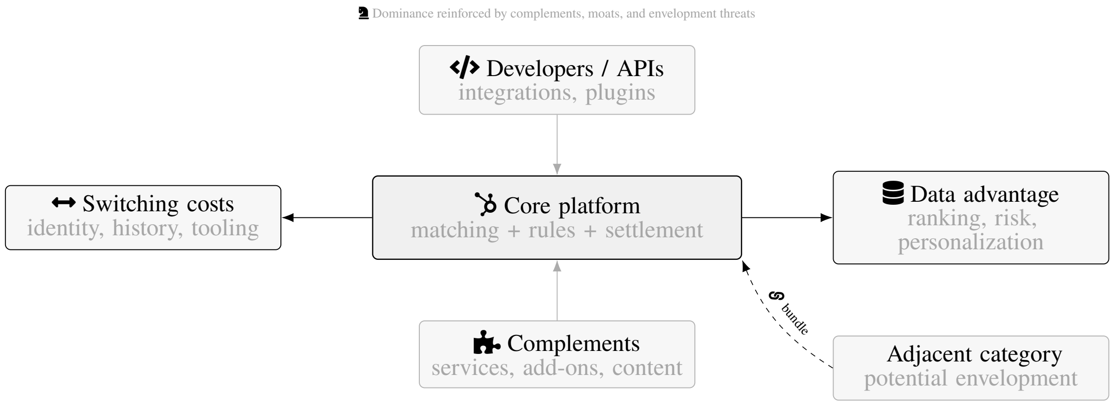

Figure 6: A dominance mechanism map: complements and APIs increase platform value, while data advantages and switching costs stabilize share; adjacent categories may attempt envelopment via bundling and integration.

increasing returns distinct from pure cross-side liquidity. Data-driven learning can also interact with selection: as higher-quality sellers join, observed outcomes improve, drawing more buyers, which further attracts sellers [9]. This quality-sorting loop can generate tipping even when baseline cross-side network effects are modest.

Congestion and negative externalities complicate the picture. As S grows, buyer search may become costly due to information overload, or matching may become noisier if low-quality listings proliferate. As B grows, sellers may face increased competition that reduces expected profit per seller [10]. Platforms can partially mitigate these forces with ranking, fees, and quality controls, but these controls are endogenous and can be perceived as unfair, affecting trust. Tipping in real categories often reflects the platform's ability to manage the balance between liquidity and congestion, not simply the existence of positive feedback.

Multi-homing introduces another dimension. When participants can join multiple platforms, cross-side network effects weaken because liquidity can be shared. Yet intermediated markets frequently impose implicit or explicit multi-homing frictions: exclusive contracts, differential pricing, loyalty programs, identity and reputation portability barriers, and operational complexity [11]. Even when formal exclusivity is absent, switching and multi-homing costs can be high because participants must learn different interfaces, build reputations separately, or manage inventory across systems. These frictions can restore tipping incentives by making liquidity less shareable.

Finally, intermediated markets in new categories often involve a problem of category construction. The platform defines listing schemas, permissible attributes, and verification processes that make the category legible and tradable [12]. This can transform a set of heterogeneous goods into comparable units, effectively increasing substitutability and enabling scale. Such standardization can be self-reinforcing: as more participants adopt the platform's schema, complementary services (analytics, logistics, financing) align with it, further increasing the platform's value. Dominance can thus reflect a coordination outcome around a particular market grammar.

3. A Dynamic Model of Adoption, Liquidity, and Policy

This section introduces a stylized dynamic model that captures cross-side network effects, belief-based coordination, congestion, and endogenous platform policy [13]. Time is discrete, indexed by $t \in \{0, 1, 2, \dots\}$. There are two populations, buyers and sellers, each with heterogeneous types. A representative buyer of type θ obtains per-period utility from joining platform i that depends on expected match surplus, prices, and participation costs. A representative seller of type σ obtains expected profit from joining based on demand, fees, and operational costs. For clarity, consider a single platform and an outside option; later, the logic extends to competing platforms.

Let B_t and S_t be the masses of active buyers and sellers at time t [14]. Let q_t denote an endogenous quality index capturing trust, ranking effectiveness, and dispute resolution, interpreted as the probability that a random match yields a satisfactory transaction. The platform chooses a policy vector u_t that includes fees and subsidies on each side, verification intensity, and ranking strictness. The policy affects both participation incentives and the evolution of q_t through data accumulation and enforcement.

A buyer of type θ who joins at time t receives expected per-period utility [15]

$$U_t^B\theta \;=\; \theta \cdot \big(vS_t, q_t - c_B B_t, S_t, u_t\big) \;-\; p^B u_t \;-\; k_t^B, \tag{3.1}$$

where vS_t, q_t is expected match value increasing in S_t and q_t, $c_B\cdot$ captures congestion or search cost, $p^B u_t$ is the effective price (possibly negative under subsidies), and k_t^B is an idiosyncratic or fixed participation cost capturing onboarding friction. Similarly, a seller of type σ receives expected per-period profit

$$U_t^S\sigma \;=\; \sigma \cdot \big(rB_t, q_t - c_S B_t, S_t, u_t\big) \;-\; p^S u_t \;-\; k_t^S, 16 \tag{3.2}$$

where rB_t, q_t is expected revenue increasing in B_t and q_t, and $p^S u_t$ is the fee schedule.

Participants face dynamic considerations because joining can create a continuing relationship with the platform, with switching costs or reputation accumulation. Let $\delta \in 0, 1$ be the discount factor, and let $x_t^B\theta$ be an indicator that the buyer is active at time t. If a buyer joins at t, she expects continuation value

$$V_t^B\theta \;=\; U_t^B\theta \quad \delta\,\mathbb{E}\big[V_{t1}^B\theta \,|\, \mathcal{I}_t\big] \;-\; \phi^B \cdot \mathbf{1}\{x_{t-1}^B\theta = 0\}, \tag{3.3}$$

where ϕ^B is the one-time onboarding cost, and $\mathcal{I}_t$ is the information set, including beliefs about future liquidity and policy. Sellers have an analogous continuation value with onboarding and switching costs that may be larger due to inventory setup, compliance, or reputation building [17]. Participation at time t is determined by threshold rules in types given beliefs, producing adoption dynamics.

To aggregate, suppose θ and σ are distributed with continuous cumulative distributions F_B and F_S. Define cutoff types $\bar\theta_t$ and $\bar\sigma_t$ such that buyers with $\theta \geq \bar\theta_t$ and sellers with $\sigma \geq \bar\sigma_t$ participate. Then

$$B_t \;=\; 1 - F_B\bar\theta_t, \qquad S_t \;=\; 1 - F_S\bar\sigma_t. \tag{3.4}$$

The cutoffs solve indifference conditions that depend on expectations about $B_{t1}, S_{t1}, q_{t1}, u_{t1}$. A reduced-form way to represent belief dependence is to express the cutoffs as

$$\bar\theta_t \;=\; \Theta\big(S_t, q_t, u_t, \mathbb{E}_t S_{t1}, \mathbb{E}_t q_{t1}\big), \qquad \bar\sigma_t \;=\; \Sigma\big(B_t, q_t, u_t, \mathbb{E}_t B_{t1}, \mathbb{E}_t q_{t1}\big), \tag{3.5}$$

with $\partial\Theta\partial S_t \;<\; 0$ and $\partial\Sigma\partial B_t \;<\; 0$ capturing cross-side network effects, and additional negative derivatives capturing the role of optimistic beliefs [18].

The quality state q_t evolves with experience and governance. A parsimonious specification captures data-driven learning and enforcement investment:

$$q_{t1} \;=\; 1 - \rho q_t \quad \rho \cdot \big(\bar q \quad \lambda \cdot gT_t \quad \eta \cdot hu_t\big), \tag{3.6}$$

where ρ is an adjustment rate, $\bar q$ is baseline quality absent learning, T_t is transaction volume (increasing in $B_t S_t$), $g\cdot$ is a concave learning function reflecting diminishing returns to data, and hu_t reflects governance investment such as verification or moderation. The parameter λ controls the strength of data feedback and η the effectiveness of policy.

Transaction volume can be represented as [19]

$$T_t \;=\; mB_t, S_t, q_t, u_t, \tag{3.7}$$

where m is increasing in both sides but can be reduced by congestion or poor ranking. In many categories, matching is not purely random; algorithmic ranking concentrates attention, effectively changing the mapping from participation to transactions. This can be captured by allowing m to be superlinear in one dimension at moderate scale and sublinear at high scale due to saturation, with the precise shape influenced by u_t.

The platform chooses u_t to maximize an objective such as discounted profit, which depends on fees, subsidy costs, and long-run scale [20]. Even if the platform is not profit-maximizing in early stages due to financing constraints or growth orientation, the logic of tipping can be studied by examining how different subsidy paths change the trajectory of B_t, S_t, q_t. The central point is that the system is a coupled dynamical process in which participation affects quality and quality affects participation, and policy affects both.

A steady state satisfies $B_{t1}, S_{t1}, q_{t1} = B_t, S_t, q_t$. Multiple steady states can exist if cross-side effects and belief dependence are strong enough. One can represent the reduced-form best-response mapping as [21]

$$B_{t1} = \mathcal{B}S_t, q_t, u_t, \qquad S_{t1} = \mathcal{S}B_t, q_t, u_t, \qquad q_{t1} = \mathcal{Q}B_t, S_t, q_t, u_t, \tag{3.8}$$

where the composition $\mathcal{B}\mathcal{S}\cdot$ can be S-shaped, creating an interior unstable fixed point. When such a threshold exists, small interventions or shocks can move the system from the basin of attraction of a low-liquidity equilibrium to that of a high-liquidity equilibrium, producing tipping.

4. Market Tipping, Stability, and the Mechanisms of Dominance

Tipping is often described as the outcome of increasing returns, but the dynamic model above shows that increasing returns can arise from different sources, and their stability implications differ. Cross-side network effects alone can generate multiple equilibria when adoption decisions depend on expectations. Data feedback can amplify this by increasing q_t with transaction volume, effectively steepening the adoption response [22]. Governance can either stabilize the system by reducing variance and preventing adverse selection, or destabilize it if enforcement is perceived as biased, creating belief shocks that reduce participation.

A tractable way to characterize tipping is to analyze local stability near fixed points. Consider a simplified case in which policy u is held constant and beliefs are adaptive rather than fully rational, so that $B_{t1} = \mathcal{B}S_t, q_t$ and $S_{t1} = \mathcal{S}B_t, q_t$. Substituting yields a two-dimensional system with q_t as a third state. Linearizing around a fixed point B^*, S^*, q^* yields a Jacobian matrix whose eigenvalues determine stability. Positive feedback corresponds to large cross-derivatives such as $\partial\mathcal{B}\partial S$ and $\partial\mathcal{S}\partial B$, and data feedback corresponds to large derivatives of $\mathcal{Q}$ with respect to B and S. When the spectral radius exceeds one in discrete time, the fixed point is unstable, and trajectories diverge toward other attractors [23]. This formalizes the idea of a critical mass: an interior fixed point that is unstable separates a low-liquidity and high-liquidity equilibrium.

Congestion can create non-monotonicities that alter tipping. If at high seller density buyers experience search overload, then $vS, q - c_B\cdot$ can peak and decline, reducing $\partial\mathcal{B}\partial S$ at high S. This can yield a single equilibrium with moderate scale rather than dominance, or can create cycles if delayed quality adjustment causes overshooting. Platforms often use ranking and curation to maintain monotonic effective network effects, which can be interpreted as policy choices that maintain the system in a region where adoption responses are steep and positive [24].

Switching costs and reputation accumulation intensify tipping by increasing inertia. If joining yields an accumulating reputation asset that is not portable, the private cost of leaving increases with tenure, which can be modeled by letting the effective outside option decline over time for active users. This produces hysteresis: once the platform crosses a threshold and participants invest in reputation, reversing dominance requires a larger negative shock than the positive shock that created it. Hysteresis can explain why dominant intermediaries persist even when rivals offer similar prices or features, particularly in categories where reputation is central to trust [25].

Multi-homing can either prevent or delay tipping, but its effect depends on whether liquidity is shareable. If buyers search across platforms and sellers list everywhere at low cost, then liquidity effects weaken and competition resembles Bertrand or Hotelling competition on fees and quality. In practice, however, attention is scarce and ranking is platform-specific, so multi-homing can coexist with tipping if transaction realization is concentrated. One can model this by distinguishing participation from effective activity [26]. Let $\tilde{B}_t$ be active attention allocated to a platform and $\tilde{S}_t$ be active supply available for immediate matching, with $\tilde{B}_t \leq B_t$ and $\tilde{S}_t \leq S_t$ depending on ranking and default choices. Even when users multi-home, defaults and convenience can cause $\tilde{B}_t$ and $\tilde{S}_t$ to tip.

Dominance in intermediated markets is also shaped by endogenous product definition. In new categories, participants may disagree on what attributes matter, and quality may be hard to verify. A platform that invests in measurement, verification, and standardized contracts increases q_t and reduces uncertainty. This can create an advantage that is not purely a network effect but interacts with it: higher q_t increases conversion, raising transaction volume, accelerating learning, and attracting more participants. The system can thereby tip toward the platform that first establishes a credible quality regime, even if competitors could in principle copy the rules later [27]. Copying may be slow due to institutional constraints, lack of data, or weaker enforcement credibility.

Table 1: Core Constructs in Intermediated Digital Markets

Construct	Conceptual definition	Operationalization
Direct network effects	Value to a user increasing with the number of same-side users	$\log$monthly active consumers in category$_{t-1}$
Indirect network effects	Value mediated through cross-side participation	$\log$active suppliers in category$_{t-1}$
Multi-homing intensity	Extent to which users participate on multiple platforms	Share of users listing at least two platforms in survey
Platform quality	Non-network attributes affecting user utility	Average app rating (1–5) in focal market
Category maturity	Stage of diffusion in the focal digital category	Years since first intermediary launch in category

A further mechanism is complementarities with adjacent intermediaries, such as payments, logistics, identity providers, and financing. When a platform integrates these services, it can reduce marginal transaction costs and increase reliability. This can be modeled as an additional component of q_t or as a reduction in c_B and c_S that increases adoption [28]. Integration can create economies of scope that raise effective switching costs, since leaving the platform may require replacing multiple services. Such bundling can tilt the stability landscape by expanding the basin of attraction of the integrated platform's high-liquidity equilibrium.

Competition between platforms can be captured by extending the model to two platforms, $i \in \{1, 2\}$, with state vectors B^i_t, S^i_t, q^i_t. Participants choose where to allocate activity, potentially multi-homing. Tipping toward one platform corresponds to an absorbing region in which one platform's liquidity attracts incremental activity, while the other falls below the threshold needed to sustain quality investment and learning [29]. A key insight is that relative advantages can be small; when the system exhibits multiple equilibria, even minor early differences in perceived quality, subsidy intensity, or default placement can determine the long-run dominant intermediary.

Table 2: Mechanisms Linking Network Effects to Market Tipping

Mechanism	Micro-level driver	Market-level outcome	Dominance pattern
Demand-side learning	Users infer quality from observed adoption	Faster convergence to a single platform	Single dominant intermediary
Supply aggregation	Suppliers prioritize platforms with higher demand	Denser supply on leading platform	High concentration on one side
Data advantages	Scale-driven improvement of matching algorithms	Higher match quality and conversion	Persistent performance gap
Standardization	Emergence of common interface and rules	Reduced compatibility with minor rivals	Lock-in to dominant standard
Switching frictions	Accumulated history and feedback on main platform	Higher user exit costs	Stable leadership once formed

Table 3: Summary of Hypotheses on the Probability of Market Tipping

Hypothesis	Focal construct	Predicted effect	Rationale
H1	Direct network effects	on tipping likelihood	Same-side feedback loops accelerate share divergence
H2	Indirect network effects	on tipping likelihood	Cross-side complementarities amplify early advantages
H3	Multi-homing intensity	– on tipping likelihood	Parallel platform use dampens feedback strength
H4	Category maturity	Inverted U	Tipping more likely at intermediate diffusion stages
H5	Platform quality differentiation	on tipping likelihood	Non-network advantages reinforce winner-takes-most

5. Dominant Intermediated Markets in New Digital Categories

New digital categories are characterized by uncertainty, thin liquidity, and heterogeneous participant expectations. The first challenge is bootstrapping: with few participants, matching is poor, and with poor matching, participants do not join. Platforms attempt to break this loop by subsidizing one side, seeding supply, or offering guarantees that shift perceived risk. In the model, these actions reduce $p^B u_t$ or $p^S u_t$, raise q_t via policy investment, or reduce participation costs through onboarding improvements [30]. The technical contribution is to treat these levers as shifting the dynamic mapping, not as one-time marketing expenses.

Dominance is particularly likely when the intermediary reduces fundamental frictions that would otherwise prevent the category from scaling. In some categories, search costs are high because the space

Table 4: Overview of Empirical Data Sources

Source	Coverage	Key variables
Platform usage logs	12 digital categories across 18 countries	Monthly active users, transactions, retention
App stores	Global app marketplaces	Ratings, reviews, release dates, feature updates
Industry reports	Market research vendors	Category revenues, entrant timelines, market size
Survey data	3,500 consumers, 1,100 suppliers	Multi-homing, switching, perceived quality
Public announcements	Press releases, news articles	Entry/exit events, funding, major partnerships

Table 5: Descriptive Statistics of Main Variables

Variable	Mean	Std. dev.	Observations
Tipping indicator	0.41	0.49	2,160 category–market pairs
Direct network size	11.27	1.84	2,160
Indirect network size	9.64	2.11	2,160
Multi-homing rate	0.37	0.18	2,160
Platform quality index	4.12	0.46	2,160
Category maturity (yrs)	6.35	3.27	2,160

Table 6: Pairwise Correlations Among Key Constructs

Variable i	Variable j	Correlation r_{ij}
Direct network size	Indirect network size	0.61
Direct network size	Tipping indicator	0.34
Indirect network size	Tipping indicator	0.39
Multi-homing rate	Tipping indicator	-0.27
Platform quality index	Tipping indicator	0.22
Category maturity	Tipping indicator	0.19
Category maturity	Multi-homing rate	0.14

of possible matches is large and preferences are idiosyncratic. In others, trust is the binding constraint because quality is hard to observe and incentives for opportunism are strong [31]. In still others, coordination around standards is required, such as consistent metadata, compatible protocols, or uniform dispute processes. When the intermediary's governance solves these problems in a way that scales with data and transactions, the system can tip toward the first platform to establish a credible regime.

Intermediation also changes strategic behavior of participants. Sellers can invest in platform-specific assets, such as reputation, optimized content, or operational integrations that raise conversion [32]. Buyers can invest in personalization histories that improve recommendations. These investments increase attachment and can be modeled as increasing the switching cost parameters over time. The consequence

Table 7: Baseline Logit Model of Market Tipping

Variable	Coefficient	Std. error	p-value
Direct network size	0.41	0.07	< 0.001
Indirect network size	0.29	0.06	< 0.001
Multi-homing rate	-0.88	0.21	< 0.001
Platform quality index	0.53	0.19	0.005
Category maturity	0.24	0.08	0.003
Category maturity^2	-0.02	0.01	0.041
Constant	-3.17	0.72	< 0.001

Table 8: Robustness Checks for Tipping Estimates

Specification	Key change	Effect on main coefficient	Interpretation
Alt. tipping threshold	60% share cutoff	Direct network coeff. decreases by 8%	Results not driven by threshold choice
Category FE	Add category fixed effects	Main coefficients stable	Across-category heterogeneity accounted for
Country FE	Add country fixed effects	Slightly larger network effects	Institutions amplify tipping
Lag structure	Two-period lags	Signs unchanged	Dynamics not sensitive to lag length
Excluding outliers	Remove top 1% size markets	Coefficients similar	Not driven by extreme markets

is that early growth can lock in not only users but also a web of complements: third-party tools, analytics, agencies, and service providers that specialize in the dominant platform's rules. This complement ecosystem amplifies network effects through indirect channels, raising the effective value of participation beyond direct matching.

An additional feature of new categories is that the intermediary often controls discovery through ranking [33]. Ranking is not neutral; it shapes which sellers receive attention and thus which sellers survive. This can create a feedback from algorithmic choice to market structure. If ranking favors incumbents with better metrics, the platform may inadvertently increase concentration among sellers, which can improve buyer experience by reducing noise but may also reduce variety. For platform dominance, the key point is that ranking can increase the efficiency with which marginal buyers translate into transactions, steepening the adoption response [34]. In the model, this raises mB, S, q, u and thus accelerates q learning, enlarging the positive feedback loop. At the same time, ranking can generate perceptions of unfairness if outcomes are opaque, creating belief shocks that reduce participation. Dominant intermediaries tend to invest in transparency, appeal processes, and predictable enforcement to stabilize beliefs.

Market tipping in new categories can also be driven by institutional adoption and risk transfer [35]. Some platforms become dominant because they provide guarantees, insurance, or escrow that shifts risk from participants to the intermediary. This increases risk-adjusted utility and can be represented as an increase in q_t or a reduction in effective participation costs. Because risk management often benefits from scale and data, such guarantees can be difficult for smaller entrants to match, reinforcing dominance. Yet

Table 9: Heterogeneity by Digital Category Type

Category type	Example	Marginal effect of direct network	Interpretation
On-demand services	Ride-hailing, food delivery	0.19 increase in tipping probability	Strong real-time matching benefits
Content platforms	Streaming, user media	0.11 increase in tipping probability	Moderate benefits from larger libraries
Peer-to-peer markets	Accommodation, resale	0.15 increase in tipping probability	Trust and selection effects dominate
Enterprise platforms	B2B marketplaces	0.07 increase in tipping probability	Tipping weaker due to multi-homing
Local discovery	Restaurant search, listings	0.13 increase in tipping probability	Network effects concentrated geographically

the same mechanism can generate fragility if losses mount or if fraud shocks overwhelm governance capacity, leading to sudden declines in q_t and rapid unraveling.

The emergence of a dominant intermediary does not imply the elimination of competition, but it changes its locus [36]. Competition may shift from direct platform rivalry to competition within the platform among sellers, and to competition among complements that integrate with the platform. From a welfare perspective, dominance can reduce duplication of fixed costs and increase liquidity, but it can also create gatekeeping power. In dynamic terms, gatekeeping power arises because policy u_t can redistribute surplus, alter ranking, and change participation incentives. If participants are locked in by switching costs and non-portable reputation, the platform can adjust fees or rules without immediate exit, though long-run exit remains possible if trust erodes [37]. This produces an endogenous limit to exploitation: extracting too much surplus can reduce q_t through lower investment or higher opportunism, eventually shrinking liquidity. In the model, the platform's optimal policy trades off short-run monetization against maintaining the high-liquidity equilibrium.

A practical implication is that dominance is often associated with investments that are costly and risky early on, such as building verification systems, absorbing fraud losses, or subsidizing transactions. These investments can be interpreted as moving the system across a tipping threshold [38]. Once dominance is achieved, the returns to these investments persist because they sustain q_t and transaction volume. However, dominance is not necessarily permanent; changes in technology, regulation, or consumer behavior can reduce switching costs or increase portability of identity and reputation, effectively flattening the adoption response and enabling multi-platform equilibria.

6. Empirical Implications and Identification in Observational Data

Testing network effects and tipping empirically is challenging because participation on each side is jointly determined, quality is endogenous, and platform policy changes over time. A naive regression of buyer activity on seller counts will typically overstate network effects because both are driven by common shocks such as marketing, seasonality, or category growth. Moreover, the reflection problem arises because buyer participation affects seller participation and vice versa contemporaneously, making causal direction ambiguous without an instrument or a design that introduces exogenous variation [**?**].

Within the model, network effects correspond to the causal derivatives of adoption propensities with respect to the other side's participation, holding fixed policy and quality. Empirically, quality is rarely directly observed; it is proxied by ratings, complaint rates, dispute rates, or conversion metrics, all of which are themselves functions of participation and selection. For example, average ratings can improve when low-quality sellers exit, even if platform governance does not change. This creates selection bias: observed quality metrics conflate governance, learning, and compositional shifts [?]. A credible strategy needs to separate these channels, often by exploiting quasi-experimental variation in platform rules, rollout timing, or exogenous shocks to one side.

One approach is to use instruments that shift supply but not demand directly, or vice versa, such as local shocks to seller availability, cost shocks affecting one side's outside option, or policy changes that apply only to a subset of participants due to eligibility rules. In the dynamic setting, lagged participation can help but does not solve endogeneity if shocks are persistent. Another approach is structural estimation of the adoption model, in which one specifies functional forms for vS, q, rB, q, and the evolution of q, and estimates parameters by matching observed adoption and transaction paths [39]. Structural methods can impose discipline, but they require careful handling of beliefs: whether agents are myopic, adaptive, or forward-looking affects the inferred strength of coordination. Mis-specifying beliefs can lead to incorrect conclusions about the existence or location of tipping thresholds.

Tipping itself can be studied by looking for non-linearities and regime shifts. In the model, an unstable interior fixed point implies that small differences in initial conditions can lead to divergent long-run outcomes. Empirically, this suggests that markets with similar fundamentals may end up with different dominant intermediaries due to early shocks [40]. One can test for such path dependence by examining cohorts of geographic markets or subcategories with staggered entry, comparing long-run concentration outcomes as a function of early adoption differences. However, such comparisons must account for endogenous platform prioritization: platforms may invest more heavily in markets that already show growth potential, creating reverse causality.

Another implication concerns the role of governance and trust as a state variable. If q_t is important, then interventions that improve verification or dispute resolution should have effects larger than what can be explained by immediate price changes [41]. Empirically, one can look for changes in conversion, repeat usage, and seller retention following governance upgrades, while controlling for contemporaneous marketing and fee changes. Yet governance interventions are often bundled with other changes, requiring decomposition. When decomposition is infeasible, one can still test qualitative predictions: for example, categories where fraud risk is high should exhibit stronger sensitivity to governance changes, consistent with a larger η in the quality evolution equation.

The model also predicts that multi-homing and portability affect concentration [42]. If reputation becomes portable or if interoperability reduces onboarding costs, then switching costs fall and the system may move from a tipped equilibrium to a shared-liquidity regime. Empirically, one can examine natural experiments such as the introduction of standardized identity verification, cross-posting tools, or regulatory mandates that increase data portability. The prediction is not necessarily that dominance disappears, but that dominance becomes less stable and more sensitive to relative quality and fees.

Finally, careful measurement distinguishes participation from effective activity. Observed registrations or listings may not reflect active attention or available supply [43]. Because tipping may occur at the level of attention allocation rather than mere presence, measures such as session time, search queries, impressions, and share of transactions are more informative than counts of accounts. Empirical work that relies on coarse measures can miss tipping dynamics or mistakenly attribute them to preferences rather than platform design.

7. Conclusion

Intermediated digital markets exhibit feedback loops that can produce market tipping and the emergence of dominant intermediaries, especially in new categories where search, trust, and standardization frictions are first-order. A technical view of these markets treats liquidity, quality, and policy as jointly evolving state variables [44]. Cross-side network effects link the two sides of participation, belief-mediated coordination can generate multiple equilibria separated by critical-mass thresholds, and data-driven learning and governance investment can amplify increasing returns by improving match quality as transaction volume grows. Congestion, multi-homing, and switching costs shape whether these forces yield stable dominance, transient concentration, or shared-liquidity outcomes.

The dynamic framework presented here emphasizes that dominance is not mechanically implied by the presence of network effects. Instead, dominance emerges when the coupled system of adoption and quality admits a high-liquidity stable equilibrium with a large basin of attraction, and when frictions limit the extent to which liquidity can be shared across platforms [45]. In new digital categories, the intermediary's role in defining the category, standardizing contracts and information, and enforcing rules can be a decisive advantage that interacts with scale and data. Empirically, identifying these mechanisms requires designs that address simultaneity, selection, and endogenous policy, and that distinguish mere participation from effective activity and attention.

A broader implication is that competition in tipped intermediated markets often occurs through market design and governance as much as through price. Changes in verification, ranking, dispute resolution, and interoperability can shift adoption dynamics by altering trust and switching costs. As technologies and institutions that enable portability evolve, the stability of dominance may change, making the long-run structure of new digital categories sensitive to both design choices and the surrounding regulatory and infrastructural environment [46].

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