Sampling Strategies for Information Goods*

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Abstract

This paper analyzes optimal decisions concerning the size of the sample and the price of the paid content for online publishers of digital information goods when sampling serves the dual purpose of disclosing content quality and generating advertising revenue. We show in a reduced-form model how the publisher's optimal ratio of advertising revenue to sales revenue is linked to characteristics of both the content market and the advertising market. Assuming that consumers learn about content quality from the free samples in a Bayesian fashion, we find that it can be optimal for the publisher to generate advertising revenue by offering free samples even when sampling reduces high prior expectations and content demand. In addition, we show that it can be optimal for the publisher to refrain from revealing quality through free samples when advertising effectiveness is low and content quality is high.

Keywords: Information Goods, Sampling, Bayesian Learning, Advertising

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1 Introduction

Digital information goods have now been available on the Internet for almost twenty years. During that time, publishers have developed different business models to distribute content. Some publishers provide all their information for free, and some charge consumers for access to their content. Other publishers employ a hybrid business model and give away a portion of their content to consumers for free and charge for access to the rest of their content. The reason for employing such a hybrid strategy is twofold: Offering free samples allows the publishers to both disclose their content quality and to generate revenues from advertisements shown to online visitors. According to Alisa Bowen, general manager of *The Wall Street Journal Digital Network*, "working with advertisers to offer open houses has proven to be one of the most valuable and efficient ways to expose our premium content to new readers and potential subscribers" (*GlobeNewswire*, 2012). The main contribution of this paper is to provide a formal analysis of how publishers should choose between the different business models and make decisions on size of the sample and on price of the paid content.

Recently, hybrid business models where publishers set the size of the sample and consumers select the samples of their choice have emerged.[1] For example, *The Daily*, a subscription based digital news publication created for *Apple*'s *iPad*, offers seven issues for free. Likewise, the *New York Times* and the Minneapolis-based *StarTribune* currently offer access, respectively, to ten and twenty articles for free on its website each month.[2] Such advertising supported "random sampling" is also employed by distributors of music such as *Spotify* or *Rhapsody*. Allowing consumers to choose for themselves which content to sample creates randomness for publishers in that they have no control over the content consumers actually sample. Taking this into account is important for publishers to set the optimal sample size.

Digital information goods are particularly suitable for sampling because the costs of providing free samples are negligible and it is relatively easy to limit access to free content. In addition, sampling digital information goods allows the publisher to include advertisements in the free samples. These features dis-

[1] An alternative approach to sampling is where the firm chooses not only the number of free sample articles but also the sample content itself (see, for instance, *www.wsj.com*). This of course allows the firm to strategically manipulate the sample and creates an environment where customers are likely to discount the sample quality in estimating actual quality.

[2] See Chiou and Tucker (2011) for a survey of different types of "paywalls" that separate free content from paid content.

tinguish sampling of information goods from other products such as perishable goods or durable goods. The business model where publishers set a sample size and let the consumers choose which content to sample differs from versioning or "freemium," where a basic version of the content is offered to consumers for free and access to the full version is restricted to those who pay for the content.[3] Irrespective of the specific good, sampling aims at shifting the demand function outwards. However, offering free samples may also cannibalize the demand for the product.

This paper develops an analytical model to study optimal decisions concerning the size of the sample and the price of the paid content for online publishers of digital information goods when sampling serves the dual purpose of disclosing content quality and generating revenues from advertising. The publisher is assumed to receive revenues from both selling content and from selling advertisements, which are included in the free content. Consumers have prior expectations about content quality, which they update in a Bayesian fashion through inspection of the free samples. The information transmitted through samples affects the consumers' posterior expectations about content quality, which in turn influences demand for the paid content (content demand). Taking the consumers' quality updating into account, the publisher faces a tradeoff between an expansion effect (through learning) and a cannibalization effect (through free offerings) on content demand induced by sampling. When the publisher makes its sampling and pricing decisions, it takes both these two countervailing effects on content demand and the effects on the advertising revenue into account. We assume that the publisher can either adopt a "sampling strategy," a "paid content strategy," or a "free content strategy."

We derive the following main results. *First*, we show in a reduced-form model how the publisher's optimal ratio of advertising revenue to sales revenue is determined by characteristics of both the content market and the advertising market. Specifically, the key determinants of the advertising-sales revenue ratio are the elasticities of expected content demand with respect to price and sample size, the price elasticity of advertising demand, and the elasticity of consumers' updated expectations with respect to the sample size. The latter plays a crucial role in the determination of the ratio of advertising to sales revenue: When expectations are increasing in sample size, the ratio tends to be lower, whereas it tends to be higher if expectations are decreasing in sample size. This last result follows because an increase in expectations mitigates or even com-

[3] Bhargava and Choudhary (2008) analyze optimal versioning of information goods.

pensates for the cannibalization effect, thus leading to a lower advertising-sales revenue ratio. If instead sampling reduces expectations, offering free samples reinforces the cannibalization effect, which in turn leads to a higher ratio of advertising revenue to sales revenue. Nevertheless, the publisher will engage in ad-supported sampling if the advertising price per impression is high enough.

Second, we characterize the publisher's optimal sample size and price decisions in a benchmark model where content quality is common knowledge. The optimal strategy is determined by the relationship between the advertising effectiveness and content quality. In addition, a paid content strategy is optimal for the publisher only if the effectiveness of advertising is sufficiently low. For intermediate levels of the advertising effectiveness, the publisher should employ a sampling strategy and generate revenues from both sales and advertising. Once advertising is sufficiently effective, the publisher should switch to a free content strategy. Thus, it may be optimal for the publisher to offer free content samples even if sampling cannibalizes content demand.

Third, we characterize the publisher's optimal sample size and price decisions when consumers learn about content quality through inspection of the free samples. Assuming that consumers are uncertain about content quality, we find that sampling has a demand-enhancing effect when the elasticity of consumer's posterior expectations with respect to sample size exceeds the ratio of sampled to paid content. The optimal strategy is determined by the relationship between the advertising effectiveness and the interplay between prior expectations and actual content quality. As in the benchmark model, employing a paid content strategy is optimal only if the advertising effectiveness is sufficiently low, a sampling strategy is optimal for intermediate levels of the advertising effectiveness, and the publisher should switch to a free content strategy once advertising is sufficiently effective.

Our paper is related to two literature streams. The first stream is on media firm strategy in two-sided markets.[4] For instance, Kind et al. (2009) analyze how competition, captured by the number of media platforms and content differentiation between platforms, affects the composition of revenues from advertising and sales. Godes et al. (2009) investigate a similar question, but focuses on competition between platforms in different media industries. Our paper examines optimal advertising supported content sampling and content pricing when the firm can choose to be financed by content sales, advertising, or both. The mod-

[4]See Rysman (2009) for a general review of the two-sided markets literature. Anderson and Gabszewicz (2006) provide a canonical survey of media and advertising.

els with competition by Godes et al. (2009) and Kind et al. (2009) are not suitable for this analysis, because they use a framework where the media firms always charge for their content and where readers purchase from every media firm (multi-homing). Papers that examine content sampling from different perspectives include Xiang and Soberman (2011) for preview provision and Chellappa and Shivendu (2005) for piracy-mitigating strategies, but they do not consider the impact of sampling on advertising revenues. To the best of our knowledge, optimal content sampling when sampling impacts revenues from both content sales and online advertising has not been addressed by the literature.

This paper is also related to the broad literature on consumer learning about product attributes. Firms often enable consumer learning through disclosing information about their products and services. Information can be disclosed in various ways; for instance, through informative advertising (see Anderson and Renault 2006, and Bagwell 2007 for a comprehensive survey). Sun (2011) and Hotz and Xiao (forthcoming) consider information disclosure through product descriptions or third-party reviews. Another common way for firms to disclose information is through sampling. The distinctive feature of product samples is that they allow consumers to have actual experience with the good before purchase.[5] Heiman et al. (2001) and Bawa and Shoemaker (2004) study how sample promotions affect demand and the evolution of market shares for consumer goods. While free sample promotions for consumer goods are "expensive," Boom (2009) and Wang and Zhang (2009) argue that sampling information goods is essentially "for free." However, when firms sample information goods, they only offer a portion of the good for free to avoid the "information paradox" (Akerlof, 1970).[6] The consumers' inference from this portion about the product's attributes is most naturally modeled in a Bayesian framework. Bayesian learning processes based on product experience have been widely employed in the literature, for instance, by Erdem and Keane (1996), Ackerberg (2003), and Erdem et al. (2008), and we follow this approach here.

We organize the remainder of the paper as follows. Section 2 presents the general framework. Section 3 describes the model and the consumer's learning mechanism in particular. Section 4 characterizes optimal sampling and pricing

[5] In most cases, consumers experience the product only after purchase. See Villas-Boas (2004) and Kopalle and Lehmann (2006) for cases where consumers' first-period experience influences their second-period choice.

[6] Samples of information goods typically come in the form of demo or light versions (software), abstracts (academic publishing), previews (books and movies), or simply "samples" (music). For an analysis of software sampling see, for instance, Faugère and Tayi (2007) and Cheng and Tang (2010).

decisions when consumers know content quality. Section 5 extends the analysis to the case of incomplete information and assumes that quality is initially the publisher's private information. Conclusions and directions for future research are offered in Section 6. To facilitate the exposition, we have relegated the proofs to the Appendix.

2 General Framework

Consider a publisher who offers a digital information good with content of size $N > 0$ through an online channel. Content size may be thought of as the number of chapters of a book or movie, the number of songs on an album, or the number of articles on a news platform. The publisher has constant unit costs $c \geq 0$ and fixed costs $F \geq 0$ to produce the content.[7] The costs of providing free samples are normalized to zero. We assume that the publisher has two decision variables: the sample size $n \in [0, N]$ and the price p at which to sell the good.

We consider a market with a unit measure of consumers that observe the publisher's sampling and pricing decisions. However, consumers are uncertain about content quality. We assume that they update their prior expectations in a Bayesian fashion through inspection of the free samples and denote by $\tilde{V}(n)$ the consumers' posterior expectations about content quality. The demand for unsampled content depends on price p, sample size n, and $\tilde{V}(n)$. Specifically, we assume that the publisher's *expected* content demand is given by

$$D^{\mathrm{E}}(p, n) \equiv D(p, n, \tilde{V}(n)). \tag{1}$$

This representation emphasizes that the sample size has both a direct effect on content demand and an indirect effect that operates through the impact of n on posterior quality expectations $\tilde{V}(n)$.

We assume that content demand satisfies the following basic assumptions. First, we assume that $\frac{\partial D}{\partial p} < 0$, i.e. content demand depends negatively on price. Second, we impose that $\frac{\partial D}{\partial n} < 0$, so that a larger sample size has a *direct* negative effect on demand for the remaining content. Third, we require that $\frac{\partial D}{\partial \tilde{V}} > 0$, i.e. content demand depends positively on (posterior) quality. The overall effect of the sample size n on expected content demand is given by

$$\frac{\partial D^{\mathrm{E}}}{\partial n} = \frac{\partial D}{\partial n} + \frac{\partial D}{\partial \tilde{V}} \tilde{V}'(n),$$

[7]Throughout the analysis, we assume that the fixed cost do not exceed the optimized profits. Hence they do not change the analysis and can therefore be omitted.

where term $\frac{\partial D}{\partial \tilde{V}}\tilde{V}'(n)$ captures the *indirect* effect of the samples size on expected content demand. It is not clear a priori how the sample size affects posterior expectations, which clearly affects $\frac{\partial D^{\mathrm{E}}}{\partial n}$. If $\tilde{V}'(n) < 0$, sampling reduces posterior expectations and is thus *demand-reducing*. Note that even if $\tilde{V}'(n) > 0$, that is, if sampling increases posterior expectations, offering an additional sample may be demand-reducing if direct effect dominates the indirect effect. Once $\tilde{V}'(n)$ is sufficiently large, the indirect effect is stronger than the direct effect so that $\frac{\partial D^{\mathrm{E}}}{\partial n} > 0$ and thus sampling has a *demand-enhancing effect*. In line with Bawa and Shoemaker (2004), we refer to the direct effect of sampling on content demand as the "cannibalization effect" and to the indirect effect as the "expansion effect."

The publisher receives revenues from two sources: selling paid content and including advertisements in the free samples. Specifically, we assume that each of the free samples comes with an advertisement. A representative advertiser delivers the n advertisements to the publisher at a price per impression, which is denoted by $a(n)$. The price for advertisements is assumed to decrease in sample size, so that $a'(n) < 0$. When offering n free samples, the publisher's advertising revenues are given by $a(n)n$.

The publisher makes pricing and sampling decisions so as to maximize its profits from the two sources of revenue:

$$\begin{aligned} \max_{p,n} \quad & \pi(p,n) = (p-c)D(p,n;\tilde{V}(n)) + a(n)n \\ \text{s.t.} \quad & p \geq 0 \\ & 0 \leq n \leq N. \end{aligned} \tag{2}$$

Assuming that the publisher's profit function $\pi(p,n)$ is concave and noting that the constraint set is convex, standard optimization theory posits that there is a unique constraint global maximizer (p^*, n^*). Depending on the optimal pricing and sampling decision, the following definition gives the strategies available to the publisher.

Definition 1 (Strategies). *Given the optimal pricing and sampling decision (p^*, n^*), the publisher adopts either (i) a "sampling strategy" if $p^* > 0$ and $n^* \in (0, N)$, (ii) a "paid content strategy" if $p^* > 0$ and $n^* = 0$, or (iii) a "free content strategy" if $p^* = 0$ and $n^* = N$.*

Notice that both the paid content strategy and the free content strategy are nested within the sampling strategy. The publisher will thus receive no advertising revenue under a paid content strategy and no sales revenue under a free content strategy. The following result describes the optimal ratio of advertising revenue to sales revenue.

Proposition 1 (Advertising-Sales Revenue Ratio). *When the publisher chooses the sample size and the price optimally, its ratio of advertising revenue to sales revenue is given by*

$$\frac{an^*}{Dp^*} = \frac{\eta_n - \eta_{\tilde{V}}\varepsilon_{\tilde{V}}}{(1-\frac{1}{\eta_a})\eta_p}, \tag{3}$$

where $\eta_p \equiv -(\partial D/\partial p)(p/D)$ *denotes the elasticity of content demand with respect to price,* $\eta_n \equiv -(\partial D/\partial n)(n/D)$ *denotes the elasticity of content demand with respect to sample size,* $\eta_{\tilde{V}} \equiv (\partial D/\partial \tilde{V})(\tilde{V}/D)$ *denotes the elasticity of content demand demand with respect to quality,* $\varepsilon_{\tilde{V}} \equiv \tilde{V}'(n)(n/\tilde{V})$ *denotes the elasticity of posterior quality with respect to sample size, and* $\eta_a \equiv -n'(a)(a/n)$ *denotes the price elasticity of advertising demand.*

This result is proved in the Appendix (as are the subsequent ones). It has two important managerial insights: First, it shows that the publisher's advertising-sales revenue ratio is determined by characteristics of both the content market and the advertising market. Specifically, the elasticities of content demand with respect to price, sample size, and quality, the price elasticity of advertising demand, and the elasticity of posterior expectations with respect to sample size jointly determine the optimal advertising-sales revenue ratio. This general result thus provides guidance for managers seeking to better understand the contributions of sales and advertising to total revenue.

Second, Proposition 1 shows how changes in the "market environment," captured by the various elasticities, will affect the composition of revenues. Unsurprisingly, if η_p increases, the advertising-sales revenue ratio is lower. Intuitively, for a given sample size, the optimal price for the content is lower, which results in a higher content demand.[8] In contrast, a higher elasticity of content demand with respect to the sample size η_n increases the advertising-sales revenue ratio because sampling results in a stronger cannibalization effect. Furthermore, a higher price elasticity of advertising demand η_a reduces the advertising-sales revenue ratio as the price per impression is lower.

Proposition 1 also highlights the crucial role which the elasticity of posterior expectations with respect to sample size plays in the determination of the advertising-sales revenue ratio. While the elasticity of content with respect to

[8] Alternatively, for a given price, a higher η_p reduces the demand for the paid content, which results in a lower sample size, which in turn reduces advertising revenues.

quality $\eta_{\tilde{V}}$ is always positive, the impact of sampling on posterior quality determines the sign of $\eta_{\tilde{V}}\varepsilon_{\tilde{V}}$. Thus, if $\varepsilon_{\tilde{V}}$ is negative, the ratio of advertising revenue to sales revenue tends to be high, while it tends to be low if $\varepsilon_{\tilde{V}}$ is positive. Intuitively, if $\varepsilon_{\tilde{V}} < 0$, sampling reduces expected content demand as $\tilde{V}'(n) < 0$, and hence the advertising-sales revenue ratio is high. In contrast, if $\varepsilon_{\tilde{V}} > 0$, sampling increases expected content demand as consumer revise their expectations about quality upwards, which in turn results in a lower advertising-sales revenue ratio.

Interestingly, the optimal advertising-sales revenue ratio is reminiscent of the Dorfman-Steiner condition, which states that a monopolist's ratio of advertising spending to sales revenue is equal to the ratio of the elasticities of demand with respect to advertising and price (Dorfman and Steiner, 1954). Proposition 1 reduces to this result in the special case when offering additional samples does not affect posterior quality ($\varepsilon_{\tilde{V}} = 0$) and if the advertising demand is perfectly elastic ($\eta_a \to \infty$).

Our general framework is agnostic about how consumers form posterior expectations. To shed light on how sampling determines posterior quality expectations and in turn expected content demand, the next section introduces a Bayesian learning mechanism in which consumers update their prior expectations about content quality through their sample experience. In order to generate more insights, we use specific functional forms for content and advertising demand.

3 Model

This section introduces the elements of our model. We begin by laying out the assumptions regarding the publisher and the advertiser. We then describe the consumers' learning process about content quality. Finally we lay out the timeline of the model.

3.1 The Publisher

Suppose that the publisher offers an information good with $N \in \mathbb{N}$ content parts. The qualities of the $n \in \mathbb{N}_0$ free samples are uniformly distributed on the quality spectrum $[0, \bar{V}]$ and are labeled $V_1, \ldots, V_n$. We assume that the publisher has private information about $\bar{V}$ and normalize both the marginal costs c of producing content and the costs of providing free samples to zero. We treat the quality spectrum as an outcome of a previous strategic decision and focus on the publisher's short-run pricing and sampling decisions.

3.2 The Advertiser

Assume that there is a representative advertiser (e.g., an advertising agency) that places product advertisements in the free samples offered by the publisher. The benefit to the advertiser from running n advertisements is given by

$$u(n) = \phi n - \frac{1}{2N} n^2,$$

where ϕ is a positive number. Letting a denote the price per impression charged by the publisher, the advertiser's overall cost of running the n advertisements are given by $a(n)n$. The advertiser's willingness to pay for an advertisement is derived from equating the marginal benefit and the marginal cost of placing an advertisement and is given by

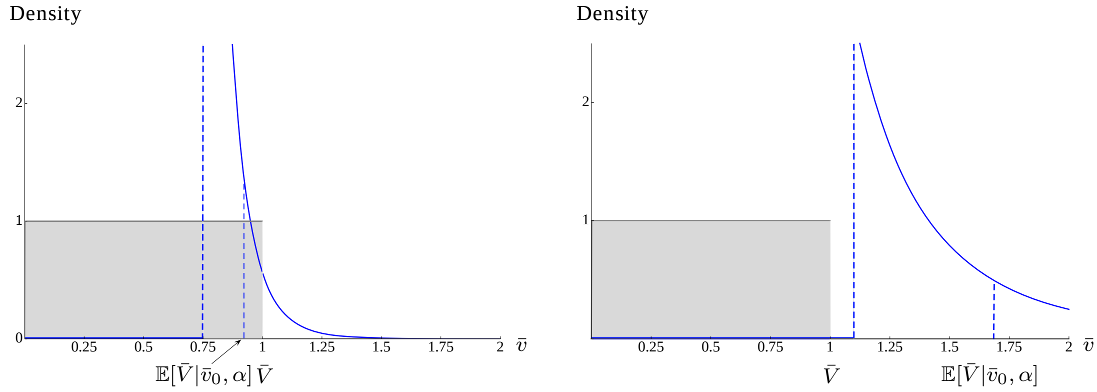
$$a(n) = \phi - \frac{n}{N}.$$

This inverse demand function for placing advertisements slopes downward, implying that the publisher's value per ad impression is decreasing in sample size. We impose the regularity condition $\phi > 1$ to ensure that the publisher faces a positive willingness to pay for advertisements under a free content strategy. Notice that ϕ has the interpretation of the maximum willingness to pay for placing an advertisement. Following Godes et al. (2009), we will refer to ϕ as "advertising effectiveness." Intuitively, ϕ can be thought of as a parameter shifting the inverse demand function "outwards."

3.3 Consumers

Consumers know that the qualities of the content parts are uniformly distributed on the interval $[0, \bar{V}]$. However, they do not know the upper bound $\bar{V}$ of the publisher's quality spectrum and are hence uncertain about (average) content quality.[9] Consumers have a common prior belief about $\bar{V}$ that may stem, for instance, from reviews, ratings or "word of mouth." The natural conjugate family for a representative random sample from a uniform distribution with unknown upper bound is the Pareto distribution (DeGroot, 1970). We capture uncertainty

[9] Note that the upper bound $\bar{V}$ is monotonically related to the mean, which may be an alternative way for consumers to think about content quality.



(A) $\bar{v}_0 = 0.75$ and $\alpha = 10$ (B) $\bar{v}_0 = 1.10$ and $\alpha = 3$

Figure 1: Prior expectations about $\bar{V}$ (where $\bar{V} \equiv 1$).

about $\bar{V}$ by a prior belief that consists of a minimum estimate $\bar{v}_0$ of the upper bound $\bar{V}$ and a level of uncertainty α about this value. Specifically, we assume that the prior belief follows a Pareto distribution with density function

$$f(\bar{v}|\bar{v}_0, \alpha) = \begin{cases} \dfrac{\alpha \bar{v}_0^{\alpha}}{\bar{v}^{\alpha+1}}, & \text{for } \bar{v} > \bar{v}_0 \\ 0, & \text{otherwise.} \end{cases}$$

We assume that $\alpha > 1$ to ensure existence of the prior expectations.[10] Further, we assume that the consumers' prior parameters $\bar{v}_0$ and α are common knowledge.[11] Based on the consumers' prior knowledge about $\bar{v}_0$ and α, their prior expectation about $\bar{V}$ is

$$\mathbb{E}[\bar{V}|\bar{v}_0, \alpha] = \frac{\alpha \bar{v}_0}{\alpha - 1}. \quad (4)$$

Obviously, prior expectations increase in $\bar{v}_0$ and decrease in α. Figure 1 illustrates prior expectations along with the corresponding expectations for different parameter values. Prior expectations are lower than actual quality in Panel A and higher than actual quality in Panel B. Notice, however, that prior expectations can be higher than actual quality even if $\bar{v}_0 < \bar{V}$.

Consumers update their prior belief about $\bar{V}$ by taking the observed qualities of the free content pieces into account. Specifically, consumers evaluate the n sample qualities $V_i = v_i$ ($i = 1, \ldots, n$) to form their posterior beliefs $\tilde{v}(n)$ about

[10]Our measure of uncertainty corresponds to the scale parameter α of the Pareto distribution. Hence, when the uncertainty is higher, the prior distribution is more spread out.

[11]For instance, the publisher can learn about prior expectations employing standard market research techniques such as surveys.

quality $\bar{V}$. Using standard Bayesian analysis, $\tilde{v}(n)$ follows a Pareto distribution with minimum value parameter $\tilde{v}_0(n) = \max\{\bar{v}_0, v_1, \ldots, v_n\}$ and shape parameter $\alpha + n$ (De Groot, 1970).[12] Hence, the posterior expectation of $\bar{V}$ is given by

$$\mathbb{E}[\bar{V}|\tilde{v}_0(n), \alpha] = \frac{(\alpha + n)\tilde{v}_0(n)}{\alpha + n - 1}.$$

Consumers infer the expected quality of the information good $\mathbb{E}[V|v_1, \ldots, v_n]$ from posterior expectations and knowing that qualities are uniformly distributed on the quality spectrum offered. Therefore their expected quality of the information good is given by

$$\mathbb{E}[V|v_1, \ldots, v_n] = \frac{\mathbb{E}[\bar{V}|\tilde{v}_0(n), \alpha]}{2}. \tag{5}$$

Consumers agree that higher quality is better than lower quality but differ in the way they value quality. To capture this heterogeneity, we introduce a preference parameter for quality θ, which is uniformly distributed on the interval [0,1]. We consider discrete choice and assume that consumers have unit demand for the content: Each consumer either purchases the information good at price p or stays with the n free samples. A consumer's (indirect) utility from these two options is given by

$$u(p, n) = \begin{cases} N\theta\,\mathbb{E}[V|v_1, \ldots, v_n] - p, & \text{from purchasing at price } p \\ n\theta\,\mathbb{E}[V|v_1, \ldots, v_n], & \text{from staying with the free samples.} \end{cases} \tag{6}$$

This specification assumes that consumers are neutral about advertisements and neither find them a nuisance nor appreciate them. In effect, this means they can skip over them (or mechanically screen them out) at essentially zero cost.

3.4 Timeline

The publisher first decides on the sample size n and the price p at which to sell the information good. Next, consumers select the samples of their choice and use the observed sample qualities $V_1 = v_1, \ldots, V_n = v_n$ to update their prior expectations about content quality $\bar{V}$. Finally, consumers decide whether or not to purchase the information good based on posterior expectations.

[12]The proof of this result is reproduced in the Appendix.

4 Strategy with Known Quality

We first analyze as a benchmark the case in which the consumers know $\bar{V}$ and hence the publisher's quality spectrum. In this setting, sampling does not affect the consumers' expectations about quality and simply serves to generating advertising revenues. We derive content demand for each strategy and then characterize the optimal strategy.

4.1 Content Demand

We first derive content demand under a sampling strategy and subsequently the demands for the two boundary strategies.

Sampling Strategy. When consumers know the upper bound $\bar{V}$ of the quality spectrum, they expect content quality to be equal to $\mathbb{E}[V] = \frac{\bar{V}}{2}$. When the publisher employs the sampling strategy, consumers get some of the content for free but have to purchase the information good if they want to obtain the full content. Based on the preferences in (6), a consumer will purchase if and only if her indirect utility from buying it exceeds her indirect utility from consuming the free samples only. Specifically, if $\theta(N-n)\frac{\bar{V}}{2} - p \geq 0$, the consumer purchases the product. This condition has the interpretation that the utility of the content that has not been sampled must exceed the price. Recalling that θ follows a uniform distribution on $[0, 1]$, content demand can be expressed as

$$\begin{aligned} D(p,n) &= \Pr\left\{\theta \geq \frac{p}{(N-n)\frac{\bar{V}}{2}}\right\} \\ &= \max\left\{0, 1 - \frac{p}{(N-n)\frac{\bar{V}}{2}}\right\}. \end{aligned} \tag{7}$$

This demand function has the intuitive properties that it decreases in price p and increases in average quality $\frac{\bar{V}}{2}$. Moreover, sampling has a direct negative effect on content demand as $\frac{\partial D}{\partial n} < 0$. Intuitively, this follows because a larger sample size reduces the utility of the content consumers have to pay for.

Paid Content Strategy. When the publisher employs the paid content strategy, setting $n = 0$ in (7) produces

$$D(p,0) = \max\left\{0, 1 - \frac{p}{N\frac{\bar{V}}{2}}\right\}. \tag{8}$$

Free Content Strategy. When the publisher employs a free content strategy, consumers never purchase the information good as they can download it for free. We thus have that $D(p, N) \equiv 0$.

4.2 Optimal Pricing and Sampling

The publisher's chooses its pricing and sampling decision so as to

$$\begin{aligned} \max_{p,n} \quad & \pi(p,n) = p\left(1 - \frac{p}{(N-n)\frac{\bar{V}}{2}}\right) + \left(\phi - \frac{n}{N}\right) n \\ \text{s.t.} \quad & p \geq 0 \\ & 0 \leq n \leq N. \end{aligned}$$

From the first-order conditions, the (best-response) price for a given sample size can be derived as

$$p(n) = \frac{(N-n)\bar{V}}{4}. \tag{9}$$

This implies an inverse relationship between sample size and price: The more free samples the publisher chooses to offer, the less he will be able to charge the consumer for the (remaining) content. The next result summarizes the optimal pricing and sampling decisions for each of the three strategies.

Lemma 1 (Pricing and Sampling). *Suppose that the upper bound of content quality $\bar{V}$ is common knowledge. Then, (i) under a sampling strategy, $p^* = N\bar{V}(8(2-\phi) + \bar{V})/64$ and $n^* = N(8\phi - \bar{V})/16$, (ii) under a paid content strategy, $p^* = N\bar{V}/4$ and $n^* = 0$, and (iii) under free content strategy, $p^* = 0$ and $n^* = N$.*

The parameters $\bar{V}$ and ϕ have opposite effects on the optimal price and on the optimal sample size under a sampling strategy: As we can expect, p^* increases in $\bar{V}$ while n^* decreases in the highest quality. In contrast, p^* decreases in ϕ, and n^* increases in advertising effectiveness. Furthermore, both the optimal price and the optimal sample size increase in content size N.

The main objective in what follows is to characterize the publisher's optimal strategy. As a first step, we compare the two boundary strategies to understand under which conditions each of them yields a higher profit.

Lemma 2 (Boundary Strategies). *Suppose that the upper bound of content quality $\bar{V}$ is common knowledge. Then, the publisher attains a higher profit under a free content strategy than a paid content strategy if and only if $\phi > \frac{\bar{V}}{8} + 1$.*

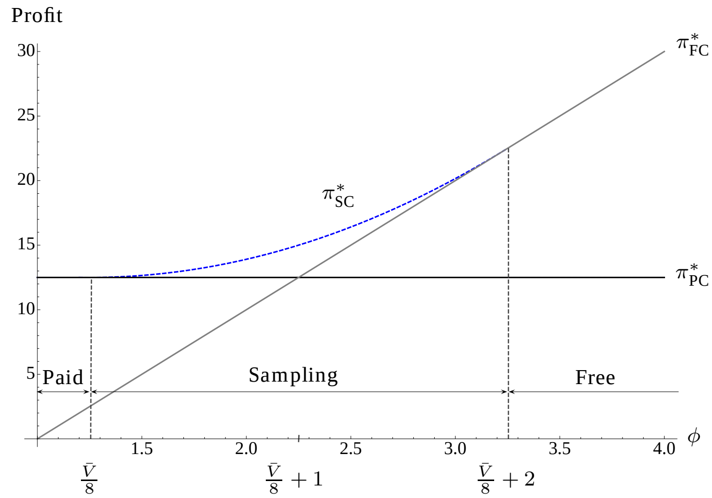


Figure 2: Optimal strategy with known quality.

The condition in Lemma 2 shows that the choice between the two boundary strategies depends simply on the relationship between the quality $\bar{V}$ and the advertising effectiveness ϕ. As long as advertising effectiveness is low, the publisher should employ a paid content strategy. Instead, if advertising effectiveness exceeds the threshold level $\frac{\bar{V}}{8}+1$, the publisher should switch to a free content strategy and offer its content for free. Next, we characterize the publisher's optimal strategy.

Proposition 2 (**Optimal Strategy**). *Suppose that the consumers know the quality spectrum. Then, (i) if $\phi \in (\frac{\bar{V}}{8}, \frac{\bar{V}}{8}+2)$, the publisher should employ a sampling strategy, (ii) if $\phi \leq \frac{\bar{V}}{8}$, the publisher should follow a paid content strategy, and (iii) if $\phi \geq \frac{\bar{V}}{8}+2$, the publisher's optimal strategy is to use a free content strategy.*

Proposition 2 shows that the choice of the optimal strategy is solely driven by the relationship between content quality $\bar{V}$ and advertising effectiveness ϕ. Thus, a paid content strategy is optimal if the effectiveness of advertising is sufficiently low. For intermediate levels of advertising effectiveness, a sampling strategy that generates revenues from both sales and advertising is optimal. Once advertising is sufficiently effective, the publisher should switch to a free content strategy. Figure 2 illustrates the optimal strategy for given parameters values ϕ and $\bar{V}$ along with the profits for each strategy (which are π^*_{SC} for the sampling strategy, π^*_{PC} for the paid content strategy, and π^*_{FC} for the free content strategy).[13]

[13]The parameter values underlying the figure are $\bar{V} = 10$ and $N = 10$. Qualitatively, the choice of specific parameter values does not affect Figure 2.

The effects of ϕ and $\bar{V}$ on the optimal strategy can also be understood by inspection of the advertising-sales revenue ratio. The ratio follows from (3) and is

$$\frac{an^*}{Dp^*} = \frac{(\phi - \frac{\bar{V}}{8})(\frac{\bar{V}}{8} + \phi)}{\frac{\bar{V}}{4}(\frac{\bar{V}}{8} + 2 - \phi)}.$$

The ratio of advertising revenue to sales revenue tends to zero as ϕ approaches the lower bound $\frac{\bar{V}}{8}$, implying that the publisher should employ a paid content strategy. Also, a sampling strategy is optimal only if advertising is not "too effective," that is, as long as $\phi \leq \frac{\bar{V}}{8} + 2$. Once ϕ exceed this threshold level, the publisher should switch to a free content strategy.

4.3 Summing up

When content quality is common knowledge, the publisher's optimal strategy is determined by the relation between the advertising effectiveness and content quality. The more effective advertising is, the more free samples the publisher should offer—even though it solely cannibalizes content demand. In the next section, we study optimal pricing and sampling decisions when the quality spectrum is not known to consumers and they learn about quality through inspection of the free samples.

5 Strategy with Unknown Quality

We now focus on a setting in which $\bar{V}$ and hence the product spectrum is not known to consumers. In this setting, sampling not only serves the purpose of generating advertising revenues but is employed to influence the consumers' expectations about quality. As in the benchmark model, we first derive content demand for each strategy and then characterize the optimal sampling strategy.

5.1 Content Demand

We first derive content demand under a sampling strategy and subsequently derive the demands for the two boundary strategies.

Sampling Strategy. When consumers do not know the upper bound of the quality spectrum $\bar{V}$ with certainty, content demand is influenced by the consumers' posterior quality expectations. However, when the publisher makes decisions about the sample size and the price, it has to base them on *expected* content demand as consumers have not yet evaluated sample qualities and updated their expectations about content quality.

Calculating expected content demand involves a two-step procedure. In a first step, the publisher computes the expected posterior quality by averaging posterior expectations about $\bar{V}$ as given in (5) across *all* possible realizations of sample qualities:

$$\mathbb{E}\left[\mathbb{E}[V|V_1,\ldots,V_n]\right] = \frac{(\alpha+n)\,\mathbb{E}\left[\tilde{v}_0(n)\right]}{2\,(\alpha+n-1)}.$$

In a second step, the publisher substitutes the expected posterior quality into the indirect utility function given in (6) to obtain expected content demand:

$$D^{\mathrm{E}}(p,n) = \max\left\{0, 1 - \frac{p}{(N-n)}\frac{2\,(\alpha+n-1)}{(\alpha+n)\,\mathbb{E}\left[\tilde{v}_0(n)\right]}\right\}. \tag{10}$$

Next, we calculate $\mathbb{E}\left[\tilde{v}_0(n)\right]$ and insert it into the expected content demand given in (10). The following lemma summarizes the result.

Lemma 3 (Expected Demand). *When the publisher sells the information good at price p and offers $n \in \{1, N-1\}$ samples, then*

(a) if $\bar{v}_0 < \bar{V}$, expected content demand is given by

$$D^{E}_{\{\bar{v}_0<\bar{V}\}}(p,n) = \max\left\{0, 1 - \frac{p}{(N-n)}\frac{2\,(\alpha+n-1)\,(n+1)\bar{V}^{n}}{(\alpha+n)\left(\bar{v}_0^{n+1}+n\bar{V}^{n+1}\right)}\right\}. \tag{11}$$

(b) if $\bar{v}_0 \geq \bar{V}$, expected content demand is given by

$$D^{E}_{\{\bar{v}_0\geq\bar{V}\}}(p,n) = \max\left\{0, 1 - \frac{p}{(N-n)}\frac{2\,(\alpha+n-1)}{(\alpha+n)\,\bar{v}_0}\right\}. \tag{12}$$

These demand functions have the intuitive properties that they decrease in price p and increase in expected posterior quality. However, sampling has both a direct demand-reducing effect and an indirect effect that operates through its impact on posterior expectations. The direct effect kicks in through the factor $\frac{1}{N-n}$ and mirrors the cannibalization effect $\frac{\partial D}{\partial n} < 0$ in our reduced-form model.

Paid Content Strategy. When the publisher employs the paid content strategy, consumers cannot update their quality expectations. Setting $n = 0$ in (10) and rearranging produces

$$D^{\mathrm{E}}(p,0) = \max\left\{0, 1 - \frac{p}{N\frac{\alpha\bar{v}_0}{2(\alpha-1)}}\right\}. \tag{13}$$

This demand function is a close cousin of the corresponding demand for paid content given in (8) when consumers know quality. The difference is that the expected content demand is driven by prior expectations about $\bar{V}$ rather than expected quality $\frac{\bar{V}}{2}$ itself.

Free Content Strategy. When the publisher employs a free content strategy, consumers never purchase the information good as they can download it for free. Thus, $D^{\mathrm{E}}(p, N) \equiv 0$.

5.2 The Role of Quality Expectations

For a given level of prior expectations about content quality, sampling either increases or decreases expected content demand. Whether or not sampling compensates for the cannibalization effect through consumers' learning depends on the gap between posterior quality and actual quality. To investigate the quality gap, we define expected posterior quality as

$$\tilde{V}(n) = \begin{cases} \dfrac{(\alpha+n)\left(\bar{v}_0^{n+1} + n\bar{V}^{n+1}\right)}{2\,(\alpha+n-1)\,(n+1)\bar{V}^{n}}, & \text{if } \bar{v}_0 < \bar{V} \\ \dfrac{(\alpha+n)\,\bar{v}_0}{2\,(\alpha+n-1)}, & \text{if } \bar{v}_0 \geq \bar{V}. \end{cases} \tag{14}$$

With this definition in mind, we define the quality gap as $\tilde{V}(n) - \frac{\bar{V}}{2}$. Consumers overestimate (underestimate) quality if the expected posterior quality is higher (lower) than actual quality. This leads to the following result.

Lemma 4 (Quality Gap). *When $\bar{v}_0 < \bar{V}$, consumers underestimate quality if*

$$\frac{\bar{v}_0}{\bar{V}} < \left(\frac{\alpha-1}{\alpha+n}\right)^{\frac{1}{n+1}}, \tag{15}$$

and overestimate it if the inequality is reversed. If $\bar{v}_0 \geq \bar{V}$, consumers overestimate quality irrespective of the sample size and their level of uncertainty $\alpha > 1$.

For the case where $\bar{v}_0 < \bar{V}$, Figure 3 illustrates the set of prior parameters for which consumers overestimate and underestimate quality, respectively. The figure also illustrates that the set of prior parameters for which consumers underestimate quality increases as n gets larger. This can perhaps best be seen by noting that $\tilde{V}(n) \to \frac{\bar{V}}{2}$ as $n \to \infty$, meaning that consumers learn actual quality once the sample size gets "large enough."

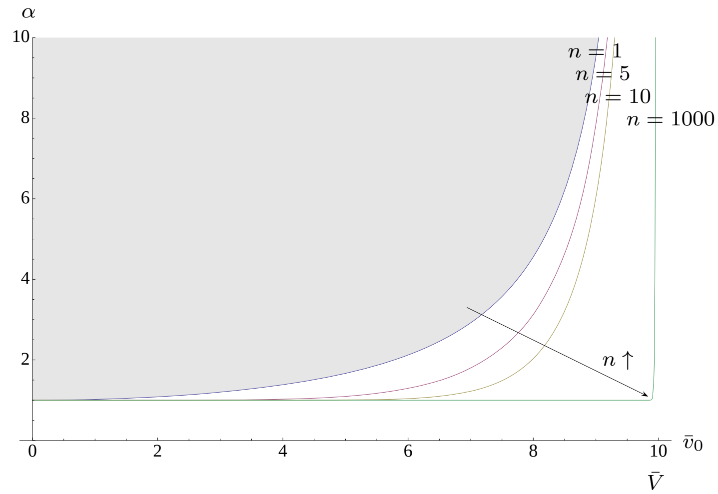


Figure 3: The quality gap for the case $v_0 < \bar{V}$ (where $\bar{V} \equiv 10$). The shaded area indicates where consumers underestimate quality.

The definition of $\tilde{V}(n)$ allows us to rewrite the expected content demands derived in Lemma 3 more compactly as

$$D^{\mathrm{E}}(p,n) = \max\left\{0, 1 - \frac{p}{(N-n)\tilde{V}(n)}\right\}. \tag{16}$$

Notice that this demand function is a specific form of the reduced-form demand function in Equation (1). In it the number of free samples n has both a direct effect on expected content demand and an indirect effect that operates through posterior quality expectations $\tilde{V}(n)$. The next result uses this demand function to identify conditions under which sampling has a demand-enhancing effect (that is, $\frac{\partial D^{\mathrm{E}}}{\partial n} > 0$).

Lemma 5 (Effects of Sampling). *Offering free samples has a demand-enhancing effect if $\varepsilon_{\tilde{V}} > \frac{n}{N-n}$, that is, if the elasticity of consumers' posterior expectations exceeds the ratio of sampled to paid content.*

Lemma 5 shows that offering free samples may increase expected content demand through consumers' learning, even though it produces a cannibalization effect. Intuitively, the indirect effect dominates the direct cannibalization effect if sampling induces a sufficiently large upwards revision of consumers' prior expectations.

5.3 Optimal Strategy

The publisher's makes its pricing and sampling decisions so as to

$$\begin{aligned} \max_{p,n} \quad & \pi^{\mathrm{E}}(p,n) = p\left(1 - \frac{p}{(N-n)\tilde{V}(n)}\right) + \left(\phi - \frac{n}{N}\right) n \\ \text{s.t.} \quad & p \geq 0 \\ & 0 \leq n \leq N. \end{aligned}$$

Comparing expected profits to the profits when content quality is known to consumers shows that the only difference is the dependence on expected posterior quality rather than actual (average) quality. Based on comparison to (9) and recalling that $\tilde{V}(n)$ is the posterior estimate of average quality $\frac{\bar{V}}{2}$, we thus obtain that

$$p(n) = \frac{(N-n)\tilde{V}(n)}{2}.$$

Substituting $p(n)$ back into the profit function allows us to rewrite the profit maximization problem more conveniently as

$$\begin{aligned} \max_{n} \quad & \pi^{\mathrm{E}}(n) = (N-n)\,\frac{\tilde{V}(n)}{4} + \left(\phi - \frac{n}{N}\right) n \\ \text{s.t.} \quad & 0 \leq n \leq N. \end{aligned} \tag{17}$$

As in the benchmark model, we first investigate the conditions under which each of the boundary strategies yields a higher profit. The next result shows when a paid content strategy is more profitable than a free content strategy.

Lemma 6 (Boundary Strategies). *Given that content quality $\bar{V}$ is not known to consumers, the optimal pricing and sampling decisions are, respectively, $p^* = \frac{N\alpha\bar{v}_0}{4(\alpha-1)}$ and $n^* = 0$ under a paid content strategy and $p^* = 0$ and $n^* = N$ under a free content strategy. Consequently, the publisher attains a higher profit under a free content strategy than under a paid content strategy if and only if $\phi > \frac{\alpha\bar{v}_0}{8(\alpha-1)} + 1$.*

This result shows that when prior expectations are correct in the sense that they are equal to $\frac{\bar{V}}{2}$, the condition under which the paid content strategy is more profitable than the free content strategy is the same as in the benchmark model with known quality (see Lemma 2). When consumers' prior expectations are "too high," ϕ must be higher in order to support a free content strategy. The reason is that higher quality expectations translate into a higher demand under a paid content strategy, and hence higher profits due to demand-markup complementarities (Athey and Schmutzler, 2001).

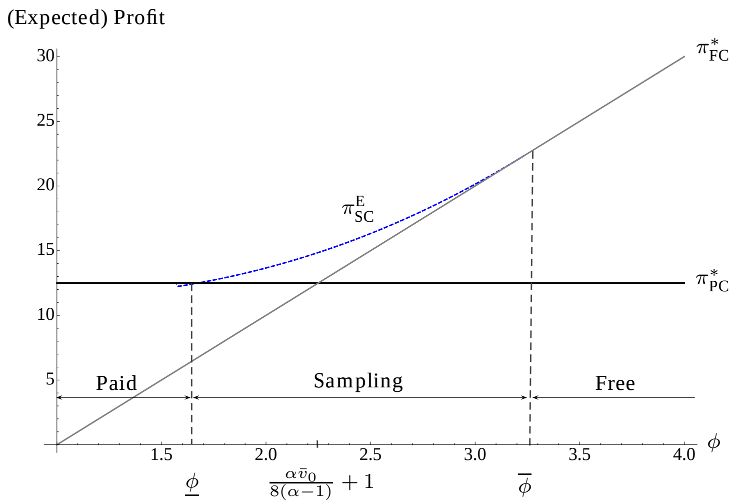


Figure 4: Optimal strategy with unknown quality.

To determine the publisher's optimal strategy, we now also consider the sampling strategy. In contrast to our benchmark model, it is not possible to characterize the optimal pricing and sampling decisions (and hence profits) analytically. Nevertheless, we can derive the following result.

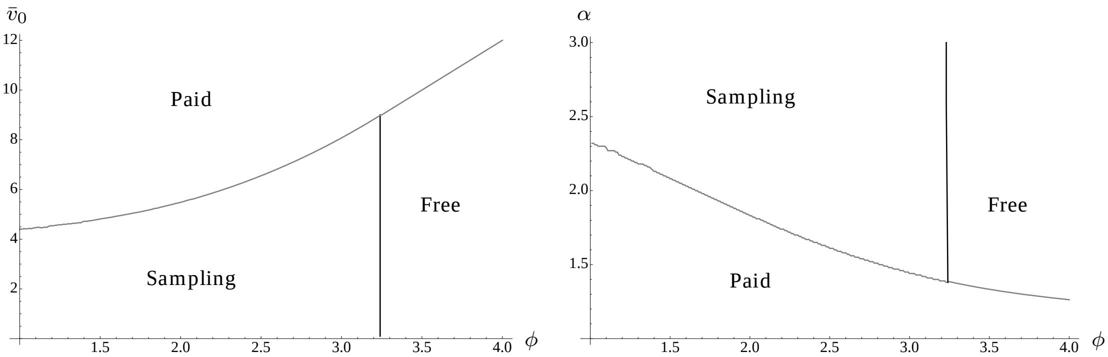
Proposition 3 (Optimal Strategy). *Suppose that consumers are uncertain about $\bar{V}$ and that the profit function $\pi^E(n)$ is strictly concave. Then, there are cut-off values $\underline{\phi} = \frac{1}{4}(\tilde{V}(0) - N\tilde{V}'(0))$ and $\overline{\phi} = 2 + \frac{\tilde{V}(N)}{4}$ such that a sampling strategy is optimal for $\phi \in (\underline{\phi}, \overline{\phi})$, a paid content strategy is optimal for $\phi \leq \underline{\phi}$, and a free content strategy is optimal for $\phi \geq \overline{\phi}$.*

This proposition is consistent with the insights from the benchmark model that a paid content strategy is optimal only if the advertising effectiveness is sufficiently low, that a sampling strategy is optimal for intermediate levels of the advertising effectiveness, and that the publisher should switch to a free content strategy once advertising is sufficiently effective (see Proposition 2).[14] Figure 4 illustrates the optimal strategy for varying ϕ and the expected profits for each strategy (which are π^E_{SC} for the sampling strategy, π^*_{PC} for the paid content strategy, and π^*_{FC} for the free content strategy).[15]

Proposition 3 reveals that prior expectations determine the lower of the two cut-off values whereas posterior expectations for sample size $n = N$ determine

[14] Observe that we assume in Proposition 3 that the profit function $\pi^E(n)$ is globally concave. However, there are parameter constellations for which this assumption is not satisfied. In this case, the cut-off values must be determined numerically by the comparing profits that arise from the different strategies.

[15] The parameter values underlying the figure are $\bar{v}_0 = 5$, $\alpha = 2$, $\bar{V} = 10$, and $N = 10$.



(A) Based on $\bar{v}_0$ and ϕ (B) Based on α and ϕ

Figure 5: Optimal strategy for different parameter values.

the upper cut-off value. In effect, $\underline{\phi}$ is determined by the impact of the "first sample" on posterior expectations, while $\overline{\phi}$ is determined by posterior expectations after inspection of the "last sample." The next lemma shows that the model where quality $\bar{V}$ is not known to consumers nests the full information benchmark model (see Proposition 2).

Lemma 7 (Cut-off Values). *Suppose that consumers are uncertain about content quality $\bar{V}$ and that the profit function $\pi^E(n)$ is strictly concave. Then, when consumers have correct quality expectations, that is, if $\bar{v}_0 = \bar{V}$ and $\alpha \to \infty$, the lower bound $\underline{\phi}$ converges to $\frac{\bar{V}}{8}$ and the upper bound $\overline{\phi}$ converges to $\frac{\bar{V}}{8} + 2$.*

We next explore the comparative statics effect of changes in the consumers's prior parameters on the optimal strategy. Proposition 3 shows that the optimal strategy depends not only on advertising effectiveness ϕ and quality $\bar{V}$ as in the benchmark model, but also on the specific values of the prior parameters $\bar{v}_0$ and α (as well as content size N). Figure 5 illustrates the comparative statics effects of changes in the consumers' prior parameters.[16] Panel A depicts the cut-off thresholds between the different strategies in the $(\bar{v}_0, \phi)$-space (given $\alpha = 2$). Similarly, Panel B illustrates the optimal choice of strategy in the (α, ϕ)-space (given $\bar{v}_0 = 5$). Notice that prior expectations are correct and coincide with actual quality when $\bar{v}_0 = 5$ and $\alpha = 2$ (see Equation 4). The following observation summarizes our insights.

[16]The figure uses the normalizations $\bar{V} = 10$ and $N = 10$.

Observation 1 (**Comparative Statics**). *Suppose that consumers are uncertain about quality $\bar{V}$. Then, (a) when both the prior quality expectations and the advertising effectiveness are low, the publisher should employ a sampling strategy to reveal his higher than expected quality, (b) when prior expectations increase, that is, either $\bar{v}_0$ increases or α decreases, the publisher should switch to a paid content strategy, and (c) when the advertising effectiveness ϕ increases, the publisher should adopt a free content strategy.*

5.4 Summing Up

When content quality is the publisher's private information, sampling has a demand-enhancing effect when the elasticity of consumer's posterior expectations with respect to sample size exceeds the ratio of sampled to paid content. When this condition is not satisfied, sampling mitigates or reinforces the cannibalization effect. As in the benchmark model, we show that employing a paid content strategy is optimal only if advertising effectiveness is sufficiently low, that a sampling strategy is optimal for intermediate levels of advertising effectiveness, and that the publisher should switch to a free content strategy once advertising is sufficiently effective.

6 Summary and Implications

This paper has analyzed optimal decisions concerning the size of the sample and the price of the paid content for online publishers of digital information goods when sampling serves the dual purpose of disclosing content quality and generating advertising revenue. One of the key features of the analytical model is that consumers evaluate free samples of their choice within the limit set by the publisher. Consumers then use the information transmitted in the free samples to update their prior expectations about content quality in a Bayesian fashion to make more informed purchase decisions. Taking the consumers' quality updating into account, the publisher can either adopt a "sampling strategy," a "paid content strategy," or a "free content strategy."

We derived the following three key results. *First*, the publisher's optimal ratio of advertising revenue to sales revenue is determined by the elasticities of expected content demand with respect to price and sample size, the price elasticity of advertising demand, and the elasticity of consumers' updated expectations with respect to the sample size. *Second,* when content quality is known to consumers, the optimal strategy is determined by the relationship between advertising effectiveness and content quality. Interestingly, we found that it may be optimal for the publisher to offer free content samples even if sampling solely cannibalizes content demand. *Third*, when consumers learn about content quality through inspection of the free samples, sampling has a demand-enhancing effect when the elasticity of consumer's posterior expectations with respect to sample size exceeds the ratio of sampled to paid content. The optimal strategy is determined in such a setting by the relationship between advertising effectiveness and the interplay between prior expectations and actual content quality.

Our predictions are consistent with casual observations from the media industry.[17] Once advertising effectiveness is sufficiently high, our model predicts that the publisher should offer its entire content for free. Such a business model was often followed in the early days of the Internet where the provision of content was largely financed by advertising. More recently, many publishers have moved from a pure advertising-financed business model, suggesting that either advertisers overestimated Web advertising effectiveness or that its effect has diminished over time.

Our analysis suggests several avenues for future research. *First*, regarding the consumers, we assume they correctly update quality expectations based on their sample experience. One alternative is to assume a consistent bias in the consumers' judgments. In addition, in certain circumstances consumers may adjust (discount) observed quality, assuming that the publisher has provided a non-representative set of samples to choose from in order to persuade them to buy the paid content. *Second*, one could argue that consumers do not evaluate the qualities of all free samples because of "sampling costs." For instance, these costs may be due to the opportunity cost of time, mental costs, or the disutility of advertisements. *Third*, one could enrich the model by allowing for competition. One way is to allow for internal competition where the publisher offers two websites to serve different categories of consumers, which in essence relates to the versioning literature.[18] Another way is to allow for external competition where multiple publishers compete in terms of sample size, content price, and advertising rates. Clearly, there are many directions which research in this area could take. We view this paper a step in this process and hope the paper encourages work in these and related directions.

[17] See, for instance, Abramson (2010).

[18] For instance, *The Boston Globe* operates the ad-supported site *boston.com* and the subscriber-only site *BostonGlobe.com*.

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Appendix

A.1 Sampling From a Uniform Distribution

The Pareto Distribution. A random variable X has a Pareto distribution with parameters w_0 and α ($w_0 > 0$ and $\alpha > 0$) if X has a density

$$f(x|w_0, \alpha) = \begin{cases} \frac{\alpha w_0^\alpha}{x^{\alpha+1}} & \text{for } x > w_0 \\ 0 & \text{otherwise.} \end{cases}$$

For $\alpha > 1$ the expectation of X exists and it is given by $E(X) = \frac{\alpha w_0}{\alpha - 1}$. Regarding sampling from a uniform distribution, we use the following result.

Theorem (DeGroot, 1970).[19] *Suppose that $X_1, \ldots, X_n$ is a random sample from a uniform distribution of the interval $(0, W)$, where the value of W is unknown. Suppose also that the prior distribution of W is a Pareto distribution with parameters w_0 and α such that $w_0 > 0$ and $\alpha > 0$. Then the posterior distribution of W when $X_i = x_i$ ($i = 1, \ldots, n$) is a Pareto distribution with parameters w_0' and $\alpha + n$, where $w_0' = \max\{w_0, x_1, \ldots, x_n\}$.*

Proof. For $w > w_0$, the prior density function ξ of W has the following form:

$$\xi(w) \propto \frac{1}{w^{\alpha+1}}.$$

Furthermore, $\xi(w) = 0$ for $w \le w_0$. The likelihood function $f_n(x_1, \ldots, x_n|w)$ of $X_i = x_i$ ($i = 1, \ldots, n$), when $W = w$ ($w > 0$) is given by:[20]

$$f_n(x_1, \ldots, x_n|w) = f(x_1|w) \cdots f(x_n|w) = \begin{cases} \frac{1}{w^n} & \text{for } \max\{x_1, \ldots, x_n\} < w \\ 0 & \text{otherwise.} \end{cases}$$

It follows from these relations that the posterior p.d.f. $\xi(w|x_1, \ldots, x_n)$ will be positive only for values w such that $w > w_0$ and $w > \max\{x_1, \ldots, x_n\}$. Therefore, $\xi(w|\cdot) > 0$ only if $w > w_0'$. For $w > w_0'$, it follows from Bayes' theorem that

$$\xi(w|x_1, \ldots, x_n) \propto f_n(x_1, \ldots, x_n|w)\xi(w) = \frac{1}{w^{\alpha+n+1}}$$

(the marginal joint probability density function $f_n(x_1, \ldots, x_n)$ of $X_1, \ldots, X_n$ is a normalizing constant). □

[19] Theorem 1, p. 172.

[20] Given $W = w$, the random variables $X_1, \ldots, X_n$ are independent and identically distributed and the common probability density function of each of the random variables is $f(x_i|w)$.

A.2 Proofs

Proof of Proposition 1. The solution of problem (2) must satisfy the first-order conditions

$$D(p,n;\tilde{V}(n)) + (p-c)\,\frac{\partial D(p,n;\tilde{V}(n))}{\partial p} + \lambda_1 \;=\; 0 \tag{A.1}$$

$$(p-c)\left(\frac{\partial D(p,n;\tilde{V}(n))}{\partial n} + \frac{\partial D(p,n;\tilde{V}(n))}{\partial \tilde{V}}\,\tilde{V}'(n)\right)$$
$$+\, a'(n)n + a(n) + \lambda_2 - \lambda_3 \;=\; 0 \tag{A.2}$$

and the constraints $\lambda_1 p = 0$, $\lambda_2 n = 0$, and $\lambda_3(n-N) = 0$, where the λ_i's are non-negative real numbers (whose existence is assured by the Kuhn-Tucker theorem). Suppressing the arguments of content demand, (A.1) can be rewritten as

$$\frac{p-c}{p} = \frac{1}{\eta_p}\left(1 + \frac{\lambda_1}{D}\right). \tag{A.3}$$

Dividing (A.2) through p and substituting from (A.3) produces

$$\frac{1}{\eta_p}\left(1+\frac{\lambda_1}{D}\right)\left(\frac{\partial D}{\partial n} + \frac{\partial D}{\partial \tilde{V}}\,\tilde{V}'(n)\right) + \frac{a'(n)n}{p} + \frac{a(n)}{p} + \frac{\lambda_2-\lambda_3}{p} = 0.$$

Recalling that $n'(a) = \frac{1}{a'(n)}$ (from the inverse function theorem) and using the definitions of the respective elasticities, the preceding equation can be rearranged to obtain

$$\frac{pD}{an}\frac{1}{\eta_p}\left(1+\frac{\lambda_1}{D}\right)\left(\eta_n - \eta_{\tilde{V}}\tilde{V}_n\right) = \left(1 - \frac{1}{\eta_a}\right) + \frac{\lambda_2-\lambda_3}{a}. \tag{A.4}$$

Under a sampling strategy, there is an interior solution. Hence, the λ_k's are zero and (A.4) can be rewritten as

$$\frac{an}{Dp} = \frac{\eta_n - \eta_{\tilde{V}}\varepsilon_{\tilde{V}}}{(1-\frac{1}{\eta_a})\eta_p}.$$

□

Proof of Lemma 1. The optimal decisions on size of the sample and on the price follow from solving the Kuhn-Tucker conditions in Proposition 1.[21] Under a sampling strategy, the λ_k's are zero and it follows that $p^* = N\bar{V}(8(2-\phi)+\bar{V})/64$ and $n^* = N(8\phi - \bar{V})/16$. Under a paid content strategy, $\lambda_1 = \lambda_3 = 0$, leading to $p^* = N\bar{V}/4$ and $n^* = 0$. Under a free content strategy, we have that $p^* = 0$ and $n^* = N$. □

Proof of Lemma 2. Using Lemma 1, it is straightforward to derive the profits under a free content strategy (FC) and a paid content strategy (PC). The profits are given by, respectively, $\pi^*_{\text{FC}} = (\phi-1)N$ and $\pi^*_{\text{PC}} = N\bar{V}/8$. Comparing the two profits shows that $\pi^*_{\text{FC}} \geq \pi^*_{\text{PC}}$ if and only if $\phi > \frac{\bar{V}}{8} + 1$. □

[21] It is straightforward to show that the objective function is concave for all parameter values.

Proof of Proposition 2. The profit under a sampling strategy (SC) follows from Lemma 1 and is given by $\pi^*_{\text{SC}} = N\left(\bar{V}^2 - 16\bar{V}(\phi - 2) + 64\phi^2\right)/256$. Using Lemma 2, employing a sampling strategy is optimal if $\pi^*_{\text{SC}} > \pi^*_{\text{PC}}$ and $\pi^*_{\text{SC}} > \pi^*_{\text{FC}}$. It is immediate that these conditions hold if $\phi \in (\frac{\bar{V}}{8}, \frac{\bar{V}}{8} + 2)$. A paid content strategy is optimal if $\pi^*_{\text{PC}} \geq \pi^*_{\text{SC}}$ and $\pi^*_{\text{PC}} \geq \pi^*_{\text{FC}}$. These conditions hold if $\phi \leq \frac{\bar{V}}{8}$. A free content strategy is optimal if $\pi^*_{\text{FC}} \geq \pi^*_{\text{SC}}$ and $\pi^*_{\text{FC}} \geq \pi^*_{\text{PC}}$. These conditions hold if $\phi \geq \frac{\bar{V}}{8} + 2$. □

Proof of Lemma 3. (a) In order to calculate $\mathbb{E}\left[\tilde{v}_0(n)\right]$ when $\bar{v}_0 < \bar{V}$, we first derive the distribution of $\tilde{v}_0(n) = \max\{\bar{v}_0, V_1, \ldots, V_n\}$. Before doing so, we state a preliminary fact: Let $M = \max\{V_1, \ldots, V_n\}$. Then, the distribution function of M is given by:

$$\begin{aligned} F_M(t) &\equiv \Pr\{\max\{V_1, \ldots, V_n\} \leq t\} \\ &= \Pr\left\{\{V_1 \leq t\} \cap \ldots \cap \{V_n \leq t\}\right\} \\ &= \prod_{i=1}^{n} \Pr\left\{V_i \leq t\right\} = \left(\frac{t}{\bar{V}}\right)^n . \end{aligned} \tag{A.5}$$

As an immediate implication, the density function of M is given by

$$f_M(t) = \frac{nt^{n-1}}{\bar{V}^n}. \tag{A.6}$$

Next we derive the density function of $\tilde{v}_0(n)$. By definition, $\tilde{v}_0(n)$ cannot be smaller than $\bar{v}_0$. Therefore, $\tilde{v}_0(n) = \bar{v}_0$ if and only if $\max\{V_1, \ldots, V_n\} \leq \bar{v}_0$. The probability of this event follows from (A.5) and it is given by

$$F_M\left(\bar{v}_0\right) = \left(\frac{\bar{v}_0}{\bar{V}}\right)^n .$$

For $\tilde{v}_0(n) > \bar{v}_0$, let $\tilde{F}(\cdot)$ denote the truncated distribution function of $\tilde{v}_0(n)$. After removing the lower part of the distribution, we have $\tilde{F}(t) = F_M\left(t\right) - F_M\left(\bar{v}_0\right)$ for $t \in [\bar{v}_0, \bar{V}]$. This implies $\tilde{f}(t) = f_M\left(t\right)$ for $t \in [\bar{v}_0, \bar{V}]$, and hence

$$\tilde{f}(t) = \frac{nt^{n-1}}{\bar{V}^n}, \quad \text{if} \quad \bar{v}_0 \leq t \leq \bar{V}$$

by (A.6). The distribution of $\tilde{v}_0(n)$ has a mixed structure with

$$\Pr\left\{\tilde{v}_0(n) = \bar{v}_0\right\} = \left(\frac{\bar{v}_0}{\bar{V}}\right)^n \tag{A.7}$$

and density

$$\tilde{f}(t) = \frac{nt^{n-1}}{\bar{V}^n}, \quad \text{if} \quad \bar{v}_0 \leq t \leq \bar{V}. \tag{A.8}$$

The expectation of this mixed distribution is given by

$$\begin{aligned} \mathbb{E}\left[\tilde{v}_0(n)\right] &= \bar{v}_0\left(\frac{\bar{v}_0}{\bar{V}}\right)^n + \int_{\bar{v}_0}^{\bar{V}} \frac{nt^n}{\bar{V}}dt \\ &= \frac{\bar{v}_0^{n+1} + n\bar{V}^{n+1}}{(n+1)\bar{V}^n}. \end{aligned}$$

Substituting this expression into (10) produces (11). (b) If $\bar{v}_0 \geq \bar{V}$, then $\tilde{v}_0(n)$ is equal to $\bar{v}_0$, which in turn implies that $\mathbb{E}\left[\tilde{v}_0(n)\right] = \bar{v}_0$. Substituting this expression into (10) yields (12). □

Proof of Lemma 4. If $\bar{v}_0 < \bar{V}$, the quality gap can be expressed as

$$\tilde{V}(n) - \frac{\bar{V}}{2} = \frac{\bar{v}_0^{n+1}(\alpha+n) - \bar{V}^{n+1}(\alpha-1)}{2(\alpha+n-1)(n+1)\bar{V}^n}. \tag{A.9}$$

Clearly, the sign of the quality gap depends only on the sign of numerator (A.9). The latter can easily be rearranged to obtain (15). If $\bar{v}_0 \geq \bar{V}$, the quality gap can be written as

$$\tilde{V}(n) - \frac{\bar{V}}{2} = \frac{(\alpha+n)\left(\bar{v}_0 - \bar{V}\right) + \bar{V}}{2(\alpha+n-1)},$$

which is strictly positive by our assumptions. □

Proof of Lemma 5. Differentiating (16) with respect to n yields

$$\frac{\partial D^{\text{E}}(p,n)}{\partial n} = \frac{\Big((N-n)\tilde{V}(n)' - \tilde{V}(n)\Big)\,p}{\Big((N-n)\tilde{V}(n)\Big)^2}.$$

Clearly, sampling is demand-enhancing if $(N-n)\tilde{V}'(n) - \tilde{V}(n) > 0$, which can be rearranged as $\frac{\tilde{V}'(n)n}{\tilde{V}(n)} > \frac{n}{N-n}$. □

Proof of Lemma 6. The optimal price under a paid content strategy follows from Lemma 1 by replacing $\bar{V}$ with the prior expectation $\frac{\alpha\bar{v}_0}{\alpha-1}$. It is then easy to derive expected profits $\pi^*_{\text{PC}} = \frac{N}{4}\frac{\alpha\bar{v}_0}{2(\alpha-1)}$. The profit under a free content strategy is given by $\pi^*_{\text{FC}} = (\phi-1)N$. Comparing the two profit levels immediately yields the result. □

Proof of Proposition 3. If the reduced-form profit function $\pi^{\text{E}}(n)$ in (17) is strictly concave, the optimal sample size n^* satisfies at an interior solution the first-order condition

$$(N-n^*)\frac{\tilde{V}'(n^*)}{4} - \frac{\tilde{V}(n^*)}{4} + \phi - \frac{2n^*}{N} = 0.$$

For a corner solution involving $n^* = 0$, the Kuhn-Tucker conditions imply

$$\frac{N\tilde{V}'(0)}{4} - \frac{\tilde{V}(0)}{4} + \phi \leq 0 \quad \Longleftrightarrow \quad \phi \leq \underline{\phi}.$$

At the other extreme, when $n^* = N$, the Kuhn-Tucker conditions hold that

$$-\frac{\tilde{V}(N)}{4} + \phi - 2 \geq 0 \quad \Longleftrightarrow \quad \phi \geq \overline{\phi}.$$ □

Proof of Lemma 7. Using the definition of $\tilde{V}(n)$ in (14), the lower bound can be expressed in terms of the underlying model parameters as

$$\underline{\phi} = \frac{(2\alpha(\alpha-1)+N)\,\bar{v}_0}{16(\alpha-1)^2}.$$

Setting $\bar{v}_0 = \bar{V}$ and letting $\alpha \to \infty$ immediately yields that $\underline{\phi} \to \frac{\bar{V}}{8}$. Likewise, we obtain

$$\overline{\phi} = \frac{(\alpha+N)\,\bar{V}}{8(\alpha+N-1)} + 2.$$

Letting $\alpha \to \infty$, we obtain $\overline{\phi} \to \frac{\bar{V}}{8} + 2$. $\square$