Optimal Sampling of Paid Content*

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Abstract

This paper analyzes optimal sampling and pricing of paid content for publishers of news websites. Publishers offer free content samples both to disclose journalistic quality to consumers and to generate online advertising revenues. We examine sampling where the publisher sets the number of free sample articles and consumers select the articles of their choice. Consumers learn from the free samples in a Bayesian fashion and base their subscription decisions on posterior quality expectations. We show that sampling enhances subscription demand only if consumers have low quality expectations in relation to actual quality. Taking advertising and subscription revenues into account, we find that the publisher should employ either a paid-only or a free content strategy when consumers have high quality expectations. When consumers have low quality expectations, employing a sampling strategy may be optimal for the publisher.

Keywords: Sampling, Pricing, Product Quality, Bayesian Learning, News Websites

JEL Classification: L11, L15, L21, M21, M30

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1 Introduction

Sampling paid content is a business model where publishers offer some of their content for free and charge readers to access content behind the "paywall." For instance, the *New York Times* offers access to 20 articles for free on its website each month and asks visitors to become digital subscribers if they would like to read more (*New York Times*, 2011).[1] *The Daily*, a subscription based digital news publication created for *Apple*'s *iPad*, offers 14 issues for free.[2] Likewise, both the *Financial Times* and *The Wall Street Journal* have a paywall on their website giving access to limited free content. Offering samples of paid content allows publishers to generate revenues from online advertising in addition to revenues from digital subscriptions. Sampling paid content as a business model has recently become popular in the news industry after steep cutbacks in online advertising. However, to our knowledge, the implications of this business model for digital content providers have not been formally addressed. This paper addresses this issue and studies profit-maximizing sampling and pricing in online news industries. Specifically, we study the two interrelated questions of how many articles the publisher should offer for free and how much the publisher should charge for the content behind the paywall.

Sampling paid content currently has seen a renaissance in the news industry. The *New York Times* had offered *TimesSelect*, an online subscription program giving access to the work of columnists and to the newspaper's archives, from 2005 to 2007 (*New York Times*, 2007). The publisher decided to abandon its digital subscription program because the projections for growth from subscriptions were low compared to the growth from online advertising. For a similar reason *CNN*'s subscription-based breaking news service *CNN Pipeline* was replaced by a free advertising-supported service in June 2007, only a year and a half after its introduction.[3]

Although publishers have several reasons to introduce digital subscription programs with paywalls, three are of particular relevance. First, paywalls allow publishers to generate revenues from digital subscriptions which are necessary to sustain quality journalism. Purely advertising based business models did not generate enough revenues for publishers to cover expensive forms of newsgathering such as international coverage and investigative reporting (Abramson 2011). Arthur Sulzberger, Publisher of the *New York Times*, explained in a letter to the readers reasons why *The Times* introduced digital subscriptions in

[1] Visitors are offered one of three subscription plans: $15 a month for unlimited visits online and access to *The Times*'s various apps for smartphones; $20 a month for *The Times* online and its app on *Apple*'s *iPad*; and for $35 a month, an "All Digital Access" package.

[2] See http://www.thedaily.com.

[3] See http://en.wikipedia.org/wiki/CNN_Pipeline.

the end of March 2011: "It will allow us to develop new sources of revenue and to strengthen our ability to continue our journalistic mission as well as to undertake digital innovations that will enable us to provide you with high-quality journalism" (*New York Times*, 2011). Second, offering free sample articles allows publishers to generate online advertising revenues from online visitors. According to *comScore*, between a third and a half of all traffic to five major U.S. newspaper sites comes from search engines (*CBS Interactive Business Network*, 2010). The study emphasizes the reliance that the big newspapers have on *Yahoo*, *Google* and *Microsoft* to drive their online revenue models. Third, offering free sample articles allows publishers to disclose the "journalistic quality" of their news website to online visitors. This information transmission to potential subscribers affects their willingness to pay and may enhance the demand for digital subscriptions. The use of free samples as advertisements for the content behind the paywall can be viewed as a form of "the old marketing tactic offering free samples of consumer products, but updated for the digital age" (Shapiro and Varian 1998, p. 86).

Our paper seeks to shed light on the business model of sampling paid content taking the aforementioned three reasons into account. In particular, we are interested in characterizing the profit-maximizing sampling and pricing decisions of publishers employing digital subscription programs with paywalls when consumers are uncertain about journalistic quality. In doing so, we develop a model for news websites with the following main features:

- *Paid Content:* Publishers sell digital subscriptions and generate revenues from subscription fees as well as from advertisements included in the paid content.
- *Free Content:* Publishers offer free sample articles and thereby generate revenues from advertisements shown to online visitors.
- *Quality Disclosure:* Publishers also offer free content samples to disclose the journalistic quality of their product offering to online visitors which can induce paid digital subscriptions.

Besides these main features, our model assumes consumers update their prior beliefs about quality in a Bayesian fashion taking the observed sample qualities into account. The updating of prior beliefs is not only relevant for recently launched news publications such as *The Daily*, but also for well-established news publications such as the *New York Times*. Even if the prior for *The Times* is less "diffuse," sampling nonetheless reduces uncertainty about quality. The posterior quality expectations then determine consumers' willingness to pay and hence their subscription decisions.

On the supply side, we consider a publisher operating in a two-sided market environment who receives revenues from both subscriptions and advertisements. Taking the consumers' quality updating into account, the publisher faces a fundamental tradeoff between an expansion effect (through learning) and a cannibalization effect (through free offerings) on subscription demand induced by sampling. In our setting, the publisher can choose among three possible strategies: a "sampling strategy," a "paid-only strategy," and a "free content strategy."

Distinctive of our approach to modeling sampling is that the publisher sets the number of free sample articles and consumers select the articles of their choice. This type of sampling is used, for example, by the *New York Times* and *Audible.com*, a distributor of digital audiobooks.[4] An alternative approach to sampling is where the firm chooses not only the number of free sample articles but also the sample content itself. 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. We leave this type to future research.

We derive the following three key results. First, we derive subscription demand based on consumers' posterior expectations about content quality and distinguish between the cases of high and low quality expectations in relation to actual quality. We show that offering free samples is always demand-reducing when consumers have high quality expectations. The reason is that sampling reduces quality expectations and thus has only a cannibalization effect and no expansion effect on demand. When consumers have low quality expectations, sampling has both a cannibalization and an expansion effect, and hence sampling may be demand-enhancing. Compared to high quality expectations, sampling may increase quality expectations, and hence subscription demand. We show that sampling is demand-enhancing when the cannibalization effect is small compared to the expansion effect.

Second, we examine how the publisher's optimal sampling and pricing decisions are related. We show that the subscription price and the number of free samples are negatively related when consumers have high quality expectations. This is a consequence of the reduction in consumers' willingness to pay that stems from lower posterior expectations. When consumers have low quality expectations, there is a negative relation between the subscription price and the number of free samples if sampling is demand-reducing and a positive relation if sampling is demand-enhancing. When sampling is demand-reducing,

[4]Classic examples of this type of sampling include many "clubs" such as *Columbia House* by the Columbia Records division of *CBS* where, as an inducement to join, individuals are offered a number of free records.

the publisher can mitigate the negative effect on profits from a lower subscription demand by charging a lower price. However, when sampling is demand-enhancing, it is optimal for the publisher to set a higher subscription price.

Third, we derive how the publisher's optimal strategy is linked to consumers' prior expectations. When consumers have high quality expectations, we show that the publisher should never employ a sampling strategy. Whether the publisher employs a paid-only strategy or a free content strategy depends on the advertising revenues. We find that the firm should employ a free content strategy when online advertising revenues from the samples are high and a paid-only strategy when online advertising revenues from the samples are low. When consumers have low quality expectations, employing a sampling strategy may be optimal for the publisher. We illustrate this by analyzing profit-maximizing pricing and sampling decisions and find that the publisher should offer more articles for free when consumers have lower quality expectations and when online advertising revenues are higher.

Our paper is related to two literature streams. The first is the literature on two-sided markets. Several studies focus on business models for media firms operating in two-sided markets, and in particular, on how competition influences the choice of content financing.[5] For instance, Kind et al. (2009) analyze how competition, captured by the number of media platforms and content differentiation between platforms, affects the decision of whether to raise revenues from advertisers or consumer payments. Godes et al. (2009) investigate a similar question, but focus on competition between platforms in different media industries. However, the literature on two-sided markets has not addressed the profit impact from providing free content samples on publishers. The paper by Xiang and Soberman (2011) makes a step in this direction and analyzes preview provision for media firms through the front page. To the best of our knowledge, optimal content sampling—especially its impact on revenues from subscription and online advertising—has not been addressed.

Second, this paper is related to the broad literature on consumer learning about product attributes. Firms 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 commonly used way for firms to disclose information is through sampling. The distinctive feature of product

[5] Anderson and Gabszewicz (2006) focus on the case of television. See, for instance, Rochet and Tirole (2004), Armstrong (2006), and Rysman (2009) for a broader perspective on two-sided markets.

samples is that they allow consumers to have an actual experience with the good before purchase.[6] 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 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 can only offer a portion of the good for free to avoid the "information paradox" (Akerlof, 1970).[7] 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 marketing literature, for instance, by Erdem and Keane (1996), Ackerberg (2003), and Erdem et al. (2008).

We organize the remainder of the paper as follows. Section 2 presents the model. Section 3 derives consumer demand and introduces the strategies available to the publisher. Section 4 presents the analysis of optimal behavior and Section 5 illustrates the publisher's optimal strategy. Conclusions and directions for future research are offered in Section 6. To facilitate the exposition, all proofs have been relegated to the Appendix.

2 Model

This section introduces the model. We begin with the publisher, then move on to consumers, and finally consider the sequencing of the decisions.

2.1 Publisher

A publisher produces N articles $(N \in \mathbb{N})$ and offers them through a news website to potential readers. Producing the content involves fixed costs $F \geq 0$.[8] The marginal costs of producing content are typically negligible and are therefore set to zero. Article quality summarizes various quality attributes and may be interpreted as "journalistic quality." We assume that article qualities are uniformly distributed on the quality spectrum $[0, \bar{V}]$, which extends from the low-

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

[7] 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).

[8] We assume that the fixed cost do not exceed the (equilibrium) profit. Hence they do not change the analysis and can therefore be omitted.

est quality (normalized to zero) to the highest quality ($\bar{V} > 0$). The publisher has private information about $\bar{V}$ and allows consumers to download a free content sample at zero cost. Specifically, the publisher allows consumers to choose n articles ($n \in \mathbb{N}_0$) with qualities $V_1, \ldots, V_n$ to download for free (for a prominent example of this practice, see *www.nytimes.com*). In such an environment, the publisher has no control over which articles the consumers read for free.

Besides subscription revenues, the publisher also receives advertising revenues from selling online advertising space to advertisers. We assume that there are two sources of advertising revenues: from offering free content and from selling paid content. Specifically, the publisher generates advertising revenue a_f (the price per impression) from each free sample article and average advertising revenues a_p from each digital subscriber.[9] We assume that the average advertising revenues reflect the ongoing competitive market prices for ad impressions and hence that both a_f and a_p are exogenous to the publisher. Since we are not interested in the advertising market per se, but only on its impact on sampling, it is reasonable to assume that the demand for advertising is perfectly elastic (Spence and Owen, 1977).

The publisher's decision variables are the subscription price p and the number of articles n offered to consumers for free. The publisher can adopt one of the following three strategies: a "sampling strategy," a "paid-only strategy," or a "free content strategy." In a sampling strategy $0 < n < N$ and $p > 0$, in a paid-only strategy $n = N$ and $p > 0$, and in a free content strategy $n = 0$ and subscription is not an option.

2.2 Consumers

We consider a market with a unit measure of consumers who are uncertain about the journalistic quality of the content. Specifically, consumer uncertainty is due to not knowing the upper bound of the publisher's quality spectrum $\bar{V}$.[10] Consumers have a common prior belief about $\bar{V}$ which they update in a Bayesian fashion. The consumers' prior belief 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). Thus we capture the uncertainty about $\bar{V}$ by a prior belief $\bar{v}_{\text{prior}}$ that follows a Pareto distribution with parameters $\bar{v}_0 > 0$ and $\alpha > 1$.[11] In contrast to $\bar{V}$, the parameters of the prior

[9] Implicit in our formulation of per-subscriber advertising revenues a_p is that readers' eyeballs are limited to a certain number of impressions.

[10] Note that the upper bound $\bar{V}$ is monotonically related to the mean, which may be more intuitive for consumers to think about.

[11] The restriction $\alpha > 1$ ensures that the expectation of the prior distribution exists.

belief are common knowledge.[12] The (Pareto) probability density function of $\bar{v}_{\text{prior}}$ is given by

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

and illustrated in Figure 1. Intuitively, consumers have a prior belief about the lower bound of the highest quality $\bar{V}$ (captured by $\bar{v}_0$) and the dispersion of bounds above this level (captured by the shape parameter α). Given the consumers' prior knowledge about $\bar{v}_0$ and α, their prior expectation about $\bar{V}$ is

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

The prior belief about $\bar{V}$ is updated taking the observed qualities of the free samples into account. Specifically, consumers evaluate the n sample qualities $V_i = v_i$ ($i = 1, \dots, n$) to form the posterior belief $\tilde{v}_{\text{post}}(n)$ about $\bar{V}$. Using standard Bayesian analysis, $\tilde{v}_{\text{post}}(n)$ follows a Pareto distribution with minimal possible value $\tilde{v}_0(n) = \max\{\bar{v}_0, v_1, \dots, v_n\}$ and shape parameter $\alpha + n$.[13] The posterior expectation of $\bar{V}$ is given by

$$\mathbb{E}[\bar{V}|\tilde{v}_0(n), \alpha] = \frac{(\alpha + n)\tilde{v}_0(n)}{\alpha + n - 1}. \tag{2}$$

Consumers infer expected content quality $\mathbb{E}[V|v_1, \dots, v_n]$ from posterior beliefs and knowing that qualities V are uniformly distributed on the quality spectrum offered. We therefore have that

$$\mathbb{E}[V|v_1, \dots, v_n] = \frac{\mathbb{E}[\bar{V}|\tilde{v}_0(n), \alpha]}{2}. \tag{3}$$

We assume that consumers are heterogenous in their valuations for quality.[14] The heterogeneity is captured by θ which is uniformly distributed on the interval [0,1]. We further assume that consumers have unit demand for the paid content and thus have two options. Each consumer can either subscribe to the news website and buy the N articles at price p or access only the n free articles. A consumer's indirect utility $\tilde{V}(p, y; n)$ from these two options is given by

$$\tilde{V}(p, y; n) = \begin{cases} N\theta\,\mathbb{E}[V|v_1, \dots, v_n] + y - p & \text{if she subscribes at price } p \\ n\theta\,\mathbb{E}[V|v_1, \dots, v_n] + y & \text{if she stays with the free articles,} \end{cases}$$

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

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

[14] This assumption is borrowed from the literature on vertical product differentiation (see, for instance, Mussa and Rosen, 1978; Gabszewicz and Thisse, 1979; Shaked and Sutton, 1982).

where y denotes (real) income. This specification assumes that readers are neutral about ads, that is, they neither find advertisements a nuisance nor do they appreciate them.[15] In effect, this means they can skip over them (or mechanically screen them out) at essentially zero cost.

2.3 Timing

The publisher first decides on both its digital subscription price p and the number of free sample articles n. Next, consumers observe a realization of sample qualities $V_1 = v_1, \ldots, V_n = v_n$ and update their beliefs about the highest quality $\bar{V}$. Finally, consumers decide whether to subscribe or to stay with the free samples.

3 Consumer Demand

In this section, we derive consumer demand for each strategy available to the publisher. We start with the demand for the sampling strategy and follow this by characterizing demands for the two boundary strategies, paid-only and free content, respectively. Note that, if free samples have been offered, at this stage consumers have already observed the sample qualities of the free articles and updated their prior believes about the journalistic quality.

3.1 Sampling Strategy

When the publisher employs a sampling strategy, consumers decide whether or not to subscribe after observing qualities $v_1, \ldots, v_n$ (where $0 < n < N$). A consumer will subscribe to the news website if and only if her indirect utility from a digital subscription exceeds her indirect utility from consuming only the free content. Therefore, if $(N-n)\theta\,\mathbb{E}[V|v_1,\ldots,v_n] - p \geq 0$, the consumer will subscribe. This condition has the interpretation that the expected utility from the content behind the paywall must exceed the subscription price. Using (2) and (3) and recalling that θ follows a uniform distribution on $[0,1]$, consumer demand for paid content can be expressed as

$$\begin{aligned} D(p,n) &= \Pr\left\{\theta \geq \frac{p}{(N-n)\,\mathbb{E}[V|v_1,\ldots,v_n]}\right\} \\ &= \max\left\{0, 1 - \frac{2(\alpha+n-1)}{(N-n)(\alpha+n)}\frac{p}{\tilde{v}_0(n)}\right\}. \end{aligned} \tag{4}$$

[15] Implications of ad-loving and ad-avoiding behavior are, for instance, analyzed in Gabszewicz et al. (2005).

Table 1: Summary of strategies.

	Decision variables		
Available strategies	Free samples	Price	Subscriptions
Sampling strategy	$0 < n < N$	$p(n)$	$D^{\mathrm{E}}(p(n), n)$
Paid-only strategy	$n = 0$	$p(0)$	$D(p(0), 0)$
Free content strategy	$n = N$	n.a.	0

Notes: $D^{\mathrm{E}}(p(n), n)$ denotes the (expected) subscription demand, and $p(n)$ is the publisher optimal price given its sampling decision.

Clearly, demand decreases with price p. If $p = 0$, all consumer subscribe and if p exceeds a specified threshold level, there is no subscription demand. Demand for the paid content has the desirable property that it is increasing in the consumers' posterior expectations about content quality.

3.2 Paid-Only Strategy

When the publisher employs the paid-only strategy ($n = 0$), the prior and the posterior expectations about $\bar{V}$ coincide (and hence $\tilde{v}_0 = \bar{v}_0$) as there is no learning through sampling. Therefore, setting $n = 0$ in (4), the consumer demand for paid content is given by

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

3.3 Free Content Strategy

When the publisher employs a free content strategy ($n = N$), consumers never subscribe as they get access to the content for free. Thus, there is a zero subscription demand.

3.4 Summing Up

Table 1 summarizes the strategies available to the publisher. If the publisher offers free samples, she employs a sampling strategy; if she does not offer free samples, she uses a paid-only strategy; and if she offers the content for free, she employs a free content strategy. The publisher's pricing decision depends on its sampling decision, as captured by the notation $p(n)$. The next section analyzes optimal behavior of the publisher and gives conditions under which each strategy will be optimal.

4 Analysis

We start with analyzing the expected subscription demand under a sampling strategy and follow with the analysis of the publisher's decisions considering both digital subscriptions and advertising revenues from free and paid content.

4.1 Subscription Demand

Consumer demand for paid content in (4) is based on prior beliefs, taking the quality of the sample articles into account. However, when the publisher makes decisions about the price and the number of sample articles, she has to base them on expected demand as consumers have not yet evaluated sample qualities and updated their beliefs. Taking expectation of the consumer demand produces the (expected) subscription demand

$$D^{\mathrm{E}}(p,n) = \max\left\{0, 1 - \frac{2(\alpha+n-1)}{(N-n)(\alpha+n)}\frac{p}{\mathbb{E}\left[\tilde{v}_0(n)\right]}\right\}. \tag{5}$$

Offering a larger number of free samples has two effects on expected subscription demand. Following Bawa and Shoemaker (2004), we label the two effects, respectively, the "cannibalization effect" and the (expected) "expansion effect." To capture these effects, we define

$$c(n) \equiv \frac{2(\alpha+n-1)}{(N-n)(\alpha+n)} \quad \text{and} \quad e(n) \equiv \frac{1}{\mathbb{E}\left[\tilde{v}_0(n)\right]}.$$

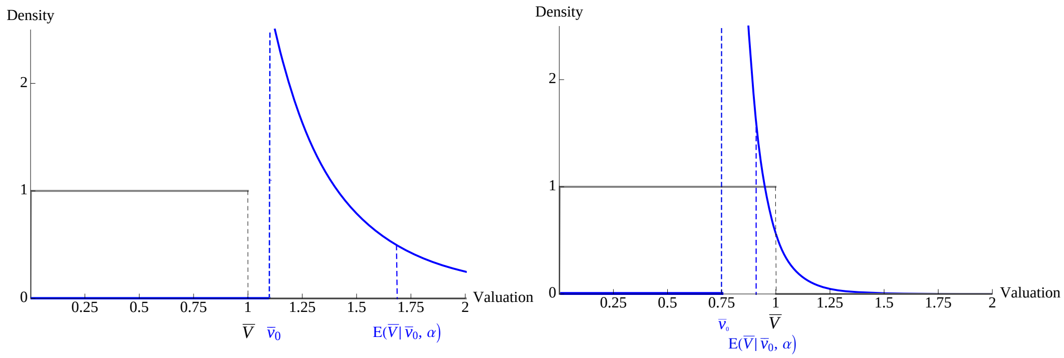
This allows us to express the subscription demand in (5) more compactly as $D^{\mathrm{E}}(p,n) = \max\{0, 1 - c(n)e(n)p\}$. The cannibalization effect of sampling, defined by $c'(n)$, is always positive.[16] It captures the reduction of the expected subscription demand that results from offering more free articles. Intuitively, an increase in the number of free samples decreases the value a consumer obtains from the content behind the paywall. The expansion effect is defined by $e'(n)$. It captures consumers' learning about the highest quality $\bar{V}$ through sampling.

The expansion effect plays a role if and only if offering free samples results in an upward revision of the prior on the lower bound on the highest quality $\bar{v}_0$. Whether or not sampling leads to such a revision depends on the relative

[16] Using the definition of $c(n)$ in equation (5), we find that

$$c'(n) = \frac{2\left[N + n^2 + 2n(\alpha-1) + \alpha(\alpha-1)\right]}{(N-n)^2(\alpha+n)^2},$$

which is positive as $\alpha > 1$ by assumption.



(1a) $\bar{v}_0 = 1.10$ and $\alpha = 3$ (1b) $\bar{v}_0 = 0.75$ and $\alpha = 10$

Figure 1: Different prior expectations about $\bar{V}$ (the figure uses the normalization $\bar{V} \equiv 1$). Actual qualities are distributed uniformly on $[0, \bar{V}]$.

magnitudes of $\bar{v}_0$ and $\bar{V}$. We distinguish the two cases of "high quality expectations" ($\bar{v}_0 \geq \bar{V}$) and "low quality expectations" ($\bar{v}_0 < \bar{V}$). In the case of high quality expectations, there is no revision in the lower bound for the highest quality. That is, $\tilde{v}_0(n) = \bar{v}_0$ irrespective of how many articles are sampled for free (for a graphical illustration, see Figure 1, Panel a). Hence, offering free samples does not have an expansion effect and therefore $e'(n) = 0$. However, sampling may have a demand-enhancing effect in the low-quality expectations case. That happens when one of the sampled qualities exceeds $\bar{v}_0$ (this possibility is illustrated in Figure 1, Panel b). Hence, in this case $e'(n) \leq 0$ (with strict inequality if $\tilde{v}_0(n) > \bar{v}_0$). Clearly, the expansion effect is more likely to kick in when consumers have low expectations about $\bar{v}_0$ relative to $\bar{V}$.[17] This discussion leads to the following lemma:

Lemma 1. *If the publisher employs a sampling strategy, then increasing the number of free samples has two effects on subscription demand; a "cannibalization effect" which reduces the subscription demand as $c'(n) > 0$, and an "expansion effect" which may increase the subscription demand as $e'(n) \leq 0$.*

The challenge in calculating the expansion effect $e'(n)$ analytically is to derive an expression for $e(n) = \mathbb{E}\left[1/\tilde{v}_0(n)\right]$ in (5), thereby taking into account the consumers' preferences and their Bayesian updating. The following proposition presents the subscription demands along with analytical expressions for $e(n)$ arising in the two cases; the subscripts H and L refer, respectively, to high and low quality expectations.

[17]The restriction $\bar{v}_0 < \bar{V}$ does not imply that the prior expectation is smaller than $\bar{V}$: Whether or not this happens to be the case depends on the prior of the shape parameter α.

Proposition 1. *When the publisher offers a random content sample that consists of $n \geq 1$ articles with qualities $V_1, \ldots, V_n$ and subscription at a price of p, then*

(a) if $\bar{v}_0 \geq \bar{V}$ (high quality expectations), the subscription demand is given by

$$D_H^E(p,n) = \max\left\{0, 1 - \frac{c(n)p}{\bar{v}_0}\right\}.$$

(b) if $\bar{v}_0 < \bar{V}$ (low quality expectations), the subscription demand for $n = 1$ is given by

$$D_L^E(p,1) = \max\left\{0, 1 - \frac{c(1)\left[1 + \ln\left(\bar{V}/\bar{v}_0\right)\right]p}{\bar{V}}\right\},$$

and for $n > 1$ it is given by

$$D_L^E(p,n) = \max\left\{0, 1 - \frac{c(n)\left(n\bar{V}^{n-1} - \bar{v}_0^{n-1}\right)p}{(n-1)\bar{V}^n}\right\}.$$

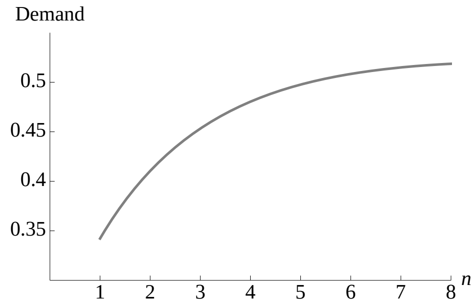
This proposition allows us to derive the expansion effect analytically. For the case of high quality expectations, we have that $e'(n) = 0$ and hence sampling has only a cannibalization effect. Therefore, subscription demand $D_H^{\mathrm{E}}(p,n)$ is unambiguously decreasing in the sample size n. For the case of low quality expectations, Proposition 1 implies that the expansion effect is strictly negative for $n > 1$. More precisely, we have

Corollary 1. *For $n > 1$ and when $\bar{v}_0 \leq \bar{V}$, the expansion effect is negative, that is, $e'(n) < 0$.*

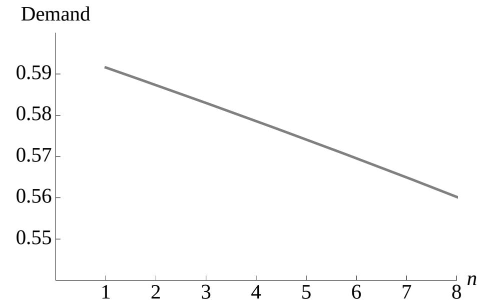
Proposition 1 also allows us to investigate the tension between the cannibalization effect and the expansion effect on more detail. To this end, it is useful to define the elasticities of the slope components $c(n)$ and $e(n)$ as $\epsilon_c(n) \equiv c'(n)n/c(n)$ and $\epsilon_e(n) \equiv -e'(n)n/e(n)$, respectively. The next result shows that the two elasticities determine the effect of sampling on subscription demand.

Corollary 2. *For $n > 1$ and $\bar{v}_0 \leq \bar{V}$, sampling increases subscription demand if and only if $\epsilon_c(n) < \epsilon_e(n)$ and decreases the subscription demand if and only if $\epsilon_c(n) > \epsilon_e(n)$.*

The result shows that sampling is demand-enhancing if the cannibalization is relatively small when compared to the expansion effect. For instance, a large expansion effect can be expected when consumers have a low prior expectation about $\bar{V}$. Clearly, whether or not sampling is demand-enhancing depends on all other model parameters as well. Figure 2 illustrates the two cases: Panel (a) demonstrates a case where the subscription demand is increasing in n while Panel (b) demonstrates one where it is decreasing in n.



(2a) Demand-enhancing sampling



(2b) Demand-reducing sampling

Figure 2: Sampling effects for different values of $\bar{v}_0$ on subscription demand ($\bar{v}_0 = 0.5$ in Panel a; and $\bar{v}_0 = 0.95$ in Panel b), when $\alpha = 25$, $\bar{V} = 1$, $N = 100$, and $p = 20$.

We conclude this section by noting the comparative statics effects of the consumers' prior parameters. From Proposition 1, subscription demand is increasing in expected quality measured by $\bar{v}_0$ and decreasing in the degree of prior uncertainty about $\bar{v}_0$ measured by α. Therefore, subscription demand has the intuitive property that it is increasing in the consumers' prior expectations about content quality. The effect of α can be grasped intuitively by observing that a higher α reduces the posterior expectations (for a given $\bar{v}_0$) and therefore subscription demand.

4.2 Optimal Decisions

The publisher makes two decisions: How many articles n to sample for free and the subscription price p. For expositional convenience, we assume that the publisher makes the sampling decision before the pricing decision.[18] The optimal strategy of the publisher then follows from comparing the profit levels that arise from the three strategies. We start with analyzing the sampling strategy.

Sampling Strategy. Indexing the profit function with S for "sampling," the publisher's (expected) profits are given by

$$\pi_S(p, n) = (p + a_p)D^{\mathrm{E}}(p, n) + a_f n. \tag{6}$$

The profits are the sum of subscription revenues and direct advertising revenues generated from sampling. Subscription revenues stem from two sources:

[18]The solution to the problem is the same when n and p are chosen simultaneously as the decisions do not have external effects.

$pD^{\mathrm{E}}(p,n)$ from subscription fees and $a_p D^{\mathrm{E}}(p,n)$ from including ads in the paid version. The advertising revenues from sampling are given by $a_f n$.

To study optimal pricing given a sampling decision, we derive the first-order condition of the profit function with respect to p. This yields

$$\frac{\partial \pi_S}{\partial p}(p,n) = D^{\mathrm{E}}(p,n) + (p + a_p)\frac{\partial D^{\mathrm{E}}}{\partial p}(p,n) = 0.$$

From the first-order condition we find the optimal (best-response) price

$$p(n) = \frac{1}{2}\left(\frac{1}{c(n)e(n)} - a_p\right). \tag{7}$$

Inspection of the best-response function shows that the publisher should set a lower subscription price when the per-subscriber ad revenues a_p are higher. Moreover, the best-response function reveals that ad revenues from sampling do not affect the choice of the optimal price, a consequence of advertising revenues being fixed for a given n. However, it should be clear that a_f is an important determinant of the profit level. Our next results shows how the best-response price varies with the number of free samples.

Proposition 2. *(a) If $\bar{v}_0 \geq \bar{V}$, the optimal price decreases with n. (b) If $\bar{v}_0 \leq \bar{V}$ and sampling is demand-reducing, the optimal subscription price decreases with n, and (c) if sampling is demand-enhancing, the optimal subscription price increases with n.*

Whether sampling leads to a lower or a higher subscription price depends on the relative magnitudes of the cannibalization effect and the expansion effect. For high expectations, optimal subscription prices are lower when the number of free samples is larger. This reflects the reduction of the consumers' willingness to pay for the content behind the paywall. For low expectations, the publisher can mitigate the profit impact from the reduction in subscription demand that stems from demand-reducing sampling by lowering its price. In contrast, if sampling is demand-enhancing, it is optimal for the publisher to increase its price when she offers more free samples.

The next step is to study the optimal sampling decision. In order to find the optimal sample size, we substitute $p(n)$ back into the profit function to obtain the reduced-form profit function $\pi_S(n)$ and derive its first-order condition with respect to n. Suppressing the arguments of the demand function for convenience, the first-order condition is

$$\frac{d\pi_S(n)}{dn} = p'(n)D^{\mathrm{E}} + (p(n) + a_p)\left(\frac{\partial D^{\mathrm{E}}}{\partial p}p'(n) + \frac{\partial D^{\mathrm{E}}}{\partial n}\right) + a_f = 0. \tag{8}$$

Given the analytical complexity of the profit function, we have to rely on numerical methods to determine the optimal sampling and pricing decision. This approach involves four steps:[19] First, we determine the solution(s) to the first-order condition given in (8). Second, we compute a corresponding subscription price for each solution using the best-response function in (7). Third, we check for each candidate decision $(\tilde{p}, \tilde{n})$ whether it satisfies the sufficient conditions for a relative profit maximum. Fourth, and last, we determine the optimal integer solution n^*: This solution can be determined by rounding admissible values of $\tilde{n}$ down and up, calculating the corresponding prices, and comparing the two profit levels. The optimal pricing and sampling decision employing a sampling strategy then is the one that delivers the highest profits. For brevity, we denote this profit level by $\pi(n^*)$.

Paid-Only Strategy. When employing a paid-only strategy, the publisher's profits are obtained by maximizing $(p + a_p)D(p, 0)$ with respect to p. As a results, the publisher's optimized profits can be expressed as

$$\pi(0) = \frac{(2(\alpha - 1)a_p + \alpha N \bar{v}_0)^2}{8\alpha(\alpha - 1)N\bar{v}_0}.$$

Free Content Strategy. When employing a free content strategy, profits are simply given by the revenues from online advertising. Hence, the profit level is given by $\pi(N) = a_f N$.

Optimal Strategy. The publisher's overall optimal sampling decision is the one that yields the highest profit among the three different strategies. It is characterized by $\hat{n} \in \{0, n^*, N\}$ where $\pi(\hat{n}) > \pi(n)$ for all $n \neq \hat{n}$ in $\{0, n^*, N\}$. The corresponding optimal subscription price then is $\hat{p} = p(\hat{n})$. Thus, the publisher's optimal pricing and sampling strategy can compactly be written as $(\hat{p}, \hat{n})$.

5 Results

This section presents the optimal strategy of the publisher for the two cases of high and low quality expectations. In addition, we study how changes in the market environment affect the optimal pricing and sampling decisions.

5.1 High Quality Expectations

When consumers have high quality expectations, it turns out that it is never optimal for the publisher to employ a sampling strategy. As a consequence, the publisher will always employ one of its two boundary strategies. Whether a paid-only or a free content strategy yields higher profits depends on the comparison of the respective profit levels $\pi(0)$ and $\pi(N)$. Optimally, the publisher

[19]The full details of the numerical analysis are available from the authors upon request.

will employ a paid-only strategy if and only if $\pi(0) > \pi(N)$ and a free content strategy otherwise. This leads to the following result.

Proposition 3. *When $\bar{v}_0 \geq \bar{V}$, the publisher never employs a sampling strategy. The publisher uses a paid-only strategy if $a_f < \frac{(\alpha N \bar{v}_0 + 2(\alpha-1)a_p)^2}{8\alpha(\alpha-1)N^2\bar{v}_0}$ and a free content strategy if the inequality is reversed.*

There are several remarks in order. First, the publisher should implement a paid-only strategy when the price of online ad impressions a_f is low. Therefore, a sufficiently large increase in a_f induces a change from a paid-only strategy to a free content-strategy. It also shows that the publisher is more inclined to adopt a subscription strategy if a_p is high. Second, the larger the platform size N, the less likely it is that the publisher adopts a subscription strategy for a given structure of advertising revenues. Third, the effects of both prior parameters α and $\bar{v}_0$ on the threshold level are ambiguous. The threshold is increasing in $\bar{v}_0$ and decreasing in α for sufficiently high prior expectations. Intuitively, higher prior expectations go along with a higher subscription price, thereby increasing the profit of a paid-only strategy.

5.2 Low Quality Expectations

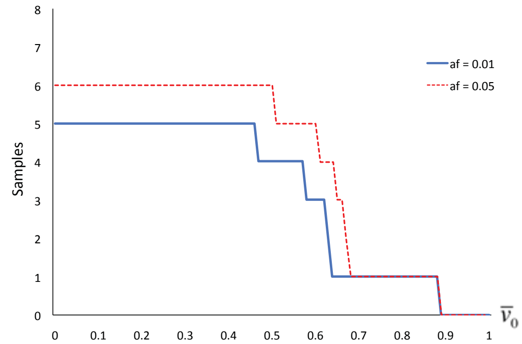
When consumers have low quality expectations, the sampling strategy may yield the highest profits. As a consequence, offering free samples may be optimal.

Proposition 4. *When $\bar{v}_0 < \bar{V}$, the publisher may employ a sampling strategy. In some market environments, the sampling strategy leads to higher profits than the paid-only strategy or the free content strategy.*

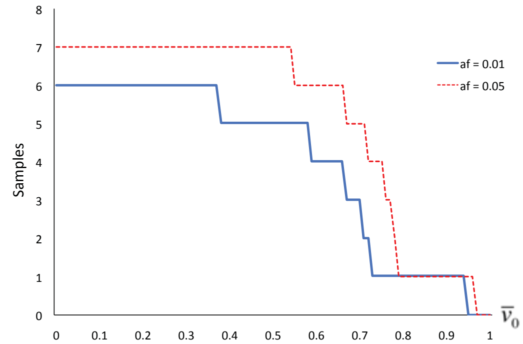
This result is illustrated in Figures 3 through 5 which portrays the numerical solutions of our model for various market environments, each resulting from a particular parameter constellation. For expositional convenience, we normalize the highest quality offered $\bar{V} \equiv 1$ and the per-subscriber advertising revenues $a_p \equiv 1$.[20]

Figure 3 shows that the publisher should offer free content samples in some market environments. More specifically, Panel (a) plots the optimal sampling strategy $\hat{n}$ as a function of $\bar{v}_0$ and reveals that sampling is indeed optimal when consumers have low quality expectations. In plotting $\hat{n}$, we treat all model parameters other than $\bar{v}_0$ as fixed. Figure 4 and Figure 5 plot, respectively, the corresponding optimal prices $\hat{p}$ and the profit levels $\pi(\hat{n})$.

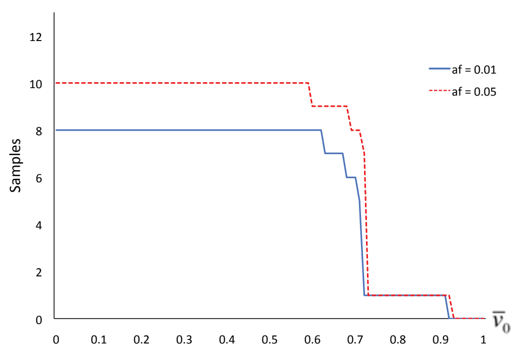
[20] Qualitatively, the choice of specific parameter values do not affect the figures.



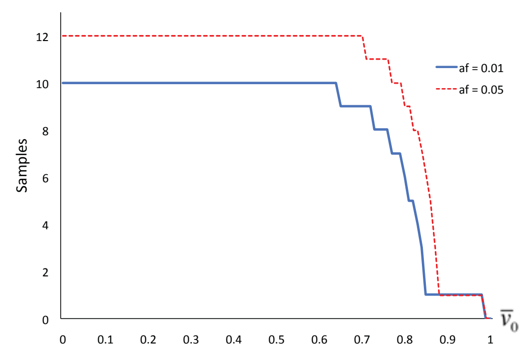
(3a) $N = 30$ and $\alpha = 5$



(3b) $N = 30$ and $\alpha = 25$



(3c) $N = 100$ and $\alpha = 5$

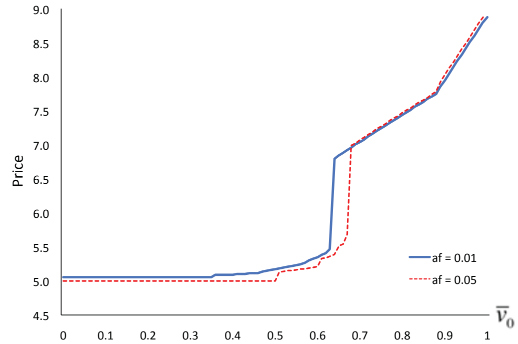


(3d) $N = 100$ and $\alpha = 25$

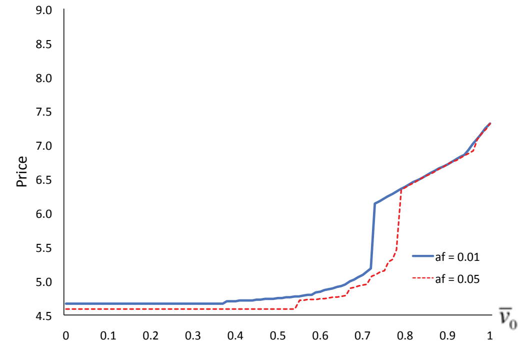
Figure 3: Optimal number of free samples $\hat{n}$ for low quality expectations.

Our graphical analysis illustrates that the optimal price $\hat{p}$ is decreasing in the number of free samples $\hat{n}$. This is perhaps best seen by observing that a higher value of $\bar{v}_0$ leads to a lower $\hat{n}$ (Figure 3) and a higher price $\hat{p}$ (Figure 4). The inverse relationship between the optimal number of free samples and the subscription price is implied by Proposition 2 as sampling is demand-reducing in most market environments for our parametrization. Nevertheless, sacrificing subscription demand by offering samples leads to higher profits (Figure 5).

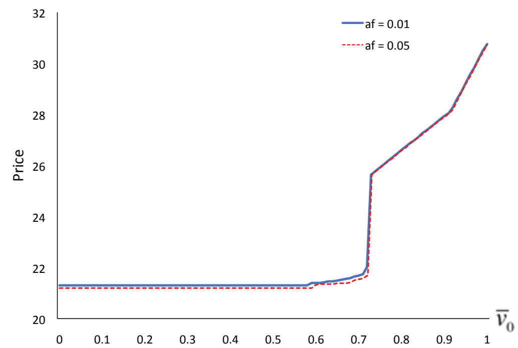
Our graphical analysis allows us to study the effects of changes in the market environment on optimal sampling, pricing and profits. Specifically, alterations in the market environment may be brought about by changes in consumers' expectations (captured by changes in $\bar{v}_0$ and α) or by changes in the publisher's exogenous parameters (captured by a_f and N). Here a higher value of a a_f leads to an increase in the ratio of ad revenues a_f/a_p, as a_p is fixed in our graphical analysis. We begin with the effects on optimal sampling.



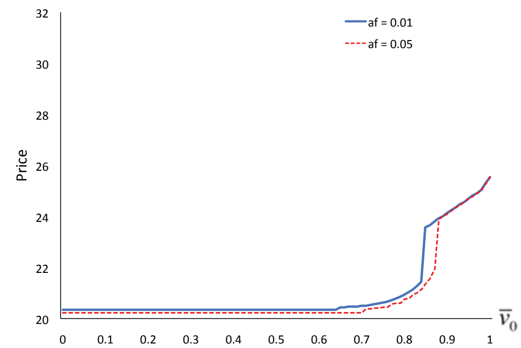
(4a) $N = 30$ and $\alpha = 5$



(4b) $N = 30$ and $\alpha = 25$



(4c) $N = 100$ and $\alpha = 5$

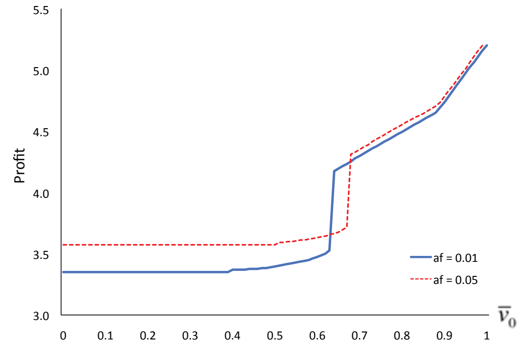


(4d) $N = 100$ and $\alpha = 25$

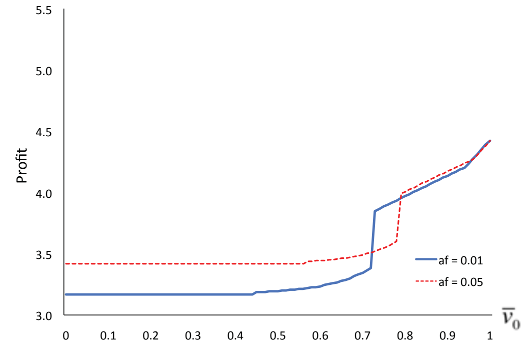
Figure 4: Optimal prices $\hat{p}$ for low quality expectations.

Finding 1. *The number of optimal samples $\hat{n}$ is higher (i) the lower consumers' expected quality measured by $\bar{v}_0$, (ii) the lower consumers' prior uncertainty about $\bar{v}_0$ measured by α, (iii) the higher advertising revenue for online impressions a_f, and (iv) the more articles N the publisher produces.*

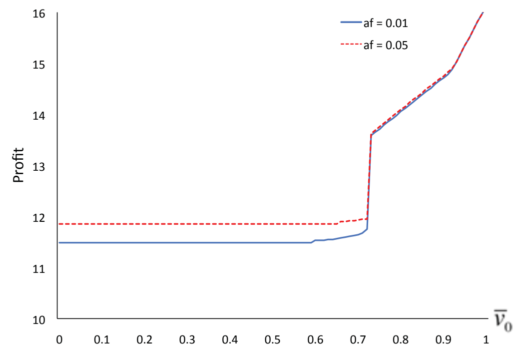
These effects can all be seen graphically in Figure 3: The effect of $\bar{v}_0$ on $\hat{n}$ in each panel, the effect of α by comparing the panels across columns, the effect of a_f within each panel, and the effect of N by comparing panels across rows. Publisher should offer fewer articles for free when consumers have higher prior expectations about content quality (either because of a high $\bar{v}_0$ or a low α). Intuitively, higher prior expectations increase the demand-reducing effect of sampling and thereby reduce the publisher's incentives to offer free samples. Once prior expectations are high enough, it is no longer optimal for the publisher to employ the sampling strategy. Instead, it is optimal for the publisher to employ a paid-only strategy and refrain from sampling. A third comparative statics effect shows that the publisher should offer more free samples when online



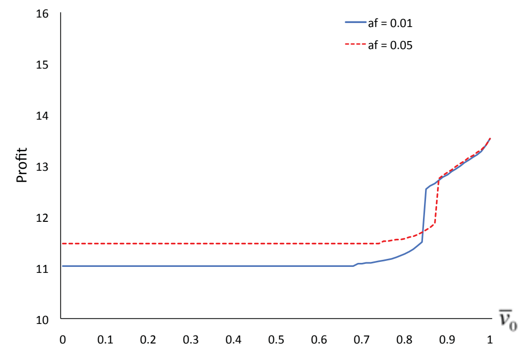
(5a) $N = 30$ and $\alpha = 5$



(5b) $N = 30$ and $\alpha = 25$



(5c) $N = 100$ and $\alpha = 5$



(5d) $N = 100$ and $\alpha = 25$

Figure 5: Optimized profits $\pi(\hat{n})$ for low quality expectations.

advertising revenues increase. When the marginal revenue of sampling a_f is higher, the publisher has an incentive to increase the number of free samples, thereby increasing its marginal cost because of demand-reducing sampling, up to the point where the equality between marginal cost and revenue is restored. The last comparative statics result is that the publisher should offer more free content samples when she produces more content (as measured by N), but that the proportion sampled decreases. The intuition is that a larger content size leads to a lower demand-reducing effect of sampling, which in turn increases the publisher's incentive to offer free samples.

An immediate implication of Finding 1 is how alterations in the market environment affect the optimal proportion to sample ($\hat{n}/N$).

Finding 2. *The optimal sample portion $\hat{n}/N$ is higher (i) the lower consumers' expected quality $\bar{v}_0$, (ii) the lower consumers' prior uncertainty measured by α, (iii) the higher advertising revenue for online impressions a_f, and (iv) the fewer articles N the publisher produces.*

Table 2: Summary of comparative statics effects.

Sampling	Pricing		
	Direct effect	Indirect effect	Total effect
$\frac{d\hat{n}}{d\bar{v}_0} < 0$	$\frac{\partial p}{\partial \bar{v}_0} = -\frac{c(\partial e/\partial \bar{v}_0)}{2(ce)^2} > 0$	$\frac{\partial p}{\partial n}\frac{d\hat{n}}{\bar{v}_0} > 0$	$\frac{d\hat{p}}{\bar{v}_0} > 0$
$\frac{d\hat{n}}{d\alpha} > 0$	$\frac{\partial p}{\partial \alpha} = -\frac{e(\partial c/\partial \alpha)}{2(ce)^2} < 0$	$\frac{\partial p}{\partial n}\frac{d\hat{n}}{\alpha} < 0$	$\frac{d\hat{p}}{\alpha} < 0$
$\frac{d\hat{n}}{da_f} > 0$	$\frac{\partial p}{\partial a_f} = 0$	$\frac{\partial p}{\partial n}\frac{d\hat{n}}{a_f} < 0$	$\frac{d\hat{p}}{a_f} < 0$
$\frac{d\hat{n}}{dN} > 0$	$\frac{\partial p}{\partial N} = -\frac{e(\partial c/\partial N)}{2(ce)^2} > 0$	$\frac{\partial p}{\partial n}\frac{d\hat{n}}{N} < 0$	$\frac{d\hat{p}}{N} > 0$

Notes: Recall that $\partial p/\partial n$ has a negative sign.

Next, we consider the effects of changes in the market environment on optimal pricing.

Finding 3. *The optimal price $\hat{p}$ is higher (i) the higher consumers' expected quality $\bar{v}_0$, (ii) the higher consumers' prior uncertainty measured by α, (iii) the lower advertising revenue for online impressions a_f, and (iv) the more articles N the publisher produces.*

The comparative statics effects can be best understood by decomposing the total price effect into a "sampling-mediated effect" and a "direct effect." To make this explicit, we let the generic variable x stand for one of the model parameters. Writing the price as $p = p(n(x), x)$, the price change induced by varying x is given by $dp/dx = (\partial p/\partial n)(dn/dx) + \partial p/\partial x$, where the first term on the right-hand side is the sampling-mediated effect and the second term the direct effect. The sign of the sampling-mediated effect is determined by the slope of the best-response function (derived from Eq. (7) above) and the sign of dn/dx (from Finding 1). The sign of the direct effect is obtained from differentiating the best-response function with respect to the parameter x of interest. Table 2 summarizes the comparative statics effects for various model parameters.

Table 2 shows that the direct effect of $\bar{v}_0$ on the price is positive. Higher quality expectations reinforce the positive sampling-mediated effect and thus lead to a higher optimal price. Intuitively, the direct effect is positive because higher quality expectations reduce the expansion effect (see Table 2). Second, the direct effect of α on the price is negative, which exacerbates the negative indirect effect, thereby leading to a lower optimal price. The explanation is that the indirect effect is negative because lower uncertainty about quality increases the cannibalization effect. Third, a higher a_f has no direct effect on the price.

Hence, the optimal price is lower because the sampling-mediated effect is negative. Fourth, the direct effect of N on price is positive as it reduces the cannibalization effect. The positive direct effect dominates, however, the negative sampling-mediated effect, which in turn leads to a higher optimal price.

Finally, we summarize the profit impact of changes in the market environment. With the previous results in mind, the effects should be intuitive.

Finding 4. *Optimal profits $\pi(\hat{n})$ are higher (i) the higher consumers' expected quality $\bar{v}_0$, (ii) the higher consumers' prior uncertainty measured by α, (iii) the higher advertising revenue for online impressions a_f, and (iv) the more articles N the publisher produces.*

6 Conclusions

This paper has examined the two interrelated questions of many articles a publisher of news websites should offer for free and how much the publisher should charge for the content behind the paywall. The key feature of this model is that publishers offer representative free content samples to disclose journalistic quality to consumers and thereby generate online advertising revenues. Consumers choose the specific sample articles themselves and learn from them in a Bayesian fashion. Based on posterior quality expectations, consumers make their subscription decisions.

We derived the following three principle results. First, we show how subscription demand depends on consumers' posterior expectations about content quality. Distinguishing the cases of high and low quality expectations, we show that offering free samples is always demand-reducing when consumers have high quality expectations while that it may be demand-increasing when consumers have low quality expectations. Second, we show that the subscription price and the number of free samples are negatively related when consumers have high quality expectations and that they may be positively related when consumers have low quality expectations. Third, we show that the publisher should never employ a sampling strategy when consumers have high quality expectations. Whether the publisher employs a paid-only strategy or a free content strategy depends on the advertising revenues. We find that the firm should employ a free content strategy when online advertising revenues from the samples are high and a paid-only strategy when online advertising revenues from the samples are low. When consumers have low quality expectations, employing a sampling strategy may be optimal for the publisher. In our numerical study we find that the publisher should offer more free samples when consumers have lower quality expectations and when online advertising revenues are higher.

Our predictions are consistent with casual observations from the media industry. Once online advertising rates are high enough, our model predicts that the publisher should offer its entire content for free. This might explain why the *New York Times* abandoned its online subscription program, *TimesSelect*, in 2007 when online advertising revenues were soaring. Likewise, our model predicts that the publisher should introduce digital subscriptions and offer a limited number of free samples when online advertising revenues decrease. This might be an explanation of why the *New York Times* re-introduced digital subscriptions in 2011.

The proposed model can also be applied in other contexts as well. Optimal sampling of paid content and advertising plays a role in distributing apps such as *Angry Birds* or *Talking Tom Cat* for *Apple* devices. A consumer can either download a free trial version peppered with advertisements or purchase the full version of these games. More broadly, our model also seems relevant for any experience good, including books, music and movies.

Our analysis contributes to a scant literature on sampling of information goods and suggests several avenues for future research. First, it would be natural to allow for competing news websites. Second, it would interesting to endogenize the outcome of the online advertising market. Third, it would be desirable to generalize our model to a dynamic, multi-period model that includes multiple updatings of consumers' product quality valuations. We hope this paper encourages work in these and related directions.

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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

$$E(X) = \frac{\alpha w_0}{\alpha - 1}.$$

Theorem (DeGroot, 1970).[21] *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:[22]

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

Furthermore, $\xi(w) = 0$ for $w \leq w_0$. 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:[23]

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

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).

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[21] Theorem 1, p. 172.

[22] The glyph "$\propto$" means "proportional to."

[23] 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. (a) For given n, expected demand can be derived from (4):

$$D_H^{\mathrm{E}}(p,n) \equiv \mathbb{E}\left[D_H(p,n)\right] = \max\left\{0, 1 - c(n)\,\mathbb{E}\left[\frac{1}{\tilde{v}_0'(n)}\right]p\right\}. \tag{A.1}$$

As $\bar{v}_0 \geq \bar{V}$, $\tilde{v}_0(n) = \max\{\bar{v}_0, V_1, \ldots, V_n\}$ is equal to $\bar{v}_0$ with probability 1. Thus, the expected expansion effect is given by

$$\mathbb{E}[e(n)] = \mathbb{E}\left[\frac{1}{\tilde{v}_0(n)}\right] = \frac{1}{\bar{v}_0},$$

and the expected demand follows as stated in the proposition. (b) For given n, expected demand $D_L^{\mathrm{E}}(p,n)$ can be derived similarly as in (A.1). In the present case, we need to calculate the expected expansion effect under the assumption that $\bar{v}_0 < \bar{V}$. To this end, we begin by deriving 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:

$$\begin{aligned} F_M(t) &\equiv \Pr\{\max\{V_1, \ldots, V_n\} \leq t\} \\ &= \Pr\left\{\{V_1 \leq t\} \cap \ldots \cap \{V_n \leq t\}\right\} \\ &= \prod_{i=1}^{n} \Pr\left\{V_i \leq t\right\} = \left(\frac{t}{\bar{V}}\right)^n. \end{aligned} \tag{A.2}$$

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

$$f_M(t) = \frac{n t^{n-1}}{\bar{V}^n}. \tag{A.3}$$

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.2) 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

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

by (A.3). The distribution of $\tilde{v}_0(n)$ has a mixed structure with

$$\Pr\left\{\tilde{v}_0(n) = \bar{v}_0\right\} = \left(\frac{\bar{v}_0}{\bar{V}}\right)^n \tag{A.4}$$

and density

$$\tilde{f}(t) = \frac{n t^{n-1}}{\bar{V}^n}, \quad \text{if} \quad \bar{v}_0 \leq t \leq \bar{V}. \tag{A.5}$$

Next, we derive the distribution of $1/\tilde{v}_0(n)$. Define $G(t)$ as the cumulative distribution function function of $1/\tilde{v}_0(n)$. Note that $G(t) = 1 - \tilde{F}(1/t)$, which in turn implies $g(t) = \left(1/t^2\right) \tilde{f}\left(1/t\right)$. From (A.5),

$$g(t) = \frac{n}{\bar{V}^n t^{n+1}}.$$

Furthermore, observing that $\Pr\left\{1/\tilde{v}_0(n) = 1/\bar{v}_0\right\} = \Pr\left\{\tilde{v}_0(n) = \bar{v}_0\right\}$ by definition, (A.4) implies that $\Pr\left\{1/\tilde{v}_0(n) = 1/\bar{v}_0\right\} = \left(\bar{v}_0/\bar{V}\right)^n$. Thus, the random variable $1/\tilde{v}_0(n)$ follows a mixed distribution with density

$$g(t) = \frac{n}{\bar{V}^n t^{n+1}}, \quad \text{for} \quad \frac{1}{\bar{V}} \leq t \leq \frac{1}{\bar{v}_0}$$

and takes value $1/\bar{v}_0$ with probability $\left(\bar{v}_0/\bar{V}\right)^n$.

Thus we finally obtain

$$\begin{aligned} E\left[\frac{1}{\tilde{v}_0(n)}\right] &= \frac{1}{\bar{v}_0}\left(\frac{\bar{v}_0}{\bar{V}}\right)^n + \int_{1/\bar{V}}^{1/\bar{v}_0} t\hat{f}(t)dt \\ &= \begin{cases} \frac{1+\ln\left(\bar{V}/\bar{v}_0\right)}{\bar{V}}, & \text{for } n = 1 \\ \frac{n\bar{V}^{n-1}-\bar{v}_0^{n-1}}{(n-1)\bar{V}^n}, & \text{for } n > 1, \end{cases} \end{aligned}$$

and the expected demand follows as stated in the proposition. This completes the proof.

Proof of Corollary 1. If $n > 1$,

$$e'(n) = -\frac{\bar{V}^{n-1} - \bar{v}_0^{n-1}\left(1 + \ln\left(\bar{V}/\bar{v}_0\right)^{n-1}\right)}{(n-1)^2\bar{V}^n}. \tag{A.6}$$

Expanding the right-hand side of (A.6) by $1/\bar{v}_0^{n-1}$ and letting $r = \left(\bar{V}/\bar{v}_0\right)^{n-1}$, the numerator can be written as $r - (1 + \ln r)$. Clearly, the denominator is positive. Using a Taylor expansion around $r = 1$ and noting that $r > 1$ by the hypothesis, we have that $r - 1 > \ln r$, which in turn implies that the numerator is positive as well. Hence, the expected expansion effect is negative. This completes the proof.

Proof of Corollary 2. Differentiating (5) with respect to the n yields

$$\begin{aligned} \frac{\partial D_L^{\mathsf{E}}(p,n)}{\partial n} &= -\left(c'(n)e(n) + c(n)e'(n)\right)p \\ &= -\frac{c(n)e(n)(\epsilon_c(n) - \epsilon_e(n))p}{n}, \end{aligned}$$

where the second equality follows from using the definition of the two elasticities. Lemma 1 implies that $\epsilon_c(n) > 0$. From from Corollary 1, we know that $e'(n) < 0$ and hence that $\epsilon_e(n) > 0$. Thus, $\partial D_L^{\mathsf{E}}(p,n)/\partial n < 0$ if and only if $\epsilon_c(n) < \epsilon_e(n)$. This completes the proof.

Proof of Proposition 2. Differentiating the best-response function given in (7) with respect to n and using the definitions of $\epsilon_c(n)$ and $\epsilon_e(n)$, the slope of $p(n)$ is given by

$$p'(n) = \frac{\epsilon_e(n) - \epsilon_c(n)}{2nc(n)e(n)}.$$

With high quality expectations $\epsilon_e(n) = 0$ by Lemma 1. As $c'(n) > 0$, we thus have that $p'(n) < 0$. With low quality expectations, the sign of $p'(n)$ depends on the sign of $\epsilon_c(n) - \epsilon_e(n)$: Using Corollary 2, $p'(n) > 0$ if and only if sampling is demand-enhancing and $p'(n) < 0$ if and only if sampling is demand-reducing. This establishes the claim.

Proof of Proposition 3. The profit function $\pi_S(p, n)$ as given in (6) has a relative maximum at $(\tilde{p}, \tilde{n})$ if $\partial^2\pi_S(\tilde{p}, \tilde{n})/\partial p^2 < 0, \partial^2\pi_S(\tilde{p}, \tilde{n})/\partial n^2 < 0$, and the determinant of the Hessian matrix of $\pi_S(p, n)$, evaluated at the critical point $(\tilde{p}, \tilde{n})$, is positive.[24] However, after tedious but straightforward calculations, it turns out that the determinant is negative for all parameter constellations.[25] Therefore, the profit function $\pi_S(p, n)$ has a saddle point at $(\tilde{p}, \tilde{n})$, which in turn implies that there is no interior maximum.

All that remains to do is to compare the profits from the two boundary strategies. The publisher should adopt a subscription strategy if and only if $\pi(0) > \pi(N)$ or, equivalently, if and only if

$$a_f < \frac{(\alpha N\bar{v}_0 + 2(\alpha - 1)a_p)^2}{8\alpha(\alpha - 1)N^2\bar{v}_0}.$$

This completes the proof.

[24] See, for instance, Chiang (1984, p. 317).

[25] The detailed proof is available from the authors upon request.