Slide or Feed: Recommendation Layout, Monetization, and Data-Driven Learning

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Digital platforms increasingly use recommender systems not only to select content but also to determine who completes the matching process: the algorithm or the viewer. We study recommendation layout as a strategic design choice that allocates residual matching authority between the platform's algorithm and viewers. In a slide interface, viewers consume one algorithmically selected item at a time, largely delegating matching to the platform. In a feed interface, viewers observe multiple recommended items and screen among them, retaining part of the matching task. We develop a model of a content platform that chooses its recommendation layout and advertising load while the recommendation quality improves with viewer-generated data. The model identifies a tradeoff between algorithmic delegation and viewer-side screening. Feed improves realized match quality when recommendations are imprecise or content supply is sparse, while slide reduces browsing and decision frictions when the platform's matching environment is strong. A key implication is that the engagement-maximizing layout need not be revenue-maximizing: in intermediate matching environments, slide may generate more consumption, while feed generates higher advertising revenue by increasing the value of consumed attention and viewers' tolerance for ads. A dynamic extension shows that forward-looking platforms moderate early advertising and may transition from feed to slide as data and content supply improve. The results position recommendation layout as a strategic information-systems design choice that shapes matching, monetization, and platform learning.

Key words: recommender systems; digital platforms; interface design; data-driven learning; AI flywheel; advertising monetization; two-sided markets

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1. Introduction

Digital content platforms increasingly rely on recommendation systems to organize viewer attention. A central driver of their recommendation algorithms is using accumulated viewers' behavioral data to improve subsequent recommendations. As engagement generates more data and better recommendations stimulate further engagement, recommendation systems can create a self-reinforcing data-learning loop often described as an AI flywheel [1]. For example, TikTok utilizes this cycle to refine their recommendation algorithms, ensuring that content aligns closely with viewer preferences, thereby enhancing engagement and satisfaction [2]. This iterative data-learning process allows platforms to optimize their recommendations even as viewer preferences evolve dynamically over time.

Beyond algorithm design, platforms must also decide how much choice to leave to viewers. This design choice matters because algorithmic delegation and viewer screening have different implications for engagement, advertising tolerance, and learning. One fundamental choice faced by platform designers in practice is **the recommendation layout**. In the case of online platforms, there are two commonly used layouts of recommendation: the *slide layout*, where platforms present one item at a time and viewers move sequentially across content, and the *feed layout*, where viewers observe multiple recommended items simultaneously and actively choose among them. These two recommendation layouts differ in how they allocate the matching task between the platform's algorithm and viewers. In a slide interface, the viewer delegates the matching decision almost entirely to the recommender: the platform selects one item, and the viewer consumes or skips it. In a feed interface, the platform provides a set of candidate recommendations, but viewers retain an active screening role by comparing alternatives before consumption. Thus, the layout choice determines the division of labor between algorithmic matching and viewer-side screening. This division of labor is not necessarily fixed over a platforms lifecycle. Some platforms historically relied more on feed layout and then switch to slide layout, whereas others popularized slide layout. For example, Kuaishou was long associated with a feed-like discovery interface and later moved toward a more slide-like full-screen viewing experience, while TikTok made slide-like sequential consumption a central part of the viewing experience earlier.

This layout choice is also closely tied to platform monetization. Most content platforms monetize through advertising embedded in the viewing experience, and advertising intensity directly affects engagement. Higher advertising load may increase short-run revenue, but it can also reduce viewer satisfaction and content consumption. Because engagement generates the interaction data, advertising decisions and layout choices jointly influence both current revenue and future algorithmic strength. The operational question is therefore broader than algorithm design alone.

While existing research has studied recommendation systems and their role in optimizing viewer satisfaction and platform engagement, it has largely focused on optimizing the algorithm itself (e.g. Adomavicius and Tuzhilin 2005, Adomavicius et al. 2018, Berman and Katona 2020, Wu et al. 2023, Qian and Jain 2024). We lack an understanding of how these layouts interact with the algorithmic strength and the content environment, affect the platform revenue, and impact viewer experience. This leads to our central research questions: How should a platform strategically choose between the slide and feed layouts? How does this allocation of matching authority affect the trade-off between engagement and advertising revenue? How should the allocation evolve as recommendation quality and content supply improve?

To answer these questions, we develop a stylized model of a two-sided content platform with creators, viewers, and advertisers. We consider a platform that employs a data-driven recommendation system, which can improve its strength by learning from viewer interaction data. Creators offer content such as videos or articles, viewers visit the platform to consume the recommended content, and the platform monetizes attention through advertising. We first study a stationary model in which recommendation quality and viewer engagement are jointly determined in steady state. In this benchmark, we treat content supply conditions as exogenous and examine how they moderate the layout choice. We then introduce a two-period model to make the lagged learning channel explicit and allow first-period creator revenue to affect future content density, thereby capturing a reduced-form supply-side feedback channel. The model isolates two differences between layouts. First, feed allows viewer-side screening: viewers observe multiple recommended items and select the better match. Second, slide reduces consumption friction: viewers face less browsing and decision cost when consuming sequentially. Recommendation quality depends on both exogenous matching primitives and endogenous viewer consumption, which generates data for learning.

In our static analysis, we characterize the platform's optimal advertising load and revenue under each layout. The results show that the optimal layout follows cutoff structures in both algorithmic strength and content richness. When the candidate set is broad or the learning ability of the recommender is limited, feed can dominate because viewer-side screening compensates for algorithmic imprecision. On the other hand, when the candidate set is narrow, learning ability is high, content density is large, or the value of a good match is high, slide becomes optimal because the platform can convert accurate recommendations into continuous low-friction consumption.

An important finding is that interface design creates a wedge between attention volume and attention monetizability. A slide interface can increase consumption by reducing browsing and decision frictions. However, when the matching environment is intermediate, a feed interface can generate higher revenue even with lower consumption because viewer-side screening improves the expected match quality of consumed content and increases viewers' tolerance for advertising. Hence, a platform that chooses layouts based only on engagement may select the wrong interface from a monetization perspective. This wedge is disciplined by cutoff results. Feed is preferred when the algorithm is weak or content richness is low; slide is preferred when the platform operates in a strong matching environment. But between these regions lies an economically important zone where engagement and revenue rankings diverge. This distinction echoes a broader insight in operations: reducing viewers' exposure to advertising can increase consumption (Yan et al. 2022), whereas greater platform traffic need not translate into better economic outcomes (Niu et al. 2025). In our setting, the wedge arises because recommendation layouts differ in the match value and monetizability of consumed attention.

We then extend the model to a two-period setting to examine the dynamic implications of platform's matching environment. In the dynamic model, first-period consumption improves second-period recommendation quality, viewer utility affects future viewer participation, and creator revenue affects future content density. This extension captures the idea that interface design shapes not only current consumption but also the future state of the platform ecosystem, especially in cold-start-like environments where recommendation data and content supply are still limited.. We show that a forward-looking platform chooses a lower first-period advertising load than a myopic platform. This advertising restraint can be interpreted as subsidy-like, by which the platform forgoes short-run advertising revenue to protect engagement, generate data, and support future market growth. We also compare fixed-layout policies with switching policies. We first provide a partial analytical characterization of switching incentives: condition on the first period layout, the decision to choose feed or slide in period 2 follows a cutoff in the inherited matching environment. Numerical comparisons across fixed and switching policies further illustrates a lifecycle pattern in which feed can serve as an early-stage screening interface, while slide becomes attractive once accumulated data and content growth make algorithmic delegation more effective.

This paper makes three contributions. First, we conceptualize recommendation layout as an allocation of residual matching authority. Whereas prior work often treats recommendations as algorithmic outputs, we show that the interface determines whether the final matching step is completed by the platform or by viewers. This perspective turns layout from a visual design feature into an economic design instrument. Second, we identify an engagement-revenue wedge in layout design. The layout that generates more consumption need not generate higher advertising revenue. In intermediate matching environments, slide can generate more consumption because it reduces decision friction, whereas feed can generate higher revenue because viewer-side screening raises the match value of consumed attention and supports a higher advertising load. This result cautions against using engagement alone to evaluate recommender interfaces. Third, we show that the optimal layout depends on the platform's matching environment. Feed is more valuable when recommendations are weak or content supply is sparse, because viewer-side screening compensates for weak matching. Slide becomes more valuable when algorithms and content supply are strong, because low-friction sequential consumption allows the platform to monetize accurate recommendations more effectively. A dynamic extension further shows that forward-looking platforms moderate early advertising and suggests a lifecycle pattern in which platforms may benefit from a feed-to-slide transition as data accumulation and content growth improve the matching environment.

The results have direct managerial implications. Platforms with immature recommendation systems or sparse content pools may benefit from feed-like layouts that preserve viewer choice and exploration. Platforms with mature algorithms and rich content ecosystems may benefit from slide-like layouts that reduce friction and promote sequential consumption. More broadly, the analysis suggests that recommendation layout should be aligned with the platform's stage of algorithmic and ecosystem development. Interface design is therefore not simply a matter of viewer-experience aesthetics; it is a strategic lever for managing matching, monetization, and learning on digital content platforms.

The remainder of the paper is organized as follows. In Section 2, we discuss the related literature and our contributions. Section 3 presents the basic model. Section 4 characterizes the platform's optimal decisions and compares the slide and feed layouts under different algorithmic and supply conditions. Section 5 extends the model to a two-period setting to examine the AI flywheel effect and the role of learning ability in shaping dynamic advertising and layout performance. Section 6 concludes. All proofs can be found in the appendix.

2. Literature Review

Recommendation Systems Design on Platform. A large literature studies recommendation systems and their economic consequences on digital platforms. Early work in recommender systems emphasizes the design of algorithms that improve prediction accuracy and match users with relevant products or content (Adomavicius and Tuzhilin 2005). Subsequent research shows that recommendations can meaningfully affect viewer evaluations, choices, and downstream market outcomes, implying that recommendation design has economically important effects beyond pure prediction accuracy (Adomavicius et al. 2013, 2018). More broadly, this literature highlights the importance of data-driven personalization and algorithmic precision in shaping platform performance (Wu et al. 2023). Recent studies further examine how recommender systems affect platform participants' behavior and market performance through personalization, ranking, search, and allocation mechanisms. For example, Berman and Katona (2020) show that curation algorithms can either mitigate or amplify content polarization depending on their design. Zhong (2023) studies how platform search precision affects consumer search and seller competition. Qian and Jain (2024) analyze how recommendation systems affect digital content creators' incentives and platform outcomes. Recent research also recognizes that recommendation design on multi-sided platforms may require balancing multiple objectives and accounting for the hierarchical organization of recommended items (Wang et al. 2025b).

Most existing work treats recommendations primarily as algorithmic outputs, such as ranked lists or allocation rules. Our paper contributes to this literature by highlighting the interface as an independent design instrument in recommendation environments. This factor is important because the economic value of a recommendation depends not only on what the algorithm selects, but also on how much opportunity viewers have to inspect, compare, and screen recommended alternatives before consumption. We identify interface design as a mechanism that allocates residual matching authority after algorithmic recall.

Our paper also speaks to cold-start challenges in recommender platforms. The literature has long recognized cold start as a central problem that arises when historical interaction data are limited

(Schein et al. 2002). This stream mainly asks how the recommendation algorithm can overcome data sparsity. We highlight a complementary design mechanism: when algorithmic matching is weak, feed-like interfaces preserve viewer-side screening and allow viewers to partially correct imperfect algorithmic recall before consumption. Even holding recall technology fixed, the interface changes who completes the final match, which changes monetization and learning.

Data-driven Algorithms, Data Network Effects, and the AI Flywheel Our work is also related to the literature on data-driven learning and data network effects. In AI-enabled platforms, user engagement generates behavioral data, which can improve algorithmic performance and thereby increase future user engagement. This self-reinforcing process is often described as a data network effect or an AI flywheel (Gregory et al. 2021). Clough and Wu (2022) emphasize that data-driven learning differs from traditional network effects because the value of data depends on its quality, relevance, and the firm's ability to convert behavioral traces into improved services. Gurkan and de Véricourt (2022) study how this feedback loop affects firms' incentives in pricing, contracting, and data collection strategies. Related research examines how firms learn from accumulating data while making operational decisions. For example, Miao and Chao (2021) study joint assortment and pricing optimization when customer choice parameters are initially unknown. Another related literature studies problem where platforms must attract participation on multiple sides before network effects become self-sustaining, often through asymmetric pricing or subsidies (Parker and Van Alstyne 2005, Veisdal 2020). There are also studies showing how firms can obtain additional revenue by selling their data (Zhang et al. 2023), whether streaming platforms should purchase external consumer data for targeted advertising (Wang et al. 2025a), and how access to external data can improve advertising targeting capabilities (Zhang et al. 2025).

This stream highlights the importance of feedback between user activity, data accumulation, and algorithmic improvement. However, existing research typically focuses on firms' incentives to collect, price, or use data, or on how firms optimize decisions while learning from available data. Less attention has been paid to how front-end operational design choices affect the generation of data in the first place. Our paper contributes by linking interface design to the data-learning feedback loop. We first analyze a steady-state benchmark in which recommendation quality and viewer consumption are mutually consistent. We then extend the model to a dynamic setting in which first-period consumption improves second-period recommendation quality. This dynamic analysis identifies recommendation layout and advertising discipline as operational levers that shape the initiation of data-driven learning. Layout choice affects not only current engagement and advertising revenue, but also the future state of the platform's matching environment. In particular, feed can be valuable in early stages because it protects consumption when recommendations are noisy, while slide becomes more attractive as accumulated data improve recommendation precision.

Two-Sided Content Platforms and Supply-Side Environment. Our study also relates to the literature on two-sided content platforms, where platforms intermediate interactions among content creators, viewers, and often advertisers. Prior research has shown that creator-side participation, content quality, producer competition, and revenue-sharing arrangements can all shape equilibrium outcomes on content platforms (Jain and Qian 2021, Bhargava 2022, Karacaoglu et al. 2022). This literature establishes that the richness of the content ecosystem is a fundamental determinant of platform value creation and revenue generation. A related stream studies how platform-side allocation and recommendation policies shape outcomes through their effects on creators. Ren (2024b) study how content platforms should allocate limited views between content quality and promotional effort, and Qian and Jain (2024) analyze how recommendation bias can affect creators' incentives under revenue sharing.

While this stream has generated important insights, it has mainly focused on creator incentives, compensation design, promotional allocation, or recommendation bias toward creators. Much less is known about how the viewer-side layout should be designed when the content pool is denser or the content quality is higher. Our paper complements this literature by focusing on how a given content environment is converted into viewer consumption and advertising revenue through recommendation layout. Rather than emphasizing creator entry or content-quality investment as the main strategic variable, our baseline model treats content density as a primitive and studies how its value depends on the platform's interface design. We further allow creator revenue to affect future content density in the dynamic extension, capturing a reduced-form supply-side feedback channel between monetization and future content availability.

Interface Design and Recommendation Presentation. A related literature studies how interface design and recommendation presentation affect viewer behavior. Research in this area shows that layout, navigation structure, and on-screen organization influence how viewers browse content, allocate attention, and evaluate recommended alternatives. For example, Kammerer and Gerjets (2010) compare list and grid interfaces and find that layout format affects exploration patterns and realized choice quality. Qu et al. (2025) analyze strategic channel design for UGC platforms and show that maintaining a web-based channel can stimulate content generation and shape platform profitability. Close to our perspective, Gallino et al. (2025) study algorithmic assortment curation through the Buybox in online marketplaces and show that platform curation can reduce customer search frictions and alter marketplace outcomes. More recent work further emphasizes that recommendation quality should be evaluated jointly with the overall interface structure rather than in isolation. For instance, Felicioni et al. (2021) show that viewer satisfaction on multi-carousel recommendation pages depends on the arrangement and positioning of recommendation modules, and Starke et al. (2023) find that organizing recommendations into multiple lists significantly affects perceived diversity, choice difficulty, satisfaction, and the content ultimately selected. These findings imply that the value of recommendation is contingent on the layout in which they are embedded.

Existing interface research shows that presentation affects choice, but it typically does not study how the platform should allocate matching authority when it also monetizes attention through advertising. Our paper provides a platform-level theory of this allocation. Our paper builds on this insight by developing an economic model of recommendation layout choice. The model shows that interface design is not merely a matter of visual presentation. It determines whether matching is primarily delegated to the algorithm or partially retained by viewers through active screening.

3. Model

We consider a two-sided online content platform where independent viewers visit to consume content. The market consists of creators, viewers and advertisers. Creators produce content consumed by viewers, and the platform can monetize attention through advertising revenue. Figure 1 summarizes these interactions with a more detailed illustration provided later, and Table 1 lists the key variables.

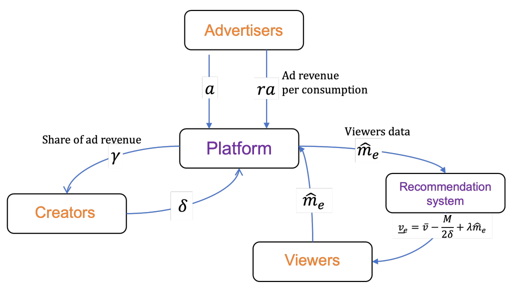


Figure 1 Model Overview

For the sequence of events in our setting, the platform first chooses layout and the advertising load. Viewers then arrive at the platform and consume content under the chosen layout and advertising level. The consumption data are fed into the platform's data-driven recommendation system, so that recommendation performance is endogenously shaped by contemporaneous viewer consumption through the data-learning mechanism. We therefore impose a fixed-point consistency condition: the engagement level induced by recommendation quality must be consistent with the engagement level that supports that recommendation quality in steady state. Finally, given the resulting equilibrium consumption, the platform's advertising revenue is realized.

3.1. Viewers and content creators.

We model the content marketplace using a Salop circle (Salop 1979). We set the circumference to be 2 for ease of modeling. Viewers are uniformly distributed on the circumference with the population mass normalized to 1. A viewer's match value for a content item is determined by its distance from

Table 1 Table of Key Variables

Parameters	$M \in (0, 2\delta]$	Baseline recommendation candidate set size
	$\lambda > 0$	Recommendation algorithm's learning ability from viewer consumption data
	$\delta > 0$	Content density
	$\overline{v} > 0$	The value of the perfect-match content
	$c_e > 0$	Viewers' consumption cost per unit consumption under layout e
	$\phi > 0$	Viewers' nuisance cost per unit advertising
	$r > 0$	Platform's monetization coefficient
	$\gamma \in [0, 1]$	Platform's revenue sharing ratio
Decision	$e \in \{s, f\}$	Recommendation layout (slide or feed)
	$a \geq 0$	Advertising load
Outcome	$\underline{v}_e$	The effective value lower bound of candidate content
	$\hat{m}_e$	Total consumption quantity under layout e
	π_e	Platform revenue under layout e

the viewer on the circle. Content items are also uniformly distributed along the circumference with density δ per unit length, yielding a total content mass of 2δ. Each creator supplies exactly one content item. In the baseline model, we take δ as exogenous. This allows us to isolate how the platform's viewer-side layout interacts with the richness of the content environment. Section 5 relaxes this static treatment by allowing future content density to respond to creators' first-period average revenue.

Content on the platform is horizontally differentiated. For a viewer located at a given point on the circumference, the gross utility from consuming a content is $V = \overline{v} - d$, where d is the shortest distance between the viewer and this content along the circumference, and $\overline{v}$ is the value of a perfectly matched content item. Thus, a smaller distance implies a better interest match and a higher consumption value.

Conditional on a viewer's location on the loop, the distribution of content items on the circle is uniform. At the same time, the content item is uniformly distributed on the circle. Given the independence of locations for the content and the viewers, the shortest distance between the viewer and a content item is also uniformly distributed on $[0, 1]$. From $V = \overline{v} - d$, the viewer's value of consuming any item follows $V \sim U[\overline{v} - 1, \overline{v}]$.

3.2. Recommendation layout and advertising load by the platform.

Two distinct recommendation layouts are available for the platform designer, denote by $e \in \{s, f\}$: the slide layout ($e = s$) and the feed layout ($e = f$). The slide layout has lower consumption frictions but places greater demands on recommendation accuracy; in comparison, the feed layout enables active viewer screening that can offset weaker recommendations at the expense of higher browsing and cognitive costs. Under layout e, we denote by $\hat{m}_e$ the expected consumption of each viewer, which is an equilibrium outcome that will be specified later. Since total viewer mass is 1, the expected total consumption is therefore $\hat{m}_e$.

The platform cannot perfectly match each viewer with their most interested content. Instead, its recommendation algorithm recalls a candidate region around the viewer's location on the circle, consisting a number of M content items. We assume that $M \le 2\delta$. Since content density is δ per unit length, this candidate set corresponds to a neighborhood of length $\frac{M}{\delta}$ on the circle. The parameter M captures the imprecision of the recommendation system, where a larger M means the algorithm's recalled candidate region is broader and therefore less precise.

Recommendation accuracy in our model refers to the extent to which recommended content aligns with a viewer's preference. We model this as the lower bound value of content in the recommendation candidate set. Specifically, under layout e, we let this lower bound value be:

$$\underline{v}_e = \left(\overline{v} - \frac{M}{2\delta}\right) + \lambda \hat{m}_e. \tag{1}$$

In (1), the first term $\overline{v} - \frac{M}{2\delta}$ captures the baseline recommendation accuracy without data-learning. Here, $\frac{M}{2\delta}$ parametrizes the breadth of the candidate set identified by the algorithm: because the neighborhood is centered at the viewer, the most distant recalled item is at distance $\frac{M}{2\delta}$ (see Figure 2). A large M means an imprecise recall, which could lower the minimum match value $\underline{v}_e$; on the other hand, a higher content density δ has the opposite effect by placing content of interest closer to the viewer. Thus, baseline recommendation accuracy decreases in M and increases in δ.

The second term $\lambda \hat{m}_e$ captures the *learning effect*. We assume that greater viewer engagement generates richer interaction data such as views and watch time, which can be proxied by expected total consumption $\hat{m}_e$. This data allows the recommendation system to better infer preferences and avoid poorly matched recommendations through data-learning. The parameter $\lambda > 0$ measures how effectively the system converts such data into improved recommendation accuracy, where a higher λ leads to a larger increase in the value lower bound $\underline{v}_e$ given the fixed amount of data. In the rest of the paper, we refer to this data-driven improvement in recommendation quality as *learning*, and to the resulting increase in accuracy as the *learning effect*. This formulation captures the idea of AI flywheel: more consumption generates more data, which improves recommendation quality and can further stimulate viewer engagement.

We interpret (1) as a stationary reduced-form representation of the platform's data-learning environment a layout that sustains higher engagement generates a larger stock of behavioral data, and this data stock supports stronger effective recommendation quality in steady state. The core economic trade-off relies on the direction of the flywheel. In Section 5, we extend the model to a dynamic two-period setting in which first-period consumption improves second-period recommendation quality, and shows that the main economic mechanism continues to hold. Throughout the main analysis, we restrict attention to the local-learning region in which $\underline{v}_e \leq \overline{v}$ for $e \in \{s, f\}$, so that the support of the recommended-content distribution is well defined. A formal condition is introduced after characterizing the equilibrium.

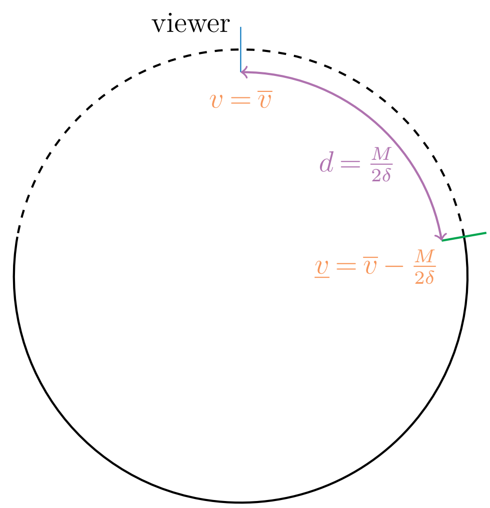


Figure 2 The Recommendation System

The dash line represent the candidate set region without data-learning.

The platform randomly draws items from the content set with this lower bound value and recommend the items to the viewers. The random draw captures residual algorithmic uncertainty. Viewers then determine their consumption. The value distribution of *recommended and consumed* content is therefore an outcome of the recommendation system's truncation of the candidate set toward more suitable matches. We can then derive the expected consumed value $\mathbb{E}[V_e]$ under layout e which will be formally introduced later.

The platform earns revenue by incorporating third-party advertisers and inserting advertisements into content items. Specifically, the platform determines $a \geq 0$, the load of ads to embed in each content. By setting ads, each content can generate revenue $a \cdot r$ per viewer consumption, where $r > 0$ is the per-unit monetization rate. In practice, r can be interpreted as the average price that advertisers are willing to pay for viewer consumption on the platform, which summarizes the platform's ability to convert viewer attention into advertising revenue. Creators receive a share of advertising revenue generated by their content items from the platform with a sharing proportion $\gamma \in [0, 1]$.

3.3. Equilibrium consumption.

Given the platform's recommendation layout e and the advertising load a, viewers consume the content on the platform. Viewers incur a consumption cost $c_e \in \{c_s, c_f\}$ upon consuming one content item under layout e. This cost represents the effort or inconvenience that viewers face during consumption, including factors such as time spent or cognitive load in choosing or consuming content.

Under the slide layout, the platform displays a single content item drawn uniformly at random from the candidate set, i.e., items with value $V > \underline{v}_s$. The value of the consumed content therefore follows the distribution $V_s \sim U[\underline{v}_s, \overline{v}]$. Under the feed layout, the platform simultaneously displays two items independently drawn from the candidate set, and the viewer observes basic preview information about each displayed item, such as title, thumbnail, or short descriptions. We assume that viewers can rank the displayed alternatives by their realized values, and then select and consume the content with the higher value. This assumption should be interpreted as a reduced-form representation of viewer-side screening in feed interfaces. The platform's recall technology is the same under the two layouts; what differs is who performs the final selection among recalled candidates. We also discuss the imperfect viewer selection under feed in Appendix B.1 and show that the main results continue to hold. Towards this direction, the value of the consumed content under the feed layout follows the distribution $V_f = \max\{V_{f1}, V_{f2}\}$, where $V_{fj} \overset{i.i.d}{\sim} U[\underline{v}_f, \overline{v}]$ for $j = 1, 2$. To capture the additional decision-making effort required from viewers to evaluate and select content under the feed layout, we assume $c_s < c_f$. Appendix B.2 extends this framework to cases where the feed layout displays $J > 2$ content items and shows that the same screening-friction trade-off remains.

A viewer can view multiple content items with a unit consumption cost c_e under layout e and a per-unit advertising nuisance cost ϕ. We assume a quadratic form of cumulative consumption cost which is standard in the literature (e.g., Amaldoss et al. 2021, Zhou and Zou 2023, Ren 2024a). Specifically, under layout $e \in \{s, f\}$, if a viewer has consumed m content items so far, her expected cumulative utility is $U_e(m) = \mathbb{E}[V_e] \cdot m - \frac{1}{2} c_e m^2 - \phi a m$, where V_e is a random variable capturing the value of a recommended and consumed content item under layout e, and $\mathbb{E}[V_e]$ denotes its expectation. The viewer consumes to maximize her expected cumulative utility (Mas-Colell et al. 1995), and leaves the platform after she reaches her utility-maximized point, denote by $\hat{m}_e$.

The equilibrium is characterized by the interaction between the algorithmic performance $\underline{v}_e$ and the viewer consumption $\hat{m}_e$. On one hand, stronger recommendation performance increases the expected value of consumed content and thereby stimulates viewer consumption. On the other hand, greater viewer consumption generates more behavioral data, which improves the recommendation system's strength. Hence, equilibrium requires a self-consistency condition: the viewer consumption induced by recommendation performance must coincide with the consumption level that in turn determines recommendation performance through learning. In this sense, the equilibrium imposes a steady-state consistency condition, as the engagement level governing algorithmic quality must be validated by the engagement generated under that recommendation quality.

Formally, given the platform's layout $e \in \{s, f\}$ and the advertising load a_e, the equilibrium is the viewer consumption $\hat{m}_e^*$ such that (i) the consumption level $\hat{m}_e^\star$ maximizes a viewer's utility U_e; (ii) recommendation performance is consistent with realized engagement, i.e., $\underline{v}_e^* = \overline{v} - \frac{M}{2\delta} + \lambda \hat{m}_e^*$. Comparing the equilibrium outcomes under $e = s$ and $e = f$ allows us to characterize the platform's preferred recommendation layout and the optimal advertising level under different algorithmic and content environments.

To ensure that the lower bound of the recommendation support remains within the bounded support of viewer-content match values, we impose the following condition.

Assumption 1. *For each layout $e \in \{s, f\}$, the model primitives are such that $\lambda \hat{m}_e^* \leq \frac{M}{2\delta}$.*

Assumption 1 is not intended to rule out strong learning in practice, but to restrict attention to the local-learning region in which the lower bound of match quality cannot exceed the perfect-match value at the optimum. Appendix B.4 therefore examines a bounded concave learning specification and shows that the main cutoff pattern continues to hold. Despite that $\hat{m}_e^\star$ is endogenous, note that in the learning-saturated region where $\lambda \hat{m}_e > \frac{M}{2\delta}$, the platform's algorithm is sufficiently accurate such that feed's viewer-side screening advantage disappears because all recommended items already attain the maximal match value. Therefore, the slide layout always dominates the feed one since it retains its lower consumption friction.

Before proceeding, we characterize the equilibrium viewer consumption under each layout e for a given advertising load a. For any realized expected content value $\mathbb{E}[V_e]$, a viewer's expected cumulative utility is strictly concave in her consumption quantity m, which yields the optimal consumption rule $\hat{m}_e = \max\left\{0, \frac{\mathbb{E}[V_e] - \phi a}{c_e}\right\}$. Given the value distribution of consumed content, the expected realized content value under the two layouts is

$$\mathbb{E}[V_s] = \frac{\underline{v}_s + \overline{v}}{2}, \qquad \mathbb{E}[V_f] = \frac{\underline{v}_f + 2\overline{v}}{3}. \tag{2}$$

Accordingly, the interior consumption candidate satisfies

$$\hat{m}_s = \frac{\underline{v}_s + \overline{v}}{2c_s} - \frac{\phi a}{c_s}, \qquad \hat{m}_f = \frac{\underline{v}_f + 2\overline{v}}{3c_f} - \frac{\phi a}{c_f}. \tag{3}$$

To focus on the economically meaningful equilibria with nonnegative consumption, we impose the following maintained assumption.

Assumption 2. *The model primitives satisfy $2c_s > \lambda$ and $4\delta\overline{v} \geq M$.*

The first condition ensures that the fixed-point equation admits a unique and stable equilibrium under both layouts. It requires that the learning be sufficiently moderate relative to content-side frictions. Although stronger viewer interaction improves recommendation quality and raises effective content value, this feedback cannot be so strong as to generate a runaway self-reinforcing process, which ensures that the data-learning remains stabilizing rather than explosive. The second guarantees that the content environment is sufficiently rich relative to the recommendation scope, so that the equilibrium consumption at zero advertising load is nonnegative and thereby allowing us to focus on the region with nonnegative engagement. These conditions rule out unstable or economically degenerate parameter regions that are not the focus of our analysis.

Notice that the effective content value lower bound $\underline{v}_e$ is endogenous because recommendation quality improves with viewer interaction data. Substituting the expression into 3 above yields a fixed-point condition in $\hat{m}_e$, which gives the equilibrium viewer consumption under each layout.

LEMMA 1 **(Equilibrium viewer consumption)**. *For any layout $e \in \{s, f\}$ and advertising load $a \geq 0$, the unique equilibrium viewer consumption is*

$$\hat{m}_s(a) = \begin{cases} \frac{4\delta\overline{v} - 4\delta\phi a - M}{2\delta(2c_s - \lambda)}, & \text{if } a \leq \frac{4\delta\overline{v} - M}{4\delta\phi} \\ 0, & \text{else} \end{cases}$$

$$\hat{m}_f(a) = \begin{cases} \frac{6\delta\overline{v} - 6\delta\phi a - M}{2\delta(3c_f - \lambda)}, & \text{if } a \leq \frac{6\delta\overline{v} - M}{6\delta\phi} \\ 0, & \text{else} \end{cases}$$

Lemma 1 shows that equilibrium viewer consumption decreases with advertising intensity a, candidate-set size M, and consumption cost c_e, but increases with content density δ, perfect-match value $\overline{v}$, and algorithmic learning ability λ. Intuitively, heavier advertising and greater consumption frictions reduce engagement, whereas richer content environments and stronger algorithmic strength improve viewer-content matching and stimulate consumption.

More importantly, the lemma formalizes the platform's learning feedback mechanism: viewer consumption generates interaction data that improves recommendation quality, which in turn increases future consumption incentives. Consequently, equilibrium consumption is jointly shaped by interface frictions and endogenous recommendation improvement. The distinction between slide and feed layouts therefore reflects not only differences in consumption costs, but also differences in how interface design interacts with recommendation learning.

Taking the induced equilibrium consumption as a function of advertising intensity, the platform next chooses the advertising load a to maximize revenue.

4. Analysis

In this section, we first characterize the platform's equilibrium outcomes under the slide and feed layout. Then we investigate the optimal layout. We proceed in two steps: we first derive the revenue-maximizing advertising load $a_e^\star$, and characterize the corresponding optimal revenue and viewer consumption for each layout e in Section 4.1; we then compare the two layouts to identify the conditions under which each dominates in Section 4.2.

4.1. Revenue-Optimal Advertising Load

Fix a layout $e \in \{s, f\}$. The platform chooses the advertising load $a \geq 0$ to maximize its advertising revenue. Let $r > 0$ denote the per-ad-unit monetization rate and $\gamma \in (0,1)$ the creator's revenue-sharing ratio. The platform's revenue maximization problem under layout e is

$$\max_{a \geq 0} \quad \pi_e(a) = a\, r(1-\gamma)\hat{m}_e(a), \tag{4}$$

where $\hat{m}_e(a)$ is the equilibrium viewer consumption induced by advertising load a under layout e.

By Lemma 1, viewer consumption becomes zero once the advertising load exceeds the corresponding cutoff. Thus, it is without loss of generality to restrict attention to

$$0 \leq a_s \leq \frac{4\delta\overline{v} - M}{4\delta\phi} \quad \text{under the slide layout, and}$$

$$0 \leq a_f \leq \frac{6\delta\overline{v} - M}{6\delta\phi} \quad \text{under the feed layout.}$$

These feasible sets are compact, and $\pi_e(a)$ is continuous on them. Therefore, an optimal advertising load exists under each layout. Proposition 1 summarizes the platform's optimal advertising decision and the resulting outcomes under each layout.

Proposition 1 **(Optimal advertising load under layout** e**)**. *For a fixed layout $e \in \{s, f\}$, the platform's optimal advertising decision and the induced equilibrium outcomes are as follows:*

(i) The optimal advertising loads under slide and feed layouts are

$$a_s^* = \frac{4\delta\overline{v} - M}{8\delta\phi}, \qquad a_f^* = \frac{6\delta\overline{v} - M}{12\delta\phi}.$$

(ii) The platform's optimal revenues are

$$\pi_s^* = \frac{(4\overline{v}\delta - M)^2}{\delta^2}\frac{(1-\gamma)r}{32\phi(2c_s - \lambda)}, \qquad \pi_f^* = \frac{(6\overline{v}\delta - M)^2}{\delta^2}\frac{(1-\gamma)r}{48\phi(3c_f - \lambda)}.$$

(iii) The induced optimal viewer consumptions are

$$\hat{m}_s^* = \frac{4\overline{v}\delta - M}{4\delta(2c_s - \lambda)}, \qquad \hat{m}_f^* = \frac{6\overline{v}\delta - M}{4\delta(3c_f - \lambda)}.$$

Proposition 1 yields two useful observations for the subsequent layout comparison. First, the optimal advertising load is governed by viewer-side primitives rather than advertising-side revenue-sharing primitives. In both layouts, the monetization rate r, the platform's retained revenue share $1-\gamma$, and the advertising nuisance parameter ϕ enter optimized revenue in the same way. Therefore, changes in the advertising market shift the level of revenue under both layouts, but the relative advantage of slide versus feed is governed by how each layout generates viewer consumption.

Second, the closed-form revenues reveal the central trade-off between matching quality and consumption friction. Feed improves expected match quality because viewers can conduct preview-based screening. This benefit is reflected in the larger matching term $6\delta v - M$. Slide does not offer the same viewer-side screening opportunity, but it reduces browsing and cognitive frictions, reflected in the lower consumption-cost term $2c_s - \lambda$. Hence, after the platform optimizes advertising, the slide-feed comparison depends on whether feed's additional matching benefit is large enough to compensate for its higher consumption friction. This observation provides the key mechanism for the cutoff results in Section 4.2.

The closed-form solutions immediately yield the following comparative statics.

Corollary 1 **(Comparative statics of optimum).** *Fix a layout $e \in \{s, f\}$.*

(i) The optimal advertising load $a_e^\star$ increases with content density δ and perfect-match value $\overline{v}$, and decreases with candidate-set size M.

(ii) The platform's optimal revenue $\pi_e^\star$ increases with content density δ, perfect-match value $\overline{v}$ and learning ability λ, and decreases with the candidate-set size M.

(iii) The optimal viewer consumption $\hat{m}_e^*$ increases with content density δ, perfect-match value $\overline{v}$, and learning ability λ, and decreases with candidate-set size M.

Corollary 1 shows how the platform's optimized outcomes respond to the primitives governing platform's ability to generate valuable attention: larger content density δ, higher perfect-match value $\overline{v}$, a smaller candidate set M, and stronger learning ability λ all improve the value of recommended content and therefore increase consumption and revenue. Improvements in matching fundamentals raise both viewer consumption and advertising revenue, whereas advertising nuisance affects monetization mainly through the platform's chosen advertising load. Appendix B.3 shows that these properties continue to hold under a broader class of convex ad-nuisance specifications.

These observations provide a useful benchmark for comparing interface layouts. The comparative statics indicate that platform performance depends critically on how the matching transforms available content into realized viewer consumption, and on how much advertising nuisance can be absorbed without discouraging consumption. Slide and feed layouts differ precisely along these dimensions. We next compare the two layouts and characterize the operating conditions under which each layout yields higher viewer consumption and platform revenue.

4.2. Optimal Layout

We now compare the platform's optimal viewer consumption and revenue under the feed and slide layouts. The feed layout allows viewers to inspect and screen content more actively, which helps mitigate recommendation errors through viewer-side selection. By contrast, the slide layout reduces browsing frictions and facilitates continuous consumption, but it relies more heavily on the platform's ability to deliver sufficiently accurate matches upfront. As a result, the comparison between the two layouts is governed by a common tradeoff between screening value and friction reduction. We use the term *matching environment* to summarize the primitives that determine how effectively viewers can be matched with suitable content. This environment has two components. The first is algorithmic strength, captured by the learning ability λ and the candidate-set size M. The second is content richness, captured by the content density δ and the perfect-match value $\overline{v}$. Together, these primitives determine the platform's ability to generate high-quality viewer–content matches.

Fix the content environment parameters δ and $\overline{v}$, the following proposition shows that the relative performance of slide and feed is characterized by a cutoff boundary in the (M, λ) space.

PROPOSITION 2 **(Layout comparison in algorithmic strength).** *(i) For any M, there exists $\lambda^*_m(M) = \frac{M(3c_f-2c_s)-12\overline{v}\delta(c_f-c_s)}{2\overline{v}\delta}$ and $\lambda^*_\pi(M) = 2c_s - \frac{3c_f-2c_s}{\frac{2(6\overline{v}\delta-M)^2}{3(4\overline{v}\delta-M)^2}-1}$ such that slide generates higher viewer consumption than feed if and only if $\lambda > \lambda^*_m(M)$, and slide generates higher platform revenue than feed if and only if $\lambda > \lambda^*_\pi(M)$.*

(ii) For any λ, there exists $M^*_m(\lambda) = \frac{12\overline{v}\delta(c_f-c_s)+2\overline{v}\delta\lambda}{3c_f-2c_s}$ and $M^*_\pi(\lambda) = 4\overline{v}\delta - \frac{2\overline{v}\delta}{\sqrt{\frac{3(3c_f-\lambda)}{2(2c_s-\lambda)}-1}}$ such that slide generates higher viewer consumption than feed if and only if $M < M^*_m(\lambda)$, and slide generates higher platform revenue than feed if and only if $M < M^*_\pi(\lambda)$.

Proposition 2 highlights the role of recommendation technology and shows how algorithmic strength shapes the value of viewer-side screening. When M is large or λ is small, the platform's recommendations are relatively inaccurate. In this environment, feed lets the viewers selection to partially correct algorithmic mismatch and protects engagement. This screening benefit can outweigh the higher browsing cost of the feed layout.

By contrast, when M is small or λ is large, the recommendation system already performs much of the screening role. The incremental matching gain from showing multiple alternatives becomes smaller, while the additional browsing friction of feed remains. In this case, slide becomes more attractive because it converts accurate recommendations into continuous, low-friction consumption. This mechanism is particularly important for revenue. Strong recommendations under slide make it easier for viewers to keep consuming content, thereby expanding the stock of monetizable attention. The platform can then extract more advertising revenue without relying on viewers to actively search and compare. Hence, slide is not merely a lower-cost interface; it becomes a more effective revenue-extraction layout when algorithmic matching is sufficiently strong.

The value of a layout also depends on the content primitives that determine the quality and abundance of potential matches. Content density δ affects the likelihood that the platform has relevant items to recommend, whereas the perfect-match value $\overline{v}$ determines the payoff from successfully directing viewer attention to the right content. We therefore next examine how the content environment, summarized by content density δ and the perfectly-matched content value $\overline{v}$, affects the comparison between slide and feed layouts. Fix the algorithmic strength parameters M and λ, the relative performance of slide and feed is similarly characterized by a cutoff boundary in the $(\delta,\overline{v})$ space, showing in the following proposition.

Proposition 3 **(Layout comparison in content richness)**. *(i) For any fixed δ, there exist $\overline{v}^*_m(\delta) = \frac{M(3c_f-2c_s)}{12(c_f-c_s)\delta+2\lambda\delta}$ and $\overline{v}^*_\pi(\delta) = \frac{\frac{M}{8\delta}}{\sqrt{\frac{3(3c_f-\lambda)}{2(2c_s-\lambda)}}-\frac{3}{2}} + \frac{M}{4\delta}$ such that slide generates higher viewer consumption than feed if and only if $\overline{v} > \overline{v}^*_m$, and slide generates higher platform revenue than feed if and only if $\overline{v} > \overline{v}^*_\pi$.*

(ii) For any fixed $\overline{v}$, there exist $\delta^*_m(\overline{v}) = \frac{M(3c_f-2c_s)}{12(c_f-c_s)\overline{v}+2\lambda\overline{v}}$ and $\delta^*_\pi(\overline{v}) = \frac{\frac{M}{8\overline{v}}}{\sqrt{\frac{3(3c_f-\lambda)}{2(2c_s-\lambda)}}-\frac{3}{2}} + \frac{M}{4\overline{v}}$ such that slide generates higher viewer consumption than feed if and only if $\delta > \delta^*_m$, and slide generates higher platform revenue than feed if and only if $\delta > \delta^*_\pi$.

Proposition 3 shows that content richness can substitute for viewer-side screening. When content density δ is low or the value of a good match $\overline{v}$ is limited, the platform faces a thin or low-quality content environment. In such cases, feed remains useful because viewers can inspect multiple alternatives and avoid poor matches. However, as δ increases, suitable items become more likely to appear near each viewer's preference location. As $\overline{v}$ increases, the payoff from accurate matching also rises. Under these richer content conditions, slide can better exploit the content ecosystem by reducing decision friction.

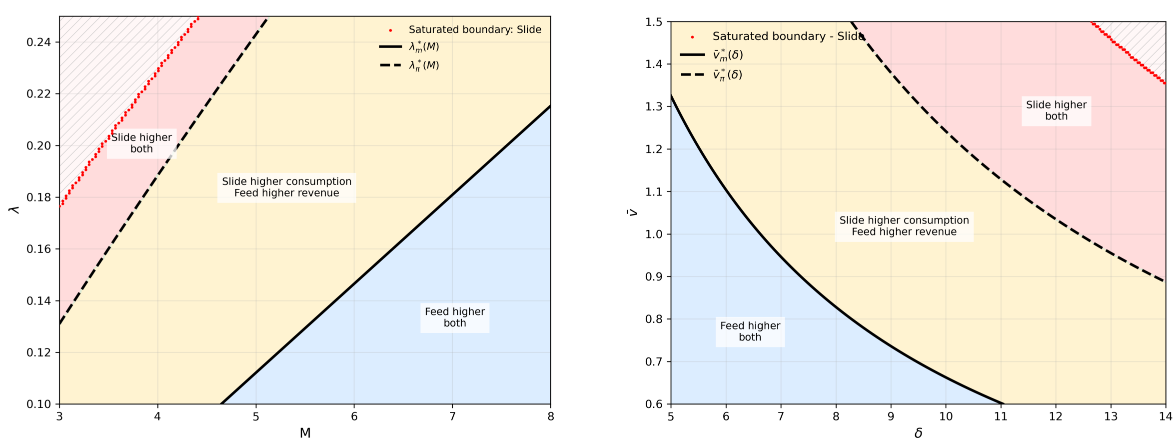
The revenue implication is again important. A rich content ecosystem increases the amount of valuable attention that can be generated by the platform. Slide is especially effective at monetizing this attention because its lower-friction interface keeps viewers consuming once recommendations are sufficiently attractive. Feed's screening function is more valuable in thin environments, but becomes less necessary when the content pool itself already supports high match quality.

Propositions 2 and 3 compare slide and feed along two dimensions: viewer consumption and platform revenue. A common managerial heuristic is to evaluate layout designs by engagement metrics such as views, watch time, or consumption volume. A notable implication is that this heuristic can be misleading. Because advertising revenue depends both on consumption volume and on viewers' tolerance for advertising, a layout that generates more consumption may nevertheless generate less revenue. The reason is that feed changes the composition and value of consumed attention: viewers consume fewer items, but those items are better matched on average. The following corollary formalizes this wedge between engagement and monetization.

COROLLARY 2 **(Engagement-revenue wedge.)**. *For layout comparison, the consumption-equality cutoff lies weakly below the revenue-equality cutoff. Therefore, whenever the interval between the two cutoffs lies within the admissible parameter region, there exist intermediate regions in which slide generates higher viewer consumption whereas feed generates higher platform revenue. Specifically:*

(i) In the algorithmic-strength space (M,λ)*, we have* $\lambda_m^*(M) \le \lambda_\pi^*(M)$*. For admissible* λ *satisfying* $\lambda_m^*(M) \le \lambda \le \lambda_\pi^*(M)$*, slide generates higher viewer consumption, whereas feed generates higher platform revenue.*

(ii) In the content-richness space $(\delta,\overline{v})$*, we have* $\overline{v}_m^*(\delta) \le \overline{v}_\pi^*(\delta)$*. For admissible* $\overline{v}$ *satisfying* $\overline{v}_m^*(\delta) \le \overline{v} \le \overline{v}_\pi^*(\delta)$*, slide generates higher viewer consumption, whereas feed generates higher platform revenue.*



(a) (b)

Figure 3 Slide versus Feed: dominance regions The solid curve denotes the consumption-equality cutoff $\lambda_m^*(M)$ and $\overline{v}_m^*(\delta)$, and the dashed curve denotes the revenue-equality cutoff $\lambda_\pi^*(M)$ and $\overline{v}_\pi^*(\delta)$. The dotted curve marks the interior-learning boundary implied by Assumption 1; the hatched region is the slide learning-saturated region where slide always dominates. Baseline parameters: $r=2; \gamma=0.2; c_s=0.5; c_f=0.51; \phi=0.1$. We fix $\delta=7$, $\overline{v}=1.1$ for Panel (a), and $\lambda=0.1$, $M=4$ for Panel (b).

Figure 3 illustrates the layout comparison results. Panel (a) compares two layouts in (M,λ) space, and Panel (b) compares two layouts in $(\delta,\overline{v})$ space. Notably, feed does not saturate in the considered parameter regions while slide saturates and dominates when the matching environment is sufficiently strong. The intermediate regions indicate the engagement-revenue wedge, where slide generates higher viewer consumption, whereas feed generates higher platform revenue, as depicted in Corollary 2. This wedge reflects the difference between attention volume and monetization efficiency. Slide is more effective at increasing viewer consumption because it reduces browsing and decision frictions. However, when the matching environment is intermediate, the platform's algorithm and content pool are not yet strong enough to fully substitute for viewer-side screening. Under the feed layout, viewer-side screening raises the expected value of consumed content and makes viewers more tolerant of advertising nuisance. As a result, feed allows the platform to sustain a higher advertising load in intermediate environments, even if total consumption is lower. Hence, feed can generate greater revenue even when it induces less consumption.

Together, these results provide an interface-design interpretation of platform matching environment. Early-stage platforms or platforms with sparse content pools should not necessarily imitate slide-first interfaces, because viewers still benefit from active comparison and self-selection. As the platform accumulates behavioral data, improves recall precision, and expands its content ecosystem, the value of active screening declines. This implication is consistent with the observed evolution of many content platforms. Platforms often begin with layouts that expose multiple alternatives and allow viewers to compare and self-select. As their recommendation systems accumulate data and their content ecosystems become richer, they increasingly adopt slide-like interfaces that emphasize sequential, low-friction consumption. More importantly, the revenue performance depends on monetizable attention, not raw attention. In intermediate matching environments, slide wins on volume but feed wins on monetization intensity. Hence, a platform that chooses layouts based only on engagement may select the wrong interface from a monetization perspective.

5. Two-period Setting

The one-period analysis treats algorithmic strength and content supply as fixed primitives. In practice, however, these fundamentals evolve over time. Viewer consumption generates behavioral data that improves future recommendations, creator revenue affects future content supply, and viewer experience affects future viewer participation. To capture this intertemporal feedback loop among creators' incentives, viewers' engagement, and the platform's data-driven learning, we extend the one-period static environment to a two-period dynamic setting in this section. The two-period model preserves the within-period consumption and monetization structure of the baseline model, while allowing creator entry, viewer adoption, and recommendation system's accuracy to evolve endogenously with the first period outcomes.

5.1. Model

We consider a two-period model of the platform where the platform maximizes the total expected revenue over periods $t=1,2$. The platform decides layout $e\in\{s,f\}$ at the beginning of period 1. In the baseline two-period model, the platform commits to a single layout. We later relax this restriction in the switching-policy analysis. In each period t, after observing the state variables of that period, the platform decides the advertising load $a_e^{(t)}$.

Given period t and the chosen layout e, let $\delta_e^{(t)}$ denote the content density. Let $\beta_e^{(t)}$ denote the viewer mass, and $\hat{m}_e^{(t)}$ the expected consumption of each viewer at the utility maximization point, therefore the total viewer consumption is $\beta_e^{(t)}\hat{m}_e^{(t)}$ in each period t. Let $V_e^{(t)}$ be the random variable denoting the value of a consumed content item under layout e in period t. Viewer's expected cumulative utility at her utility maximization point is $\mathbb{E}U_e^{(t)}=\mathbb{E}V_e^{(t)}\cdot\hat{m}_e^{(t)}-\frac{1}{2}c_e[\hat{m}_e^{(t)}]^2-\phi a_e^{(t)}\hat{m}_e^{(t)}$. The platform revenue in each period can be represented by $\pi_e^{(t)}=a_e^{(t)}\cdot r(1-\gamma)\cdot\beta_e^{(t)}\hat{m}_e^{(t)}$, and creators' average revenue per unit density is $\bar{R}_e^{(t)}=a_e^{(t)}\cdot r\cdot\gamma\cdot\frac{\beta_e^{(t)}\hat{m}_e^{(t)}}{\delta_e^{(t)}}$.

The initial market states of the first period are the same for both layouts, including the content density $\delta_s^{(1)}=\delta_f^{(1)}=\delta^{(1)}$ and the viewer mass $\beta_s^{(1)}=\beta_f^{(1)}=\beta^{(1)}$. To capture the intertemporal feedback effect, we allow both sides of the market to evolve with first-period outcomes. Specifically, we assume that content density in period 2 grow with creators' average revenue in period 1, and viewer mass in period 2 grows with each viewer's expected cumulative utility in period 1:

$$\delta_e^{(2)}=\delta^{(1)}(\eta_1+\eta_2\cdot\bar{R}_e^{(1)}),\qquad \beta_e^{(2)}=\beta^{(1)}(\xi_1+\xi_2\cdot\mathbb{E}U_e^{(1)}). \tag{5}$$

The parameters η_1 and ξ_1 capture baseline persistence of the creator and viewer bases, respectively. The parameters η_2 and ξ_2 measure the responsiveness of future creator entry and viewer participation to first-period outcomes. A higher average creator revenue $\bar{R}_e^{(1)}$ attracts more creators and increases the second-period content density. A higher expected viewer utility $EU_e^{(1)}$ improves retention and word-of-mouth adoption, thereby increasing the second-period viewer mass. Moreover, we model the AI flywheel by letting the recommendation system learns from historical viewer interaction data, the amount of which is represented by the total viewer consumption in the last period, $\beta_e^{(t-1)}\hat{m}_e^{(t-1)}$. The lowest value of content in the candidate set is

$$\underline{v}_e^{(t)}=\overline{v}-\frac{M}{2\delta_e^{(t)}}+\lambda\beta_e^{(t-1)}\hat{m}_e^{(t-1)},\quad t=1,2. \tag{6}$$

Different from the one-period setting, where learning is captured by a contemporaneous fixed point, the two-period model uses a lagged-learning specification. That is, first-period consumption affects recommendation quality in the second period. This formulation preserves the central feedback mechanism in the one-period benchmark, but makes its dynamic implications explicit. Since there is no historical viewer interaction before the first period, we let $\hat{m}_e^{(0)}=0$. The platform chooses layout e and period-specific advertising loads $a^{(1)}$ and $a^{(2)}$ to maximize total expected revenue.

5.1.1. Timing of the Model. In the initial state of period 1, the platform has content density $\delta^{(1)}$ and viewer mass $\beta^{(1)}$. The lowest value of candidate content is $\underline{v}_e^{(1)} = \overline{v} - \frac{M}{2\delta^{(1)}}$. The platform decides layout e and advertising load $a^{(1)}$. Then viewers consume, and total consumption and revenue realize.

In period 2, the market sizes and the algorithmic strength first grow with the outcomes in period 1: content density grows with creator average revenue $\delta_e^{(2)} = \delta^{(1)}(\eta_1 + \eta_2 \cdot \bar{R}_e^{(1)})$, viewer mass grows with viewers' expected cumulative utility $\beta_e^{(2)} = \beta^{(1)}(\xi_1 + \xi_2 \cdot \mathbb{E}U_e^{(1)})$, and the lowest value of candidate content improves from viewer interaction data obtained from the first period $\underline{v}_e^{(2)} = \overline{v} - \frac{M}{2\delta_e^{(2)}} + \lambda\beta^{(1)}\hat{m}_e^{(1)}$. The platform then decides the advertising load $a^{(2)}$. After that, viewers consume to realize total consumption and revenue.

5.1.2. Equilibrium Consumption. We first characterize the equilibrium viewer consumption under each layout e in each period t for a given advertising load $a_e^{(t)}$, denote by $\hat{m}_e^{(t)}$. Similar as the one-period setting, the viewer's optimal consumption rule is $\hat{m}_e^{(t)} = \max\left\{0, \frac{\mathbb{E}[V_e^{(t)}] - \phi a_e^{(t)}}{c_e}\right\}$. The expected realized content value under the two layouts is

$$\mathbb{E}V_s^{(t)} = \frac{\underline{v}_s^{(t)} + \overline{v}}{2}, \qquad \mathbb{E}V_f^{(t)} = \frac{\underline{v}_f^{(t)} + 2\overline{v}}{3} \tag{7}$$

with $\underline{v}_e^{(t)} = \overline{v} - \frac{M}{2\delta_e^{(t)}} + \lambda\beta_e^{(t-1)}\hat{m}_e^{(t-1)},\ t = 1, 2$ where $\hat{m}_e^{(0)} = 0$. Substituting the expression gives the equilibrium viewer consumption under each layout in each period. The results are summarized in the following Lemma.

LEMMA 2 **(Equilibrium viewer consumption in each period)**. *For any layout $e \in \{s, f\}$, the unique equilibrium viewer consumption in period 1 under given advertising load $a^{(1)} \geq 0$ is*

$$\hat{m}_s^{(1)}(a^{(1)}) = \begin{cases} \frac{4\delta^{(1)}\overline{v} - M}{4\delta^{(1)}c_s} - \frac{\phi a^{(1)}}{c_s}, & \text{if } a^{(1)} \leq \frac{4\delta^{(1)}\overline{v} - M}{4\delta^{(1)}\phi} \\ 0, & \text{else} \end{cases}$$

$$\hat{m}_f^{(1)}(a^{(1)}) = \begin{cases} \frac{6\delta^{(1)}\overline{v} - M}{6\delta^{(1)}c_f} - \frac{\phi a^{(1)}}{c_f}, & \text{if } a^{(1)} \leq \frac{6\delta^{(1)}\overline{v} - M}{6\delta^{(1)}\phi} \\ 0, & \text{else} \end{cases}$$

Given period 2 content density $\delta_e^{(2)}$ and period 1 viewer consumption $\hat{m}_e^{(1)}$, the unique equilibrium viewer consumption in period 2 under given advertising load $a^{(2)} \geq 0$ is

$$\hat{m}_s^{(2)}(a^{(2)}) = \begin{cases} \frac{4\delta_s^{(2)}\overline{v} - M + 2\delta_s^{(2)}\lambda\beta^{(1)}\hat{m}_s^{(1)}}{4\delta_s^{(2)}c_s} - \frac{\phi a^{(2)}}{c_s}, & \text{if } \ 4\delta_s^{(2)}\overline{v} + 2\delta_s^{(2)}\lambda\beta^{(1)}\hat{m}_s^{(1)} > M \\ & \quad \text{and } \ a^{(2)} \leq \frac{4\delta_s^{(2)}\overline{v} - M + 2\delta_s^{(2)}\lambda\beta^{(1)}\hat{m}_s^{(1)}}{4\delta_s^{(2)}\phi} \\ 0, & \text{else} \end{cases}$$

$$\hat{m}_f^{(2)}(a^{(2)}) = \begin{cases} \frac{6\delta_f^{(2)}\overline{v} - M + 2\delta_f^{(2)}\lambda\beta^{(1)}\hat{m}_f^{(1)}}{6\delta_f^{(2)}c_f} - \frac{\phi a^{(2)}}{c_f}, & \text{if } \ 6\delta_f^{(2)}\overline{v} + 2\delta_f^{(2)}\lambda\beta^{(1)}\hat{m}_f^{(1)} > M \\ & \quad \text{and } \ a^{(2)} \leq \frac{6\delta_f^{(2)}\overline{v} - M + 2\delta_f^{(2)}\lambda\beta^{(1)}\hat{m}_f^{(1)}}{6\delta_f^{(2)}\phi} \\ 0, & \text{else} \end{cases}$$

Because there is no pre-period interaction data, first-period recommendation quality contains no learning term. Hence λ affects first-period decisions only through the continuation value, not through first-period consumption directly. Similar as Assumption 2, we impose the maintained assumption $4\delta^{(1)}\overline{v} \geq M$ to guarantees that the equilibrium consumption at zero advertising load is nonnegative and thereby allowing us to focus on the region with nonnegative engagement.

5.2. Analysis

Under layout e, platform's revenue function in both periods $t = 1, 2$ is $\pi_e^{(t)} = a_e^{(t)} \cdot r(1-\gamma) \cdot \beta_e^{(t)} \hat{m}_e^{(t)}$. The platform's problem is to maximize the expected total revenue. We analyze the decision by backward induction starting from the second period.

We denote by $\Pi_e^{(2)}$ the platform's optimal revenue in the second period given the current period market state and the expected total consumption in the first period:

$$\begin{aligned} \Pi_e^{(2)} \left(\hat{m}_e^{(1)}, \beta_e^{(2)}, \delta_e^{(2)} \right) &:= \max_{a_e^{(2)} \geq 0} \; \pi_e^{(2)} \\ &= \max_{a_e^{(2)} \geq 0} \; a_e^{(2)} r(1-\gamma) \cdot \beta_e^{(2)} \hat{m}_e^{(2)} \end{aligned} \tag{8}$$

Solving the second-period problem yields a closed-form continuation value as a function of the inherited market state; the derivation is provided in Appendix A.6. Now we can define the platform's maximization problem in the first period as:

$$\max_{a_e^{(1)} \geq 0} \; \Pi_e := \pi_e^{(1)} + \Pi_e^{(2)} \left(\hat{m}_e^{(1)}, \beta_e^{(2)}, \delta_e^{(2)} \right) \tag{9}$$

The first period advertising load choice balances immediate advertising revenue and the continuation value from market growth. Note that the feasible set for $a^{(1)}$ is the same as in one period setting, and the total revenue function Π_e is continuous in $a^{(1)}$, so there exists an optimal solution. However, Π_e is not concave since there are multiplicative intertemporal feedback channels. Let $\mathcal{A}_e^{(1)*}$ denote the set of optimal first period advertising load choices under layout e. We next benchmark this forward-looking choice against a myopic decision rule that maximizes only the first period revenue in the following proposition.

PROPOSITION 4 **(Dynamic advertising discipline)**. *Fix a recommendation layout* $e \in \{s, f\}$*. Let* $\mathcal{A}_{e,\text{myopic}}^{(1)*}$ *denote the set of optimal solution to the first period myopic problem:*

$$\max_{a_e^{(1)} \geq 0} \; \pi_e^{(1)} \tag{10}$$

Suppose both the dynamic problem and the myopic problem admit interior maximizers. Then for any $a_{e,\text{myopic}}^{(1)*} \in \mathcal{A}_{e,\text{myopic}}^{(1)*}$ *and* $a_e^{(1)*} \in \mathcal{A}_e^{(1)*}$*, we have* $a_{e,\text{myopic}}^{(1)*} \geq a_e^{(1)*}$.

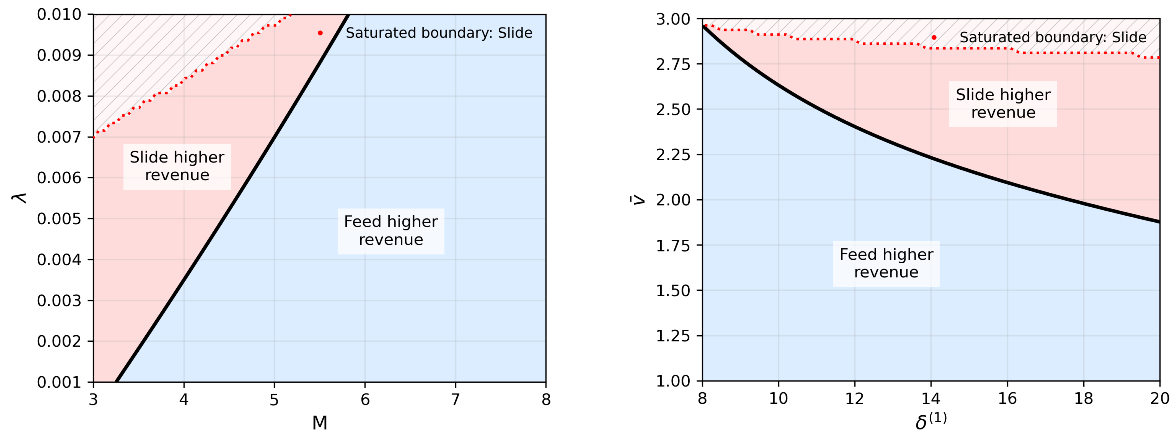
Proposition 4 formalizes the idea that ignoring market-growth considerations tends to yield a more aggressive advertising load choice. This is because that the myopic rule does not internalize the future-value loss caused by reduced consumption and weaker viewer-side growth. This advertising restraint for forward-looking platform can be interpreted as subsidy, by which the platform sacrifices short-run revenue in order to protect viewer engagement to support future market growth, and generate interaction data to improve recommendation by data-learning.

We next compare the platform's optimal revenue across two layouts and the cross-period dynamic mechanisms through numerical analysis. We numerically solve the platform's optimal advertising load decision under each interface layout and compare the resulting optimal revenues. We vary the key primitives governing recommendation performance and the content environment, including the baseline candidate set size M, the learning ability λ, the perfect-match value $\overline{v}$, and the initial content density $\delta^{(1)}$. In all parameter configurations reported below, the platform's objective is numerically single-peaked in advertising load, and the corresponding optimal solution is unique.

Layout comparison in platform revenue. Across specifications, the results exhibit a clear cutoff structure, as shown in Figure 4: the preferred interface depends jointly on algorithmic strength and the health of the content ecosystem. When the recommendation system is sufficiently strong (low M or high λ) or the content environment is sufficiently favorable (high $\overline{v}$ or high $\delta^{(1)}$), the slide layout dominates because its lower viewing friction allows the platform to convert accurate recommendations more effectively into engagement and advertising revenue. Slide achieves saturated-learning boundary faster than feed when the matching environment get stronger and keep dominate in that region. This pattern is consistent with the layout comparison in our analytical results and with the numerical revenue comparisons showing that the revenue difference $\Pi_s^* - \Pi_f^*$ increases as learning strengthens and baseline inaccuracy declines.

Dynamic advertising discipline and its value. Under each layout, we compute the gap between the myopic first-period advertising load and the dynamically optimal first-period advertising load, $a_{e,\text{myopic}}^{(1)*} - a_e^{(1)*}$, shown in Figure 5a and 5b. This gap measures advertising discipline for future growth and captures the AI flywheel incentive embedded in the platform's advertising load decision. As λ increases, the platform has stronger incentives to "build" in the first period and "harvest" in the second period, implying a lower first-period advertising load than under a myopic benchmark because the forward-looking platform internalizes the future cost of degrading viewer experience and slowing subsequent market growth. Feed exhibits stronger restraint when the initial strength is weak (large M) or the learning is weak (small λ). Slide overtakes feed when learning productivity is sufficiently high (large λ) or when the initial algorithm is strong (small M).

Figure 5c and 5d further shows the platform's total revenue gap between optimal $\Pi\left(a_e^{(1)*}\right)$ and myopic $\Pi\left(a_{e,myopic}^{(1)*}\right)$. Slide delivers a larger revenue gain when the algorithm initial strength or the



(a) (b)

Figure 4 Slide versus Feed: revenue dominance regions in the two-period setting

Red regions indicate parameter values under which slide yields higher total two-period revenue than feed; blue regions indicate the opposite. The black curve is the equal-revenue boundary. The dotted curve is the learning-saturated boundary, where the red dot represents the boundary for slide and the black dot represents the boundary for both layouts.

Baseline parameters: $r = 2; \gamma = 0.2; \beta^{(1)} = 5; c_s = 0.5; c_f = 0.51; \phi = 0.1; \xi_1 = 0.1; \xi_2 = 0.9; \eta_1 = 0.1; \eta_2 = 0.9$

Fix $\delta^{(1)} = 12; \overline{v} = 2.5$ for Panel (a). Fix $\lambda = 0.008. M = 5$ for Panel (b).

learning is strong; feed delivers a larger gain when the algorithm is weak. Together, the pattern suggests that slide behaves like a high-learning flywheel layout, whereas feed behaves like a weak-environment insurance layout.

5.2.1. Switching policy. The baseline setting assumes that the platform commits to a fixed layout for both periods. We now allow the platform to choose different layouts across periods. In particular, motivated by the contrasting strengths of the two interfaces, we evaluate a switching strategy that adopts one layout in the first period and another layout in the second period, alongside the two fixed-layout benchmarks.

Four layout policies are available: fix slide, fix feed, slide-to-feed, and feed-to slide. A full closed-form ranking of all switching policies is generally intractable. However, the model yields a clean conditional characterization of the second-period switching decision. Holding the first-period layout fixed, the two policies that differ only in the second-period layout induce the same inherited state. Thus, the second-period choice reduces to the static comparison evaluated at the inherited state.

PROPOSITION 5 **(Conditional cutoff for second-period switching)**. *Fix a first-period layout* $e^{(1)} \in \{s, f\}$. *Let the inherited second-period state be* $\left(\hat{m}^{(1)}_{e^{(1)}}, \delta^{(2)}_{e^{(1)}}, \beta^{(2)}_{e^{(1)}}\right)$. *Define*

$$\rho = \sqrt{\frac{c_s}{c_f}} \in (0,1), \qquad L_{e^{(1)}} = \lambda \beta^{(1)} \hat{m}^{(1)}_{e^{(1)}}.$$

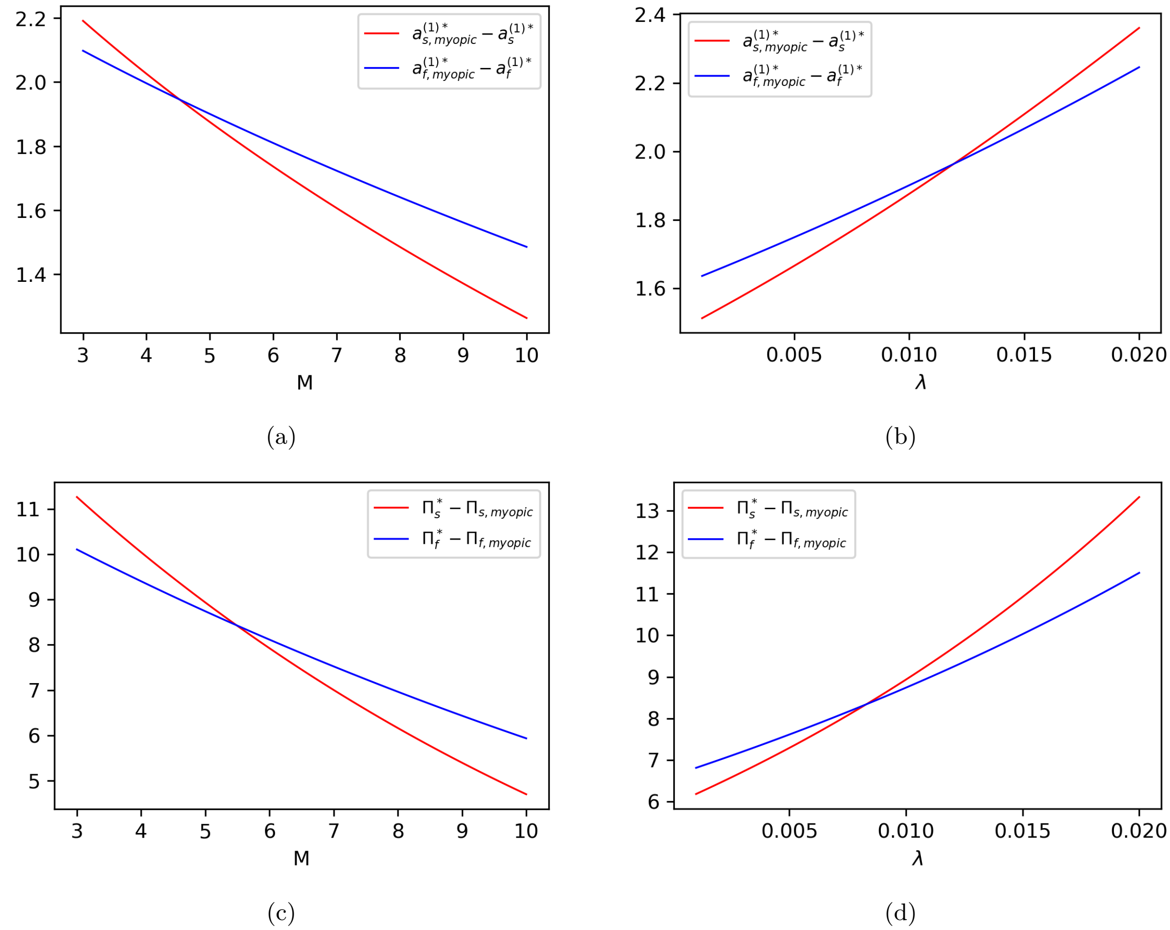


Figure 5 Advertising discipline and its revenue value under each layout The top panels report the reduction in first-period optimal advertising relative to the myopic benchmark. The bottom panels report the associated revenue gain. Baseline parameters: $r = 2; \gamma = 0.2; \beta^{(1)} = 10; \delta^{(1)} = 15; \overline{v} = 2.5;$ $c_s = 0.5; c_f = 0.51; \phi = 0.1; \xi_1 = 0.1; \xi_2 = 0.9; \eta_1 = 0.1; \eta_2 = 0.9$. We fix $\lambda = 0.01$ for Panel (a) and (c), and $M = 5$ for Panel (b) and (d).

Conditional on this inherited state, the second-period layout choice follows cutoff rules in the inherited matching environment.

(i) For any fixed λ, $\delta^{(2)}_{e(1)}$, *and* $\overline{v}$, *there exists* $M^{(2)*}_\pi = 2\delta^{(2)}_{e(1)} L_{e(1)} + 4\delta^{(2)}_{e(1)} \overline{v} \frac{1-\rho}{1-\frac{2}{3}\rho}$ *such that slide generates higher platform revenue than feed if and only if* $M < M^{(2)*}_\pi$.

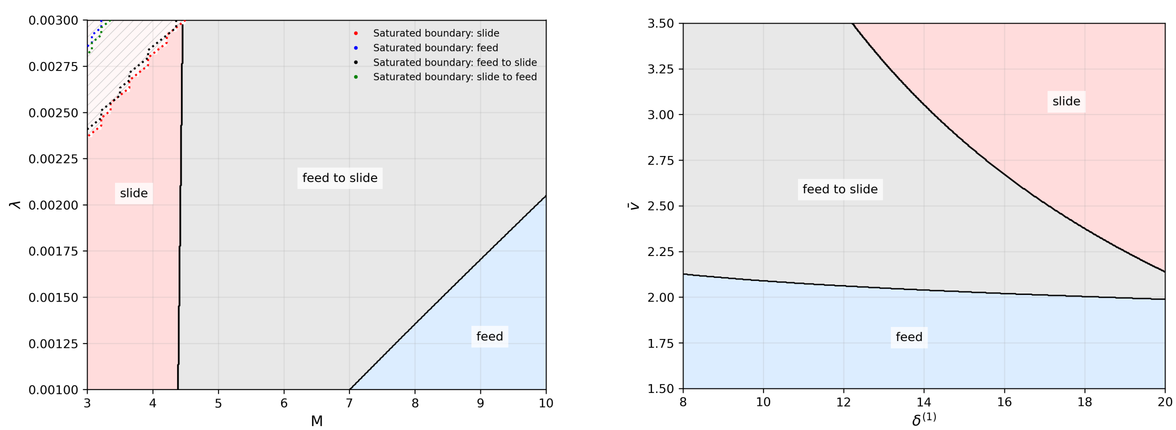
(ii) For any fixed M, $\delta^{(2)}_{e(1)}$, *and* $\overline{v}$, *there exists* $\lambda^{(2)*}_\pi = \frac{M\left(1-\frac{2}{3}\rho\right) - 4\delta^{(2)}_{e(1)} \overline{v}(1-\rho)}{2\delta^{(2)}_{e(1)} \beta^{(1)} \hat{m}^{(1)}_{e(1)} \left(1-\frac{2}{3}\rho\right)}$ *such that slide generates higher platform revenue than feed if and only if* $\lambda > \lambda^{(2)*}_\pi$.

(iii) For any fixed M, λ, *and* $\overline{v}$, *there exists* $\delta^{(2)*}_\pi = \frac{M - 2\delta^{(2)}_{e(1)} L_{e(1)}}{4\overline{v}} \frac{1-\frac{2}{3}\rho}{1-\rho}$ *such that slide generates higher platform revenue than feed if and only if* $\delta^{(2)}_{e(1)} > \delta^{(2)*}_\pi$.

(iv) For any fixed M, λ, *and* $\delta^{(2)}_{e(1)}$, *there exists* $\overline{v}^{(2)*}_\pi = \frac{M - 2\delta^{(2)}_{e(1)} L_{e(1)}}{4\delta^{(2)}_{e(1)}} \frac{1-\frac{2}{3}\rho}{1-\rho}$ *such that slide generates higher platform revenue than feed if and only if* $\overline{v} > \overline{v}^{(2)*}_\pi$.

Therefore, conditional on the first-period layout, the platform chooses the slide layout in period 2 when the inherited matching environment is sufficiently strong. This result provides support for the lifecycle interpretation. It shows that once the platform reaches a given inherited matching state, the decision to rely on viewer-side screening or algorithmic delegation follows the same cutoff logic as in the static layout. We then numerically compare total revenue of all four policies to examine when this conditional switching incentive translates into an optimal dynamic path.

The numerical results in Figure 6 show that the feed-to-slide policy can maximize total revenue when the initial matching environment is not yet strong enough to justify an immediate commitment to slide, but learning potential is sufficiently high. In such cases, feed serves as a resilient ramp-up interface that protects early engagement and data generation, while the subsequent switch to slide allows the platform to capitalize on improved recommendation quality and lower viewing friction in the second period. In contrast, the slide-to-feed policy does not show advantage in any parameter region. This policy fail to utilize feed advantage on ramp-up at the first period where the algorithm is not strong enough, and also reject the low friction advantage of slide in the second period where the algorithm has been improved. The total revenue of each policy is reported in Appendix B.5. In our simulations, the slide-to-feed remains below the feed-to-slide path across the reported parameter ranges and therefore does not alter the qualitative comparison. More broadly, these results suggest that the optimal recommendation layout is not static, but depends on both the platform's current algorithmic strength and the evolutionary stage of its AI flywheel.



(a) (b)

Figure 6 Dominance regions under alternative layout policies: fixed slide, fixed feed, and feed-to-slide switching

Baseline parameters: $r=2; \gamma=0.2; \beta^{(1)}=10; c_s=0.5; c_f=0.51; \phi=0.1; \xi_1=0.1; \xi_2=0.9; \eta_1=0.1; \eta_2=0.9$

Fix $\delta^{(1)}=15; \overline{v}=2.5$ for Panel (a). Fix $\lambda=0.001; M=5$ for Panel (b).

The switching logic also offers a lens for interpreting layout transitions observed in real-world online content platforms. Platforms that initially rely on feed-like interfaces may benefit from preserving viewer-side screening when recommendation accuracy is still limited or when the content ecosystem is still developing. As behavioral data accumulate and content density improves, however, the value of viewer-side screening declines relative to the friction-reduction benefit of slide-like interfaces. Industry accounts of Kuaishou, a large short-vedio platform in China, further note that the platform added a single-column, swipe-up-and-down Selected tab while retaining its dual-column selection mode [3]. This transition is consistent with our lifecycle interpretation.

Collectively, this two-period analysis reinforces and extends the one-period results. Feed is valuable when the platform starts with weak recommendations or a thin content ecosystem because it protects early engagement and data generation. Slide becomes more attractive after the matching environment improves, because it converts stronger matching into low-friction consumption and advertising revenue. The dynamic model therefore suggests that layout choice should be viewed as an evolutionary decision rather than a static interface choice: platforms may optimally begin with feed-like exploratory interfaces and transition toward slide-like sequential interfaces as their data flywheel and content ecosystem mature.

6. Conclusion

This paper studies recommendation layout as a strategic design choice that allocates matching authority between a platform's algorithm and its viewers. We compare two canonical layout. In a slide layout, viewers consume one algorithmically selected item at a time, so the final matching task is largely delegated to the platform. In a feed layout, viewers observe multiple recommended items and screen among them, retaining part of the matching task. The analysis identifies a tradeoff between viewer screening and consumption friction. Feed improves realized match quality by allowing viewers to compare alternatives, whereas slide reduces browsing and decision costs and facilitates sequential consumption.

In the baseline model, the relative performance of the two layouts depends on the strength of the platform's matching environment. When recommendations are imprecise, either because the candidate set is broad or learning ability is limited, feed can outperform slide by allowing viewers to correct algorithmic mismatch through active screening. Feed is also more valuable when content is sparse or the value of a good match is limited. By contrast, when recommendation quality is high or content richness is sufficient, the incremental value of viewer screening declines, and slide's friction-reduction advantage becomes dominant. The model therefore generates cutoff conditions under which the platform's preferred layout shifts from feed to slide as the matching environment improves.

A central implication is that the engagement-maximizing layout need not be the revenue-maximizing layout. Slide can generate more consumption by reducing decision friction, but feed can generate higher advertising revenue in intermediate matching environments because viewer screening raises the expected value of consumed content and increases viewers' tolerance for advertising. This engagementmonetization wedge cautions against evaluating recommendation interfaces solely by consumption volume or engagement metrics. For advertising-supported platforms, the relevant object is not only how much attention the interface captures, but also how monetizable that attention is.

The dynamic extension highlights how layout and advertising decisions shape the platform's future matching environment. Because viewer consumption generates data that improve future recommendations, a forward-looking platform moderates early advertising relative to a myopic benchmark. Excessive advertising may increase current revenue, but it also reduces engagement, weakens learning, and slows future growth. The two-period analysis further suggests that the optimal layout need not be static. A feed-to-slide transition can dominate fixed-layout policies when the platform begins with a weak matching environment but has sufficient learning potential. In this case, feed serves as an early-stage screening interface that protects engagement and data generation, while slide becomes more attractive once accumulated data and content growth make algorithmic delegation more effective.

These results suggest that recommendation interfaces should be evaluated as economic design instruments rather than as purely cosmetic presentation choices. A layout affects who produces match quality, how much friction viewers face, how much advertising they tolerate, and how quickly the platform improves its future recommendations. Platforms should rely more heavily on viewer screening when algorithms or content ecosystems are immature, and shift toward algorithmic delegation when accumulated data and content richness make recommendations sufficiently reliable. More broadly, the paper provides a dynamic interface-design perspective: recommendation layout should be aligned with the platform's stage of algorithmic and ecosystem development.

The model abstracts away from several institutional features that provide opportunities for future research. First, we model a monopolistic platform. In reality, platforms compete fiercely for viewers attention. Future research could explore how the AI flywheel acts as a competitive weapon in a duopoly, and whether competition forces platforms to lower advertising loads even further to prevent data starvation. Second, the baseline model treats content supply as exogenous, and the dynamic extension captures supply-side feedback in reduced form. In practice, creator behavior is influenced by platform monetization. Also, content quality can be endogenous chosen by creators. Future work could endogenize creator entry, content quality, and revenue-sharing decisions to examine how recommendation layout affects both viewer matching and creator incentives. Third, real interfaces differ along dimensions such as autoplay, ranking depth, social signals, ad formats, and the informativeness of user feedback. Incorporating these features would help connect the screening-friction mechanism studied here to richer platform-design environments.

Notes

[1]See https://eriktrautman.com/posts/the-virtuous-cycle-of-ai-products

[2]See https://www.wired.com/story/tiktok-finally-explains-for-you-algorithm-works/

[3]See https://www.cmbi.com/upload/202103/20210317683414.pdf?

Acknowledgments

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Appendices

Appendix A: Proofs and Derivations

A.1. Proof of Lemma 1.

First, viewer's expected cumulative utility form is $U_e(m) = \mathbb{E}[V_e]\cdot m - \frac{1}{2}c_e m^2 - \phi a\, m$, which is strictly concave in m. The utility-maximized consumption is:

$$\hat{m}_e = \max\left\{0,\ \frac{\mathbb{E}[V_e]-\phi a}{c_e}\right\}$$

Here, the interior solution $\frac{\mathbb{E}[V_e]-\phi a}{c_e}$ is endogenously determined through $\hat{m}_e$. We first discuss the interior solution case.

Second, the value distribution of recommended and consumed content is $V_s \sim U[\underline{v}_s, \overline{v}]$ under the slide layout and $V_f = \max\{V_{f1}, V_{f2}\}$ where $V_{fj} \overset{i.i.d}{\sim} U[\underline{v}_f, \overline{v}]$ for $j = 1,2$ under the feed layout. We can therefore derive their expected value $\mathbb{E}[V_s] = \frac{\underline{v}_s+\overline{v}}{2}$, $\mathbb{E}[V_f] = \frac{\underline{v}_f+2\overline{v}}{3}$. Substitute the expected value into the optimal consumption formula to get $\hat{m}_s = \frac{\underline{v}_s+\overline{v}}{2c_s} - \frac{\phi a}{c_s}$, $\hat{m}_f = \frac{\underline{v}_f+2\overline{v}}{3c_f} - \frac{\phi a}{c_f}$.

Third, by definition we have $\underline{v}_e = \left(\overline{v} - \frac{M}{2\delta}\right) + \lambda \hat{m}_e$ (equation 1). Substituting this expression for $\underline{v}_s$ and $\underline{v}_f$ into the equations above yields the following fixed-point condition in $\hat{m}_s$ and $\hat{m}_f$:

$$\hat{m}_s = \frac{\left(\overline{v} - \frac{M}{2\delta}\right) + \lambda \hat{m}_s + \overline{v}}{2c_s} - \frac{\phi a}{c_s}, \qquad \hat{m}_f = \frac{\left(\overline{v} - \frac{M}{2\delta}\right) + \lambda \hat{m}_f + 2\overline{v}}{3c_f} - \frac{\phi a}{c_f}.$$

The equations are equivalent to:

$$(2c_s - \lambda)\hat{m}_s(a) = 2\overline{v} - 2\phi a - \frac{M}{2\delta}, \qquad (3c_f - \lambda)\hat{m}_f(a) = 3\overline{v} - 3\phi a - \frac{M}{2\delta}$$

With the assumption $2c_s > \lambda$ (which follows that $3c_f > \lambda$, since we assume $c_f > c_s$), we can have the unique solution for this fixed-point equations:

$$\hat{m}_s(a) = \frac{4\delta\overline{v} - 4\delta\phi a - M}{2\delta(2c_s - \lambda)}, \qquad \hat{m}_f(a) = \frac{6\delta\overline{v} - 6\delta\phi a - M}{2\delta(3c_f - \lambda)}.$$

We finally include the corner solution case. To assure $\hat{m}_e(a) \geq 0$, we need $a \leq \frac{4\delta\overline{v}-M}{4\delta\phi}$ under the slide layout and $a \leq \frac{6\delta\overline{v}-M}{6\delta\phi}$ under the feed layout. Therefore, the equilibrium consumption is:

$$\hat{m}_s(a) = \begin{cases} \frac{4\delta\overline{v}-4\delta\phi a-M}{2\delta(2c_s-\lambda)}, & \text{if } a \leq \frac{4\delta\overline{v}-M}{4\delta\phi} \\ 0, & \text{else} \end{cases}$$

$$\hat{m}_f(a) = \begin{cases} \frac{6\delta\overline{v}-6\delta\phi a-M}{2\delta(3c_f-\lambda)}, & \text{if } a \leq \frac{6\delta\overline{v}-M}{6\delta\phi} \\ 0, & \text{else} \end{cases}$$

□

A.2. Proof of Proposition 1

Given the equilibrium consumption $\hat{m}_e$ form from Lemma 1, the platform's problem 4 under each layout in the given feasible set ($\{a_s : 0 \leq\ a_s \leq \frac{4\delta\overline{v}-M}{4\delta\phi}\}$ for slide and $\{a_f : 0 \leq\ a_f \leq \frac{6\delta\overline{v}-M}{6\delta\phi}\}$ for feed) is:

$$\max_{a\geq 0} \quad a\, r(1-\gamma)\cdot \frac{4\delta\overline{v} - 4\delta\phi a - M}{2\delta(2c_s - \lambda)}$$

$$\max_{a\geq 0} \quad a\, r(1-\gamma)\cdot \frac{6\delta\overline{v}-6\delta\phi a - M}{2\delta(3c_f-\lambda)}$$

The objective functions are quadratic concave in a. The unique optimal solutions:

$$a_s^* = \frac{4\delta\overline{v}-M}{8\delta\phi}, \quad a_f^* = \frac{6\delta\overline{v}-M}{12\delta\phi}.$$

These solution satisfy the interior condition by Lemma 1 and satisfy the nonnegative constraint by assumption 2. Therefore they are the unique optimal solution of the problem.

Substitute the optimal ads from proposition 1 into the equilibrium consumption from Lemma 1 and the objective function form in 4 yields the rest results. □

A.3. Proof of Proposition 2 and Proposition 3

1. Optimal revenue comparison: The condition $\pi_s^* < \pi_f^*$ is equivalent to

$$\frac{(4\overline{v}\delta-M)^2}{\delta^2}\frac{(1-\gamma)r}{32\phi(2c_s-\lambda)} < \frac{(6\overline{v}\delta-M)^2}{\delta^2}\frac{(1-\gamma)r}{48\phi(3c_f-\lambda)}$$

Sort to have

$$\frac{3c_f-\lambda}{2c_s-\lambda} < \frac{2(6\overline{v}\delta-M)^2}{3(4\overline{v}\delta-M)^2}$$

This is equivalent to:

$$\lambda < 2c_s - \frac{3c_f-2c_s}{\frac{2(6\overline{v}\delta-M)^2}{3(4\overline{v}\delta-M)^2}-1} := \lambda_\pi^*$$

$$\text{or} \;\; M > 4\overline{v}\delta - \frac{2\overline{v}\delta}{\sqrt{\frac{3(3c_f-\lambda)}{2(2c_s-\lambda)}}-1} := M_\pi^*$$

$$\text{or} \;\; \delta < \frac{\frac{M}{8\overline{v}}}{\sqrt{\frac{3(3c_f-\lambda)}{2(2c_s-\lambda)}}-\frac{3}{2}} + \frac{M}{4\overline{v}} := \delta_\pi^*$$

$$\text{or} \;\; \overline{v} < \frac{\frac{M}{8\delta}}{\sqrt{\frac{3(3c_f-\lambda)}{2(2c_s-\lambda)}}-\frac{3}{2}} + \frac{M}{4\delta} := \overline{v}_\pi^*$$

Note that the denominators are positive. First:

$$\begin{aligned}
&2(6\overline{v}\delta-M)^2-3(4\overline{v}\delta-M)^2\\
&=2(36\overline{v}^2\delta^2-12\overline{v}\delta+M^2)-3(16\overline{v}^2\delta^2-8\overline{v}\delta+M^2)\\
&=24\overline{v}^2\delta^2-M^2\\
&\geq 24\overline{v}^2\delta^2-(4\overline{v}\delta)^2\\
&=8\overline{v}^2\delta^2>0
\end{aligned}$$

Therefore $\frac{2(6\overline{v}\delta-M)^2}{3(4\overline{v}\delta-M)^2}-1>0$.

Second:

$$\begin{aligned}
&2(3c_f-\lambda)-3(2c_s-\lambda)\\
&=6(c_f-c_s)+\lambda\\
&>\lambda>0
\end{aligned}$$

Therefore

$$\frac{2(3c_f-\lambda)}{3(2c_s-\lambda)} > 1$$

Which is equivalent to

$$\frac{(3c_f-\lambda)}{(2c_s-\lambda)} > \frac{3}{2}$$

Therefore $\sqrt{\frac{3(3c_f-\lambda)}{2(2c_s-\lambda)}} > \frac{3}{2} > 1$.

2. Total consumption comparison: The condition $\hat{m}_s^* < \hat{m}_f^*$ is equivalent to

$$\frac{4\overline{v}\delta - M}{4\delta(2c_s-\lambda)} < \frac{6\overline{v}\delta - M}{4\delta(3c_f-\lambda)}$$

Sort to have:

$$(6\overline{v}\delta - M)(2c_s-\lambda) - (4\overline{v}\delta - M)(3c_f-\lambda) > 0$$
$$\Leftrightarrow \ M(3c_f-2c_s) - 12\overline{v}\delta(c_f-c_s) - 2\overline{v}\delta\lambda > 0$$

This is equivalent to:

$$\begin{aligned}
&\lambda < \frac{M(3c_f-2c_s)-12\overline{v}\delta(c_f-c_s)}{2\overline{v}\delta} := \lambda_m^*\\
\text{or}\ \ &M > \frac{12\overline{v}\delta(c_f-c_s)+2\overline{v}\delta\lambda}{3c_f-2c_s} := M_m^*\\
\text{or}\ \ &\delta < \frac{M(3c_f-2c_s)}{12(c_f-c_s)\overline{v}+2\lambda\overline{v}} := \delta_m^*\\
\text{or}\ \ &\overline{v} < \frac{M(3c_f-2c_s)}{12(c_f-c_s)\delta+2\lambda\delta} := \overline{v}_m^*
\end{aligned}$$

Note that the denominators are all positive with $c_f > c_s$.

□

A.4. Proof of Corollary 2

For $\lambda_m^*(M) = \frac{M(3c_f-2c_s)-12\overline{v}\delta(c_f-c_s)}{2\overline{v}\delta}$ and $\lambda_\pi^*(M) = 2c_s - \frac{3c_f-2c_s}{\frac{2(6\overline{v}\delta-M)^2}{3(4\overline{v}\delta-M)^2}-1}$.

Let $x = \frac{M}{\overline{v}\delta}$. Since $4\overline{v}\delta \geq M$, we have $0 < x \leq 4$. We can rearrange the form to have,

$$\lambda_m^*(M) = \frac{x(3c_f-2c_s)-12(c_f-c_s)}{2},$$

and

$$\lambda_\pi^*(M) = 2c_s - \frac{3c_f-2c_s}{\frac{2(6-x)^2}{3(4-x)^2}-1} = 2c_s - \frac{3(4-x)^2(3c_f-2c_s)}{24-x^2}.$$

Substituting the above expressions gives

$$\begin{aligned}
\lambda_m^*(M) - \lambda_\pi^*(M) &= \frac{x(3c_f-2c_s)-12(c_f-c_s)}{2} - \left[2c_s - \frac{3(3c_f-2c_s)(4-x)^2}{24-x^2}\right]\\
&= \frac{x(3c_f-2c_s)-12c_f+8c_s}{2} + \frac{3(3c_f-2c_s)(4-x)^2}{24-x^2}.
\end{aligned}$$

Combining terms yields

$$\lambda_m^*(M) - \lambda_\pi^*(M) = (3c_f-2c_s)\cdot\frac{x(x-4)(6-x)}{2(24-x^2)}.$$

Since $0 < x \leq 4$, we have $x-4 \leq 0$, $6-x>0$. Moreover, since $c_f > c_s > 0$, $3c_f - 2c_s > 0$. Therefore,

$$\lambda_m^*(M) - \lambda_\pi^*(M) \leq 0.$$

Thus,

$$\lambda_m^*(M) \leq \lambda_\pi^*(M).$$

That concludes the proof. □

For $\overline{v}_m^*(\delta) = \frac{M(3c_f - 2c_s)}{12(c_f - c_s)\delta + 2\lambda\delta}$ and $\overline{v}_\pi^*(\delta) = \frac{\frac{M}{8\delta}}{\sqrt{\frac{3(3c_f-\lambda)}{2(2c_s-\lambda)}} - \frac{3}{2}} + \frac{M}{4\delta}$

Let

$$R = \sqrt{\frac{3(3c_f - \lambda)}{2(2c_s - \lambda)}}.$$

Appendix A.3 has show $R > \frac{3}{2}$. Then

$$\overline{v}_\pi^*(\delta) = \frac{M}{8\delta}\frac{1}{R-\frac{3}{2}} + \frac{M}{4\delta}.$$

Combining the two terms gives

$$\overline{v}_\pi^*(\delta) = \frac{M}{8\delta}\left(\frac{1}{R-\frac{3}{2}} + 2\right) = \frac{M}{4\delta} \cdot \frac{R-1}{R-\frac{3}{2}}.$$

Now define

$$a = 3c_f - 2c_s, \qquad b = 2c_s - \lambda.$$

Since $0 < \lambda < 2c_s$ and $c_f > c_s > 0$, we have $a > 0,\ b > 0$. Then $3c_f - \lambda = a + b$ and $6(c_f - c_s) + \lambda = 2a - b$. Therefore,

$$\overline{v}_m^*(\delta) = \frac{M}{2\delta}\frac{a}{2a-b}.$$

Moreover,

$$R = \sqrt{\frac{3(a+b)}{2b}}.$$

Let

$$t = \frac{a}{b} = \frac{3c_f - 2c_s}{2c_s - \lambda}.$$

Then

$$R = \sqrt{\frac{3(t+1)}{2}},$$

and

$$\overline{v}_m^*(\delta) = \frac{M}{2\delta}\frac{t}{2t-1}, \qquad \overline{v}_\pi^*(\delta) = \frac{M}{4\delta}\frac{R-1}{R-\frac{3}{2}}.$$

Since $\frac{M}{4\delta} > 0$, comparing $\overline{v}_m^*(\delta)$ and $\overline{v}_\pi^*(\delta)$ is equivalent to comparing

$$\frac{2t}{2t-1} \quad \text{and} \quad \frac{R-1}{R-\frac{3}{2}}.$$

Their difference is

$$\frac{2t}{2t-1} - \frac{R-1}{R-\frac{3}{2}} = \frac{2t\left(R-\frac{3}{2}\right) - (R-1)(2t-1)}{(2t-1)\left(R-\frac{3}{2}\right)}.$$

The numerator simplifies as

$$2tR - 3t - (2tR - R - 2t + 1) = R - t - 1.$$

Hence,

$$\frac{2t}{2t-1}-\frac{R-1}{R-\frac{3}{2}}=\frac{R-t-1}{(2t-1)\left(R-\frac{3}{2}\right)}.$$

Since

$$R^2=\frac{3(t+1)}{2},$$

we have

$$R^2-(t+1)^2=\frac{3(t+1)}{2}-(t+1)^2.$$

Thus,

$$R^2-(t+1)^2=(t+1)\left(\frac{3}{2}-(t+1)\right)=(t+1)\left(\frac{1}{2}-t\right).$$

Since $R+t+1>0$,

$$R-t-1=\frac{R^2-(t+1)^2}{R+t+1}=\frac{(t+1)\left(\frac{1}{2}-t\right)}{R+t+1}.$$

Therefore,

$$\frac{2t}{2t-1}-\frac{R-1}{R-\frac{3}{2}}=\frac{\frac{(t+1)\left(\frac{1}{2}-t\right)}{R+t+1}}{(2t-1)\left(R-\frac{3}{2}\right)}.$$

Since

$$\frac{1}{2}-t=-\frac{2t-1}{2},$$

we get

$$\frac{2t}{2t-1}-\frac{R-1}{R-\frac{3}{2}}=-\frac{t+1}{2(R+t+1)\left(R-\frac{3}{2}\right)}.$$

It follows that

$$\overline{v}_m^*(\delta)-\overline{v}_\pi^*(\delta)=-\frac{M(t+1)}{8\delta(R+t+1)\left(R-\frac{3}{2}\right)}.$$

Since $R>\frac{3}{2}$. we have,

$$\overline{v}_m^*(\delta)-\overline{v}_\pi^*(\delta)\le 0.$$

Thus,

$$\overline{v}_m^*(\delta)\le\overline{v}_\pi^*(\delta).$$

That concludes the proof. □

A.5. Proof of Lemma 2

At each viewer utility-maximized point, the expected quantity of consumption is:

$$\hat{m}_e^{(t)}=\max\left\{0,\frac{\mathbb{E}[V_e^{(t)}]-\phi a_e^{(t)}}{c_e}\right\}$$

From distribution of V_e, we have:

$$\mathbb{E}v_s^{(t)}=\frac{\underline{v}_s^{(t)}+\overline{v}}{2},\qquad \mathbb{E}v_f^{(t)}=\frac{\underline{v}_f^{(t)}+2\overline{v}}{3}$$

We also have:

$$\underline{v}_s^{(1)}=\overline{v}-\frac{M}{2\delta^{(1)}},\quad \underline{v}_s^{(2)}=\overline{v}-\frac{M}{2\delta_s^{(2)}}+\lambda\beta_s^{(1)}\hat{m}_s^{(1)}$$
$$\underline{v}_f^{(1)}=\overline{v}-\frac{M}{2\delta^{(1)}},\quad \underline{v}_f^{(2)}=\overline{v}-\frac{M}{2\delta_f^{(2)}}+\lambda\beta_f^{(1)}\hat{m}_f^{(1)}$$

Directly insert value to have the results. □

A.6. Period 2 Revenue Optimization

By Lemma 2, given period 2 content density $\delta_e^{(2)}$, period 1 viewer consumption $\hat{m}_e^{(1)}$ and advertising load $a^{(2)} \geq 0$ is

$$\hat{m}_s^{(2)}(a^{(2)}) = \begin{cases} \frac{4\delta_s^{(2)}\overline{v} - M + 2\delta_s^{(2)}\lambda\beta^{(1)}\hat{m}_s^{(1)}}{4\delta_s^{(2)}c_s} - \frac{\phi a^{(2)}}{c_s}, & \text{if } 4\delta_s^{(2)}\overline{v} + 2\delta_s^{(2)}\lambda\beta^{(1)}\hat{m}_s^{(1)} > M \\ & \quad \text{and } a^{(2)} \leq \frac{4\delta_s^{(2)}\overline{v} - M + 2\delta_s^{(2)}\lambda\beta^{(1)}\hat{m}_s^{(1)}}{4\delta_s^{(2)}\phi} \\ 0, & \text{else} \end{cases}$$

$$\hat{m}_f^{(2)}(a^{(2)}) = \begin{cases} \frac{6\delta_f^{(2)}\overline{v} - M + 2\delta_f^{(2)}\lambda\beta^{(1)}\hat{m}_f^{(1)}}{6\delta_f^{(2)}c_f} - \frac{\phi a^{(2)}}{c_f}, & \text{if } 6\delta_f^{(2)}\overline{v} + 2\delta_f^{(2)}\lambda\beta^{(1)}\hat{m}_f^{(1)} > M \\ & \quad \text{and } a^{(2)} \leq \frac{6\delta_f^{(2)}\overline{v} - M + 2\delta_f^{(2)}\lambda\beta^{(1)}\hat{m}_f^{(1)}}{6\delta_f^{(2)}\phi} \\ 0, & \text{else} \end{cases}$$

We here consider the case where $4\delta_s^{(2)}\overline{v} + 2\delta_s^{(2)}\lambda\beta^{(1)}\hat{m}_s^{(1)} > M$ under slide and $6\delta_f^{(2)}\overline{v} + 2\delta_f^{(2)}\lambda\beta^{(1)}\hat{m}_f^{(1)} > M$ under feed. Else, it turns to a trivial case where the optimal revenue is always 0.

Given this form, it is without loss of generality to restrict attention to the feasible set $\{a_s : 0 \leq \ a_s \leq \frac{4\delta_s^{(2)}\overline{v} - M + 2\delta_s^{(2)}\lambda\beta^{(1)}\hat{m}_s^{(1)}}{4\delta_s^{(2)}\phi}\}$ for slide and $\{a_f : 0 \leq \ a_f \leq \frac{6\delta_f^{(2)}\overline{v} - M + 2\delta_f^{(2)}\lambda\beta^{(1)}\hat{m}_f^{(1)}}{6\delta_f^{(2)}\phi}\}$ for feed. The platform's period 2 problem is

$$\max_{a \geq 0} \quad \pi_e^{(2)}(a) = ar(1-\gamma)\beta_e^{(2)}\hat{m}_e^{(2)}(a)$$

The objective functions are quadratic concave in a. The unique optimal solutions:

$$a_s^* = \frac{4\delta_s^{(2)}\overline{v} - M + 2\delta_s^{(2)}\lambda\beta^{(1)}\hat{m}_s^{(1)}}{8\delta_s^{(2)}\phi}$$

$$a_f^* = \frac{6\delta_f^{(2)}\overline{v} - M + 2\delta_f^{(2)}\lambda\beta^{(1)}\hat{m}_f^{(1)}}{12\delta_f^{(2)}\phi}$$

These solution satisfy the interior condition the nonnegative constraint. Therefore they are the unique optimal solution of the problem. The optimal value $\Pi_e^{(2)}$ is:

$$\Pi_s^{(2)} = \frac{r(1-\gamma)}{\phi c_s}\beta_s^{(2)} \cdot \left[\frac{4\delta_s^{(2)}\overline{v} - M + 2\delta_s^{(2)}\lambda\beta^{(1)}\hat{m}_s^{(1)}}{8\delta_s^{(2)}}\right]^2$$

$$\Pi_f^{(2)} = \frac{r(1-\gamma)}{\phi c_f}\beta_f^{(2)} \cdot \left[\frac{6\delta_f^{(2)}\overline{v} - M + 2\delta_f^{(2)}\lambda\beta^{(1)}\hat{m}_f^{(1)}}{12\delta_f^{(2)}}\right]^2$$

Per viewer consumption under optimal advertising is:

$$\hat{m}_s^{(2)} = \frac{4\delta_s^{(2)}\overline{v} - M + 2\delta_s^{(2)}\lambda\beta^{(1)}\hat{m}_s^{(1)}}{8\delta_s^{(2)}c_s}$$

$$\hat{m}_f^{(2)} = \frac{6\delta_f^{(2)}\overline{v} - M + 2\delta_f^{(2)}\lambda\beta^{(1)}\hat{m}_f^{(1)}}{12\delta_f^{(2)}c_f}$$

□

A.7. Proof of Proposition 4

Fix a layout $e \in \{s, f\}$. To simplify notation, write a for the first-period advertising load $a_e^{(1)}$. The platform's dynamic objective is

$$\Pi_e(a) = \pi_e^{(1)}(a) + \Pi_e^{(2)}\left(\hat{m}_e^{(1)}(a), \beta_e^{(2)}(a), \delta_e^{(2)}(a)\right),$$

where $\Pi_e^{(2)}$ denotes the optimized second-period value.

We can easily verify $\frac{\partial \Pi_e^{(2)}}{\partial \hat{m}_e^{(1)}} \geq 0$, $\frac{\partial \Pi_e^{(2)}}{\partial \delta_e^{(2)}} \geq 0$, $\frac{\partial \Pi_e^{(2)}}{\partial \beta_e^{(2)}} \geq 0$ by form in Appendix A.6.

Suppose that $a_e^{(1)*}$ is an interior maximizer of the dynamic problem. The first-order condition is

$$\frac{d\Pi_e}{da} = \frac{d\pi_e^{(1)}}{da} + \frac{\partial \Pi_e^{(2)}}{\partial \hat{m}_e^{(1)}} \frac{\partial \hat{m}_e^{(1)}}{\partial a} + \frac{\partial \Pi_e^{(2)}}{\partial \beta_e^{(2)}} \frac{\partial \beta_e^{(2)}}{\partial a} + \frac{\partial \Pi_e^{(2)}}{\partial \delta_e^{(2)}} \frac{\partial \delta_e^{(2)}}{\partial a} = 0.$$

Using

$$\beta_e^{(2)} = \beta^{(1)} \left(\xi_1 + \xi_2 \mathbb{E} U_e^{(1)}\right), \qquad \delta_e^{(2)} = \delta^{(1)} \left(\eta_1 + \eta_2 \bar{R}_e^{(1)}\right),$$

and

$$\bar{R}_e^{(1)} = ar\gamma \frac{\beta^{(1)} \hat{m}_e^{(1)}}{\delta^{(1)}} = \frac{\gamma}{1-\gamma} \frac{\pi_e^{(1)}}{\delta^{(1)}},$$

we obtain

$$\frac{\partial \bar{R}_e^{(1)}}{\partial a} = \frac{\gamma}{\delta^{(1)}(1-\gamma)} \frac{d\pi_e^{(1)}}{da}.$$

Therefore, the first-order condition can be rewritten as

$$\frac{d\pi_e^{(1)}}{da} K_e + \frac{\partial \Pi_e^{(2)}}{\partial \hat{m}_e^{(1)}} \frac{\partial \hat{m}_e^{(1)}}{\partial a} + \frac{\partial \Pi_e^{(2)}}{\partial \beta_e^{(2)}} \frac{\partial \beta_e^{(2)}}{\partial \mathbb{E} U_e^{(1)}} \frac{\partial \mathbb{E} U_e^{(1)}}{\partial a} = 0,$$

where

$$K_e = 1 + \frac{\partial \Pi_e^{(2)}}{\partial \delta_e^{(2)}} \frac{\partial \delta_e^{(2)}}{\partial \bar{R}_e^{(1)}} \frac{\gamma}{\delta^{(1)}(1-\gamma)}.$$

Since $\frac{\partial \Pi_e^{(2)}}{\partial \delta_e^{(2)}} \geq 0$ and $\frac{\partial \delta_e^{(2)}}{\partial \bar{R}_e^{(1)}} = \delta^{(1)} \eta_2 \geq 0$, we have $K_e \geq 1 > 0$.

Next, by Lemma 2,

$$\frac{\partial \hat{m}_e^{(1)}}{\partial a} = -\frac{\phi}{c_e} < 0.$$

Since $\frac{\partial \Pi_e^{(2)}}{\partial \hat{m}_e^{(1)}} \geq 0$, we have $\frac{\partial \Pi_e^{(2)}}{\partial \hat{m}_e^{(1)}} \frac{\partial \hat{m}_e^{(1)}}{\partial a} \leq 0$.

At the viewer's optimal first-period consumption level, using the first-order condition, the indirect utility is

$$\mathbb{E} U_e^{(1)} = \frac{1}{2} c_e [\hat{m}_e^{(1)}]^2,$$

and hence

$$\frac{\partial \mathbb{E} U_e^{(1)}}{\partial a} = c_e \hat{m}_e^{(1)} \frac{\partial \hat{m}_e^{(1)}}{\partial a} < 0.$$

Since $\frac{\partial \Pi_e^{(2)}}{\partial \beta_e^{(2)}} \geq 0$ and $\frac{\partial \beta_e^{(2)}}{\partial \mathbb{E} U_e^{(1)}} = \beta^{(1)} \xi_2 \geq 0$, we have $\frac{\partial \Pi_e^{(2)}}{\partial \beta_e^{(2)}} \frac{\partial \beta_e^{(2)}}{\partial \mathbb{E} U_e^{(1)}} \frac{\partial \mathbb{E} U_e^{(1)}}{\partial a} \leq 0$.

It follows from the dynamic first-order condition that

$$\frac{d\pi_e^{(1)}}{da} K_e \geq 0.$$

Because $K_e > 0$, we obtain

$$\left. \frac{d\pi_e^{(1)}}{da} \right|_{a = a_e^{(1)*}} \geq 0.$$

Now consider the myopic first-period problem:

$$\max_{a \geq 0} \pi_e^{(1)}(a).$$

By Lemma 2, $\hat{m}_e^{(1)}(a)$ is affine and decreasing in a. Therefore, $\pi_e^{(1)}(a) = ar(1-\gamma)\beta^{(1)}\hat{m}_e^{(1)}(a)$ is strictly concave quadratic in a over the interior region. Hence $\frac{d\pi_e^{(1)}}{da}$ is strictly decreasing in a. Since the myopic optimum is interior,

$$\left.\frac{d\pi_e^{(1)}}{da}\right|_{a=a_{e,\text{myopic}}^{(1)*}} = 0.$$

Combining this with

$$\left.\frac{d\pi_e^{(1)}}{da}\right|_{a=a_e^{(1)*}} \geq 0$$

implies

$$a_e^{(1)*} \leq a_{e,\text{myopic}}^{(1)*}.$$

This completes the proof. □

A.8. Proof of Proposition 5

Fix a first-period layout $e^{(1)} \in \{s,f\}$. Policies $(e^{(1)},s)$ and $(e^{(1)},f)$ use the same first-period layout. Therefore, they generate the same first-period viewer consumption, the same first-period creator revenue, the same first-period viewer utility, and hence the same inherited second-period content density and viewer mass. Denote these common inherited second-period state by $\hat{m}^{(1)}, \delta^{(2)}, \beta^{(2)}$.

Substitute these values in the optimal value of period 2 from Appendix A.6 is:

$$\Pi_{e^{(1)}s}^{(2)} = \frac{r(1-\gamma)}{\phi c_s}\beta^{(2)} \cdot \left[\frac{4\delta^{(2)}\overline{v} - M + 2\delta^{(2)}\lambda\beta^{(1)}\hat{m}^{(1)}}{8\delta^{(2)}}\right]^2$$
$$\Pi_{e^{(1)}f}^{(2)} = \frac{r(1-\gamma)}{\phi c_f}\beta^{(2)} \cdot \left[\frac{6\delta^{(2)}\overline{v} - M + 2\delta^{(2)}\lambda\beta^{(1)}\hat{m}^{(1)}}{12\delta^{(2)}}\right]^2$$

The condition $\Pi_{e^{(1)}s}^{(2)} > \Pi_{e^{(1)}f}^{(2)}$ is equivalent to:

$$\frac{r(1-\gamma)}{\phi c_s}\beta^{(2)} \cdot \left[\frac{4\delta^{(2)}\overline{v} - M + 2\delta^{(2)}\lambda\beta^{(1)}\hat{m}^{(1)}}{8\delta^{(2)}}\right]^2 > \frac{r(1-\gamma)}{\phi c_f}\beta^{(2)} \cdot \left[\frac{6\delta^{(2)}\overline{v} - M + 2\delta^{(2)}\lambda\beta^{(1)}\hat{m}^{(1)}}{12\delta^{(2)}}\right]^2$$

This can be rewritten as

$$\frac{c_f}{c_s}\left[\frac{3}{2}\right]^2 > \left[\frac{6\delta^{(2)}\overline{v} - M + 2\delta^{(2)}\lambda\beta^{(1)}\hat{m}^{(1)}}{4\delta^{(2)}\overline{v} - M + 2\delta^{(2)}\lambda\beta^{(1)}\hat{m}^{(1)}}\right]^2$$

Equivalently

$$\lambda > \frac{M\left[1 - \frac{2}{3}\sqrt{\frac{c_s}{c_f}}\right] - 4\delta^{(2)}\overline{v}\left[1 - \sqrt{\frac{c_s}{c_f}}\right]}{2\delta^{(2)}\beta^{(1)}\hat{m}^{(1)}\left[1 - \frac{2}{3}\sqrt{\frac{c_s}{c_f}}\right]}$$

$$\text{or } M < 2\delta^{(2)}\lambda\beta^{(1)}\hat{m}^{(1)} - 4\delta^{(2)}\overline{v}\ \frac{\sqrt{\frac{c_s}{c_f}} - 1}{1 - \sqrt{\frac{c_s}{c_f}}\frac{2}{3}}$$

$$\text{or } 4\delta^{(2)}\overline{v} > \frac{M - 2\delta^{(2)}\lambda\beta^{(1)}\hat{m}^{(1)}}{1 - \sqrt{\frac{c_s}{c_f}}}\ \left[1 - \sqrt{\frac{c_s}{c_f}}\frac{2}{3}\right]$$

Note that all denominators are positive since $c_f > c_s$.

□

Appendix B: Robustness and Extensions

B.1. Feed layout with imperfect viewer selection

In the main analysis, we assume that viewers can rank the displayed alternatives by their realized match values under the feed layout. We now consider a more realistic setting where viewer may not make the best choice and explore its implications for the relative performance of the slide and feed layouts. We assume that with probability $q \geq \frac{1}{2}$, the viewer selects the high-value item. The baseline model is recovered when $q = 1$.

For two candidate items with realized values $V_{f1}, V_{f2} \sim U[\underline{v}_f, \overline{v}]$, the expected consumed value under probabilistic selection is:

$$\mathbb{E}[V_f] = q\,\mathbb{E}[\max\{V_{f1}, V_{f2}\}] + (1-q)\,\mathbb{E}[\min\{V_{f1}, V_{f2}\}].$$

Using the uniform distribution properties, we have:

$$\mathbb{E}[\max\{V_{f1}, V_{f2}\}] = \underline{v}_f + \frac{2}{3}(\overline{v} - v_f), \quad \mathbb{E}[\min\{V_{f1}, V_{f2}\}] = \underline{v}_f + \frac{1}{3}(\overline{v} - v_f),$$

therefore

$$\mathbb{E}[V_f] = \frac{2-q}{3}\underline{v}_f + \frac{1+q}{3}\overline{v}.$$

The utility-maximized consumption is:

$$\hat{m}_f(a) = \max\left\{0, \frac{\mathbb{E}[V_f] - \phi a}{c_f}\right\}.$$

We first discuss the interior solution case. Substituting the value to get:

$$\hat{m}_f = \frac{(2-q)\left(\overline{v} - \frac{M}{2\delta}\right) + (2-q)\lambda\hat{m}_f + (1+q)\overline{v}}{3c_f} - \frac{\phi a}{c_f}.$$

With the assumption $2c_s > \lambda$ and $q \geq 0$, the unique solution for this fixed-point equations is:

$$\hat{m}_f(a) = \frac{6\delta\overline{v} - 6\delta\phi a - (2-q)M}{2\delta[3c_f - (2-q)\lambda]}.$$

Therefore, the equilibrium consumption is:

$$\hat{m}_f(a) = \begin{cases} \frac{6\delta\overline{v} - 6\delta\phi a - (2-q)M}{2\delta[3c_f - (2-q)\lambda]}, & \text{if } a \leq \frac{6\delta\overline{v} - (2-q)M}{6\delta\phi} \\ 0, & \text{else} \end{cases}$$

Given this form, it is without loss of generality to restrict attention to the feasible set $\{a_f : 0 \leq \ a_f \leq \frac{6\delta\overline{v} - (2-q)M}{6\delta\phi}\}$. The platform's problem under each layout in the feasible set is:

$$\max_a \ a\,r(1-\gamma) \cdot \frac{6\delta\overline{v} - 6\delta\phi a - (2-q)M}{2\delta[3c_f - (2-q)\lambda]}$$

The objective functions are concave in a. The unique optimal solution is:

$$a_f^* = \frac{6\delta\overline{v} - (2-q)M}{12\delta\phi}$$

Substituting a_f^* into $\hat{m}_f$ and π_f yields:

$$\hat{m}_f^* = \frac{6\delta\overline{v} - (2-q)M}{4\delta[3c_f - (2-q)\lambda]}, \quad \pi_f^* = \frac{[6\overline{v}\delta - (2-q)M]^2}{\delta^2} \frac{(1-\gamma)r}{48\phi[3c_f - (2-q)\lambda])}.$$

Comparison of two layouts The layout comparison analysis is consistent with the main model such that the same order for optimal advertising and the similar cutoff structure holds for viewer consumption and platform revenue.

1. Optimal revenue comparison: The condition $\pi_s^* < \pi_f^*$ is equivalent to

$$\frac{(4\overline{v}\delta - M)^2}{\delta^2}\frac{(1-\gamma)r}{32\phi(2c_s-\lambda)} < \frac{(6\overline{v}\delta-(2-q)M)^2}{\delta^2}\frac{(1-\gamma)r}{48\phi(3c_f-(2-q)\lambda)}$$

   This can be rewritten as

$$\frac{3c_f-(2-q)\lambda}{2(2c_s-\lambda)} < \frac{(6\overline{v}\delta-(2-q)M)^2}{(4\overline{v}\delta-M)^2}.$$

   Equivalently

$$\begin{aligned}\lambda &< 2c_s - \frac{3c_f-2c_s}{\frac{(6\overline{v}\delta-(2-q)M)^2}{(4\overline{v}\delta-M)^2}-1},\\ \text{or } M &> 4\overline{v}\delta - \frac{2\overline{v}\delta}{\sqrt{\frac{3c_f-(2-q)\lambda}{2(2c_s-\lambda)}}-1},\\ \text{or } \delta &< \frac{\frac{M}{8\overline{v}}}{\sqrt{\frac{3c_f-(2-q)\lambda}{2(2c_s-\lambda)}}-\frac{3}{2}}+\frac{M}{4\overline{v}},\\ \text{or } \overline{v} &< \frac{\frac{M}{8\delta}}{\sqrt{\frac{3c_f-(2-q)\lambda}{2(2c_s-\lambda)}}-\frac{3}{2}}+\frac{M}{4\delta}.\end{aligned}$$

   Note that the denominators are positive. First:

$$\begin{aligned}&2(6\overline{v}\delta-M)^2-3(4\overline{v}\delta-M)^2\\ =&2(36\overline{v}^2\delta^2-12\overline{v}\delta+M^2)-3(16\overline{v}^2\delta^2-8\overline{v}\delta+M^2)\\ =&24\overline{v}^2\delta^2-M^2\\ \geq&24\overline{v}^2\delta^2-(4\overline{v}\delta)^2\\ =&8\overline{v}^2\delta^2>0\end{aligned}$$

   Therefore $\frac{2(6\overline{v}\delta-M)^2}{3(4\overline{v}\delta-M)^2}-1>0$.

   Second:

$$\begin{aligned}&2(3c_f-(2-q)\lambda)-3(2c_s-\lambda)\\ =&6(c_f-c_s)+(2q-1)\lambda\\ >&(2q-1)\lambda\\ >&0\end{aligned}$$

   Therefore $\sqrt{\frac{3c_f-(2-q)\lambda}{2(2c_s-\lambda)}}>\frac{3}{2}>1$.

2. Total consumption comparison: The condition $\hat{m}_s^* < \hat{m}_f^*$ is equivalent to

$$\frac{4\overline{v}\delta-M}{4\delta(2c_s-\lambda)} < \frac{6\overline{v}\delta-(2-q)M}{4\delta(3c_f-(2-q)\lambda)}$$

This can be rewritten as

$$[6\overline{v}\delta-(2-q)M]\ (2c_s-\lambda)-(4\overline{v}\delta-M)\ [3c_f-(2-q)\lambda]>0.$$

Equivalently

$$\lambda<\frac{M(3c_f-2c_s)-2\overline{v}\delta(6c_s-4c_f)}{2\overline{v}\delta}$$
$$\text{or } M>\frac{2\overline{v}\delta(6c_s-4c_f)+2\overline{v}\delta\lambda}{3c_f-2c_s}$$
$$\text{or } \delta<\frac{M(3c_f-2c_s)}{2\overline{v}(6c_s-4c_f+\lambda)}$$
$$\text{or } \overline{v}<\frac{M(3c_f-2c_s)}{2\delta(6c_s-4c_f+\lambda)}$$

All denominators are positive since $c_f>c_s$ and all parameters are nonnegative.

This results preserves the qualitative conclusions of the baseline model: feed is advantageous in low-precision or sparse content environments, slide is advantageous in high-precision or rich content environments, and the wedge between consumption and revenue remains, though quantitatively attenuated as $q<1$. The cutoff thresholds for feed vs. slide dominance shift in favor of slide as q declines.

Engagement–revenue wedge under imperfect viewer selection. We next verify that the engagement–revenue wedge in Corollary 2 continues to hold when viewers do not always select the higher-value item under the feed layout. Let

$$b_q=2-q,\qquad q\in\left(\frac{1}{2},1\right],$$

and define

$$x=\frac{M}{\overline{v}\delta},\qquad 0<x\leq 4.$$

The baseline model corresponds to $q=1$ and hence $b_q=1$. Under imperfect viewer selection, the feed layout's optimized consumption and revenue are

$$\hat{m}_f^{q,*}=\frac{6\overline{v}\delta-b_qM}{4\delta(3c_f-b_q\lambda)},$$

and

$$\pi_f^{q,*}=\frac{(6\overline{v}\delta-b_qM)^2\delta^2(1-\gamma)r}{48\phi(3c_f-b_q\lambda)}.$$

The slide layout's optimized consumption and revenue remain as in the baseline model:

$$\hat{m}_s^*=\frac{4\overline{v}\delta-M}{4\delta(2c_s-\lambda)},\qquad \pi_s^*=\frac{(4\overline{v}\delta-M)^2\delta^2(1-\gamma)r}{32\phi(2c_s-\lambda)}.$$

The consumption comparison $\hat{m}_s^*\geq\hat{m}_f^{q,*}$ is equivalent to

$$\lambda\geq\lambda_m^q(M),$$

where

$$\lambda_m^q(M)=\frac{x(3c_f-2b_qc_s)-12(c_f-c_s)}{6-4b_q}.$$

Similarly, the revenue comparison $\pi_s^*\geq\pi_f^{q,*}$ is equivalent to

$$\lambda\geq\lambda_\pi^q(M),$$

where

$$\lambda_{\pi}^{q}(M) = \frac{4c_s(6-b_qx)^2 - 9c_f(4-x)^2}{2(6-b_qx)^2 - 3b_q(4-x)^2}.$$

To establish the analogue of Corollary 2, it remains to compare these two cutoffs. Direct algebra gives

$$\lambda_{m}^{q}(M) - \lambda_{\pi}^{q}(M) = \frac{x(x-4)(2b_qc_s - 3c_f)(b_qx-6)}{2(2b_q-3)(b_qx^2-24)}.$$

For $q \in (1/2, 1]$, we have $b_q \in [1, 3/2)$. Since $0 < x \leq 4$ and $c_f > c_s$, it follows that

$$x - 4 \leq 0, \qquad 2b_qc_s - 3c_f < 0, \qquad b_qx - 6 \leq 0,$$

and

$$2b_q - 3 < 0, \qquad b_qx^2 - 24 < 0$$

for the nondegenerate interior region. Therefore,

$$\lambda_{m}^{q}(M) - \lambda_{\pi}^{q}(M) \leq 0,$$

or equivalently,

$$\lambda_{m}^{q}(M) \leq \lambda_{\pi}^{q}(M).$$

Hence, there exists an intermediate region

$$\lambda_{m}^{q}(M) \leq \lambda \leq \lambda_{\pi}^{q}(M)$$

in which the slide layout generates higher viewer consumption, whereas the feed layout generates higher platform revenue.

When $q = 1/2$, viewer selection is completely uninformative between the two displayed alternatives. In this limiting case, feed no longer provides a strict viewer-side screening advantage, while it still has higher consumption friction.

□

B.2. Feed layout with Multiple Alternatives

In the main analysis, the feed layout was limited to presenting two recommended contents ($J = 2$). We now generalize this setting to consider $J \geq 2$ and explore its implications for the relative performance of the slide and feed layouts.

In this generalization, the value of the recommended content in feed layout is determined by $V_f = \max\{V_{f1}, V_{f2}, \ldots, V_{fJ}\}$ where $V_{fj} \overset{i.i.d}{\sim} U[\underline{v}_f, \overline{v}]$ for $j = 1, \ldots, J$. The distribution is:

$$F(v) = P(V_f \leq v) = \left(\frac{v - \underline{v}_f}{\overline{v} - \underline{v}_f}\right)^J, \quad \underline{v}_f \leq v \leq \overline{v}$$

$$f(v) = \frac{J(v - \underline{v})^{J-1}}{(\overline{v} - \underline{v})^J}, \quad \underline{v}_f \leq v \leq \overline{v}$$

The expected value is:

$$\begin{aligned}\mathbb{E}V_f &= \frac{J}{\left(\overline{v} - \underline{v}_f\right)^J} \int_{\underline{v}_f}^{\overline{v}} x\left(x - \underline{v}_f\right)^{J-1} dx \\ &= \underline{v}_f + \left(\overline{v} - \underline{v}_f\right)\frac{J}{J+1}\end{aligned}$$

Substitute the expected value into the optimal consumption formula (interior) $\hat{m}_e = \frac{\mathbb{E}[V_e]-\phi a}{c_e}$ to get

$$\hat{m}_f = \frac{J\overline{v} + \underline{v}_f}{(J+1)c_f} - \frac{\phi a}{c_f}$$

Substituting $\underline{v}_e = \left(\overline{v} - \frac{M}{2\delta}\right) + \lambda \hat{m}_e$ into the equations above yields the following fixed-point condition in $\hat{m}_f$:

$$\hat{m}_f = \frac{J\overline{v} + \left(\overline{v} - \frac{M}{2\delta}\right) + \lambda \hat{m}_f}{(J+1)c_f} - \frac{\phi a}{c_f}$$

With assumption 2, the unique solution for this fixed-point equation is:

$$\hat{m}_f(a) = \frac{(J+1)\overline{v} - (J+1)\phi a - \frac{M}{2\delta}}{(J+1)c_f - \lambda}.$$

Include the corner solution case, the equilibrium consumption is:

$$\hat{m}_f(a) = \begin{cases} \frac{(J+1)\overline{v} - (J+1)\phi a - \frac{M}{2\delta}}{(J+1)c_f - \lambda}, & \text{if } a \leq \frac{2(J+1)\delta\overline{v} - M}{2(J+1)\delta\phi} \\ 0, & \text{else} \end{cases}$$

Using this equilibrium consumption, the corresponding optimal viewer consumption and the optimal revenue is:

$$\hat{m}_f^* = \frac{\frac{(J+1)\overline{v}}{2} - \frac{M}{4\delta}}{(J+1)c_f - \lambda}, \quad \pi_f^* = \frac{\left[(J+1)\overline{v} - \frac{M}{2\delta}\right]^2}{4(J+1)\phi} \frac{(1-\gamma)r}{(J+1)c_f - \lambda}$$

Comparison of two layouts under J feed alternatives. The layout comparison analysis is consistent with the main model such that the same order for optimal advertising and the similar cutoff structure holds for viewer consumption and platform revenue.

1. Optimal revenue comparison: $\pi_s^* < \pi_f^*$ is equivalent to

$$\begin{aligned}
&\frac{(4\overline{v}\delta - M)^2}{\delta^2} \frac{(1-\gamma)r}{32\phi(2c_s - \lambda)} < \frac{\left[(J+1)\overline{v} - \frac{M}{2\delta}\right]^2}{4(J+1)\phi} \frac{(1-\gamma)r}{(J+1)c_f - \lambda} \\
\Leftrightarrow\ & \frac{(J+1)c_f - \lambda}{2c_s - \lambda} < \frac{2}{J+1}\left(\frac{2(J+1)\overline{v}\delta - M}{4\overline{v}\delta - M}\right)^2 \\
\Leftrightarrow\ & \lambda < 2c_s - \frac{(J+1)c_f - 2c_s}{\frac{2}{J+1}\left(\frac{2(J+1)\overline{v}\delta - M}{4\overline{v}\delta - M}\right)^2 - 1} \\
\text{or}\ \ & M > 4\overline{v}\delta - \frac{2(J-1)\overline{v}\delta}{\sqrt{\frac{(J+1)((J+1)c_f - \lambda)}{2(2c_s - \lambda)}} - 1} \\
\text{or}\ \ & \delta < \frac{\frac{(J-1)M}{4\overline{v}}}{2\sqrt{\frac{(J+1)((J+1)c_f - \lambda)}{2(2c_s - \lambda)}} - (J+1)} + \frac{M}{4\overline{v}} \\
\text{or}\ \ & \overline{v} < \frac{\frac{(J-1)M}{4\delta}}{2\sqrt{\frac{(J+1)((J+1)c_f - \lambda)}{2(2c_s - \lambda)}} - (J+1)} + \frac{M}{4\delta}
\end{aligned}$$

It is straightforward to show that all denominator is nonnegative with maintained assumption $M \leq 4\delta\overline{v}$, $c_f > c_s$ and and $J \geq 2$.

2. Total consumption comparison: $\hat{m}_s^* < \hat{m}_f^*$ is equivalent to

$$
\begin{aligned}
&\frac{4\overline{v}\delta - M}{4\delta(2c_s-\lambda)} < \frac{\frac{(J+1)\overline{v}}{2} - \frac{M}{4\delta}}{(J+1)c_f - \lambda}\\
&\Leftrightarrow [2(J+1)\overline{v}\delta - M]\ (2c_s-\lambda) > (4\overline{v}\delta - M)\ [(J+1)c_f - \lambda]\\
&\Leftrightarrow M[(J+1)c_f - 2c_s] - 4(J+1)\overline{v}\delta(c_f-c_s) - 2(J-1)\overline{v}\delta\lambda > 0\\
&\Leftrightarrow \lambda < \frac{M[(J+1)c_f-2c_s] - 4(J+1)\overline{v}\delta(c_f-c_s)}{2(J-1)\overline{v}\delta}\\
\text{or}\ \ & M > \frac{4(J+1)\overline{v}\delta(c_f-c_s) + 2(J-1)\overline{v}\delta\lambda}{(J+1)c_f - 2c_s}\\
\text{or}\ \ & \delta < \frac{M[(J+1)c_f-2c_s]}{4(J+1)(c_f-c_s)\overline{v} + 2(J-1)\lambda\overline{v}}\\
\text{or}\ \ & \overline{v} < \frac{M[(J+1)c_f-2c_s]}{4(J+1)(c_f-c_s)\delta + 2(J-1)\lambda\delta}
\end{aligned}
$$

It is straightforward to show that all denominator is nonnegative with maintained assumption $M \le 4\delta\overline{v}$, $c_f > c_s$ and $J \ge 2$.

Remark 1. Note that viewer's expected cumulative utility with consumption quantity m is $U_e(m) = \mathbb{E}[V_e]\cdot m - \frac{1}{2}c_e m^2 - \phi a m$, implying that the cumulative consumption cost is quadratic with coefficient c_e for each decision. With J content to choose, one might expect that the unit consumption cost under feed, c_f, to rise with J. However, these cutoff structures are unaffected by how larger c_f is as long as $c_f > c_s$.

Engagement-revenue wedge under J feed alternatives. We next verify that the engagement–revenue wedge in Corollary 2 continues to hold when the feed layout displays $J \ge 2$ alternatives. Let

$$x = \frac{M}{\overline{v}\delta}, \qquad 0 < x \le 4,$$

and define

$$A_J = (J+1)c_f - 2c_s.$$

Under the maintained assumption that the feed layout has higher browsing and screening friction, we have $A_J > 0$ for $J \ge 2$.

From the cutoff comparison derived above, the consumption cutoff in the (M,λ) space can be written as

$$\lambda_m^J(M) = \frac{xA_J - 4(J+1)(c_f-c_s)}{2(J-1)},$$

whereas the revenue cutoff is

$$\lambda_\pi^J(M) = 2c_s - \frac{A_J}{\frac{2}{J+1}\left(\frac{2(J+1)-x}{4-x}\right)^2 - 1}.$$

To establish the analogue of Corollary 2, it remains to compare these two cutoffs. Direct algebra gives

$$\lambda_m^J(M) - \lambda_\pi^J(M) = \frac{x(x-4)(x-2J-2)A_J}{2(J-1)(x^2-8J-8)}.$$

For $J \ge 2$ and $0 < x \le 4$, we have $x-4 \le 0$, $x-2J-2 < 0$, and $x^2-8J-8 < 0$. Since $A_J > 0$, it follows that

$$\lambda_m^J(M) - \lambda_\pi^J(M) \le 0,$$

or equivalently,

$$\lambda_m^J(M) \le \lambda_\pi^J(M).$$

Therefore, there exists an intermediate region

$$\lambda_m^J(M) \le \lambda \le \lambda_\pi^J(M)$$

in which the slide layout generates higher viewer consumption, whereas the feed layout generates higher platform revenue.

Transforming back to $\bar{v} = M/(\delta x)$, we obtain

$$\bar{v}_m^J = \frac{M}{\delta x_m^J} \le \frac{M}{\delta x_\pi^J} = \bar{v}_\pi^J.$$

Therefore, whenever both cutoffs lie in the admissible region, there exists an intermediate content-value region

$$\bar{v}_m^J \le v \le \bar{v}_\pi^J$$

in which the slide layout generates higher viewer consumption, whereas the feed layout generates higher platform revenue. □

B.3. Convex Ad-nuisance Cost

Let ad-nuisance cost be ϕa^k where $k > 1$. This assumption implies an increasing convex cost function which is standard in literature. The viewer's expected cumulative utility form is then $U_e(m) = \mathbb{E}[V_e] \cdot m - \frac{1}{2} c_e m^2 - \phi a^k\, m$, which is strictly concave in m. The utility-maximized consumption is:

$$\hat{m}_e = \max\left\{0,\ \frac{\mathbb{E}[V_e] - \phi a^k}{c_e}\right\}$$

We first discuss the interior solution case. Substituting the expected value to get:

$$\hat{m}_s = \frac{\left(\bar{v} - \frac{M}{2\delta}\right) + \lambda \hat{m}_s + \bar{v}}{2c_s} - \frac{\phi a^k}{c_s}, \qquad \hat{m}_f = \frac{\left(\bar{v} - \frac{M}{2\delta}\right) + \lambda \hat{m}_f + 2\bar{v}}{3c_f} - \frac{\phi a^k}{c_f}.$$

With the assumption $2c_s > \lambda$, the unique solution for this fixed-point equations is:

$$\hat{m}_s(a) = \frac{4\delta\bar{v} - 4\delta\phi a^k - M}{2\delta(2c_s - \lambda)}, \qquad \hat{m}_f(a) = \frac{6\delta\bar{v} - 6\delta\phi a^k - M}{2\delta(3c_f - \lambda)}.$$

Therefore, the equilibrium consumption is:

$$\hat{m}_s(a) = \begin{cases} \frac{4\delta\bar{v} - 4\delta\phi a^k - M}{2\delta(2c_s - \lambda)}, & \text{if } a^k \le \frac{4\delta\bar{v} - M}{4\delta\phi} \\ 0, & \text{else} \end{cases}$$

$$\hat{m}_f(a) = \begin{cases} \frac{6\delta\bar{v} - 6\delta\phi a^k - M}{2\delta(3c_f - \lambda)}, & \text{if } a^k \le \frac{6\delta\bar{v} - M}{6\delta\phi} \\ 0, & \text{else} \end{cases}$$

Given these forms, viewer consumption becomes zero once the advertising load exceeds the corresponding cutoff. Thus, it is without loss of generality to restrict attention to the feasible set $\{a_s : 0 \le\ a_s^k \le \frac{4\delta\bar{v} - M}{4\delta\phi}\}$ for slide and $\{a_f : 0 \le\ a_f^k \le \frac{6\delta\bar{v} - M}{6\delta\phi}\}$ for feed. The platform's problem under each layout in is:

$$\max_a\ a\, r(1-\gamma) \cdot \frac{4\delta\bar{v} - 4\delta\phi a^k - M}{2\delta(2c_s - \lambda)}, \quad \max_a\ a\, r(1-\gamma) \cdot \frac{6\delta\bar{v} - 6\delta\phi a^k - M}{2\delta(3c_f - \lambda)}$$

The objective functions are concave in a. The unique optimal solutions:

$$a_s^* = \sqrt[k]{\frac{4\delta\bar{v} - M}{4\delta\phi(k+1)}}, \quad a_f^* = \sqrt[k]{\frac{6\delta\bar{v} - M}{6\delta\phi(k+1)}}.$$

Since $k>1$, these solution satisfy the interior condition, and is independent of learning parameter λ. We have optimal consumption:

$$\hat{m}_s^* = \frac{4\delta\overline{v} - \frac{4\delta\overline{v}-M}{k+1} - M}{2\delta(2c_s-\lambda)},$$
$$\hat{m}_f^* = \frac{6\delta\overline{v} - \frac{6\delta\overline{v}-M}{k+1} - M}{2\delta(3c_f-\lambda)}.$$

Comparison of two layouts under convex advertising nuisance. The layout comparison analysis is consistent with the main model such that the same order for optimal advertising and the similar cutoff structure holds for viewer consumption and platform revenue.

1. Optimal revenue comparison: The condition $\pi_s^* < \pi_f^*$ is equivalent to

$$\sqrt[k]{\frac{4\delta\overline{v}-M}{4\delta\phi(k+1)}}\frac{4\delta\overline{v} - \frac{4\delta\overline{v}-M}{k+1} - M}{2\delta(2c_s-\lambda)} < \sqrt[k]{\frac{6\delta\overline{v}-M}{6\delta\phi(k+1)}}\frac{6\delta\overline{v} - \frac{6\delta\overline{v}-M}{k+1} - M}{2\delta(3c_f-\lambda)}$$
$$\Leftrightarrow \frac{3c_f-\lambda}{2c_s-\lambda}\frac{4\delta\overline{v}-M}{6\delta\overline{v}-M} < \sqrt[k]{\frac{2(6\overline{v}\delta-M)}{3(4\overline{v}\delta-M)}}$$
$$\Leftrightarrow \frac{3c_f-\lambda}{2c_s-\lambda} < \sqrt[k]{\frac{2(6\overline{v}\delta-M)^{k+1}}{3(4\overline{v}\delta-M)^{k+1}}}$$
$$\Leftrightarrow \lambda < 2c_s - \frac{3c_f-2c_s}{\sqrt[k]{\frac{2(6\overline{v}\delta-M)^{k+1}}{3(4\overline{v}\delta-M)^{k+1}}}-1}$$
$$\text{or}\;\; M > 4\overline{v}\delta - \frac{2\overline{v}\delta}{\sqrt[k+1]{\frac{3}{2}\left(\frac{3c_f-\lambda}{2c_s-\lambda}\right)^k}-1}$$
$$\text{or}\;\; \delta < \frac{\frac{M}{8\overline{v}}}{\sqrt[k+1]{\frac{3}{2}\left(\frac{3c_f-\lambda}{2c_s-\lambda}\right)^k}-\frac{3}{2}} + \frac{M}{4\overline{v}}$$
$$\text{or}\;\; \overline{v} < \frac{\frac{M}{8\delta}}{\sqrt[k+1]{\frac{3}{2}\left(\frac{3c_f-\lambda}{2c_s-\lambda}\right)^k}-\frac{3}{2}} + \frac{M}{4\delta}$$

   which keep showing the cutoff structure.

2. Total consumption comparison: The condition $\hat{m}_s^* < \hat{m}_f^*$ is equivalent to

$$\frac{4\delta\overline{v} - \frac{4\delta\overline{v}-M}{k+1} - M}{2\delta(2c_s-\lambda)} < \frac{6\delta\overline{v} - \frac{6\delta\overline{v}-M}{k+1} - M}{2\delta(3c_f-\lambda)}$$

   This can be rewritten as

$$M(3c_f-2c_s) - 12\overline{v}\delta(c_f-c_s) - 2\overline{v}\delta\lambda > 0$$

   which is the same condition as linear ad-nuisance case.

Engagement-revenue wedge under convex advertising nuisance. We now show that the engagement–revenue wedge in Corollary 2 continues to hold when advertising nuisance is convex in the advertising load. Let the nuisance cost be ϕa^k with $k \geq 1$. The consumption comparison is unchanged by the convexity of advertising nuisance, and hence the consumption cutoff remains

$$\lambda_m(M) = \frac{x(3c_f-2c_s) - 12(c_f-c_s)}{2}, \qquad x = \frac{M}{\overline{v}\delta}.$$

The revenue comparison under convex advertising nuisance yields the cutoff

$$\lambda_\pi^k(M) = 2c_s - \frac{3c_f - 2c_s}{R_k - 1},$$

where

$$R_k = \left[\frac{2}{3}\left(\frac{6-x}{4-x}\right)^{k+1}\right]^{1/k}.$$

To establish the wedge, it suffices to show that the revenue cutoff lies weakly above the consumption cutoff, i.e.,

$$\lambda_m(M) \le \lambda_\pi^k(M).$$

Let

$$Y = \frac{6-x}{4-x}.$$

Since $0 < x \le 4$, we have

$$Y = \frac{6-x}{4-x} \ge \frac{3}{2}.$$

Moreover,

$$R_k \ge Y \quad \Longleftrightarrow \quad \left[\frac{2}{3}Y^{k+1}\right]^{1/k} \ge Y \quad \Longleftrightarrow \quad \frac{2}{3}Y^{k+1} \ge Y^k \quad \Longleftrightarrow \quad Y \ge \frac{3}{2}.$$

Therefore $R_k \ge Y$. Since the revenue cutoff is increasing in R_k, the revenue cutoff under convex advertising nuisance is weakly larger than the baseline revenue cutoff. By Corollary 2 in the baseline model, the baseline revenue cutoff is weakly larger than the consumption cutoff. Hence,

$$\lambda_m(M) \le \lambda_\pi^k(M).$$

It follows that there exists an intermediate region

$$\lambda_m(M) \le \lambda \le \lambda_\pi^k(M)$$

in which the slide layout generates higher viewer consumption, whereas the feed layout generates higher platform revenue.

Transforming back to $\bar{v} = M/(\delta x)$, we obtain

$$\bar{v}_m^k = \frac{M}{\delta x_m^k} \le \frac{M}{\delta x_\pi^k} = \bar{v}_\pi^k.$$

Therefore, whenever both cutoffs lie in the admissible region, there exists an intermediate content-value region

$$\bar{v}_m^k \le v \le \bar{v}_\pi^k$$

in which the slide layout generates higher viewer consumption, whereas the feed layout generates higher platform revenue. □

B.4. Numerical Robustness under Bounded Concave Learning

In the main model, algorithmic learning is modeled as $\underline{v}_e = \left(\overline{v} - \frac{M}{2\delta}\right) + \lambda \hat{m}_e$ in our model. That is, the lower bound value is linearly improved by the learning effect $\lambda \hat{m}_e$. In reality, the learning may has diminishing returns. Consider the following form of learning:

$$\underline{v}_e = \overline{v} - \frac{M}{2\delta} + \frac{M}{2\delta}\left(1 - e^{-\lambda \hat{m}_e}\right)$$

This form allows the learning effect concavely impact the lower bound value, and the lower bound value will never exceed $\overline{v}$.

The fixed-point condition for equilibrium $\hat{m}_s$ and $\hat{m}_f$ is:

$$\hat{m}_s = \frac{\left(\overline{v} - \frac{M}{2\delta}\right) + \frac{M}{2\delta}\left(1 - e^{-\lambda \hat{m}_s}\right) + \overline{v}}{2c_s} - \frac{\phi a}{c_s}, \qquad \hat{m}_f = \frac{\left(\overline{v} - \frac{M}{2\delta}\right) + \frac{M}{2\delta}\left(1 - e^{-\lambda \hat{m}_f}\right) + 2\overline{v}}{3c_f} - \frac{\phi a}{c_f}.$$

The equations are equivalent to:

$$\hat{m}_s(a) + \frac{M}{4\delta c_s} e^{-\lambda \hat{m}_s} = \frac{\overline{v} - \phi a}{c_s}, \quad \hat{m}_f(a) + \frac{M}{6\delta c_f} e^{-\lambda \hat{m}_f} = \frac{\overline{v} - \phi a}{c_f}$$

We first solve the slide equilibrium condition. Define $A_s(a) = \frac{\overline{v} - \phi a}{c_s}$, $B_s = \frac{M}{4\delta c_s}$. Then the equilibrium conditions can be written as

$$\hat{m}_s(a) + B_s e^{-\lambda \hat{m}_s(a)} = A_s(a)$$

Let $y_s = A_s(a) - \hat{m}_s(a)$. Substituting this into the previous equation yields

$$y_s = B_s e^{-\lambda (A_s(a) - y_s)} = B_s e^{-\lambda A_s(a)} e^{\lambda y_s}.$$

Therefore,

$$y_s e^{-\lambda y_s} = B_s e^{-\lambda A_s(a)}.$$

Multiplying both sides by $-\lambda$, we obtain

$$-\lambda y_s e^{-\lambda y_s} = -\lambda B_s e^{-\lambda A_s(a)}.$$

By the definition of the Lambert W function, $W(x)e^{W(x)} = x$ (Corless et al. 1996), it follows that

$$-\lambda y_s = W\left(-\lambda B_s e^{-\lambda A_s(a)}\right).$$

Since $\hat{m}_s(a) = A_s(a) - y_s$, we have

$$\hat{m}_s(a) = A_s(a) + \frac{1}{\lambda} W\left(-\lambda B_s e^{-\lambda A_s(a)}\right).$$

Substituting back $A_s(a)$ and B_s, we obtain

$$\hat{m}_s(a) = \frac{\overline{v} - \phi a}{c_s} + \frac{1}{\lambda} W\left(-\frac{\lambda M}{4\delta c_s} \exp\left\{-\frac{\lambda(\overline{v} - \phi a)}{c_s}\right\}\right)$$

Analogously solve the feed equilibrium condition, we obtain

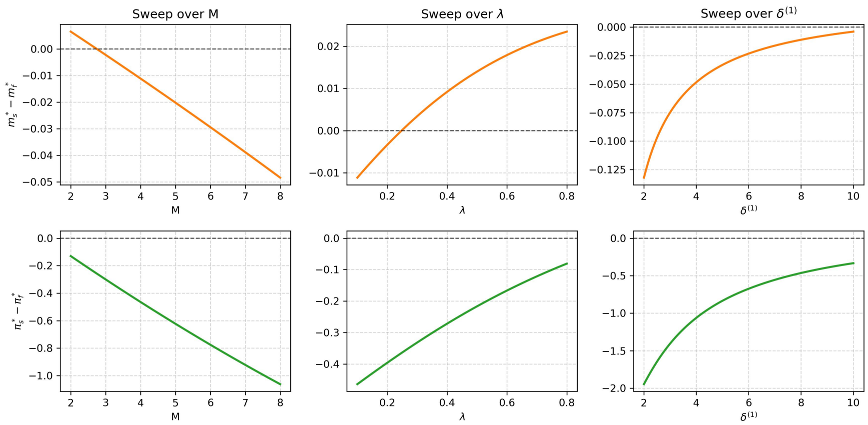
$$\hat{m}_f(a) = \frac{\overline{v} - \phi a}{c_f} + \frac{1}{\lambda} W\left(-\frac{\lambda M}{6\delta c_f} \exp\left\{-\frac{\lambda(\overline{v} - \phi a)}{c_f}\right\}\right)$$

We use the real branch that yields nonnegative equilibrium consumption.

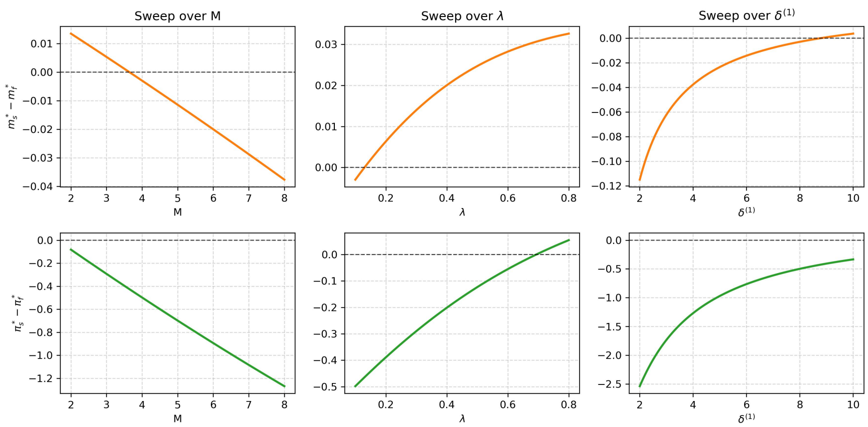
Using this form, we numerically examine the main results. In the following figure A1, we show the numeric results of layouts comparison (optimal advertising, viewer consumption and platform's optimal revenue). The results show that the main qualitative comparison between slide and feed is robust to the concave-learning specification. Across different levels of $\overline{v}$, the relative performance of the two layouts continues to exhibit a cutoff pattern. Feed performs better when the matching environment is weak, such as when M is large, λ is small, or when δ is low, because viewer-side screening helps mitigate recommendation mismatch. Slide becomes more attractive when matching environment improves, such as when M is small, λ is large, or δ is high, or $\overline{v}$ is large, because its lower consumption friction allows the platform to convert accurate recommendations into engagement and revenue more effectively. Therefore, although concave learning introduces diminishing returns to viewer interaction data, it preserves the main cutoff structure and the central trade-off between matching gains and consumption frictions.

B.5. Additional Layout-Transition Comparison

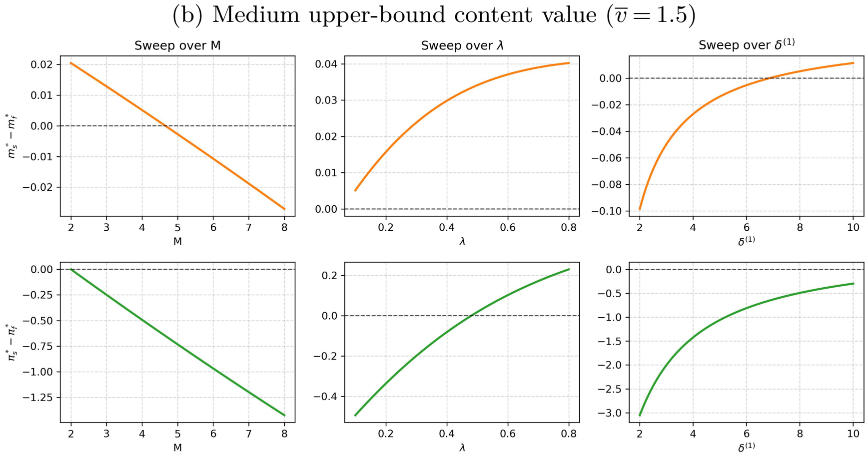
The main text focuses on four layout policies in the two-period model: fixed feed, fixed slide, slide-to-feed switching, and feed-to-slide switching. Figure A2 reports the revenue function. Across the reported parameter ranges, the reverse transition remains below the feed-to-slide path and does not change the qualitative ranking emphasized in the main text.



(a) Low upper-bound content value ($\overline{v} = 1.2$)



(b) Medium upper-bound content value ($\overline{v} = 1.5$)



(c) High upper-bound content value ($\overline{v} = 1.8$)

Figure A1 layouts comparison under concave learning

Basic parameters: $r = 2; \gamma = 0.2; c_s = 0.5; c_f = 0.51; \phi = 0.1; \xi_1 = 0.1; \xi_2 = 0.9; \eta_1 = 0.1; \eta_2 = 0.9$.

Fix $\lambda = 0.1; M = 4; \delta = 8$ unless sweeping.

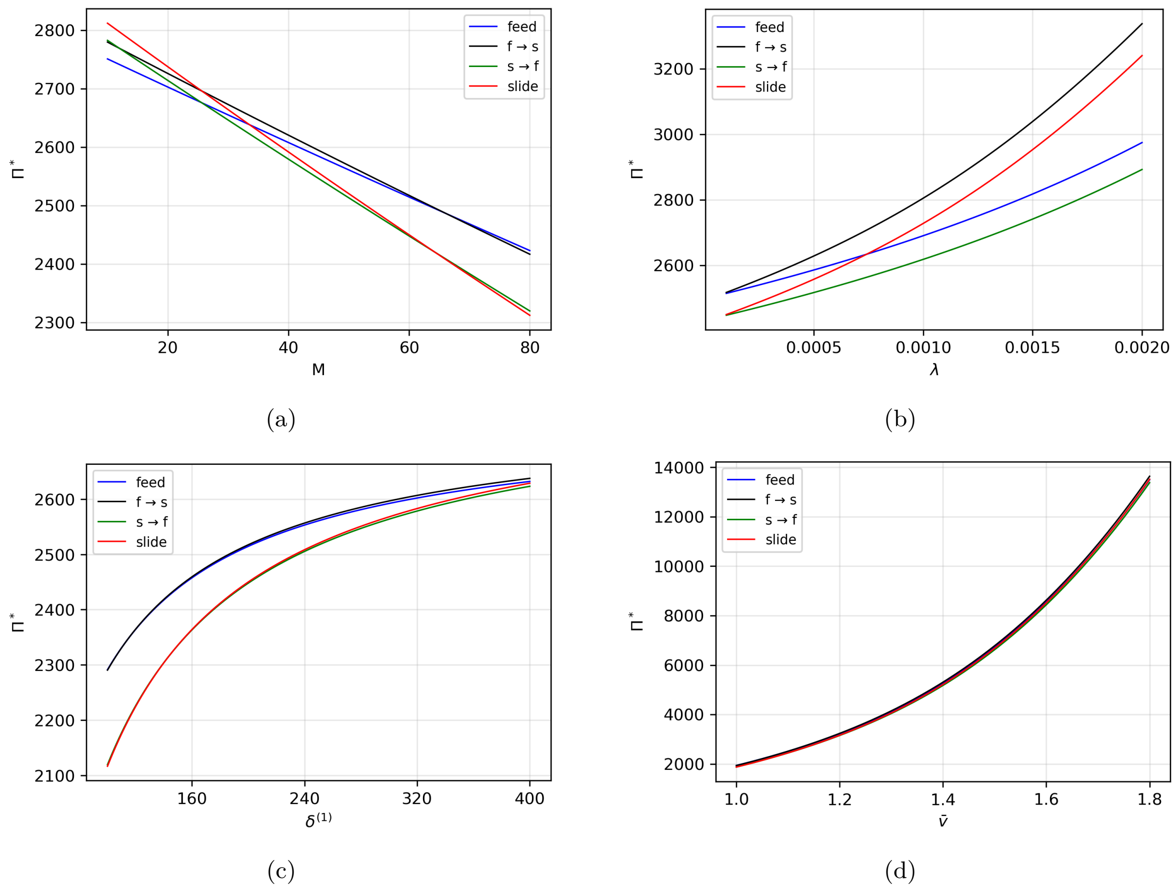


Figure A2 Total platform revenue across layout-transition policies

The figure supplements the main analysis by including the reverse transition from slide to feed. The reverse transition does not overturn the main ranking and remains below the feed-to-slide path across the reported parameter ranges.

Baseline parameters: $r = 2; \gamma = 0.2; \beta^{(1)} = 200; c_s = 0.5; c_f = 0.51; \phi = 0.1; \xi_1 = 0.1; \xi_2 = 0.9; \eta_1 = 0.1; \eta_2 = 0.9$

Fix $M = 60; \lambda = 0.0001; \delta^{(1)} = 200; \overline{v} = 1.1;$ unless sweeping.