The Creator Economy: Managing Ecosystem Supply, Revenue-Sharing, and Platform Design

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Abstract

Many digital platforms give users a bundle of goods sourced from numerous creators, generate revenue through consumption of these goods, and motivate creators by sharing of revenue. This paper studies the platform's design choices and creators' participation and supply decisions, when users' (viewers') consumption of goods (content) is financed by third-party advertisers. The model specifies the platform's scale: number of creators and content supplied, and magnitudes of viewers, advertisers, and revenues. I examine how the distribution of creator capabilities affects market concentration among creators, and how it can be influenced by platform design. Tools for ad management and analytics will be more impactful when the platform has sufficient content and viewers but has low ad demand. Conversely, reducing viewers' distaste for ads through better matching and timing—which can create win-win-win effects throughout the ecosystem—is important when the platform has strong demand from advertisers. Platform infrastructure improvements that motivate creators to supply more content (e.g., development toolkits) must be chosen carefully to avoid creating higher concentration among a few powerful creators. Investments in first-party content are most consequential when the platform scale is small and when it has greater urgency to attract more viewers. I show that revenue-sharing is (only partly) a tug of war between the platform and creators, because a moderate sharing formula will strengthen the overall ecosystem and profits of all participants. However, revenue-sharing tensions indicate a need to extend the one- rate-for-all creators approach with richer revenue-sharing arrangements that can better accommodate heterogeneity among creators.

Keywords: platforms, content, revenue-sharing, advertising, multi-sided markets, ecosystem, developers

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1 Introduction

Platforms that provide technology infrastructure to enable and coordinate interactions among multiple groups of participants are dominating business and social activity today (Parker et al., 2016). This paper discusses the economic interplay in multi-sided platforms that connect contributors (or creators or developers), viewers (or consumers) and advertisers. Several large platforms attract hundreds of millions of viewers with "goods" (or content, such as music, movies, games, TV shows, blogs, recipes, how-to videos, apps, etc.) that are sourced from thousands of creators and whose consumption is financed by advertising payments. Such platforms are booming in categories such as music, video entertainment, virtual sports, and casual gaming, and are the dominant model in many countries (Westcott, 2020). Examples include Snap Games, Twitch, Jinri Toutiao, Facebook's in-stream videos, Pandora (free version), Plex, Amazon's IMDb TV, Comcast's Peacock, Pluto TV, Xumo, Hulu, Crackle/Sony, The Roku Channel, and broadcast TV. Viewers see a bundle of content and care about bundle scale and variety; the presence of viewers attracts advertisers; and the platform shares its ad revenue spoils with creators to motivate their participation and supply. Even in platforms that feature user-generated content such as TikTok, Instagram or YouTube, a substantial part of consumer traffic is driven by content from stars, celebrities, and other popular figures, such as the 9-year old Ryan Kaji whose toy-box-opening videos made him the #1 YouTube star in 2019 and 2020.[1] Conversely, these star creators are the dominant recipients of advertising revenues from the platform, thus rendering a three-sided platform comprising viewers, creators, and advertisers.

This paper develops a model to structure and analyze this kind of enterprise, and examines the following questions. How do the economic characteristics of these three groups (creators, viewers, and advertisers) determine the overall scale of such platform, including the magnitude of content supplied by creators, demand generated by the platform, and the level of advertising featured on it? How is this supply distributed amongst creators, and what is the likely level of fragmentation or concentration in the creator ecosystem? And, how should these outcomes influence the platform's approach to internal investments and design decisions related to creator ecosystem management, level of advertising, and revenue sharing with creators? The analysis pertains to platforms that are free to consumers, which monetize their value through advertising rather than consumer fees, and where the share of advertising revenue is creators' primary motive to offer their outputs through the platform.

[1]See https://www.forbes.com/sites/maddieberg/2020/12/18/how-nine-year-old-ryan-kaji-youtubes-30-million-man-just-keeps-getting-richer/, and about TikTok: "people flock to TikTok to watch scripted clips from talented creators, not communicate with their friends." https://digiday.com/media/how-tiktok-is-taking-lessons-from-the-record-industry-in-in-building-a-media-business/

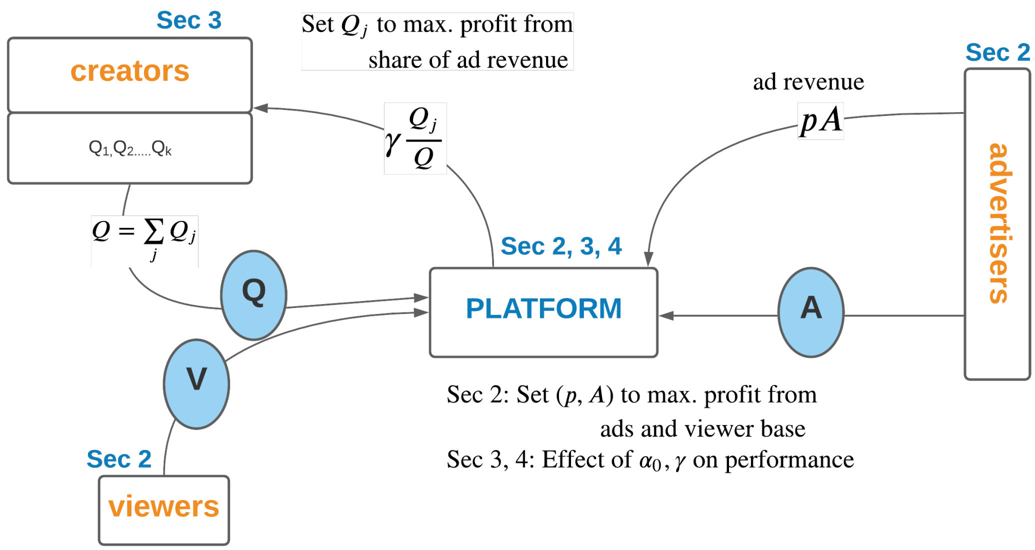

Figure 1: Stylized view of an advertising-driven 3-sided platform. The platform exhibits content sourced from creators to consumers, displays ads against these views, and shares advertising revenues with creators to motivate them to supply content and to increase consumer visits.

Fig. 1 depicts the elements of the model. *Creators* collectively supply an amount Q of content to the platform, with creator j's output labeled as Q_j (and $Q = \sum_j Q_j$). Creators vary in their ability to generate views and attract advertising, and this heterogeneity is captured by a unit creation cost $c_j (> 0)$ for generating a unit view. *Consumers* are attracted by content and collectively generate V views, with V increasing in Q (but at diminishing rate) and decreasing in the level of advertising A chosen by the platform. The platform may also have first-party content Q_0, including content purchased or licensed directly and not subject to revenue sharing, which creates intrinsic value and generates α_0 views. *Advertisers* are attracted by the platform's potential to reach customers, and the aggregate demand from advertisers when the platform charges a per-view price p is written as $\mathbf{A}(p)$. The platform earns advertising revenue $R = p \cdot A$ and returns a fraction γ to creators with each creator receiving a share proportional to their contribution. Creator j's output Q_j^* is chosen to maximize its payoff, its share of ad revenue net costs of content. The primary levers of control for the platform are (i) the advertising level A (conversely, the per-view price p), (ii) the revenue-sharing parameter γ and intrinsic value α_0 (or, first-party content Q_0), and (iii) additional platform design variables that impact the exogenous parameters in the model (e.g., β, δ, ϕ that affect price sensitivity of advertiser demand, viewer sensitivity to ads, and sensitivity of ad demand to the quantity and variety of content). The revenue-sharing rate is considered identical across all contributors (Oh et al., 2015). This is common in real-world platforms which, despite pressures and incentives to set heterogeneous sharing rates, avoid doing so to prevent a floodgate of negotiations around revenue-sharing, or to avoid the expense of negotiating with thousands of contributors to a large bundle (Shiller and Waldfogel, 2013).

A few recent papers have examined content production and revenue-sharing in multi-sided content platforms. Topics analyzed include whether platforms should pursue consumer fees or advertising or both (Amaldoss et al., 2021), creators' behavior under monetary and altruistic motivations (Tang et al., 2012), market power and industry structure (Evans, 2008), monetization models (Peitz and Valletti, 2008; Calvano and Polo, 2020), marketing allocations to the consumer and advertiser sides (Sridhar et al., 2011), the balancing of advertising and content (Dewan et al., 2002; Godes et al., 2009; Amaldoss et al., 2021), and the impact of creator-competition and consumer characteristics on the revenue-sharing incentives of the platform and creators (Jain and Qian, 2021). Relative to these papers, a key contribution of the present paper is to incorporate the decision making and preferences of the platform, its creators, and advertisers (with viewers addressed through an aggregate demand function) into a coherent framework, and to link the outcomes in this three-sided dance to platform design elements and the revenue-sharing arrangement. The modeling framework embeds a richer treatment of an ecosystem of heterogeneous creators, endogenizing both their participation in the platform and level of output, while capturing both co-dependence with the platform (creating revenue by bringing viewers and advertisers into the system) and competition against the platform and within creators (all vying for a share of revenue). With this framework, the paper shows how the incentives and behavior of the advertiser side moderate the revenue-sharing tension between the platform and creators; it explains how the predicted participant behavior and economic outcomes can guide platform design; and it studies the interaction between revenue-sharing rules and ecosystem performance along multiple metrics.

The application of this framework generates several insightful results. First, it provides a way to identify likely platform scale along multiple metrics, the content it would receive from creators, what set of creators would supply content, and the level of advertising and ad revenues that the platform would generate (§3.1). Second, it offers insights on alternate ways in which the platform can alter its design to influence creators' actions and platform scale (§3.2). Platforms have multiple levers for influencing different parts of the ecosystem, and need to deploy them astutely. For instance, a platform which has strong viewership may prioritize tools for ad management and partnerships to pull in advertisers (e.g., Facebook). Other platforms that need more content to bring in viewers might prioritize creator support tools (e.g., Snap and Instagram), or build media partnerships for more content (e.g., Toutiao). Marketing to attract more viewers may be called for when the platform sees strong demand from advertisers but lacks viewers. I show that interventions like development toolkits and creator support programs will best promote the platform's interest if they are easy to absorb by all creators and level the playing field among them, thereby making creators more homogeneous and competitive. However, if such interventions involve a steep learning curve or significant adoption costs, then they might well amplify differences among creators, which leads to greater concentration in content supply.

Third, I study the manner in which the revenue-sharing tension between creators and the platform intersects with the platform's control over advertising policy (§4). Although creators in general would desire higher revenue share γ (i.e., a greater percentage of ad revenues), this desire is moderated by the knowledge that high γ would force the platform to raise ad prices, thus lowering the amount of advertising and hence hurt their own advertising revenue share (§4.1). Conversely, the platform is deterred from setting γ too low for that would reduce the contributions of creators and cripple the basic content fuel of the ecosystem. The paper provides a foundation for analysis of a range of issues in such 3-sided platforms, including those related to platform competition, market power, industry concentration, and anti-competitive practices.

2 Model

The fundamental unit of interaction among the three types of platform participants is a "view." Views are driven by content from creators. A view creates an opportunity for the platform to display a paid ad by an advertiser. One of the key decision elements for the platform, having sourced content Q, is to decide how much advertising, A^*, to inflict on viewers. This decision (covered in §2.2) governs the ad revenue generated on the platform (revenue $R(Q) = p(Q) \cdot A(Q)$), the share available to creators, and the magnitude of content they submit to the platform (covered in §3.1), in turn influencing the number of views, advertising demand and ad revenue. Anticipating this, the platform sets its revenue-sharing level, advertising policy, and other design elements, pursuing its economic objective which combines its share of advertising revenue, its value for the viewer base, and costs of serving viewers and managing the content supplied by creators (formalized below in Eq. 1). I derive the overall equilibrium (p, A, Q) by first solving for (p, A), given Q, in §2.2, and then for $Q = \{Q_1, ..., Q_k\}$ in §3.1. The sequence of decisions is depicted in Fig. 2. I develop insights regarding the choice of Q_0 in §3.2.4, and regarding γ in §4. §3.2 examines the relationship between other platform design elements (δ, ϕ) and outcome metrics, and as moderated by several exogenous elements related to the ecosystem. Notation employed in the figure and in the model development below is summarized in Table 1.

Exogenous Elements

$V(Q) = \alpha(Q) - \delta A$	viewer demand function, when platform provides Q content with A ads
$A(Q) = \beta(Q)\mathrm{e}^{-bp}$	advertising demand function, against per-view price p
$b > 0$	price sensitivity of ad demand, reflects heterogeneity in advertisers' utility from ad views
$\beta > 0$	in $\beta(Q) = \beta Q^{\phi}$, scaling parameter for ad demand, affected by platform's ad placement and targeting techniques
$\lambda \in \mathcal{R}$	cost of matching suitable ads to viewers
$c(Q)$	platform's cost of managing content [net of per-viewer value]

Platform Design Elements

$c_j > 0$	creator j's "exogenous" cost to produce content capable of generating a unit view, arranged in increasing order, so c_1 is the most powerful creator (however, the platform can influence the magnitude and distribution of c_j's through interventions like developer toolkits, training programs, and how-to videos)
$\phi \in (0, 1)$	in the setting $\beta(Q) = \beta Q^{\phi}$, ϕ reflects elasticity of ad demand to content scale Q, increased by diversity platform's user profile and by improving ad targeting and matching of ads to users
$\delta > 0$	consumer distaste for ads, lowered by improving ad placement and timing, and with better matching of ads to users

Decision Variables

$A^*(Q, \gamma), p^*(Q, \gamma)$	(Platform) advertising level and price, to maximize $\Pi(p; Q, \gamma)$
$Q_j(\gamma) \geq 0$	(creator j) level of content contributed to platform, to maximize creator profit $\pi(Q_j; Q{-}j)$, given choices Q_{-j} of other creators
$\gamma \in (0, 1)$	(platform, creators) revenue-sharing parameter (creators get γ fraction of ad revenue)
$Q_0, \alpha_0 \geq 0$	(Platform) Own content, intrinsic value (= $\alpha(0)$) provided to consumers

Outcome Metrics

K	number of feasible creators in equilibrium (i.e., make profit from contributing Q_j)
$Q^*(\gamma)$	$\sum_{j=1}^{K} Q_j$
A, V	Equilibrium level of views and ads $A(Q^*, p^*), V(Q^*)$
$R(Q^*)$	ad revenue generated, to be shared among creators and platform
$\Pi(Q^*)$	platform's profit

Table 1: Model Elements and Notation. Optimal values of p^* and A^* are computed knowing Q and γ; Q_j's are computed knowing γ; γ is set first. See Fig. 2.

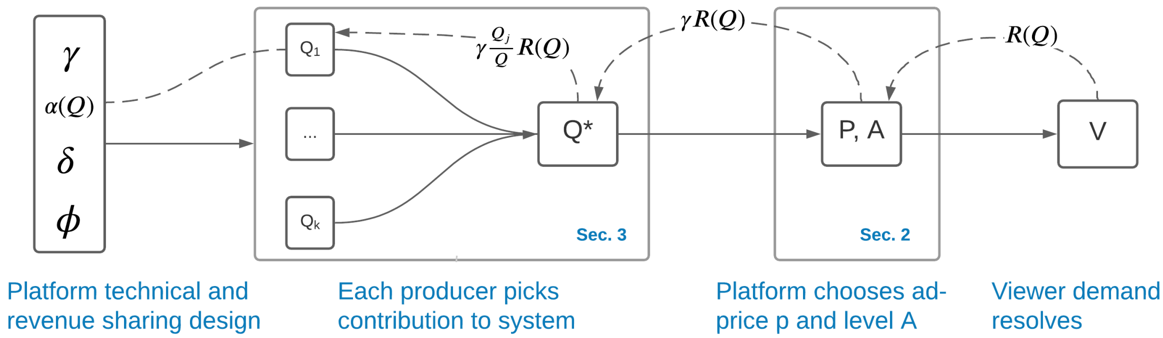

Figure 2: Key decisions and time sequence

2.1 Demand from Viewers and Advertisers

Viewers are attracted to quantity and variety in the platform's content base, and advertisers are attracted by the quantity and type of viewers. Let $v(Q)$ denote the number of viewers attracted to a platform which hosts content Q. The platform uses its matching technology to place advertisers' messages against viewers of interest to each advertiser. Let u denote an arbitrary advertiser's expected utility for a single ad view to a single viewer, and let $f(u) = b\mathrm{e}^{-bu}$ be the density of advertisers with utility level u. For an advertiser interested in viewer class k, the expected utility of a single ad-view is the product of the advertiser's value U_k for a class-k viewer times the probability $pr(k)$ that the platform targets the ad to a viewer in class k. The greater the number of viewers on the platform, the higher the chance that the platform delivers the ad to a suitable viewer, i.e., $pr(k)$ is increasing in $v(Q)$. More generally, an advertiser interested in multiple viewer classes has expected utility $u = \sum_k U_k \cdot pr(k)$, increasing in $v(Q)$. Thus, taking platform scale (i.e., number of viewers $v(Q)$) into account, an arbitrary advertiser's per-view expected utility is of the form $u = U \cdot \beta(v(Q))$, where β is increasing (likely with diminishing returns) in $v(Q)$ and U has the same distribution as u. Then, the total advertising demand $\mathbf{A}(p)$ if each ad were priced at p is $\mathbf{A}(p) = B\left(1 - \int_0^p \beta(v(Q))f(u)du\right) = B \cdot \beta(v(Q))\mathrm{e}^{-bp}$, where B is the platform's total ad-interest if advertising were free, and b reflects the price-sensitivity effect of heterogeneous advertiser utilities. With re-parameterization of the β and $v(Q)$ functions, we can rewrite $B\beta(v(Q))$ simply as $\beta(Q)$, and $A(p) = \beta(Q)\mathrm{e}^{-bp}$, and the revised β function is increasing in Q at diminishing rate. Formalizing this,

Assumption 1 (Advertiser Demand)**.** *The platform's demand from advertisers at a per-ad-view price p is*

$$\boldsymbol{A}(p) = \beta(Q)\mathrm{e}^{-bp} \qquad \textit{with } b{>}0, \beta'(Q){>}0, \beta''(Q){\leq}0, \textit{and } \frac{\beta'(Q)}{\beta(Q)/Q}{<}1.$$

Groups of items in the content vector $Q = \{Q_1, ..., Q_k\}$ could relate to each other in multiple ways: be of similar genre, be partial substitutes, independent or even complementary. Similar to Jiang et al. (2019) and Bhargava (2021), each viewer may consume multiple pieces of content, and viewers have heterogeneous preferences over type and quality, and their valuations across groups of items could be a mix of sub-additive or super-additive. Due to this, the number of viewers $v(Q)$ is increasing in Q, though at decreasing rate due to possible substitution effects (McIntyre and Srinivasan, 2017; Bhargava, 2021). Suppose that, if there were no advertising on the platform, each viewer would on average generate m views within a unit time period. This average m would itself be an increasing function of Q, because more content should cause viewers to engage more. Thus, the maximum potential views on the platform is $\alpha(Q) = m(Q)v(Q)$, interpreted as the (maximum) level of views that would occur if all content is served with no advertising. The function $\alpha(Q)$ is increasing in Q at a rate faster than $\beta(Q)$, because the latter's construction already involved a concave function applied over $v(Q)$. In the presence of advertising, and when viewers dislike advertising, the total number of views falls and is decreasing in total number of ads displayed. Let δA denote this drop, where δ reflects viewer dislike for ads, and its magnitude depends on the nature of advertising, including the level of targeting and relevance of ads. The platform may have levers to control δ, e.g., by improving ad targeting, improving its technology for matching ads to views, or by carefully timing the ads to have the best effect on user engagement (Kumar et al., 2020). The platform's scale as measured by number of views is formalized below.

Assumption 2 (Views)**.** *The platform's supply of views is*

$$V = \alpha(Q) - \delta A \qquad \textit{with } \alpha_0 = \alpha(0) \geq 0, \alpha'(Q) > \beta'(Q) > 0, \textit{and } \delta > 0.$$

Fig. 3 illustrates the platform's demand functions from viewers and advertisers, against different levels of Q. For viewer demand, the assumptions on $\alpha(Q)$ ensure that demand increases with content-level Q but at diminishing rate of increase, and $-\delta < 0$ captures negative sensitivity to advertising, as in (Dewan et al., 2002). The advertising demand function ensures that ad supply increases with Q but at diminishing rate. It implements the perspective that higher Q brings a mix of content items which are partially alike (i.e., substitutes, which drives $\beta'(Q)$ towards zero) and diverse (complements, higher $\beta'(Q)$). Finally the negative exponential demand for advertising reflects an elasticity of supply bp at per-ad-view price p. The model setup reflects a posted-price environment, but it is consistent with a mechanism where instantaneous price is discovered through a real-time auction that reflects instantaneous demand for ad impressions.

The platform's profit function has three components: i) its share of advertising revenue $((1-\gamma)pA)$,

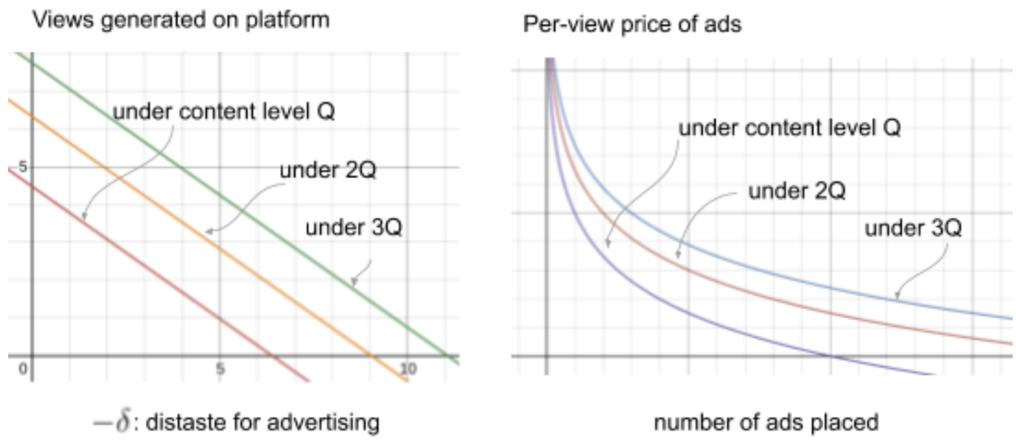

Figure 3: Platform's demand on consumer and advertiser sides, for different levels of Q.

minus ii) costs for sourcing, managing, and displaying advertisements, and iii) costs related to content management. The advertising-related cost increases both against the amount of advertising and with the level of consumer distaste for advertising, because it causes the platform to put in more efforts in figuring out the best way to display ads to viewers. Hence, the second part can be written as $\lambda\delta A$ (with $\lambda>0$). Third, the platform has an operations and marketing cost $c(Q)$ (with $c'(Q) > 0$) in serving content to consumers, covering technology, curation, data privacy, content policing, etc. Platforms often also place an intrinsic value on their user base (Gupta and Mela, 2008; Gupta, 2009), which would amount to $hV = h\alpha(Q) - h\delta A$. Collecting all these observations, we can reparameterize to make the notation more compact: redefine λ as $\lambda - h$, and $c(Q)$ as $c(Q) - h\alpha(Q)$), and the redefined λ and $c(Q)$ can each be negative if h is very high. Then, with content Q and advertising level A leading to V views, the platform's total payoff function combines its share of advertising revenue and the adjusted costs of managing content and viewers.

$$\text{Platform Profit} \quad \Pi = (1-\gamma)pA - \lambda\delta A - c(Q) = ((1-\gamma)p - \lambda\delta)\, \mathrm{e}^{-bp}\beta(Q) - c(Q). \tag{1}$$

2.2 How Much Advertising?

The platform provides consumers a free service and finances itself through ad revenues. It must balance the amount of advertising it inflicts on users: more ads have a first-order effect of diminishing the user experience and causing a reduction in views, but they also (by returning more revenue to creators) incentivize creation of more content which then plays a positive role in encouraging more views. This section explores the tradeoffs and balance in advertising, primarily as a stepping stone to examine additional issues in the ecosystem around content contribution and revenue-sharing.

The platform's choice of advertising level A^* involves a tradeoff between greater monetization of views and a reduction in number of views as advertising intrudes on the consumer experience and causes a reduction in views. A feasible advertising level is one which maintains a positive level of V (i.e., $A \leq \frac{\alpha(Q)}{\delta}$). Beyond this, a platform may impose a stricter constraint such as *no more than one ad per n views*, which places an upper bound on the equilibrium level of advertising. Let $\bar{A}(Q) = \frac{\alpha(Q)}{n+\delta}$ denote this upper bound (when there is content Q), hence the equilibrium level of advertising must be no more than $\bar{A}(Q)$. Given a revenue-sharing parameter γ and the cost parameter λ, the platform maximizes its payoff subject to this constraint. Given Q, the advertising equilibrium $(A^*(Q), p^*(Q))$ can be computed either by solving Eq. 1 for p or for A (where $\mathbf{p}(A)$ can be obtained by inverting the expression in Assumption 1). Likewise, the solution can embody an optimal posted price p^* or a price discovered via an auction in which advertisers place bids once the platform has chosen an optimal advertising level A^*.

The optimal per-view ad fee p should, in an interior solution, follow the classic rule *inverse price elasticity of advertising demand* equals *relative price markup*. The elasticity term is $\epsilon(p) = -\frac{\partial A}{\partial p} / \frac{A}{p} = bp$. To compute the price markup, note that the platform earns revenue $(1-\gamma)p$ from a unit ad, while this ad imposes a cost $\lambda\delta$, yielding the markup term $\frac{(1-\gamma)p-c}{(1-\gamma)p}$. Now, substituting and applying the optimal pricing rule yields that p^* should satisfy the equation $\frac{1}{bp} = \frac{(1-\gamma)p-\lambda\delta}{(1-\gamma)p}$. This yields the following result about the platform's optimal advertising strategy. A formal proof is included in the appendix.

Lemma 1 (Optimal advertising)**.** *The platform's optimal advertising strategy corresponding to content magnitude Q has the following per-ad price and advertising level,*

$$\begin{cases} p^* &= \frac{1}{b} + \frac{\lambda\delta}{(1-\gamma)} \\ A^*(Q) &= \beta(Q)\mathrm{e}^{-bp^*} \end{cases} \qquad \textit{if} \quad \alpha(Q) \geq (n+\delta)\mathrm{e}^{-1-\frac{b\lambda\delta}{1-\gamma}}\beta(Q), \tag{2}$$

$$\textit{with} \qquad \Pi^*(Q) = \left(\frac{1-\gamma}{b}\right)\beta(Q)\mathrm{e}^{-bp^*} - c(Q)$$

$$\textit{else there is a boundary solution } \left[\bar{A} = \frac{\alpha(Q)}{n+\delta}, \bar{p} = \frac{1}{b}\log_e\left(\frac{\beta(Q)(n+\delta)}{\alpha(Q)}\right)\right].$$

While Lemma 1 provides guidelines for setting optimal price and advertising level, comparative statics also provide additional insights regarding platform design and its implication on the advertising ecosystem. For instance, if the platform can improve ad placement to reduce δ, it can exploit this gain by showing more ads vice increasing the per-ad price, because although consumers are more willing to see more ads there is no increase in advertisers' payoff conditional on ad display.[2] The main solution stated in Eq. 2 is valid when

[2]This is an implication of the negative exponential price function for advertising demand.

viewer demand for content $\alpha(Q)$ is sufficiently strong relative to advertiser demand. If $\frac{\alpha(Q)}{n+\delta} \geq \beta Q^{\phi} \mathrm{e}^{-bp^*}$ for all Q, then an interior solution is guaranteed. If not, it must be that it fails at low values of Q but holds at higher values (because $\alpha(Q)$ grows at a faster rate than $\beta(Q)$). Then, a boundary solution in the advertising policy arises when, at the candidate Q, the platform faces relatively strong demand from advertisers but does not generate enough views on which to display ads, or if viewers drop rapidly as advertising increases (high δ). We discuss this further after computing the remaining piece (Q^*) of the equilibrium specification in §3.1.

2.3 Properties of Advertising Equilibrium

Lemma 1 satisfies a few intuitive expectations about the optimal design of advertising. First, for a given Q, the platform's optimal advertising level A^* is higher when it has a more attractive user profile or better ad targeting technology ($\beta'(Q)$ is higher or δ is low), when consumer sensitivity to advertising (δ) is low (e.g., due to more relevant ads), when ads cost less to manage and do not strongly affect the platform's installed base (low λ, e.g., when it is highly mature) or when the platform keeps a higher share of ad revenues (low γ). Conversely, the optimal per-ad price is higher under the opposite conditions, reflecting the desire to inflict less advertising on consumers rather than reflecting greater market power for advertisements. Second, if the platform increases its share of ad revenue and drops the creators' share (γ) it will then lower the advertising price. Thus, although creators prefer greater share of ad revenue, advertisers' interests are maximized when the platform keeps a higher share. These properties are consistent with anecdotal and empirical observations regarding platforms that are primarily financed by advertising. For instance, in the era of search advertising wars between Google and Yahoo! (and Microsoft) it was understood that the average per-click prices on Google were higher than those on competitors not because Google attracted more search users but because ads were better targeted, reached a broader profile, and led to more conversions.[3] When the matching between viewers and ads is superior, it can also reduce viewers' distaste for advertising (δ). This can be highly beneficial to ad-driven platforms because viewers' attitude towards ads is a critical factor in ecosystem performance. Indeed, combining the effects of δ on price and advertising level, the equilibrium advertising revenue $R(Q)$ is, *ceteris paribus*, higher as δ decreases (because $p^* > \frac{1}{b}$).

[3] `https://instapage.com/blog/bing-ads-vs-google-ads`.

3 Content Contribution

Content served on the platform is sourced from numerous creators (or their financers) who produce different types of content so that the collection, which may include substitutes and complements and unrelated goods, increases variety available to viewers. Creators have costs for making content, and their primary motivation for supplying content to the platform is the share of advertising revenue they receive from the platform (Zhu and Q. Liu, 2018), rather than exposure, ego or reputation gains (as in, e.g., Tang et al. (2012) and Y. Liu and Feng (2021)). Creators compete with each other in generating views and securing ad impressions. In this section we specify how the economic and technological characteristics of creators and the platform affect creators' absolute and relative contribution to the platform.

Creators are heterogeneous in their capability to make content. They can differ in available production technology and skills, in talent and star power, or in intellectual properties they own (e.g., rights to stories or characters. Due to these differences, the same amount of content made by two creators (e.g., ten pages of a blog post) will garner a different number of views. Conversely, two creators will need to make different amounts of content and incur different production costs in order to capture the same number of views. To model this heterogeneity we index creators according to a parameter c_j which represents the inverse of a demand-adjusted measure of production efficiency. It is the average cost that creator j would incur in creating content that would garner a unit number (say, 1000) of views on the platform. Note that this is not a measure of the magnitude of content made by creator j. For instance, a 10-minute movie made using Disney Television studios' *StageCraft* system (which was used in creating *The Mandalorians*, and considered a technological marvel that immerses the cast and production crew inside their computer-generated environments in real time with the help of a massive wraparound LED screen) would fetch many more views than a 10-minute movie created by the average content creator with a standard camera and production environment. Similarly, a 30-second clip featuring a celebrity is likely to capture more views than a similar clip with an average college student, even if the two had the same production quality standards and incurred the same production cost. In our parameterization, the celebrity would be defined with a lower unit cost parameter c_j than the college student. Typically, creators with low c_j (i.e., producers of highly popular content such as YouTube's Ryan Kaji, Epic's Fortnite, or Electronic Arts' Apex Legends) are likely to be sophisticated studios, celebrities, and social media stars. Conversely, high c_j corresponds to creators with low quality or niche content, who will therefore generate fewer views for the same expenditure.

Let $Q_j \geq 0$ represent creator j's content supply to the platform, with $Q = \sum_j Q_j$ being the total content available to viewers, and $R(Q) = p(Q)A(Q)$ the total advertising revenue generated by the platform (specified in Lemma 1). Then creator j's net payoff from sharing Q_j is $\gamma \frac{Q_j}{Q} R(Q) - c_j Q_j$. Each creator chooses a level of output to maximize its payoff. Without loss of generality, assume that creators are indexed according to increasing c_j (with c_1 being the lowest-cost, i.e., most-efficient or most-popular creator). Let Q_{-j} denote the total content provided by all creators except j (with $Q = = Q_j + Q_{-j}$). Then creator j's payoff function is

$$\pi_j(Q_j, Q_{-j}) = \gamma \frac{Q_j}{Q} R(Q) - c_j Q_j = \begin{cases} \gamma \frac{Q_j}{Q} \left(\beta(Q) p^* \mathrm{e}^{-bp^*} \right) - c_j Q_j & \text{(interior)} \\ \gamma \frac{Q_j}{Q} \frac{\alpha(Q)}{n+\delta} \frac{1}{b} \log \left(\frac{\beta(Q)(n+\delta)}{\alpha(Q)} \right) & \text{(boundary)} \end{cases} \tag{3}$$

where the interior and boundary cases correspond to the two possible advertising solutions in Lemma 1. Creators' output levels Q_j to the platform are viewed as solutions to a Cournot-type simultaneous game in which each creator picks Q_j to maximizes its payoff subject to collective output Q_{-j} from other creators, and subject to boundary constraints $Q_j \geq 0$ and *individual rationality* (IR) constraints $\Pi_j(Q_j, Q_{-j}) > 0$, i.e., $c_j \leq \gamma \frac{R(Q)}{Q}$, hence (due to the index order on c_j's) the marginal supplier K is the highest j that satisfies this condition given the remaining choices $Q{-}j$ for all $j < K$. The optimal output levels satisfy the property that marginal cost equals marginal revenue, given the output choices of other creators.

3.1 How Much Content Will the Platform Attract and Who Will Supply It?

Define a *feasible* creator as one for whom, given the equilibrium choices of other creators, an output level exists that earns it a positive profit (i.e., revenue exceeds costs). Let K denote the number of feasible creators in equilibrium under a given set of problem parameters. Creator j's economic tradeoff when deciding output level Q_j when other creators have output Q_{-j} is as follows. At level Q_j, j incurs production cost $c_j Q_j$. Now consider the effect of raising output by an additional infinitesimal increment ΔQ. The incremental advertising revenue generated by the platform is $R(Q{+}\Delta Q) - R(Q)$. Since the incremental amount ΔQ is added by creator j, its revenue increases by $\gamma \frac{Q_j + \Delta Q}{Q + \Delta Q} R(Q{+}\Delta Q) - \gamma \frac{Q_j}{Q} R(Q)$. Setting incremental cost and revenue equal, then dividing by ΔQ, rearranging terms, and taking limits, we get the set of conditions

$$\begin{aligned} c_j &= \gamma \frac{R(Q)}{Q} - \frac{Q_j}{Q} \left(\frac{R(Q)}{Q} - R'(Q) \right) \\ \equiv \quad Q_j &= \frac{1}{\gamma} \left(\gamma \frac{R(Q)}{Q} - c_j Q \right) / \left(\frac{R(Q)}{Q} - R'(Q) \right). \end{aligned}$$

By definition, $Q = \sum_{Q_j}$, however this aggregation must occur only over the K feasible creators, i.e., creators $1...K$ (because creators are indexed from low to high cost parameter). Let $\mathcal{C}_K$ denote the average of the cost indices of these top K creators. Then the content production equilibrium is as follows. A formal proof is in the Appendix.

Proposition 1 (Equilibrium)**.** *The feasible number of creators (K) who make positive profit from engaging with the platform, and the total content supplied by them (Q), satisfy the simultaneous equations*

$$K = \max_j : \left(c_j \leq \frac{\gamma R(Q)}{Q}\right), \tag{4a}$$

$$Q = K\left(1 - \frac{\mathcal{C}_K Q}{\gamma R(Q)}\right)\left(\frac{R(Q)}{\frac{R(Q)}{Q} - R'(Q)}\right), \tag{4b}$$

with outputs and output shares of each creator j being

$$Q_j = \left(1 - \frac{c_j Q}{\gamma R(Q)}\right)\left(\frac{\beta(Q)}{\frac{\beta(Q)}{Q} - \beta'(Q)}\right) \quad = \left(\gamma\frac{R(Q)}{Q} - c_j\right) / \left(\frac{\gamma R(Q)}{Q} - \gamma R'(Q)\right), \tag{5a}$$

$$\frac{Q_j}{Q} = \frac{1}{K}\left(1 - \frac{c_j Q}{\gamma R(Q)}\right) / \left(1 - \frac{\mathcal{C}_K Q}{\gamma R(Q)}\right). \tag{5b}$$

Eq. 4a-4b jointly indicate the equilibrium level of total content contributed to the platform and the set of feasible producers (identified by the average cost parameter $\mathcal{C}_K$) who supply it. Then the series of equations Eq. 5a identify the content levels of each of the feasible producers. The IR constraint for all creators is of the form $c_j \leq \frac{\gamma R(Q)}{Q}$ (with the same RHS), hence it needs to be verified only for creator K, and K can be computed uniquely once the form of $R(Q)$ is fixed. Procedurally, K is computed as the highest k that satisfies the IR constraint with the value of Q given in Eq. 4b, then combined with Eq. 4b to compute Q, and then each Q_j is obtained from Eq. 5b. Further insights are obtained by extending the analysis with an illustrative and suitable form for $\beta(Q)$, the sensitivity of ad demand to platform scale.

Writing $\beta(Q) = \beta Q^{\phi}$ (with $\phi < 1$) yields an ad demand function $A = \beta Q^{\phi} \mathrm{e}^{-bp}$ that exhibits a constant elasticity factor ϕ (i.e., $\phi = \frac{\partial A}{\partial Q}/(A/Q)$), and satisfies the requirements laid out in Assumption 1. The platform can influence the scaling parameter β through tools (such as *Hulu*'s Ad Manager) that help advertisers with ad placement, targeting, and analytics. With this additional specification, the optimality conditions for creators' choice of Q_j (in case of the interior solution) are

$$\forall\, j \quad \pi_j(Q_j, Q_{-j}) = \gamma \frac{Q_j}{Q}\left(\beta Q^{\phi} p^* \mathrm{e}^{-bp^*}\right) - c_j Q_j \tag{6a}$$

$$\left(\frac{\partial \pi_j}{\partial Q_j} = 0\right) \equiv c_j = \frac{\gamma\beta p^* \mathrm{e}^{-bp^*}}{Q^{1-\phi}}\left(1 - (1{-}\phi)\frac{Q_j}{Q}\right) \tag{6b}$$

$$\equiv Q_j = \frac{Q}{1{-}\phi}\left(1 - \frac{c_j Q^{1-\phi}}{\gamma\beta p^* \mathrm{e}^{-bp^*}}\right) \tag{6c}$$

where creators $1...K$ are the ones that have non-negative profit in equilibrium. This enables closed-form solutions of the simultaneous equations Eq. 4a-4b and leads to the following specification of the equilibrium outcome.

Proposition 2 (Equilibrium Level of Content)**.** *With* $\beta(Q) = Q^{\phi}$*,* $p^*(Q){=}\left(\frac{1}{b}{+}\frac{\lambda\delta}{1-\gamma}\right)$ *and revenue-sharing parameter* γ*, the set of creators who can profitably supply content is* $\{1...K\}$ *where*

$$K = \max_k : \left(c_k \leq \frac{\mathcal{C}_k k}{k{-}(1{-}\phi)}\right), \tag{7}$$

and the total content collected by the platform from these creators is

$$Q = \left(\frac{\gamma\beta p^* \mathrm{e}^{-bp^*}}{\mathcal{C}_K}\frac{K{-}(1{-}\phi)}{K}\right)^{\frac{1}{1-\phi}} = (\gamma p^* A^*)\left(\frac{K{-}(1{-}\phi)}{\mathcal{C}_K K}\right), \tag{8}$$

while the proportional content share of individual creators is

$$\frac{Q_j}{Q} = \frac{1}{1{-}\phi}\left(1 - \frac{c_j}{\mathcal{C}_K}\frac{K{-}(1{-}\phi)}{K}\right), \tag{9}$$

provided that Q *from Eq. 8 ensures an interior advertising-pricing solution (Eq. 2), i.e.,*

$$\alpha(Q) \geq \left(\frac{\mathcal{C}_K K}{K{-}(1{-}\phi)}\right)\left(\frac{(n{+}\delta)\mathrm{e}^{\frac{b\lambda\delta}{1-\gamma}+1}}{\gamma}\right) Q \tag{10}$$

otherwise, Q *is lower, obtained as Eq. 4b where* $R(Q) = \frac{\alpha(Q)}{n+\delta}\frac{1}{b}\log\left(\frac{\beta(Q)(n+\delta)}{\alpha(Q)}\right)$ *from Eq. 3.*

The main interior equilibrium solution applies when viewer demand for the platform is sufficiently strong as a function of Q, so that the platform generates enough views on which to display its supply of ads at p^*. As shown in Fig. 4 this is the region where $Q > \tilde{Q}$ (which demarcates the boundary in Lemma 1). If this occurs, and ignoring the market failure solution ($Q{=}0$, $A{=}0$), there is a unique (p^*, A^*, Q^*) solution because Eq. 8 provides a linear relation between A and Q while A is concave in Q in Eq. 2. Hoewver, if they intersect at $Q < \tilde{Q}$ (e.g., the point marked $x1$ in the figure), then the above solution is not valid. The alternate

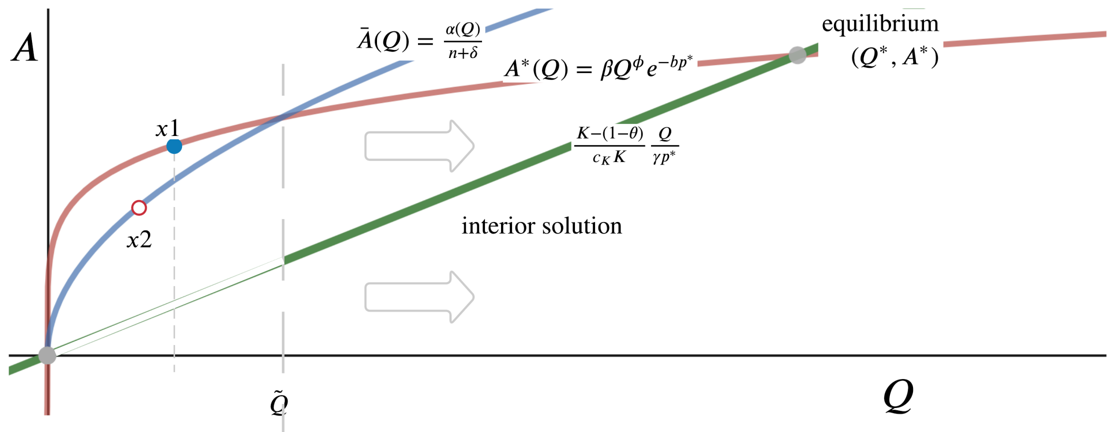

Figure 4: Equilibrium with interior solution in (p^*, A^*, Q^*) occurs either if $\frac{\alpha(Q)}{n+\delta} \geq \beta Q^\phi \mathrm{e}^{-bp^*}$ for all Q, or if the intersection of Eq. 2 and Eq. 8 in (Q, A) space has $Q \geq \tilde{Q}$ which is defined by $\frac{\alpha(Q)}{n+\delta} \geq \beta(Q)\mathrm{e}^{-bp^*}$.

solution $\bar{Q}$ corresponds to saturation advertising, and it must occur on the curve that marks $\bar{A}(Q)=\frac{\alpha(Q)}{n+\delta}$. In this solution, though, $\bar{Q}$ will be less than that indicated by point $x1$ because here the advertising revenue available to creators is lower than the level conveyed by Eq. 2; the lower revenue implies that outputs are lower than the implied Q_j^*'s, in turn causing lower demand from viewers, and feeding back into the loop of fewer ads and lower ad revenue and lower content, until converging to a point $x2$ corresponding to $(\bar{p}, \bar{A}, \bar{Q})$. To illustrate the boundary behavior, consider the special case where $\alpha(Q) = \alpha Q^\phi$ (i.e., it has the same curvature as $\beta(Q)$). Then, Q is given as in Eq. 8 except that the term $\beta p^* \mathrm{e}^{-bp^*}$ is replaced with $\frac{\alpha}{n+\delta}\frac{1}{b}\log(\frac{\beta(n+\delta)}{\alpha})$, and Eq. 7 and Eq. 9 remain valid.

From Eq. 7, the number of feasible creators—and whether or not a specific creator j can be profitable member of the ecosystem—depends not just on j's cost index, but its position among other creators and the distribution of the cost levels of more efficient creators. Loosely speaking, if creators $1...k$ are bunched together on cost, and $k+1$ is has substantially higher cost parameter, then k creators are feasible, and $k+1$ is the first non-feasible creator. Eq. 9 identifies how Q_j drops as c_j increases. To provide a better understanding, Example 1 evaluates multiple scenarios to show how K and Q_j are affected by the nature of creators' relative cost parameters.

Example 1 (Distribution of creators' outputs under different distributions of cost indices)**.** *Consider 4 scenarios each with 400 potential creators, but differing in the c_j vector. The top panel of Fig. 5 shows the cumulative distribution function for the cost indices. In Scenario 1—which has the sharpest difference between low-cost and high-cost creators—a few creators ($c_j \in [4, 6]$) have far lower cost than others (distributed in $[6, 15]$). The c_j's in Scenario 2 are quite homogeneous, huddled in $[14, 16]$. The c_j's in Scenario*

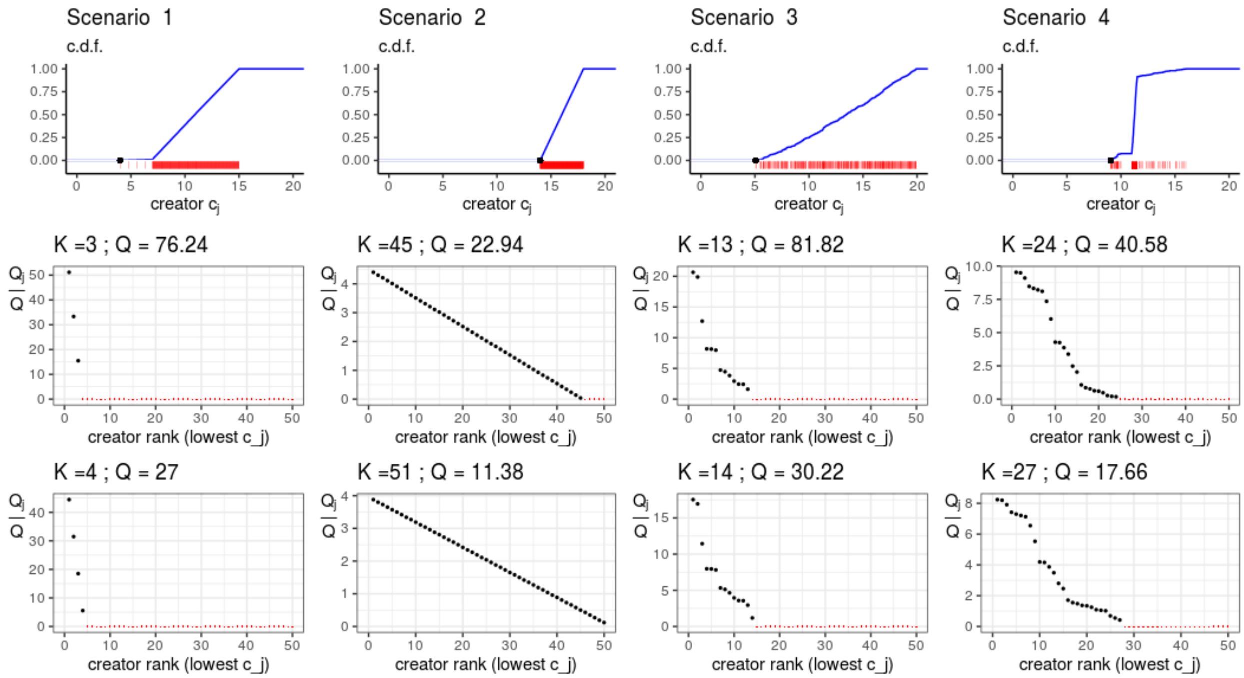

Figure 5: The top row shows c_j's of 400 potential creators on the x-axis (the black bullet marks c_1, other c_j's are displayed as x-axis ticks), and the cumulative density on the y-axis. The next two rows show associated output shares $\%\frac{Q_j}{Q}$ for $\phi = 0.3$ (middle row) and $\phi = 0.1$ (bottom row). In scenario 1, the Q_j's are highly concentrated among a few creators whose costs are far lower than all others.

3 are in $[4, 16]$ as in Scenario 1, but spaced out uniformly. In Scenario 4, a few creators have lower costs than others, but the differences between them and higher cost creators are not as amplified in Scenario 1. Scenario 1 features lowest c_j's but also greatest heterogeneity.

1. *In Scenario 1, the sharp heterogeneity between a few lowest-cost creators (with $c_j \in [4, 6]$) leads to their domination and heavy concentration of output.*

2. *Creators' c_j's in Scenario 2 are relatively homogeneous (all huddled in the [14,16] interval), hence output is distributed among many more creators (higher K, although total Q is lower), with even the most efficient (c_1) garnering only a small fraction of viewers.*

3. *Scenario 3 also has a few low-cost creators ($c_j \in [4, 6]$) however there are several of them in this range, leading to a more even distribution of output, and the higher K leads to higher Q overall than Scenario 1, although average cost of feasible creators is similar in the two scenarios.*

4. *In Scenario 4 a few lower-cost creators stand out, like in Scenario 1 but they are less extreme, causing higher K, less concentration, and lower Q.*

5. *Across all 4 panels, the middle row, with $\phi = 0.3$, has more concentration relative to the lower row with $\phi = 0.1$.*

The examples convey two primary insights. First, when creator capabilities (c_j's) are more homogeneous, then K will be higher and market concentration lower because homogeneity creates more competition among creators. Second, higher ϕ will lead to more concentration of content and rewards among fewer creators. The intuition is that already-powerful creators will be better able to leverage the higher scale enabled by higher ϕ (i.e., the rich get richer). Thus, platform design changes that enhance ϕ (e.g., more diverse user profile) can lead to greater concentration among creators. Conversely, innovations that limit consumer ad distaste (i.e., lower δ) or improve ad targeting will increase platform scale and profits without affecting the distribution of market share among creators.

3.2 Implications on Platform Design

A platform can increase its scale and other outcomes—consumer views, advertising demand, ad revenue, platform profit, and surplus of other participants—in multiple ways. These include design changes that enhance targeting and matching of ads to views (which may reduce δ and/or increase ϕ), marketing investments that attract a more diverse user base (yielding higher ϕ), increased sales effort to reach advertiser segments (higher β), better data about users' preferences (which may improve λ), creator development programs and toolkits to assist with content creation and distribution (which will cause changes in the c_j's), and better bargaining power with creators (lowering the revenue-sharing parameter γ). While all innovations help increase output from creators, and ad revenues, they have different merits with regard to other crucial factors such as number of creators, viewer response, and market concentration among creators. The discussion below is framed in terms of the interior solution (unless specifically mentioned) because even the boundary solution with lower Q has similar structural properties as noted in the illustration above.

Trivially, reducing δ has all-round advantage to the platform: viewers tolerate more ads, which increases ad revenues and attracts more content from creators, in turn bringing more viewers and increasing the platform's profits. Other elements force various trade-offs. First, under conditions that lead to an interior solution (e.g., high Q, low β, see Eq. 8), the analysis below suggests that a platform should consider a) increasing sales effort towards recruiting advertisers, in order to get higher β and higher revenues from advertising, b) building tools that help advertisers with managing targeting and impact of ads, thereby increase their value from participation in platform, and c) investing in tools that improve production efficiency of weaker creators, thereby increasing K and reducing market concentration among creators (vs. creator-focused activities that maximize Q). Conversely, under conditions for a boundary solution (e.g., low Q, low $V(Q)$), it is more impactful to a) improve timing and location of ads (vs. better ad-matching tools), in order to reduce δ and create space for more ads, b) invest in SDKs and creator-focused tools directed to popular creators, media partnerships for content, aiming to increase Q rapidly to attract more viewers and increase views (although with more market concentration among a few powerful creators), and c) increase the platform's standalone value through additional features or through first-party content.

3.2.1 Creator support programs and developer toolkits

The size of the platform ecosystem (K, the number of feasible creators that earn positive profit from their participation in the platform), is an important indicator of the health of the platform ecosystem. It exerts influence on consumer demand for the platform, total content offered on it, and potentially the relative bargaining power between the platform and creators. It is intuitively obvious that creators will benefit and make more content if their c_j parameters are lowered. Platforms aim to do this by producing toolkits for design and editing of content. YouTube runs a creator academy, offers or encourages creation of masterclasses and tips for growing one's YouTube channel. Similarly, various ad software platforms run workshops and certification programs. These interventions lower the c_j's, and lead to higher Q_j, but do they necessarily also increase K, the number of feasible creators? From Proposition 2 (Eq. 7), the *distribution* of c_j's is a crucial determinant of K, hence whether or not K increases with a reduction in c_j's depends on how the reduction alters the heterogeneity in c_j's. Example 1, discussed earlier, shows this vividly, and Fig. 5 illustrates the joint effect of the magnitude of c_j's and the degree of homogeneity among them on K. We discuss below the more general point that the effect of these resources depends on whether they help make c_j's more (or less) dissimilar vs. just lower. We evaluate the effects in terms of both the overall magnitude of content (Q) and ad revenues ($R(Q)$) and how these are distributed across creators.

Corollary 1 (Proposition 2)**.** *A reduction in c_j's leads to an increase in Q. Interventions that reduce all c_j's by a constant amount Δc, thus amplifying the cost differences between creators, lead to lower K and greater concentration in the creator ecosystem, with an increase in the share $\frac{Q_j}{Q}$ of the lower-cost creators. Conversely, interventions that make creators more homogeneous (e.g., by reducing variance, relative to mean, between c_j's) lead to higher K and to more uniform distribution of market share across creators.*

As highlighted in the second part of Corollary 1, greater homogeneity leads to larger K, because from Eq. 7, K is identified by the first c_j that is "relatively distant" from the previous one. From Eq. 9, homogeneity in c_j's also spreads output more uniformly across creators, reducing dominance of the most powerful ones. This suggests that the platform would be better served by creating technologies that not only lower c_j's but also level the playing field among creators (i.e., the new c_j's are more homogeneous). Hence, interventions like training programs and toolkits that contain specialized features for making content creation and distribution more efficient will best promote the platform's interest if they are easy to absorb by all creators and level the playing field among them (i.e., they are most novel and useful to the smaller or higher-cost creators), thereby making creators more homogeneous and competitive. Such an approach is most useful in an interior solution where the platform has sufficient viewers and content to fill in the demand from advertisers. However, if these interventions involve a steep learning curve or significant adoption costs, or otherwise are only attractive to the already-efficient creators, then these innovations will amplify differences among creators and cause greater concentration in content supply. Such a direction may be acceptable when the platform has strong demand from advertisers but not enough views (i.e., a boundary solution) making it vital to increase content and attract more viewers, even at the expense of greater reliance on a few creators.

3.2.2 Viewer diversity and ad targeting technology

The platform can also improve its scale by increasing ϕ (trivially, $\frac{\partial Q}{\partial \phi} > 0$), for instance by attracting more diverse viewers and creators, and in complement to that, developing better matching technology that serves more suitable ads to each viewer. Proposition 2 illuminates the tension faced by the platform in doing so. The platform's advertising demand increases with ϕ (which captures sensitivity of advertisers' value per-exposure to total Q or V), which it can achieve by improving consumer diversity and its technology for targeting or matching ads to consumers. Total content supplied, and flow of advertising revenue, should increase with higher ϕ. Counter to intuition, though, doing so leads to fewer viable creators: higher ϕ leads to lower K. This is because higher ϕ implies higher gains from producing more content, making the most powerful creators (ones with lower c_j) highly aggressive in supplying content to the platform and leaving little room for higher-cost creators in the revenue-splitting game.

Corollary 2 (Proposition 2)**.** *Increase in ϕ (weakly) causes greater concentration of content contribution among fewer creators, with an increase in share of the more powerful creators (low c_j's), and overall increase in output Q. Formally, $\frac{\partial K}{\partial \phi} \leq 0$, and $\frac{\partial Q_j/Q}{\partial \phi} \gtreqless 0$ when $c_j \lesseqgtr \mathcal{C}_k$.*

Thus, although the platform would like to increase ϕ and improve the economics of the ecosystem, doing so will make the most powerful creators highly aggressive in supplying content, thereby increasing their market share ($\frac{Q_j}{Q}$). This increase in degree of concentration among creators not only affects social dominance in the consumer market but also influences the bargaining power of the platform relative to creators. For a given distribution of c_j's an increase in ϕ can potentially increase the bargaining power of a few dominant creators, which raises the risk for the platform of demands for lower γ (if K gets sufficiently low). This tradeoff would be more acceptable to a platform when it is operating under a boundary solution (high demand from advertisers, creating urgency for more content and more views) than under an interior solution where the platform has attracted sufficient creators and content and would rather focus on increasing its share of ad revenues.

3.2.3 Changes in the creator ecosystem

Interventions that increase K by compressing the differences between c_j's can also increase competition among creators and make them more aggressive in supplying content to the platform. This leads to higher Q, increasing platform scale and ad revenues. Interventions such as toolkits and training academies have a substantial positive spillover effect on the platform, not only attracting more creators and higher output, but excessively higher output because more of them simultaneously compete to capture a greater *fraction* of advertising eyeballs and revenues. The distribution of c_j's can also be altered on account of events external to the platform, such as mergers between creators. Imagine two scenarios which differ in the number of creators and their c_j's but the same $\mathcal{C}_K$ (mean cost of feasible creators). Proposition 2 provides the insight that, normalizing across cost, more creators implies greater content, reflecting the "overproduction" insight mentioned earlier in Example 1 (comparing Scenarios 1 and 3).

Proposition 3 (Overproduction by competing creators)**.** *Other things being the same ($\gamma, \beta, b, \phi, \delta$), the total output in an ecosystem with creators $1...K$ whose cost indices $c_1, ..., c_K$ satisfy $c_K \leq \frac{\mathcal{C}_K K}{K-(1-\phi)}$ (where $\mathcal{C}_K$ is the average of c_j's) exceeds the output from fewer creators with the same average cost.*

The crucial aspect of the result, having normalized for mean cost, is that existence of multiple creators increases competition among them for share of advertising eyeballs, causing each of them to supply excessive content on the platform. This is good for consumers (assuming content is a "good") and for the platform. Thus interventions such as toolkits and training academies have a substantial positive spillover effect on the platform, not only attracting more creators and higher output, but excessively higher output because more of them simultaneously compete to capture a greater *fraction* of advertising eyeballs and revenues.

3.2.4 First-Party Content and Intrinsic Value

The discussion thus far assumes that the platform relies on third-party creators to provide all the value that brings in viewers. However, $\alpha(Q)$ in the viewer demand function $V{=}\alpha(Q){-}\delta A$ can include an order-zero component α_0 that represents standalone or intrinsic benefit from the platform due to features (e.g., file storage, profile development, single-sign-on to other sites, calendar, etc.) that are valued by users independent of their content preferences or advertising. Moreover, Q might include, along with the other Q_j's, a component Q_0 which represents first-party content developed by the platform or other content it purchases or licenses that is not subject to ad revenue sharing. How do these two factors α_0 and Q_0 influence ecosystem performance, advertising, and content provision by external creators?

First consider the effect of α_0 under a boundary solution $(\bar{p}, \bar{A}, \bar{Q})$. Since advertising is limited to

$\bar{A} = \frac{\alpha(Q)}{n+\delta}$ (on account of insufficient viewers to deploy ad level A^*), causing the platform to sacrifice some ad revenue, specifically $p^*A^* - p^*\bar{A}$. An increase Δ in α_0 would extend the advertising constraint by $\frac{\Delta}{n+\delta}$ and directly increase ad revenue by $\bar{p}\Delta$ to offset the cost of increasing α_0. However, there are additional spillover effects. The higher ad revenue would motivate creators to increase Q_j, bringing in more viewers, stretching the advertising constraint further, feeding the cycle again. If the investment in α_0 exceeds a tipping point (which would depend on a specific function for $\alpha(Q)$), then this process converges to an interior equilibrium (p^*, A^*, Q^*) where the constraint just no longer binds (i.e., $A^*{=}\bar{A}$), creating substantial payoff from the investment in standalone benefits. The effect of investing in Q_0 (first-party content) has similar effects because the platform can direct all possible advertising to third-party content views (because there is a scarcity of views). Finally, the effects of investing in α_0 or Q_0 are weaker when the problem has an interior solution because the advantage from increasing views is lower in the absence of sufficient advertising to exploit the extra views. This discussion confirms the intuition that investments in standalone benefit and first-party content are most consequential at the early stages of the platform when its scale is relatively low and when it has greater urgency to attract more views.

4 Sharing Advertising Revenue with Content Creators

Our analysis thus far has considered the platform's advertising strategy and content creators' supply strategy given that the platform passes γ fraction of advertising revenues to creators. The optimal or equilibrium level of γ is subject to multifaceted issues including relative market power and co-dependence. On one hand, each creator is tiny and relatively inconsequential to the platform. On the other, the platform's business model depends on creators and they potentially have an ability to create coalitions. These factors create alternative possibilities for the revenue-sharing game (Oh et al., 2015). Our focus therefore is mainly to shed light on how γ affects the overall activity levels and payoffs of different actors. and the overall health of the ecosystem.

The platform's payoff function given a revenue-sharing parameter γ, and using the advertising demand function $A(Q) = \beta Q^{\phi}\mathrm{e}^{-bp}$ is

$$\Pi(\gamma) = (1{-}\gamma)R(Q) - \lambda\delta A - c(Q) = ((1{-}\gamma)p^* - \lambda\delta)\,\beta Q^{\phi}\mathrm{e}^{-bp^*} - c(Q) \tag{11a}$$

$$= \left(\frac{1{-}\gamma}{b}\right)\beta Q^{\phi}\mathrm{e}^{-bp^*} - c(Q) \tag{11b}$$

where, with optimal advertising and content creation, the optimal values of p and Q and K are

$$p = \frac{1}{b} + \frac{\lambda\delta}{(1-\gamma)}, \qquad \frac{\partial p}{\partial \gamma} = \frac{\lambda\delta}{(1-\gamma)^2} \tag{12a}$$

$$Q = \left(\frac{\gamma\beta p \mathrm{e}^{-bp}}{\mathcal{C}_K}\frac{K-(1-\phi)}{K}\right)^{\frac{1}{1-\phi}} \qquad \frac{\partial Q}{\partial \gamma} = \frac{Q}{1-\phi}\left[\frac{1}{\gamma} + \left(\frac{1-bp}{p}\right)\frac{\partial p}{\partial \gamma}\right] \quad (Eq.\ 16) \tag{12b}$$

$$K = \max_k : \left(c_k \leq \frac{\mathcal{C}_k k}{k-(1-\phi)}\right) \tag{12c}$$

The revenue-share parameter γ determines what fraction of revenue is kept by the platform $(1-\gamma)$ vs passed on to creators. However, the choice of γ is not a zero-sum game where creators prefer γ=1 while the platform wants γ=0. For creators, the penalty from a very high γ is that it would cause the platform to shift ad prices higher, causing lower ad volume and thereby drive down creator revenues down. For the platform, if it sets γ too low then the low rewards to creators will cripple content contribution, the basic fuel that drives the entire engine. Therefore, a judicious choice of γ would consider effects throughout the ecosystem, including implications on long-term health and scale.

The identification of the optimal revenue-sharing level—from the platform's perspective while also including interests of other ecosystem participants—requires some consideration of the platform's underlying objectives. One obvious objective is to maximize the profit function in Eq. 11. However, due to $c(Q)$ and $\lambda\delta A$, the profit-maximizing choice of γ would negatively distort the total ad revenue passing through the platform, which is an important objective for the platform and a metric of overall scale. Another measure of platform scale is the total volume of content available on the platform, Q. Hence, it is meaningful to consider the implications on platform performance with regard to each of these metrics.

4.1 Maximizing Platform Scale

The revenue-sharing parameter has multiple impacts throughout the platform ecosystem, including on the levels of contributed content, viewership, advertising revenue flowing into the ecosystem, and the platform's share of the revenue. There are two key forces to consider whose effect is summarized below.

Corollary 3 (Proposition 2)**.** *The equilibrium level of Q increases in γ up to some threshold value of γ (i.e., $\frac{\partial Q}{\partial \gamma} > 0$ initially), then decreases.*

One, higher γ naturally motivates creators to provide more output per dollar of advertising revenue that it generates. The consequent increase in views has a positive impact on advertising demand. This exerts a positive effect on ad revenue into the ecosystem. Second, however, since the platform sets per-exposure

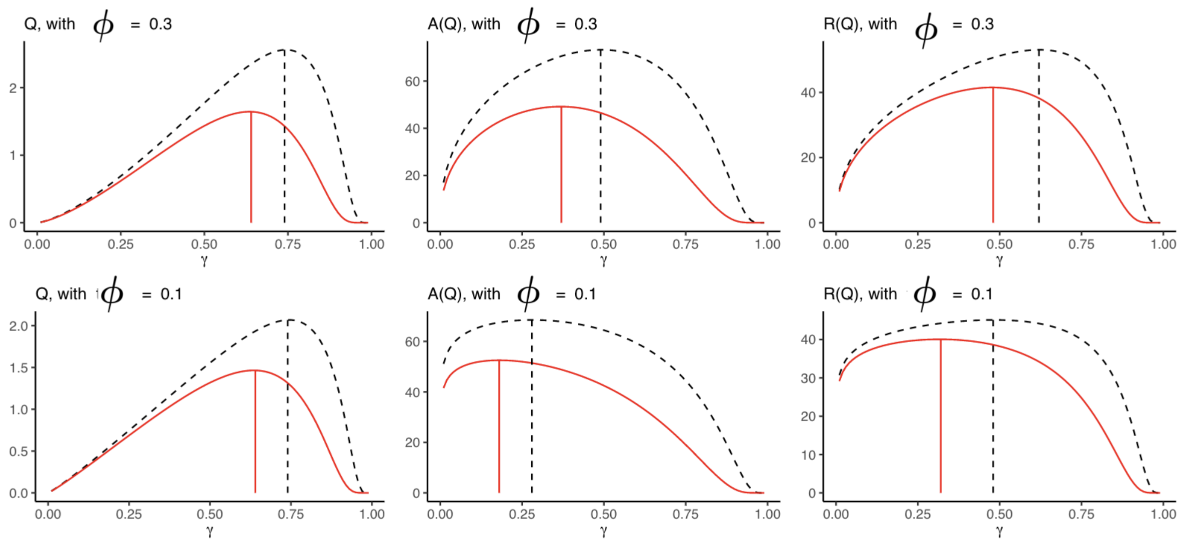

Figure 6: Effect of γ on Q, $A(Q)$, and $R(Q)$ for higher and lower values of ϕ (top and bottom rows) and with two values of $\delta = 0.1$ (black, dashed) and $\delta = 0.2$ (red).

advertising price to maximize its ad revenue payoff (adjusted for intrinsic value placed on viewership), it then sets a higher ad price thereby depressing advertising demand and consequently exerting a negative force on content creators. The interaction of these two forces leads to a first-positive and then-negative effect of γ on Q, so that Q peaks at an interior value of γ. As for the effect on $R(Q)$, note that the revenue grows as a multiple of price and advertising, hence the γ at which $R(Q)$ peaks should be lower than the peak for Q but higher than for $A(Q)$. These ideas are formalized in the result below.

Lemma 2 (Optimal γ to maximize Q and $R(Q)$)**.** *The values of γ that maximize total content on the platform and, respectively, total ad revenue, are*

$$\textit{for } Q: \quad \gamma^{Q} = Sol.\left[(1-\gamma)^3 + (b\lambda\delta)(1-\gamma)^2 + (b\lambda\delta)^2(1-\gamma) - (b\lambda\delta)^2 = 0\right] \tag{13a}$$

$$\textit{for } R(Q): \quad \gamma^{R(Q)} = Sol.\left[(1-\gamma)^3 + (b\lambda\delta)(1-\gamma)^2 + \frac{(b\lambda\delta)^2}{\phi}(1-\gamma) - \frac{(b\lambda\delta)^2}{\phi} = 0\right] \tag{13b}$$

and each equation yields a unique value inside the feasible region $(0, 1)$.

Corollary 4 (Lemma 2)**.** *The value of γ that maximizes Q is decreasing in b, λ, and δ. The same is true for γ that maximizes $R(Q)$, and this value is increasing in ϕ.*

Fig. 6 demonstrates the effect of γ on Q and $R(Q)$ (and, additionally, $A(Q)$, the scale of advertising on the platform) for multiple illustrative values of problem parameters (specifically, ϕ = 0.3 and 0.1, and δ = 0.1 and 0.2). A useful insight from the Lemma and illustrated in Fig. 6 is that an improvement in ad targeting, which can help reduce δ (consumer distaste for advertising), increases $\gamma^{R(Q)}$ (i.e., $\frac{\partial \gamma^{R(Q)}}{\partial \delta} < 0$). A reduction in δ is the platform's core desire and responsibility, and eliminates a "waste" from the ecosystem. It is notable that in order to optimally leverage the gains from improving δ the platform should increase the share of ad revenue that goes to creators! This creates a win-win-win situation with regard to investments needed to reduce δ.

Corollary 5 (Lemma 2)**.** *$\gamma^{R(Q)} < \gamma^{Q}$, and the gap between the two gets wider as b, λ, δ increase, and narrower as ϕ increases.*

It is notable too that the optimal value of γ depends only on b, λ, δ which are exogenous parameters in the model. Moreover, the platform's other decision variable, the per-ad price p^* also depends only on these three parameters (besides γ). Consequently, the platform can set and announce its operational policy once it has sufficiently accurate market research information regarding consumer demand (δ) and advertising demand (b).

4.2 Differential Revenue-Sharing and Platform-creator Conflict

Lemma 2 identifies the revenue-sharing parameter that maximizes total content on the platform and, respectively, total ad revenue. These two metrics are a measure of the vibrancy of the overall platform ecosystem. Moreover, maximizing them might well be in the interest of the platform because, in the long run, platforms do well when their ecosystem partners do well. Although this perspective of maximizing $R(Q)$ ignores the costs included in the model, namely $b\lambda\delta A$ and $c(Q)$, it is still meaningful because company leadership and analysts pay attention not just to bottom-line profit but also to top-line revenues and total volume flowing through the platform. Nevertheless, it is useful to also examine how a platform would pick γ when purely maximizing its short-term self-interest as stated in Eq. 11, i.e., $(1-\gamma)R(Q) - b\lambda\delta A - c(Q)$. It is obvious that, due to these additional costs, and because the platform collects only a fraction $(1-\gamma)$ of ad revenues $R(Q)$, the profit-maximizing value γ^* would be less than $\gamma^{R(Q)}$, with the exact form and value depending on the form of $c(Q)$ function and λ.

The fact that $\gamma^* < \gamma^{R(Q)}$, combined with the effects of γ on Q (i.e., $\frac{\partial Q}{\partial \gamma}$) suggests that if the platform were to pursue its short-term self-interest in choosing γ, this would lead to a reduction in platform scale, including in Q, V, and A. This disconnect is partly a result of the fact that the model assumes—consistent with the practice of all dominant platforms that employ revenue-sharing business models—a uniform non-discriminatory linear revenue-sharing scheme. That is, a single per-unit commission parameter is defined (i.e., $1-\gamma$, such as the 20%-30% rate that is observed in many platforms), multiplied with the value or scale of each creator, and applied identically to all creators regardless of size or nature of business. In

Congressional testimony on July 29, 2020 (in the so-called "Big Tech hearing" before the House Antitrust Subcommittee[4]), contradicting charges that Apple offered powerful app developers a larger revenue share, Apple CEO Tim Cook reemphasized the uniform revenue sharing policy, saying "it treats all apps the same." This non-discriminatory policy protects platforms from potential haggling with each creator, however it can cause conflict with a) large creators who feel that the rate is excessive given their scale, b) creators for whom the platform's enablement appears insubstantial (e.g., *ClassPass* and *Airbnb*'s complaints in the "Big Tech hearing" against Apple's 30% rate applied to virtual events)[5], and c) creators with low margins for whom a 30% revenue share can cripple their business.[6]

How might the platform avoid such conflict while still retaining the benefits of a simple, compact and non-discriminatory policy? This dilemma is analogous to pricing problems involving heterogeneous participants or coordination problems with asymmetric information and/or misaligned incentives. One common solution to mitigate the problem is to use coordination techniques such as two-part tariffs. For instance, a firm that is facing efficiency loss because it sets a uniform per-unit price to both light and heavy users of a product can avoid some of this loss by adding a fixed access fee that applies to all users regardless of scale, and then lowering the per-unit price charged for usage. In the case of our 3-sided platform that thrives on network effects and positive dependence, an access fee would have the detrimental effect of disadvantaging some creators (with high c_j's, who produce low Q_j), and increasing the power of the already dominant creators. Similarly, a typical two-part or two-block tariff—one that offers a higher revenue share γ^+ once Q_j exceeds threshold—would also favor the most powerful creators. The platform could do the reverse: *reduce* the rate to γ^- after some threshold, but this would appear as a blatant attack against creators with highest outputs. Alternately, the platform could turn a two-part tariff on its head and convert the fixed access fee into a subsidy S. For example, it could offer *all* creators free use of its development or production resources up to some scale $\hat{q}$, while simultaneously increasing the platform's share of revenues (i.e., lowering γ) for the residual revenues. That is, creator j's payoff from supplying Q_j output to the platform would change from $\gamma \frac{Q_j}{Q} R(Q)$ to $S + (\gamma - \Delta\gamma)\frac{Q_j - \hat{q}}{Q} R(Q)$. Ultimately, the challenges caused by a single non-discriminatory rate may well cause platforms to adopt full nonlinear pricing or, more likely, an efficient form of traditional nonlinear pricing such as tiers of two-part or three-part tariffs (Bagh and Bhargava, 2013).

[4] https://www.cnbc.com/2020/07/29/apple-tried-to-lure-amazon-video-app-with-lower-15percent-fee-eddy-cue-email.html

[5] https://www.nytimes.com/2020/07/28/technology/apple-app-store-airbnb-classpass.html

[6] https://www.cnbc.com/2020/07/24/epic-games-ceo-tim-sweeney-apple-crippled-app-store-with-30percent-cut.html

5 Conclusion

This paper presents a general framework to model and analyze the economics of three-sided platforms that mediate between consumers, creators, and advertisers. These platforms attract consumers on the strength of outputs from creators, thereby attracting advertisers who wish to reach these consumers, and motivating creators with a revenue-sharing arrangement on ad payments. The model particularly focuses on the interplay amongst numerous (possibly thousands of) creators and between creators and the platform's design parameters. It provides new insights about how the heterogeneous characteristics of creators affect their contribution to the platform, the impact of the revenue-sharing design, and how the level of concentration in the creator layer interacts with creator characteristics and platform design factors. I also discuss how the platform's decision on various design parameters affect the performance of this three-sided platform ecosystem. The framework provides a foundation for analysis of a range of additional issues in such multi-sided platforms, including those related to platform competition, market power, and anti-competitive practices. Although it assumes that the platform generates revenue through advertising, the main results should apply to other forms of revenue-generation, including charging viewers a subscription fee for access to content.

The framework has several limitations that create opportunities for additional research. The model assumes that higher scale automatically brings more diversity: e.g., that more content and more creators attract more diverse viewers, which in turn brings in more advertisers, then yet more creators and more viewers. The model does not explicitly consider alternate genres of content, or whether scale can have different effects on different genres, e.g., educational content or violent content. Similarly, it does not capture behavior of individual viewers, consider which viewers are shown which ads, or capture heterogeneity in advertisers' response to platform design characteristics that affect viewer distaste for ads. Also, while the paper discusses the impact of providing standalone benefit or first-party content, it would require more specificity and extensions to identify the optimal level of investments on these factors. It would also be fruitful to consider platforms where creators are motivated not solely by their share of platform revenues, or when "free" creators co-exist with a relatively smaller cadre of paid creators. With regard to ad revenues with an implied pay-per-impression model, it might be enriching to explicitly analyze alternative ad payment models under broader conditions involving incomplete information or asymmetric risks, or when intermediaries are involved to manage advertising (Dellarocas, 2012). Additional issues to consider are the dynamics of revenue-sharing between the early vs. mature stages of the platform, and multi-dimensional creators who produce multiple groups of content under a single strategic decision maker.

A Appendix

A.1 Some Simple Numerical Examples

Example 2 (creator's costs from uniform distribution)**.** *Suppose there are 9 creators in the ecosystem, with cost indices distributed uniformly in the interval* $[4,6]$*. Also, suppose* $\phi{=}\frac{1}{2}$ *in* $A = \beta Q^{\phi}\mathrm{e}^{-bp}$*, so that* $A = \beta\sqrt{Q}\mathrm{e}^{-bp}$*. Then, in equilibrium* $K{=}5$*, and the highest-cost creators are unable to earn a profit from supplying content to the platform. The 5 lowest-cost creators have output shares* $\frac{Q_j}{Q} = \{0.4, 0.3, 0.2, 0.1, 0\}$ *(the final one, 0, is included for completeness).*

Example 3 (More homogeneous creators)**.** *Suppose there are 9 creators in the ecosystem, with cost indices distributed uniformly in the interval* $[14,16]$*, and with* $A = \beta\sqrt{Q}\mathrm{e}^{-bp}$*. Then, in equilibrium* $K{=}8$*, and only the highest-cost creator is excluded. Total content level supplied is* $Q =$ *The first 8 creators' output shares are* $\frac{Q_j}{Q} = \{0.235, 0.204, 0.172, 0.141, 0.109, 0.078, 0.046, 0.015\}$.

Example 4 (Costs from right-skewed distribution)**.** *Suppose there are 9 creators in the ecosystem, with cost indices (3,4,5,7,9,12,15,19,24), and* $A = \beta\sqrt{Q}\mathrm{e}^{-bp}$*. Then, in equilibrium* $K{=}2$*, and only the two lowest-cost creators can profitably supply content, with output shares* $\frac{Q_j}{Q} = \{\frac{5}{7}, \frac{2}{7}\}$.

A.2 Technical Details and Proofs

Proof of Lemma 1. Starting with $\Pi(p;Q) = ((1{-}\gamma)p - \lambda\delta)\,\mathrm{e}^{-bp}\beta(Q) - c(Q)$, compute the optimality condition $\frac{\partial\Pi}{\partial p} = 0$. This yields $\mathrm{e}^{-bp}\beta(Q)\,((1{-}\gamma) - b(1{-}\gamma)p - \lambda\delta)) = 0$, leading to the result $p^*(Q){=}\frac{1}{b}{+}\frac{\lambda\delta}{1-\gamma}$, and the corresponding $A^*(Q){=}\beta(Q)\mathrm{e}^{-bp^*}$, which holds when $A^*(Q)$ is below the threshold $\bar{A}(Q)$, i.e., $\alpha(Q) \geq (n{+}\delta)\mathrm{e}^{-1-\frac{b\lambda\delta}{1-\gamma}}\beta(Q)$. When this fails to hold then the equilibrium is a saturation advertising level with $\left[A{=}\frac{\alpha(Q)}{n+\delta}, p{=}\frac{1}{b}\log_e\left(\frac{\beta(Q)(n+\delta)}{\alpha(Q)}\right)\right]$. The boundary solution $A^* = 0$ is avoided because the negative exponential advertising demand function implies non-zero density at arbitrarily high p. Alternately, if the platform were to auction off the ads, then the expected per-ad price p discovered in a second-price auction when A ads are shown in a unit time interval is the A^{th} order statistic arising from the density function $f(u)$, i.e., the value p such that $A = \int_p^\infty f(u)du$. Maximizing $p \cdot A$ using this relationship yields the equilibrium result. ■

Proof of Proposition 1. Using Eq. 3 compute the simultaneous set of first-order optimality conditions for the platform's creators, $\frac{\partial\pi_j}{\partial Q_j}(Q_j, Q_{-j}) = 0$. This yields the set of j simultaneous equations,

$$\forall j: \quad c_j = \frac{\gamma p^*\mathrm{e}^{-bp^*}}{Q}\left[\beta(Q){-}Q_j\left(\frac{\beta(Q)}{Q}{-}\beta'(Q)\right)\right] \tag{14a}$$

$$Q_j = \frac{1}{\frac{\beta(Q)}{Q}{-}\beta'(Q)}\left(\beta(Q) - \frac{c_jQ}{\gamma p^*\mathrm{e}^{-bp^*}}\right) = \underbrace{\frac{\beta(Q)}{\frac{\beta(Q)}{Q}-\beta'(Q)}}_{\geq 0,\text{ Assumption 1}}\underbrace{\left(1 - \frac{c_jQ}{\gamma R(Q)}\right)}_{\geq 0,\text{ IR constraint}} \tag{14b}$$

Since $R(Q) = \beta(Q)\mathrm{e}^{-bp}$, the ratio $\frac{\beta(Q)}{\frac{\beta(Q)}{Q} - \beta'(Q)}$ equals the ratio $\frac{R(Q)}{\frac{R(Q)}{Q} - R'(Q)}$. Note that the IR requirement $c_j \le \frac{\gamma R(Q)}{Q}$ is an implicit statement because the Q_j equations above are valid only for those creators that satisfy the IR constraint given the Q_{-j} choices of all other creators who are "feasible" in this way. And Q must be computed by aggregating across only those creators that earn a positive payoff. Denote the number of such feasible creators as K, so that (since the c_j's are arranging from lowest to highest cost), the set of feasible creators is $\{1, ..., K\}$. Further, let $\mathcal{C}_K$ denote $\frac{c_1 + ... + c_K}{K}$, the average cost parameter across these creators. Adding up all the equations represented by Eq. 14b across all feasible creators yields the result. ■

Proof of Proposition 2. For convenience, write $Z = \beta p^* \mathrm{e}^{-bp^*}$. Solving the simultaneous decisions game yields the series of first-order optimality conditions of the form $Q_j = \frac{Q}{1-\phi}\left(1 - \frac{c_j Q^{1-\phi}}{\gamma Z}\right)$, valid for all creators j that get non-negative profit in equilibrium, i.e., $c_j \le \frac{\gamma}{Q}\left(Q^{\phi} Z\right)$. Aggregating these over the feasible creators yields

$$Q = \frac{Q}{1-\phi} K \left(1 - \frac{\mathcal{C}_K Q^{1-\phi}}{\gamma Z}\right) \tag{15a}$$

$$\equiv \left(\frac{1-\phi}{K}\right) = \left(1 - \frac{\mathcal{C}_K Q^{1-\phi}}{\gamma Z}\right) \tag{15b}$$

$$\equiv Q = \left[\frac{\gamma Z \left(K - (1-\phi)\right)}{K \mathcal{C}_K}\right]^{\frac{1}{1-\phi}} \tag{15c}$$

$$\equiv \quad Q^{1-\phi} = \frac{(K-(1-\phi))\gamma Z}{K \mathcal{C}_K}. \tag{15d}$$

Now, the IR constraints are of the form $c_j \le \frac{\gamma Z}{Q^{1-\phi}}$. Plugging in $Q^{1-\phi}$ from above yields the requirements $c_j \le \frac{K \mathcal{C}_K}{(K-(1-\phi)}$. Because the c_j's are arranged in increasing order, it is sufficient that this equation be satisfied for creator K, yielding the result.

The condition for an interior advertising solution is $A \le \frac{\alpha(Q)}{n+\delta}$, i.e., $\beta Q^{\phi} \mathrm{e}^{-bp^*} \le \frac{\alpha(Q)}{n+\delta}$. If this holds for all Q, then an interior solution is guaranteed. If not, i.e., fails at low values of Q but holds at higher values (this is the only possibility because $\alpha(Q)$ grows at a faster rate than $\beta(Q)$) then it must be verified at Q given in Eq. 8. Multiplying both sides of the equation by $Q^{\frac{\phi}{1-\phi}}$ yields the point $Q = (\gamma p^* A)\left(\frac{K-(1-\phi)}{\mathcal{C}_K K}\right)$. The interior solution is obtained when $A^*(Q)$ at this point is below the threshold $\frac{\alpha(Q)}{n+\delta}$; then plugging in the interior p^* yields the Eq. 10 condition for the interior solution. When this condition is not satisfied, then for given Q, the optimal advertising level is $A = \frac{\alpha(Q)}{n+\delta}$ which is less than $A^*(Q)$ given in Eq. 2, and the ad revenue $p \cdot A$ available for sharing with creators is also lower than $p^* \cdot A^*$. Due to this, creators' outputs are also lower, leading to a content level $\tilde{Q} < Q$, due to which the platform attracts fewer viewers, further lowering the maximum level of advertising it can support. ■

Proof of Corollary 2. $\frac{\partial K}{\partial \phi} \leq 0$ follows from Eq. 7 because the RHS term (on the right of the $\leq$ sign) gets smaller as ϕ increases. For $\frac{\partial Q_j/Q}{\partial \phi}$, rewrite Eq. 9 as $\frac{Q_j}{Q} = \frac{1}{1-\phi} - \frac{c_j}{C_k}\left(\frac{1}{1-\phi}-1\right)$. The derivative with ϕ is $\frac{1}{(1-\phi)^2}\left(1-\frac{c_j}{C_k}\right)$, proving the result. $\frac{\partial Q}{\partial \phi} > 0$ follows trivially from Eq. 8. ■

Proof of Corollary 3. We employ the chain rule $\frac{\partial Q}{\partial \gamma} = \frac{\partial Q^{1-\phi}}{\partial \gamma} / \frac{\partial Q^{1-\phi}}{\partial Q}$, and note that, at optimal per-ad price, $\frac{\partial p}{\partial \gamma} = \frac{\lambda\delta}{(1-\gamma)^2}$ and $\frac{1-bp}{p} = \frac{-\lambda\delta(1-\gamma)}{(1-\gamma)+b\lambda\delta}$, valid when p is bounded, i.e., $b > 0, \gamma < 1$. Writing Q from Eq. 4b as $Q = \left(\gamma Z p \mathrm{e}^{-bp}\right)^{\frac{1}{1-\phi}}$, where $Z = \frac{\beta(K-(1-\phi))}{KC_K}$,

$$\frac{\partial Q^{1-\phi}}{\partial \gamma} = Zp\mathrm{e}^{-bp}\left(1 + \frac{\gamma}{p}\frac{\partial p}{\partial \gamma}(1-bp)\right) \quad = \underbrace{Z\gamma p\mathrm{e}^{-bp}}_{Q^{1-\phi}}\left[\frac{1}{\gamma} + \left(\frac{1-bp}{p}\right)\frac{\partial p}{\partial \gamma}\right] \tag{16a}$$

$$\frac{\partial Q}{\partial \gamma} = \frac{\partial Q^{1-\phi}}{\partial \gamma}\left(\frac{\partial Q^{1-\phi}}{\partial Q}\right)^{-1} \quad = \frac{Q}{1-\phi}\left[\frac{1}{\gamma} + \left(\frac{1-bp}{p}\right)\frac{\partial p}{\partial \gamma}\right] \tag{16b}$$

$$= \frac{Q}{1-\phi}\left[\frac{1}{\gamma} - \left(\frac{1}{(1-\gamma)+b\lambda\delta}\right)\left(\frac{b\lambda\delta}{1-\gamma}\right)^2\right] \tag{16c}$$

Trivially, the above expression is positive at γ=0, negative at γ=1, and the second derivative $\frac{\partial^2 Q}{\partial\gamma\partial\gamma} < 0$, implying that the first derivative is monotonically decreasing, positive until some threshold γ and then negative. ■

Proof of Lemma 2. To identify the value of γ that maximizes Q, set the first-order optimality condition $\frac{\partial Q}{\partial \gamma} = 0$ from Eq. 16. Rearranging terms, and solving (and ruling out Q=0) we see that the Q-maximizing value of γ is

$$\gamma^Q = Sol.\left[(1-\gamma)^3 + (b\lambda\delta)(1-\gamma)^2 + (b\lambda\delta)^2(1-\gamma) - (b\lambda\delta)^2 = 0\right] \tag{17}$$

where the computations are valid as long as $\phi > 0$, p is bounded (i.e., $b > 0$ and $\gamma < 1$ which works so long as $b > 0, \lambda > 0, \delta > 0$). The first 3 terms in the cubic equation are positive, while the last term is negative, with a single change in sign. Therefore, using Descartes' rule of sign for polynomial functions, both equations yield a unique optimal value of γ in the feasible range (0,1). Hence the cubic equation yields a unique feasible value γ^Q.

Now consider the value of γ which maximizes total ad revenue across the platform and creators, with

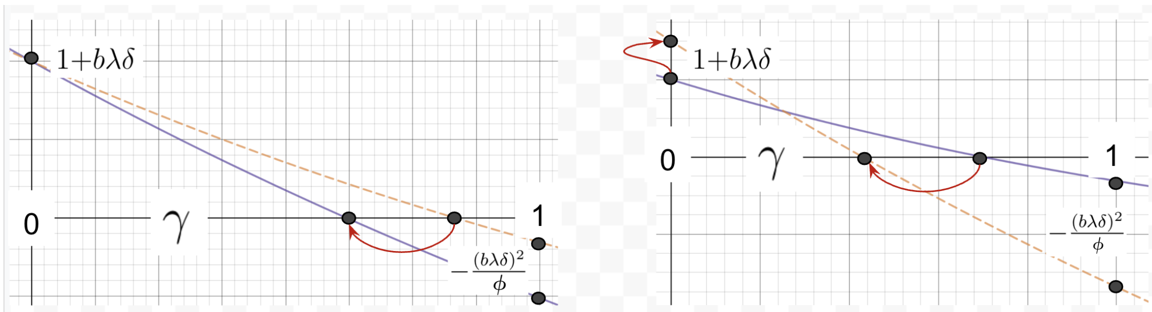

Figure 7: How Eq. 13b as a function of γ changes with an increase in ϕ (left panel) and b, λ, δ (right panel).

$R(Q) = \beta Q^{\phi} p^{*} \mathrm{e}^{-bp^{*}}$. The analysis proceeds in a similar way.

$$\frac{\partial R(Q)}{\partial \gamma} = R(Q)\left[\frac{\partial p}{\partial \gamma}\left(\frac{1-bp}{p}\right) + \frac{\phi}{Q}\frac{\partial Q}{\partial \gamma}\right] = 0 \tag{18a}$$

$$\equiv \quad R(Q)\left\{\frac{\partial p}{\partial \gamma}\left(\frac{1-bp}{p}\right) + \frac{\phi}{1-\phi}\left[\frac{1}{\gamma} + \frac{\partial p}{\partial \gamma}\left(\frac{1-bp}{p}\right)\right]\right\} = 0 \quad \text{(from Eq. 16)} \tag{18b}$$

$$\equiv \quad R(Q)\left[\frac{\partial p}{\partial \gamma}\left(\frac{1-bp}{p}\right)\left(\frac{1}{1-\phi}\right) + \frac{\phi}{\gamma(1-\phi)}\right] = 0 \tag{18c}$$

$$\frac{\phi}{\gamma} - \left(\frac{b\lambda\delta}{1-\gamma}\right)^2 \frac{1}{(1-\gamma) + b\lambda\delta} = 0 \quad \text{(using Eq. 12)} \tag{18d}$$

again yielding a cubic equation in γ,

$$\phi(1-\gamma)^3 + (b\lambda\delta\phi)(1-\gamma)^2 + (1-\gamma)(b\lambda\delta)^2 - (b\lambda\delta)^2 = 0. \tag{19}$$

which has a single change of sign, thus assuring a single feasible optimal value $\gamma^{R(Q)}$. ■

Proof of Corollary 4. First, to see the effect of changes in ϕ, write the last two terms in Eq. 13b (i.e., $\frac{(b\lambda\delta)^2}{\phi}(1-\gamma) - \frac{(b\lambda\delta)^2}{\phi}$) as $-\gamma\frac{(b\lambda\delta)^2}{\phi}$. These are the only two terms involving ϕ, and trivially, increasing in ϕ. Now consider how Eq. 13b yields $\gamma^{R(Q)}$. Note that at γ=0 the equation evaluates to $1+b\lambda\delta > 0$, and at γ=1 it is $-\frac{(b\lambda\delta)^2}{\phi}$, and has a higher value as ϕ increases (see left panel of Fig. 7). Hence, the point at which it cuts the horizontal axis (i.e., the optimal value of γ) is increasing in ϕ.

Next, consider the effect of b, λ, δ. Because these are all positive and all occur together in multiplicative form in Eq. 13b, the optimal value $\gamma^{R(Q)}$ varies identically across all three. Consider, for illustration, a change in b. The expression in Eq. 13b evaluates to $1+b\lambda\delta > 0$ at γ=0 and increases with b. At γ=1 the expression is $-\frac{(b\lambda\delta)^2}{\phi}$ and therefore reduces as b increases (see right panel of Fig. 7), therefore the intersection with horizontal axis reduces because the equation's joint derivative with γ and b is positive. ■

Proof of Corollary 5. As in the proof for Corollary 4, consider the behavior of Eq. 13b against γ. The solution γ^Q is identical to $\gamma^{R(Q)}$ for $\phi=1$. For lower values of ϕ, γ^Q remains the same while $\gamma^{R(Q)}$ falls, hence widening the gap between the two (or, conversely, getting narrower as ϕ increases). ■

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