Ecosystem Management in Advertising-driven Platforms with External Contributors

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Abstract

This paper examines ecosystem management issues in multi-sided platforms that provide infrastructure to coordinate the activities and interactions of contributors, consumers and advertisers, and which motivate external contributors through revenue-sharing of ad payments. It specifically focuses on content provision decisions and revenue-sharing when there are numerous (possibly thousands of) contributors based on the interplay amongst them and between contributors and the platform’s design parameters. We examine how the level of market concentration among contributors depends on the distribution of contributor capabilities, and how it can be influenced through elements of platform design. We show that the platform’s advertising strategy and technical design must strike a careful balance between motivating greater supply from contributors and the relative market concentration in the contributor ecosystem. The revenue-sharing arrangement faces a similar dilemma, where design elements that help to increase platform scale can also cause greater concentration in the contributor layer, possibly threatening the bargaining position of the platform. In contrast, actions that reduce viewer distaste for ads (e.g., better matching technology) create win-win-win effects throughout the ecosystem. Design tactics that level the playing field across contributors (e.g., development toolkits) improve platform revenue while also reducing market concentration among contributors. The revenue-split between the platform and contributors is (only) partly a tug of war, because a moderate sharing formula will strengthen the overall ecosystem and profits of all participants.

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

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1 Introduction

Platform business models are a vital part of leading firms today, providing technology infrastructure to enable and coordinate interactions among multiple groups of participants (Parker et al., 2016). This paper discusses the economic interplay in multi-sided platforms that connect contributors, consumers and advertisers. Several large platforms attract hundreds of millions of users or viewers with “goods” (e.g., music, movies, games, TV shows, blogs, recipes, how-to videos, apps, etc.) that are sourced from thousands of contributors. Viewers’ consumption is financed by advertising payments, and contributors supply is motivated through a share of the platform’s advertising revenues. 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, 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. Even in platforms that feature user-generated content such as Tik-Tok, Instagram or YouTube, a substantial part of consumer traffic is driven by content from stars, celebrities, and other popular figures.1 Conversely, these star contributors are the dominant recipients of advertising revenues from the platform, thus rendering a three-sided platform comprising consumers, contributors 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 (content contributors, content viewers, and advertisers) determine the overall activity in these platforms (e.g., magnitude of content supplied by contributors, demand generated by the platform? level of advertising featured on it)? What is the likely level of fragmentation or concentration in the contributor ecosystem, and what factors govern the distribution of outputs amongst contributors? And,

1About 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/
how should the platform approach internal investments and design decisions related to contributor ecosystem management, level of advertising, and revenue sharing with contributors, in order to optimize ecosystem performance?

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

Our analysis is based on the following interactions among these actors, as depicted in Fig. 1. Contributor $j$’s supply is labeled as $Q_j$ (with $Q = \sum_j Q_j$). 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.\(^2\) Advertisers are attracted by the platform’s potential to reach customers, and collectively desire an amount of advertising $A$ on the platform when the platform charges a per-view price $p$. The platform earns advertising revenue $R = p \cdot A$ and returns a fraction $\gamma$ of ad revenue to contributors with each contributor receiving a share proportional to their contribution.

The platform can guide ecosystem outcomes through various levers including (i) the advertising level $A$ (conversely, the per-view price $p$) given a consumer demand function for content, an advertising supply function, and a revenue-sharing arrangement with contributors, (ii) the revenue-sharing parameter $\gamma$, and (iii) additional design elements that impact platform performance via the parameters $\beta, \delta, \theta$. This paper primarily concentrates on the first two levers, explicitly balancing

\(^2\)We assume that consumers are attracted by the output of contributors and have negative sensitivity to advertising.
the payoffs and costs associated with setting $p^*$ and $\gamma^*$. Secondarily, we examine the impact of the platform design elements mentioned in (iii) on the primary decision variables and platform performance. 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).

Under this arrangement, this paper is distinctive in its analysis of contributors’ content provision decisions and their interaction with platform design variables such as technical quality and revenue sharing. Given the vital role of contributors in attracting consumers to the platform and in attracting advertising revenues, we specifically examine how the provision of content by contributors is governed by the platform’s policies and by competition within the contributor layer. Although existing literature has studied issues of market power (Evans, 2008) and decision tradeoffs in multi-sided advertising-driven platforms—e.g., marketing allocations to the consumer and advertiser sides (Sridhar et al., 2011), and balancing advertising and content Dewan et al., 2002—no previous studies to our knowledge have examined the above questions including the joint economic interactions between the platform and its viewers, content contributors, and advertisers. Several papers have examined the economics of content publishers who are financed by advertising (e.g., Godes et al., 2009; Peitz and Valletti, 2008; Calvano and Polo, 2020) but not the sourcing of content from third-party contributors. A few have examined the challenges in revenue-sharing between the platform and contributors, but subject to exogenous output decisions (Oh et al., 2015; Shiller and Waldfogel, 2013). (Bhargava, 2020) has examined third-party value contribution in aggregator platforms but without a role for advertising. Empirical research on user-generated content has studied motivations to contribute content (Tang et al., 2012; Y. Liu and Feng, 2020) and the effect of revenue-sharing on the type of content that is supplied (Sun and Zhu, 2013). With this paper, we hope to set 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 anticompetitive practices.

The intersection of the platform’s advertising policy with its revenue-sharing policy forces the platform to balance not only viewers and advertiser (or revenue) interests, but also the interests of contributors vs. advertisers. We show that contributors prefer a greater percentage of ad revenues but, because a high $\gamma$ causes the platform to raise ad prices, advertisers are better off (up to a point) as the platform’s share increases. Moreover, contributors’ preference for higher $\gamma$ is itself moderated due to the platform’s control on advertising: the platform will be forced to set ad price too high, causing lower ad volume and reduce contributors’ revenues. Conversely, the platform is deterred from setting $\gamma$ too low for that would cripple the basic content fuel of the ecosystem. We analyze factors that affect the distribution of outputs among contributors and market concentration in the ecosystem, and show that design changes which enhance platform scale can lead to more concentration of content and rewards among fewer contributors. Interventions like development toolkits and contributor support programs will best promote the platform’s interest if they are easy to absorb by all contributors and level the playing field among them, thereby making contributors more homogeneous and competitive. However, if such interventions involve a steep learning curve or significant adoption costs, then they might well amplify differences among contributors, which leads to greater concentration in content supply. Regarding revenue-sharing between contributors and the platform, a single non-discriminatory linear rate (which is widely practiced in industry) causes detrimental effects which could be overcome by moving towards limited forms of nonlinear reward systems.

2 Model

The fundamental unit of interaction among the three types of platform participants is a “view.” Views are driven by content from contributors. A view, of some contributor-offered content seen
by a consumer, 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. We reframe this decision in terms of the corresponding decision on the per-ad-view price $p^*$. This decision governs the ad revenue generated on the platform ($R(Q)$). For contributors, the expectation of their share of ad revenue influences how much content they submit to the platform (as in Tang et al., 2012; Y. Liu and Feng, 2020), in turn influencing the number of views, advertising demand and ad revenue. Anticipating all of these, the platform sets its revenue-sharing level, advertising policy, and other design elements. This sequence of decisions is depicted in Fig. 2. Notation employed in the figure and in the model development below is summarized in Table 1. The broad goal of the model is to shed light on the response relationship between platform design (and decision) elements and outcome metrics identified in the Table, and as moderated by several exogenous elements related to the phenomenon.

Content served on the platform is sourced from numerous contributors who produce different types of content, so that the collection increases variety but may also have substitutes. The magnitude of contributors’ output is governed by their capabilities and costs, captured via a cost parameter $c_j$, discussed in §3, which generalizes (Y. Liu and Feng, 2020)’s low/high effectiveness of contributors in generating an audience. Viewers may exhibit a mix of preferences for type and quality, and valuations across multiple items could be a mix of sub-additive or super-additive. Regardless of these details, the magnitude of views $V$ (and implicitly, the number of consumers
Exogenous Elements

\[ \begin{align*} V(Q) &= \alpha(Q) - \delta A \\
A(Q) &= \beta(Q)e^{-bp} \end{align*} \]

- Consumer demand function, when platform provides \( Q \) content with \( A \) ads
- Advertising demand function, against per-view price \( p \)

\( b \) price sensitivity of ad demand, reflects heterogeneity in advertisers’ utility from ad views

\( \beta \) In \( \beta(Q) = \beta Q^\theta \), scaling parameter for ad demand, affected by platform’s ad placement and targeting techniques

Platform Design Elements

- \( c_j \) contributor \( j \)’s “exogenous” cost to produce content capable of generating a unit view, arranged in increasing order, so \( c_1 \) is the most powerful contributor (however, the platform can influence the magnitude and distribution of \( c_j \)’s through interventions like developer toolkits, training programs, and how-to videos)

\( \theta \) In the setting \( \beta(Q) = \beta Q^\theta \), \( \theta \) 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

\( \delta \) Consumer distaste for ads, lowered by improving ad placement and timing, and with better matching of ads to users

\( \lambda \) Platform’s future value (per unit) for views or consumers, increased by improving data and analytics

Decision Variables

- \( p^*(Q, \gamma), A^*(p^*) \) (Platform) advertising level and price, to maximize \( \Pi(p; Q, \gamma) \)
- \( Q_j(\gamma) \) (contributor \( j \)’s) level of content contributed to platform, to maximize contributor profit \( \pi(Q_j; Q-j) \), given choices \( Q-j \) of other contributors
- \( \gamma \) (Platform, contributors) revenue-sharing parameter (contributors get \( \gamma \) fraction of ad revenue)
- \( Q_0, \alpha_0 \) (Platform) Own content, intrinsic value (\( = \alpha(0) \)) provided to consumers

Outcome Metrics

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

Table 1: Model Elements and Notation. Optimal values of \( p^* \) and \( A^* \) are computed knowing \( Q \) and \( \gamma \); \( Q_j \)’s are computed knowing \( \gamma \); \( \gamma \) is set first. See Fig. 2.
attracted to the platform) generated on the platform is an increasing function of $Q$, due to increased variety, though likely at decreasing rate due to substitution effects (McIntyre and Srinivasan, 2017). Alternately, $V$ might be interpreted as the number of consumers on the platform, with each consumer generating an identical number of views. Let $\alpha(Q)$ denote the maximum level of $V$ given $Q$, representing the case that all content is served with no advertising. Generally, $V$ is decreasing in total number of ads displayed and in consumer distaste for advertising. The parameter $\delta$ reflects this dislike, and its magnitude depends on the nature of advertising, including the level of targeting and relevance of ads. Initially we treat $\delta$ as an exogenous parameter, but we examine later how the outcomes vary as the platform is able to modify or improve its ad targeting and relevance algorithms. For instance, the platform can reduce $\delta$ by timing the ad to have the best effect on user engagement (Kumar et al., 2020).

**Assumption 1 (Consumer Demand for Platform).** The platform’s demand for views is

$$V = \alpha(Q) - \delta A \quad \text{with} \quad \alpha_0 = \alpha(0) \geq 0, \alpha'(Q) > 0, \alpha''(Q) < 0, \text{and} \quad \delta > 0.$$ 

The total advertising demand received by the platform is the sum of ad demand across all advertisers. Let $B$ be the total amount of ads that come into the platform if advertising were free. We capture the price effect on ad demand through a negative exponential function on the price per-view $p$, thus writing ad demand as $B e^{-bp}$, where the price sensitivity parameter $b$ reflects heterogeneity among advertisers and/or each advertiser’s diminishing value for more impressions.

Now consider how $B$ relates to the scale of the platform (measured in $Q$ or $V$). In principle, the value each advertiser receives from displaying a single ad (on a single view) is independent of the platform’s size, so that $B$ is constant and ad demand is only a function of per-ad price. However, higher $Q$ may enable the platform to collect a more diverse user profile and create better matches between users and ads, thereby increasing an advertiser’s valuation of each exposure. Hence the total ad demand received by the platform may have some positive sensitivity to $Q$. Accordingly we write $B = \beta(Q)$, with a growth constraint such that $\beta'(Q) < \frac{\beta(Q)}{Q}$, i.e., $\frac{\beta(Q)}{Q}$ is decreasing or,
equivalently, that $\beta(Q)$ has elasticity less than 1.

**Assumption 2** (Advertiser Demand for Platform). The platform’s demand from advertisers is

$$A = \beta(Q)e^{-bp} \quad \text{with } b > 0, \beta'(Q) > 0, \frac{\partial(\beta(Q)/Q)}{\partial Q} < 0 \left( \equiv \frac{\beta'(Q)}{\beta(Q)/Q} < 1 \right).$$

![Figure 3: Platform’s demand on consumer and advertiser sides, for different levels of $Q$.](image)

Fig. 3 illustrates the platform’s demand functions from consumers and advertisers, against different levels of $Q$. For consumer 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 consumers who are partially alike (i.e., substitutes, which drives $\beta'(Q)$ towards zero) and diverse (complements, higher $\beta'(Q)$). Although not imposed in the assumption, we expect that ad supply is less sensitive to $Q$ than consumer demand (i.e., $\beta'(Q) < \alpha'(Q)$). Finally the negative exponential demand for advertising reflects an elasticity of supply $bp$ at per-ad 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.
2.1 How Much Advertising?

The platform provides consumers a free service and finances itself through ad revenues. It must balance the amount of advertising it inflict 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 contributors) incentivize creation of more content which then plays a positive role in encouraging more views. In addition, advertising has a cost to the platform, covering economic costs of selling and managing advertising placement and costs associated with long-term customer dissatisfaction. Thus, we write this cost as $\lambda \delta A$ (with $\lambda > 0$) so that it is increasing in both the amount of advertising and the consumer distaste for advertising. This section explores the trade-offs and balance in advertising, primarily as a stepping stone to examine additional issues in the ecosystem around content contribution and revenue-sharing. A few previous articles such as DeWan et al. (2002) have examined the tradeoff between advertising and content for a single content owner who manages its own advertising. In our case, although the platform must balance content and advertising, it does so with content from numerous contributors who make independent decisions about provision of content. Then, with content $Q$ and advertising level $A$ leading to $V$ views, the platform’s total payoff function is

$$
\Pi = (1-\gamma)pA - \lambda \delta A - c(Q) = (1-\gamma)p - \lambda \delta e^{-bp\beta(Q)} - c(Q). 
$$

(1)

The term $c(Q)$ (with $c'(Q) > 0$) is the platform’s operations and marketing cost in serving content to consumers, covering technology, curation, data privacy, content policing, etc. 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. Given a revenue-sharing parameter $\gamma$ and the cost parameter $\lambda$, the platform maximizes its payoff, written above in terms of decision variable $p$ rather than $A$.

The optimal per-view ad fee $p$ should follow the classic rule inverse price elasticity of adver-
tising demand equals relative price markup. Computing the elasticity term, 
\[ \epsilon(p) = -\frac{\partial A}{\partial p} / \frac{A}{p} = bp. \]
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 fol-
lowing 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,

\[ p^* = \frac{1}{b} + \frac{\lambda\delta}{(1-\gamma)} \quad (2a) \]

Given \(\{Q, \gamma\}\):

\[ A^*(Q) = \beta(Q)e^{-bp^*}. \quad (2b) \]

\[ \Pi^*(Q) = \frac{1-\gamma}{b} \cdot \beta(Q)e^{-bp^*} - c(Q) \quad (2c) \]

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 \(\delta\), the 
platform exploits this gain by showing more ads vs. increasing the per-ad price, because although 
consumers are more willing to see more ads but there is no increase in advertisers’ payoff condi-
tional on ad display.\(^3\)

### 2.2 Properties of Advertising Equilibrium

Lemma 1 satisfies a few intuitive expectations about the optimal design of advertising. First, 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 \(\delta\) is low), when consumer sensitivity to advertising (\(\delta\)) 
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 \(\lambda\), e.g., when it is highly mature) or when the platform keeps a

\(^3\)This is an implication of the negative exponential price function for advertising demand.
higher share of ad revenues (low $\gamma$). 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, due to the negative exponential function, the optimal price is independent of $Q$ or the size of the platform. While this may appear incongruous, note that $p$ is a per-exposure price unlike, say, in broadcast TV or cable where the per-ad price reflects exposure to millions of users at the same time depending on the platform size. Third, the platform’s optimal advertising level is higher when $Q$ is larger, and the effect of $Q$ shows up in larger volume of ads rather than higher price per ad. Fourth, if the platform increases contributors’ share of revenue ($\gamma$) it will then compensate by setting higher price, with less advertising overall. Thus, although contributors prefer greater share of ad revenue, advertisers’ interests are maximized when the platform keeps a higher share. To summarize,

$$
\frac{\partial A^*}{\partial -\delta} > 0; \frac{\partial A^*}{\partial \lambda} < 0; \frac{\partial A^*}{\partial b} < 0; \frac{\partial A^*}{\partial Q} > 0; \frac{\partial A^*}{\partial \gamma} < 0; \\
$$

$$
\frac{\partial p^*}{\partial -\delta} < 0; \frac{\partial p^*}{\partial \lambda} > 0; \frac{\partial p^*}{\partial b} < 0; \frac{\partial p^*}{\partial Q} = 0; \frac{\partial p^*}{\partial \gamma} > 0.
$$

These sets of 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.\(^4\) In the absence of these and related effects, an advertiser should not care about which platform it delivered an impression on, therefore leading to identical price per ad but different volumes on different platforms.

Viewers’ attitude towards ads is a critical factor in ecosystem performance. Combining the effects of $\delta$ on price and advertising level, the equilibrium advertising revenue $R(Q)$ is, *ceteris

\(^4\)https://instapage.com/blog/bing-ads-vs-google-ads.
paribus, higher as \( \delta \) decreases (because \( p^* > \frac{1}{b} \)). Moreover, the intersection of the platform’s advertising policy and revenue-sharing policy (discussed later in §4) creates a dilemma with respect to different parts of the ecosystem. If \( \gamma \) is high, it motivates greater output by contributors (and more views and more ad demand) but that causes the platform to raise ad prices, weakening ad demand. At the margin, if \( \gamma \) is too high then advertisers’ interests regarding revenue-sharing are better aligned with those of the platform rather than contributors. Hence, the platform’s advertising policy must not only make the content vs. advertising tradeoff (on account of viewer distaste for ads) but also balance the interests of contributors vs. advertisers.

3 Content Contribution

Lemma 1 identifies the platform’s profit-maximizing advertising level when it is given content \( Q \). This generates advertising revenue (or surplus) \( R(Q) = p^*(Q)A^*(Q) \) to share with content contributors and to motivate them to supply goods or content that attracts consumers and advertisers to the platform. The platform’s contributors collectively receive a fraction \( \gamma \) of \( R(Q) \), with each contributor \( j \) getting a share \( \gamma \frac{Q_j}{Q} R(Q) \) proportional to its content contribution to the platform. Given this arrangement, how much content will be contributed to the platform, and how will it be distributed across contributors? We explore these questions to gain insight about platform scale and market concentration among contributors, and to examine the merits of alternative ways in which the platform could influence these factors.

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

Contributors supply content to the platform and compete with each other in generating views and securing ad impressions. Intuitively, contributors are heterogeneous in their capability to make content (e.g., production technology and skills), in talent and star power, or in intellectual properties they own (e.g., rights to stories or characters). This heterogeneity manifests itself in different
number of views captured for each unit of effort or cost (Y. Liu and Feng, 2020). To model this, we invert the relationship between output and cost, and index contributors by a heterogeneous unit cost $c_j$ for producing each unit of view. Thus, contributors with low $c_j$ are celebrities, social media stars, or other entities capable of producing highly popular content at low unit cost. Conversely, those with high $c_j$ either have low quality or niche content, hence generate fewer views for the same expenditure. Without loss of generality, assume that contributors are indexed according to increasing $c_j$ (with $c_1$ being the lowest-cost, i.e., most-efficient or most-popular contributor), and let $Q_{-j}$ denote the total content provided by all contributors except $j$ (with $Q=Q_j+Q_{-j}$). Then contributor $j$’s share of revenue generated, and hence the claim on ad revenue, is $\frac{Q_j}{Q}$, yielding the payoff function

$$
\pi_j(Q_j, Q_{-j}) = \gamma \frac{Q_j}{Q} R(Q) - c_j Q_j = \gamma \frac{Q_j}{Q} (\beta(Q) p^* e^{-b p^*}) - c_j Q_j.
$$

(3)

Contributors are primarily motivated by share of ad revenues received from the platform, consistent with evidence from platforms that source third-party content (Zhu and Q. Liu, 2018; Y. Liu and Feng, 2020). Contributors’ output levels $Q_j$ to the platform are viewed as solutions to a Cournot-type simultaneous game in which each contributor picks $Q_j$ to maximizes its payoff subject to collective output $Q_{-j}$ from other contributors, 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 $j < K$. As usual, the optimal output levels satisfy the property that marginal cost equals marginal revenue, given the output choices of other contributors. Consider contributor $j$’s dilemma when producing output $Q_j$ when other contributors have output $Q_{-j}$ for a total of $Q$. The incremental advertising revenue generated by an additional infinitesimal increment $\Delta Q$ is $R(Q+\Delta Q) - R(Q)$. If this incremental amount were added by contributor $j$, whose marginal cost is $c_j \Delta Q$, its marginal revenue is $\gamma \frac{Q_j + \Delta Q}{Q + \Delta Q} R(Q+\Delta Q) - \gamma \frac{Q_j}{Q} R(Q)$. Setting marginal
cost and revenue equal, then dividing by $\Delta Q$, rearranging terms, and taking limits, we get the set of conditions

$$c_j = \gamma \frac{R(Q)}{Q} - \frac{Q_j}{Q} \left( \frac{R(Q)}{Q} - R'(Q) \right)$$

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

By definition, $Q = \sum Q_j$, however this aggregation covers only those producers who can earn positive profit under the $Q_j$ vector. This leads to a set of contributors $1...K$ who have cost no greater than a threshold $c_k$ representing the highest-cost contributor who can make positive profit. Let $C_K$ denote the average of the cost indices of these top $K$ contributors. Then the content production equilibrium is as follows. A formal proof is in the Appendix.

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

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

$$Q = K \left( 1 - \frac{C_K Q}{\gamma R(Q)} \right) \left( \frac{R(Q)}{Q} - \frac{R'(Q)}{Q} \right).$$

with outputs and output shares of each contributor $j$ being

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

$$\frac{Q_j}{Q} = \frac{1}{K} \left( 1 - \frac{c_j Q}{\gamma R(Q)} \right) / \left( 1 - \frac{C_K Q}{\gamma R(Q)} \right).$$

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 $C_K$) 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 contributors is of the form $c_j \leq \frac{\gamma R(Q)}{Q}$ (with the same RHS), hence it needs to be
verified only for contributor $K$. Procedurally, the highest $k$ that satisfies the IR constraint with the value of $Q$ given in Eq. 4b is the equilibrium value of $K$, Eq. 4b then returns $Q$, and each $Q_j$ is obtained from Eq. 5b. We explain this with an illustrative and suitable form for $\beta(Q)$ below.

### 3.2 A Constant-Elasticity Advertising Demand Function

The term $\beta(Q)$ in $A(Q)$ captures sensitivity of ad demand to platform scale. Writing $\beta(Q) = \beta Q^\theta$ (with $\theta < 1$) yields an ad demand function $A = \beta Q^\theta e^{-bp}$ that exhibits a constant elasticity factor $\theta$ (i.e., $\theta = \frac{\partial A}{\partial Q} / (A/Q)$), and satisfies the requirements laid out in Assumption 2. The platform can influence the scaling parameter $\beta$ 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 contributors’ choice of $Q_j$ are

\[
\forall j \quad \pi_j(Q_j, Q_{-j}) = \frac{Q_j^\theta}{Q} (\beta Q^\theta p^* e^{-bp^*}) - c_j Q_j
\]

\[
\left( \frac{\partial \pi_j}{\partial Q_j} = 0 \right) \equiv c_j = \frac{\gamma \beta p^* e^{-bp^*}}{Q^{1-\theta}} \left( 1 - (1-\theta) \frac{Q_j}{Q} \right)
\]

\[
\equiv Q_j = \frac{Q}{1-\theta} \left( 1 - \frac{c_j Q^{1-\theta}}{\gamma \beta p^* e^{-bp^*}} \right)
\]

where contributors $1...K$ 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 $\beta(Q) = Q^\theta$, $p^*(Q) = \left( \frac{1}{b} + \frac{\lambda d}{1-\gamma} \right)$ and given a revenue-sharing parameter $\gamma$, the equilibrium total content collected by the platform is

\[
Q = \left( \frac{\gamma \beta p^* e^{-bp^*} K (1-\theta)}{C_K K} \right)^{\frac{1}{1-\theta}},
\]

across contributors whose cost parameter is below that of the marginal contributor $K$ given by

\[
K = \max_k \left( c_k \leq \frac{C_k k}{k-(1-\theta)} \right),
\]
and the proportional content share of individual contributors being

\[
\frac{Q_j}{Q} = \frac{1}{1-\theta} \left( 1 - \frac{c_j}{C_K} \frac{K-(1-\theta)}{K} \right) \tag{9}
\]

**Corollary 1** (Proposition 2). The equilibrium level of \(Q\) increases in \(\gamma\) up to some threshold value of \(\gamma\) (i.e., \(\frac{\partial Q}{\partial \gamma} > 0\) initially), then decreases. Trivially, \(\frac{\partial Q}{\partial \beta} > 0\), with \(\frac{\partial^2 Q}{\partial \beta^2} > 0\).

As noted previously in §2.1, the platform’s advertising policy intersects with its revenue-sharing policy on account of its effect on contributors outputs. From Eq. 4b we see that \(Q\) is intrinsically increasing in \(\gamma\) (i.e., if all other factors are constant). However, the platform’s pursuit of optimal advertising causes it to raise ad price \(p\) as \(\gamma\) increases, reducing ad demand. Still, because contributors’ interest is in ad revenues rather than number of ads, \(Q\) initially increases with \(\gamma\) but then drops as \(\gamma\) gets so high that a very high \(p\) causes a huge drop in ad volume.

### 3.3 Implications on Platform Design

Eq. 7 specifies how the total content made available on the platform—and consequently, consumer views, advertising demand, platform revenue, and surplus of other participants—varies with various platform design parameters. A platform seeking to increase scale or profit has multiple ways to alter its design and influence the actions of platform participants. These include technological factors that enhance targeting and matching of ads to views (which may reduce \(\delta\) and/or increase \(\theta\)), attracting a more diverse user base (yielding higher \(\theta\)), increased sales effort to reach advertiser segments (higher \(\beta\)), better data about users’ preferences (which may improve \(\lambda\)), contributor development programs and toolkits to assist with content creation and distribution, and better bargaining power with contributors (lowering the revenue-sharing parameter \(\gamma\)). We explore below the relative merits of investments towards improving each of these parameters, on crucial outcome considerations such as platform scale and level of concentration in contributor-sourced content?

Example 1 illustrates some insights with a group 4 scenarios, each with 400 potential contributors in the ecosystem, and differing primarily in the distribution of \(c_j\)’s across the 400 contributors,
Figure 4: Distribution of costs (c.d.f.) of 400 contributors, in 4 scenarios (top row, with the black bullet marking $c_1$), and associated output shares $Q_j$ (shown as %) under two settings of $\theta = 0.3$ (middle row) and $\theta = 0.1$ (bottom row). In Scenario 1, a few contributors have $c_j$’s in $[4, 6]$ while the rest are distributed uniformly in $[6, 15]$. In Scenario 2, all $c_j$’s are huddled in $[14, 16]$. The $c_j$’s in Scenario 3 are in $[4, 16]$ as in Scenario 1, but spaced out uniformly. In Scenario 4, a few contributors have much lower costs than others like in Scenario 1, but the differences between them and higher cost contributors are not as amplified in Scenario 1.

and with two levels of $\theta$ for each scenario. We seek to inquire not only how the $c_j$ magnitude impact performance, but importantly how the relative values within each scenario affect various outcomes of interest. In addition, we compute the outputs in each scenario against two values of $\theta$.

Example 1 (Distribution of contributors’ outputs under different distributions of cost indices). Consider 4 scenarios, each with 400 potential contributors whose cost indices are as indicated in the cumulative distribution functions in the top panel of Fig. 4. Scenario 1 features lowest $c_j$’s but also greatest heterogeneity.

1. In Scenario 1, the sharp heterogeneity between a few low-cost contributors (with $c_j \in [4, 6]$) and the rest ($c_j \in [6, 15]$) leads to their domination and heavy concentration of output.

2. Contributors’ $c_j$’s in Scenario 2 are higher but relatively homogeneous (all huddled in the $[14, 16]$ interval), hence output is distributed among many more contributors (higher $K$, although total $Q$ is lower), with even the lowest $c_1$ garnering only a small fraction of viewers.

3. Scenario 3 (relative to 1) has more low-cost contributors ($c_j \in [4, 6]$), hence a more even distribution of output, and the higher $K$ leads to higher $Q$ overall (overproduction).
4. In Scenario 4 a few lower-cost contributors stand out, like in Scenario 1 but less extreme, causing higher $K$, less concentration, and lower $Q$.

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

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

### 3.3.1 Contributor support programs and developer toolkits

The size of the platform ecosystem ($K$, the number of feasible contributors 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 contributors. Intuitively, the platform can achieve higher $K$ by lowering contributors’ $c_j$’s. This path is often pursued by platforms through 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 and software platforms run workshops and certification programs. These interventions lower the $c_j$’s, however the results can be counter to intuition. From Eq. 8 in Proposition 2, 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. 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.

Two other important metrics for the platform are total content in the ecosystem ($Q$, because
it affects consumer views, advertising demand, platform revenue, and surplus of all participants) and the distribution of content and advertising revenues across contributors (the ratios $\frac{Q_j}{Q}$) which affects relative market power between the contributor ecosystem and the platform. How are these metrics altered with changes in $c_j$’s? Fig. 4 illustrates the joint effect of the magnitude of $c_j$’s and the degree of homogeneity among them on $K$. As highlighted in the second part of Corollary 2, below, greater homogeneity leads to larger $K$, because from Eq. 8, $K$ is identified by the first $c_j$ that is “relatively distant” from the previous one. It also spreads output more uniformly across contributors, 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 contributors (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 contributors and level the playing field among them (i.e., they are most novel and useful to the smaller or higher-cost contributors), thereby making contributors more homogeneous and competitive. However, if these interventions involve a steep learning curve or significant adoption costs, then they might well amplify differences among contributors because only the more capable contributors can take advantage of these resources, and this leads to greater concentration in content supply.

**Corollary 2 (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 $\Delta c$, thus amplifying the cost differences between contributors, lead to lower $K$ and greater concentration in the contributor ecosystem, with an increase in the share $\frac{Q_j}{Q}$ of the lower-cost contributors. Conversely, interventions that make contributors 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 contributors.

### 3.3.2 Viewer diversity and ad targeting technology

The platform can also improve its scale by increasing $\theta$ (trivially, $\frac{\partial Q}{\partial \theta} > 0$), for instance by attracting more diverse viewers and contributors, 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 θ (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 θ. Counter to intuition, though, doing so leads to fewer viable contributors: higher θ leads to lower K. This is because higher θ implies higher gains from producing more content, making the most powerful contributors (ones with lower c_j) highly aggressive in supplying content to the platform and leaving little room for higher-cost contributors in the revenue-splitting game.

**Corollary 3 (Proposition 2).** Increase in θ (weakly) causes greater concentration of content contribution among fewer contributors, with an increase in share of the more powerful contributors (low c_j’s), and overall increase in output Q. Formally, \( \frac{\partial K}{\partial \theta} \leq 0 \), and \( \frac{\partial Q_j/Q}{\partial \theta} \gtrless 0 \) when \( c_j \lesssim C_k \).

Thus, although the platform would like to increase θ and improve the economics of the ecosystem, doing so will make the most powerful contributors highly aggressive in supplying content, thereby increasing their market share (\( \frac{Q_j}{Q} \)). This increase in degree of concentration among contributors not only affects social dominance in the consumer market but also influences the bargaining power of the platform relative to contributors. For a given distribution of c_j’s an increase in θ can potentially increase the bargaining power of a few dominant contributors, which raises the risk for the platform of demands for lower γ (if K gets sufficiently low).

### 3.3.3 Changes in the contributor ecosystem

Interventions that increase K by compressing the differences between c_j’s can also increase competition among contributors 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 contributors and higher output, but excessively higher output because more of them simultaneously compete to capture a greater fraction of advertising eyeballs and revenues. Of
course, the distribution of $c_j$’s can also be altered on account of events external to the platform, for instance mergers between contributors. To illustrate the effect, imagine two scenarios which differ in the number of contributors and their $c_j$’s but have the same mean. Proposition 2 provides the insight that, normalizing across cost, more contributors implies greater content, reflecting the “overproduction” insight mentioned earlier in Example 1 (comparing Scenarios 1 and 3).

**Proposition 3** (Overproduction by Competing Contributors, Effect of Mergers). Other things being the same ($\gamma, \beta, b, \theta, \delta$), the total output in an ecosystem with contributors $1\ldots K$ whose cost indices $c_1, \ldots, c_K$ satisfy $c_K \leq \frac{C_K K}{K - (1 - \theta)}$ (where $C_K$ is the average of $c_j$’s) exceeds the output from fewer contributors with the same average cost. Consequently, mergers among contributors such that the new contributor’s cost index is the average of the merged entities, leads to reduction in $Q$.

The crucial aspect of the result, having normalized for mean cost, is that existence of multiple contributors 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 contributors and higher output, but excessively higher output because more of them simultaneously compete to capture a greater fraction of advertising eyeballs and revenues.

### 4 Sharing Advertising Revenue with Content Contributors

Our analysis thus far has considered the platform’s advertising strategy and content contributors’ supply strategy given that the platform passes $\gamma$ fraction of advertising revenues to contributors. The optimal or equilibrium level of $\gamma$ is subject to multifaceted issues including relative market power and co-dependence. On one hand, each contributor is tiny and relatively inconsequential to the platform. On the other, the platform’s business model depends on contributors 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
\( \gamma \) 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 \( \gamma \), and using the advertising demand function \( A(Q) = \beta Q^\theta e^{-bp} \) is

\[
\Pi(\gamma) = (1-\gamma)R(Q) - \lambda \delta A - c(Q) = ((1-\gamma)p^* - \lambda \delta) \beta Q^\theta e^{-bp^*} - c(Q) \tag{10a}
\]

\[
= \left( \frac{1-\gamma}{b} \right) \beta Q^\theta e^{-bp^*} - c(Q) \tag{10b}
\]

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

\[
p = \frac{1}{b} + \frac{\lambda \delta}{(1-\gamma)}, \quad \frac{\partial p}{\partial \gamma} = \frac{\lambda \delta}{(1-\gamma)^2} \tag{11a}
\]

\[
Q = \left( \frac{\gamma \beta p e^{-bp} K}{C K} \frac{1}{K} \right)^{1/\theta} \quad \frac{\partial Q}{\partial \gamma} = \frac{Q}{1-\theta} \left[ \frac{1}{\gamma} + \left( \frac{1-bp^*}{p^*} \right) \frac{\partial p}{\partial \gamma} \right] \tag{Eq. 14} \tag{11b}
\]

\[
K = \max_k: \left( \frac{c_k}{k-(1-\theta)} \right) \tag{11c}
\]

The revenue-share parameter \( \gamma \) determines what fraction of revenue is kept by the platform \((1-\gamma)\) vs passed on to contributors. However, the choice of \( \gamma \) is not a zero-sum game where contributors prefer \( \gamma=1 \) while the platform wants \( \gamma=0 \). For contributors, the penalty from a very high \( \gamma \) is that it would cause the platform to shift ad prices higher, causing lower ad volume and thereby drive down contributor revenues down. For the platform, if it sets \( \gamma \) too low then the low rewards to contributors will cripple content contribution, the basic fuel that drives the entire engine. Therefore, a judicious choice of \( \gamma \) 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. 10.
However, due to $c(Q)$ and $\lambda \delta A$, the profit-maximizing choice of $\gamma$ 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. One, higher $\gamma$ naturally motivates contributors 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 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 contributors. The interaction of these two forces leads to a first-positive and then-negative effect of $\gamma$ on $Q$, so that $Q$ peaks at an interior value of $\gamma$. As for the effect on $R(Q)$, note that the revenue grows as a multiple of price and advertising, hence the $\gamma$ 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 $\gamma$ to maximize $Q$ and $R(Q)$). The values of $\gamma$ that maximize total content on the platform and, respectively, total ad revenue, are

\[
\text{for } Q: \quad \gamma^Q = \text{Sol. } \left[ (1-\gamma)^3 + (b\lambda \delta)(1-\gamma)^2 + (b\lambda \delta)^2(1-\gamma) - (b\lambda \delta)^2 = 0 \right] \tag{12a}
\]
\[
\text{for } R(Q): \quad \gamma^{R(Q)} = \text{Sol. } \left[ (1-\gamma)^3 + (b\lambda \delta)(1-\gamma)^2 + \frac{(b\lambda \delta)^2}{\theta}(1-\gamma) - \frac{(b\lambda \delta)^2}{\theta} = 0 \right] \tag{12b}
\]

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

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Corollary 4 (Lemma 2). The value of $\gamma$ that maximizes $Q$ is decreasing in $b$, $\lambda$, and $\delta$. The same is true for $\gamma$ that maximizes $R(Q)$, and this value is increasing in $\theta$.

Fig. 5 demonstrates the effect of $\gamma$ on $Q$ and $R(Q)$ (and, additionally, $A(Q)$, the scale of advertising on the platform) for multiple illustrative values of problem parameters (specifically, $\theta = 0.3$ and 0.1, and $\delta = 0.1$ and 0.2). A useful insight from the Lemma and illustrated in Fig. 5 is that an improvement in ad targeting, which can help reduce $\delta$ (consumer distaste for advertising), increases $\gamma R(Q)$ (i.e., $\frac{\partial \gamma R(Q)}{\partial \delta} < 0$). A reduction in $\delta$ 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 $\delta$ the platform should increase the share of ad revenue that goes to contributors! This creates a win-win-win situation with regard to investments needed to reduce $\delta$.

Corollary 5 (Lemma 2). $\gamma R(Q) < \gamma Q$, and the gap between the two gets wider as $b, \lambda, \delta$ increase, and narrower as $\theta$ increases.

It is notable too that the optimal value of $\gamma$ depends only on $b, \lambda, \delta$ 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 $\gamma$). Consequently, the platform can set and announce its op-
erational policy once it has sufficiently accurate market research information regarding consumer demand ($\delta$) and advertising demand ($b$).

### 4.2 Differential Revenue-Sharing and Platform-Contributor Conflict

Lemma 2 identifies the revenue-sharing parameter that maximizes total content on the platform and, respectively, total ad revenue. These two metrics are not only a measure of the vibrancy of the overall platform ecosystem, maximizing them might well be in the interest of the platform because generally it is understood that, 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 examine how a platform would pick $\gamma$ when purely maximizing its short-term self-interest as stated in Eq. 10, 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 $\gamma^*$ would be less than $\gamma^{R(Q)}$, with the exact form and value depending on the form of $c(Q)$ function and $\lambda$.

The fact that $\gamma^* < \gamma^{R(Q)}$, combined with the effects of $\gamma$ on $Q$ (i.e., $\frac{\partial Q}{\partial \gamma}$) suggests that if the platform were to pursue its short-term self-interest in choosing $\gamma$, 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 contributor, and applied identically to all contributors 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 Subcommittee⁵),

⁵https://www.cnbc.com/2020/07/29/apple-tried-to-lure-amazon-video-app-with-
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 contributor, however it can cause conflict with a) large contributors who feel that the rate is excessive given their scale, b) contributors 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)\(^6\), and c) contributors with low margins for whom a 30% revenue share can cripple their business.\(^7\)

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 contributors (with high \(c_j\)’s, who produce low \(Q_j\)), and increasing the power of the already dominant contributors. Similarly, a typical two-part or two-block tariff—one that offers a higher revenue share \(\gamma^+\) once \(Q_j\) exceeds threshold—would also favor the most powerful contributors. The platform could do the reverse: reduce the rate to \(\gamma^-\) after some threshold, but this would appear as a blatant attack against contributors 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 contribu-

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tors 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 $\gamma$) for the residual revenues. That is, contributor $j$’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).

5 Conclusion

This paper presents a model and understand the economics of three-sided platforms that mediate between consumers, contributors and advertisers. These platforms attract consumers on the strength of outputs from contributors, thereby attracting advertisers who wish to reach these consumers, and motivating contributors with a revenue-sharing arrangement on ad payments. We presented a general framework that considers the economic motivations of the three sides and the platform. The model particularly focuses on the interplay amongst numerous (possibly thousands of) contributors and between contributors and the platform’s design parameters. Useful results are obtained about the platform’s advertising strategy, contributors’ content provision strategy and how the level of concentration in the contributor layer relates the contributor characteristics and platform design factors. We also discuss how the platform’s decision on various design parameters affect the performance of this three-sided platform ecosystem. This framework generates several useful results about the interaction between a platform’s advertising-level strategy, revenue-sharing strategy, and various design elements that affect incentives or performance of ecosystem participants. We hope that the framework sets a foundation for analysis of a range of additional issues in such 3-sided platforms, including those related to platform competition, market power, industry concentration, and anticompetitive practices.

The framework has some limitations that create opportunities for additional research. The
model implicitly assumes that higher scale automatically brings more diversity: e.g., that more content and more contributors attract more diverse viewers, which in turn brings in more advertisers; to close the loop, more advertising revenue brings in more contributors and attracts more viewers. However, 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. It would be useful to examine if the framework can be extended and remain tractable if extended to cover content type. With regard to ad revenues, the exposition is laid out in a setting of pay-per-impression advertising. Under certain conditions this is equivalent to a pay-per-click or pay-per-action advertising model (Dewan et al., 2002), however 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 degree to which the platform deploys first-party content (besides relying on content from third-party contributors) and the dynamics of revenue-sharing between the early vs. mature stages of the platform.
A Appendix

A.1 Some Simple Numerical Examples

Example 2 (Contributor’s costs from uniform distribution). Suppose there are 9 contributors in the ecosystem, with cost indices distributed uniformly in the interval $[4, 6]$. Also, suppose $\theta = \frac{1}{2}$ in $A = \beta Q_0 e^{-bp}$, so that $A = \beta \sqrt{Q} e^{-bp}$. Then, in equilibrium $K = 5$, and the highest-cost contributors are unable to earn a profit from supplying content to the platform. The 5 lowest-cost contributors 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 contributors). Suppose there are 9 contributors in the ecosystem, with cost indices distributed uniformly in the interval $[14, 16]$, and with $A = \beta \sqrt{Q} e^{-bp}$. Then, in equilibrium $K = 8$, and only the highest-cost contributor is excluded. Total content level supplied is $Q = \ldots$ The first 8 contributors’ output shares are $Q_j = \{0.235, 0.204, 0.172, 0.141, 0.109, 0.078, 0.046, 0.015\}$. 

Example 4 (Costs from right-skewed distribution). Suppose there are 9 contributors in the ecosystem, with cost indices (3,4,5,7,9,12,15,19,24), and $A = \beta \sqrt{Q} e^{-bp}$. Then, in equilibrium $K = 2$, and only the two lowest-cost contributors 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 $\Pi(p; Q) = ((1 - \gamma)p - \lambda \delta) e^{-bp} \beta(Q) - c(Q)$, compute the optimality condition $\frac{\partial \Pi}{\partial p} = 0$. This yields $e^{-bp} \beta(Q) ((1 - \gamma) - b(1 - \gamma)p - \lambda \delta)) = 0$, leading to the result.

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

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

$$Q_j = \frac{1}{\beta(Q) - \beta'(Q)} \left( \frac{\beta(Q)}{Q} - \frac{c_j Q}{\gamma p^* e^{-bp^*}} \right) = \frac{\beta(Q)}{Q - \beta'(Q)} \left( 1 - \frac{c_j Q}{\gamma R(Q)} \right) \geq 0, \text{ Assumption 2} \geq 0, \text{ IR constraint}$$

(13a)

(13b)

Since $R(Q) = \beta(Q)e^{-bp}$, the ratio $\frac{\beta(Q)}{Q - \beta'(Q)}$ equals the ratio $\frac{R(Q)}{R(Q) - R'(Q)}$. Note that the IR requirement $c_j \leq \frac{\gamma R(Q)}{Q}$ is an implicit statement because the $Q_j$ equations above are valid only for those
contributors that satisfy the IR constraint given the $Q_{-j}$ choices of all other contributors who are “feasible” in this way. And $Q$ must be computed by aggregating across only those contributors that earn a positive payoff. Denote the number of such feasible contributors as $K$, so that (since the $c_j$’s are arranging from lowest to highest cost), the set of feasible contributors is $\{1, \ldots, K\}$. Further, let $C_K$ denote $\tfrac{c_1 + c_2 + \cdots + c_K}{K}$, the average cost parameter across these contributors. With that in mind, adding up all the equations represented by Eq. 13b across all feasible contributors, we get the result.

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

$$\frac{\partial Q^{1 - \theta}}{\partial \gamma} = Z p e^{-bp} \left( 1 + \frac{\gamma}{p} \frac{\partial p}{\partial \gamma} (1 - bp) \right) = Z \gamma p e^{-bp} \left[ \frac{1}{\gamma} + \left( \frac{1 - bp}{p} \right) \frac{\partial p}{\partial \gamma} \right] \quad (14a)$$

$$\frac{\partial Q}{\partial \gamma} = \left( \frac{\partial Q^{1 - \theta}}{\partial Q} \right)^{-1} = \frac{Q}{1 - \theta} \left[ \frac{1}{\gamma} + \left( \frac{1 - bp}{p} \right) \frac{\partial p}{\partial \gamma} \right] \quad (14b)$$

$$= \frac{Q}{1 - \theta} \left[ \frac{1}{\gamma} - \left( \frac{1}{(1 - \gamma) + b \lambda \delta} \right) \left( \frac{b \lambda \delta}{1 - \gamma} \right)^2 \right] \quad (14c)$$

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

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

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c_j \leq \gamma Q (Q^\theta Z). Aggregating these over the feasible contributors yields

\[ Q = \frac{Q}{1-\theta} K \left( 1 - \frac{C_K Q^{1-\theta}}{\gamma Z} \right) \]

(15a)

≡ \left( \frac{1-\theta}{K} \right) = \left( 1 - \frac{C_K Q^{1-\theta}}{\gamma Z} \right)

(15b)

≡ Q = \left[ \frac{\gamma Z (K - (1-\theta))}{KC_K} \right]^{\frac{1}{1-\theta}}

(15c)

≡ Q^{1-\theta} = \frac{(K-(1-\theta))\gamma Z}{KC_K}.

(15d)

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

Proof of Corollary 3. \( \frac{\partial K}{\partial \theta} \leq 0 \) follows from Eq. 8 because the RHS term (on the right of the \( \leq \) sign) gets smaller as \( \theta \) increases. For \( \frac{\partial Q_j}{\partial \theta} \), rewrite Eq. 9 as \( Q_j \frac{Q}{Q} = \frac{1}{1-\theta} - \frac{c_j}{C_k} \left( \frac{1}{1-\theta} - 1 \right). \) The derivative with \( \theta \) is \( \frac{1}{(1-\theta)^2} \left( 1 - \frac{c_j}{C_k} \right) \), proving the result. \( \frac{\partial Q}{\partial \theta} > 0 \) follows trivially from Eq. 7.

Proof of Lemma 2. To identify the value of \( \gamma \) that maximizes \( Q \), set the first-order optimality condition \( \frac{\partial Q}{\partial \gamma} = 0 \) from Eq. 14. Rearranging terms, and solving (and ruling out \( Q=0 \)) we see that the \( Q \)-maximizing value of \( \gamma \) is

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

(16)

where the computations are valid as long as \( \theta > 0, p \) 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 \( \gamma \) in the feasible range \((0,1)\). Hence the cubic equation yields a unique feasible value \( \gamma^Q \).

Now consider the value of \( \gamma \) which maximizes total ad revenue across the platform and con-
tributors, with $R(Q) = \beta Q^\theta p^* e^{-bp^*}$. The analysis proceeds in a similar way.

\[
\frac{\partial R(Q)}{\partial \gamma} = R(Q) \left[ \frac{\partial p}{\partial \gamma} \left( \frac{1 - bp}{p} \right) + \frac{\theta}{Q} \frac{\partial Q}{\partial \gamma} \right] = 0 \tag{17a}
\]

\[
\equiv R(Q) \left\{ \frac{\partial p}{\partial \gamma} \left( \frac{1 - bp}{p} \right) + \frac{\theta}{1 - \theta} \left[ \frac{1}{\gamma} + \frac{\partial p}{\partial \gamma} \left( \frac{1 - bp}{p} \right) \right] \right\} = 0 \text{ (from Eq. 14)} \tag{17b}
\]

\[
\equiv R(Q) \left[ \frac{\partial p}{\partial \gamma} \left( \frac{1 - bp}{p} \right) \left( \frac{1 - \theta}{1 - \theta} \right) + \frac{\theta}{\gamma(1 - \theta)} \right] = 0 \tag{17c}
\]

\[
\frac{\theta}{\gamma} - \left( \frac{b\lambda\delta}{1 - \gamma} \right)^2 \frac{1}{(1 - \gamma) + b\lambda\delta} = 0 \text{ (using Eq. 11)} \tag{17d}
\]

\(\theta(1-\gamma)^3 + (b\lambda\delta)(1-\gamma)^2 + (1-\gamma)(b\lambda\delta)^2 - (b\lambda\delta)^2 = 0. \tag{18}\)

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 $\theta$, write the last two terms in Eq. 12b (i.e., $\left(\frac{b\lambda\delta}{\theta}\right)^2 (1-\gamma) - \left(\frac{b\lambda\delta}{\theta}\right)^2$) as $-\gamma \left(\frac{b\lambda\delta}{\theta}\right)^2$. These are the only two terms involving $\theta$, and trivially, increasing in $\theta$. Now consider how Eq. 12b yields $\gamma_{R(Q)}$. Note that at $\gamma=0$ the equation evaluates to $1+b\lambda\delta > 0$, and at $\gamma=1$ it is $-\left(\frac{b\lambda\delta}{\theta}\right)^2$, and has a higher value as $\theta$ increases (see left panel of Fig. 6). Hence, the point at which it cuts the horizontal axis (i.e., the optimal value of $\gamma$) is increasing in $\theta$.

Next, consider the effect of $b, \lambda, \delta$. Because these are all positive and all occur together in multiplicative form in Eq. 12b, the optimal value $\gamma_{R(Q)}$ varies identically across all three. Consider, for illustration, a change in $b$. The expression in Eq. 12b evaluates to $1+b\lambda\delta > 0$ at $\gamma=0$ and increases with $b$. At $\gamma=1$ the expression is $-\left(\frac{b\lambda\delta}{\theta}\right)^2$ and therefore reduces as $b$ increases (see right panel of Fig. 6), therefore the intersection with horizontal axis reduces because the equation’s joint derivative with $\gamma$ and $b$ is positive.

**Proof of Corollary 5.** As in the proof for Corollary 4, consider the behavior of Eq. 12b against
Figure 6: How Eq. 12b as a function of $\gamma$ changes with an increase in $\theta$ (left panel) and $b, \lambda, \delta$ (right panel).

$\gamma$. The solution $\gamma^Q$ is identical to $\gamma^{R(Q)}$ for $\theta=1$. For lower values of $\theta$, $\gamma^Q$ remains the same while $\gamma^{R(Q)}$ falls, hence widening the gap between the two (or, conversely, getting narrower as $\theta$ increases).

References


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