Data privacy, service addictiveness, and pricing in online markets*

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Abstract

This paper considers a model of an online host platform with one service provider and a group of users to analyze the interplay between the users' data privacy, determined by the host's data disclosure policy, and the service provider's choice of service addictiveness level. This choice involves a trade-off between advertisement revenue through user attention and admission price. When the host platform receives a share of the admission price, I demonstrate that it benefits from a restrictive privacy policy. Under this policy, the service provider chooses a lower addictiveness level and a higher admission price as compared to a policy involving a higher level of data disclosure. Furthermore, it is shown that network effects among users may result in a positive level of addictiveness, even when the host's policy fully restricts advertisement revenue. These findings may help explain the shifts in corporate privacy policies recently observed in online markets.

Keywords: addiction, attention, network effects, privacy, two-sided platforms

JEL-Codes: D4, L1, L2, L5, M3

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1 Introduction

Online service providers and users interact on a host platform. iOS, Apple's operating system that powers the iPhone, connects the providers of digital services, or apps, with potential users, and is used by approximately 1.3 billion people worldwide (Curry, 2023). In April 2021, Apple rolled out a privacy update introducing App Tracking Transparency (ATT), making it difficult for app providers to generate user profiles based on third-party data unless users actively permit tracking.[1] Nevertheless, the majority of users still do not allow tracking (e.g., Wetzler, 2023). As a consequence, the app providers' capabilities for targeted advertisement have been restricted by the introduction of ATT, and advertisement revenues for online platforms have dropped.[2] In order to boost user attention that can be monetized via targeted advertisements, app providers may adopt addictive design features that potentially harm users (e.g., Alter, 2018; Newport, 2019; Allcott, Gentzkow, and Song, 2022). Examples include feeds that allow endless scrolling, the use of social pressure via read notifications, and the implementation of gambling elements such as loading spinners or loot boxes (e.g., Montag, Lachmann, et al., 2019; Scott Morton et al., 2019).

The aim of this paper is to examine how a host platform's data disclosure policy, which restricts advertisement revenue for online service providers, impacts these providers' subsequent pricing and service design decisions, especially considering the implementation of potentially user-harming addictive design features.

For this purpose, the paper presents a simple theoretical framework that captures features of online markets, where one service provider faces a homogeneous group of users on a two-sided host platform. First, the host commits to a policy regime dictating a level of data disclosure. After observing the host's policy, the service provider chooses an admission price and a service design, represented by a level of service addictiveness. Lastly, each user simultaneously decides if she makes use of the service and how much attention she spends on it. Each active user incurs attention costs and pays an admission fee, and her utility is derived from the service itself combined with network effects. The extent of network effects a user experiences depends on the attention of other users. The service provider's payoff consists of revenues generated from

[1] For an overview of ATT and its implications, see, e.g., Jerath (2022) and Kourinian (2021).

[2] Advertisement generates a large share of today's online businesses' revenues. For instance, Alphabet Inc. (2023) announces that roughly 80 percent of its revenues originate from Google and YouTube ads services. Referring to a study by Lotame, McGee (2021) shows that ad revenues of the largest online platforms dropped significantly after the introduction of ATT. Following the ATT rollout, Snap, Facebook, Twitter, and YouTube have lost nearly $10bn in ad revenues in the last two quarters of 2021. See also, e.g., Bergan (2022).

admission fees, of which an exogenous share must be given to the host, and from monetizing user attention through targeted advertisements, which may be restricted by the host's policy. Following Ichihashi and Kim (2023), the choice of addictiveness is associated with a trade-off between advertisement revenue through user attention and admission price.

The main contribution of this work is the endogenization of the data disclosure policy of a host platform and the investigation of its effect on the service provider's pricing and addictiveness decisions. The analysis reveals that the host prefers a restrictive privacy policy because this induces the service provider to set an addictiveness level that maximizes the users' willingness to pay. In fact, privacy-focused policies yield higher prices and superior service quality through reduced addictiveness in equilibrium compared to disclosure-oriented policies. Furthermore, the article investigates two countervailing effects of increasing the level of service addictiveness on the service provider's profits: the *Attention Monetization Effect* and the *Price Effect*. Increasing service addictiveness results in an increase in user attention but may respectively decrease users' willingness to pay. The first effect, which describes the increase of profits from targeted advertisement due to an increase in user attention, is always weakly positive as long as users make use of the service. Interestingly, I find that the latter effect can be ambiguous when network effects are considered. On one hand, an increase in addictiveness corresponds to a loss in service utility, resulting in a lower willingness to pay and, therefore, a decreasing price. On the other hand, it boosts user attention which, in turn, leads to a utility and therefore price increase due to network effects. I provide conditions under which the prevalence of positive network effects results in positive levels of addictiveness even when advertisement revenues are fully restricted. Under these conditions, the service provider chooses a combination of strict positive prices and a strict positive level of addictiveness under each policy regime. I further demonstrate that the equilibrium level of addictiveness increases with stronger network effects.

The remainder of the article is organized as follows: In Section 2, I position the paper within the existing literature. The model setup is described in Section 3. In Section 4, I derive the equilibrium. A brief comparative statics analysis is presented in Section 5. After a discussion of model assumptions and possible extensions in Section 6, I conclude in Section 7.

2 Related Literature

This article contributes to the literature on online markets. Closest to this work is the article by Ichihashi and Kim (2023), who introduce service addictiveness as a choice variable in an oligopoly model in which competing online service platforms choose a level of addictiveness to capture the attention of a representative multi-homing user. Referring to a three-period habit formation model with a time-inconsistent consumer, based on Gruber and Köszegi (2001), they assume that the platforms face a trade-off: the higher the addictiveness of a platform, the higher the attention level it may generate, but the lower the corresponding user utility. Building upon this framework, I add a game stage in which an additional player, a host platform, commits to a data disclosure policy. This choice, in turn, determines to which extent a monopolistic service provider that makes profits from selling access to its service can also generate revenues from attention of a group of users. Furthermore, I incorporate network effects among users and show that they provide a channel to relax the trade-off between utility and attention generation associated with service addictiveness. While the strictly negative effect of increasing addictiveness on user utility results in zero addictiveness under price competition in Ichihashi and Kim (2023), I show that the presence of positive network effects can result in positive levels of addictiveness even if user attention cannot be monetized directly. While Ichihashi and Kim investigate the effects of competition and attention limitation on platform behavior and consumer welfare, this article considers an endogenous privacy policy and its implications for service provider business models and service quality.

Zennyo (2024) investigates the business model choice of an app provider in a mobile app market with endogenous commissions from an app and an ad platform. Similar to the present model, the app provider makes profits from admission prices and advertisements. In contrast, the present work considers a data disclosure policy that endogenously determines the feasibility of profits from advertisements. Furthermore, it considers the implementation of addictive features to boost user attention in exchange for service quality and network effects — features not included in the model of Zennyo. Another article in this field is by Fainmesser et al. (2023), who investigate how the collection and protection of user data are affected by the revenue model of an online business, and conclude recommendations for regulating these businesses. Going one step further, I examine the incentives of the platform on which service providers and users interact, where this platform can determine the possible revenue model of the service provider by setting a data disclosure policy. I show that host platforms prefer a restrictive data disclosure policy because it incentivizes third-party service providers to maximize prices rather than maximizing attention, which improves service quality.

This work is related to literature regarding the effects of online services on users. Mainly in the context of social media, recent literature points out the negative effects of digital features on user well-being (e.g., Allcott and Gentzkow, 2017; Allcott, Braghieri, et al., 2020; Mosquera et al., 2020; Bhargava and Velasquez, 2021; Allcott, Gentzkow, and Song, 2022; Montag and Elhai, 2023). Features that boost attention can harm users (e.g., Alter, 2018; Newport, 2019; Scott Morton et al., 2019; Rosenquist et al., 2021). Throughout this paper, I adopt a framework in which a service provider may sacrifice service quality and therefore user utility for attention and show that a higher level of privacy corresponds to less implementation of user harming features.

The article is also connected to the literature about the implications of privacy policies. Acquisti, Taylor, et al. (2016) and Goldfarb and Que (2023) provide overviews of the trade-offs connected with privacy. Scholars investigate the implications of a privacy-centered environment on online advertisement. Johnson, Runge, et al. (2022) name research avenues relevant from a marketing perspective. An environment with limited tracking capabilities may raise issues related to advertisement campaign strategy (e.g., Blake et al., 2015; Schwartz et al., 2017; Goldfarb and Tucker, 2011), ad targeting (e.g., Neumann et al., 2019; Rafieian and Yoganarasimhan, 2021; Ada et al., 2022), and ad measurement (e.g., Bruce et al., 2017; Lin and Misra, 2022). More specific, Johnson, Shriver, et al. (2020) and Ravichandran and Korula (2019) show that advertising revenues are positively connected to the ability for third-party tracking. Referring to Apple's ATT update, Aridor et al. (2024) provide evidence for decreasing ad effectiveness and advertisement revenues as a consequence of Apple's policy change. De Cornière and De Nijs (2016) analyze the impact of privacy policies in an advertisement slot auction setting and consider precisely targeted advertisement as utility enhancing. Throughout this work, I adopt their notion and distinguish between a Privacy and a Disclosure policy. The focus of this work lies not on governmental policies that influence the possibilities of data usage, like, e.g., the European Union's General Data Protection Regulation (GDPR), but on the restrictions that may arise from the corporate side and their implications (e.g., Baye and Sappington, 2020). In a recent article, Kesler (2023) examines the impact of privacy policy on business models based on the example of Apple's ATT. He empirically analyzes the market for mobile applications and investigates business models of apps and developers before and after the introduction of Apple ATT. In the course of this, he shows that, following ATT, apps from Apple's App Store become more often chargeable and are more likely to include in-app purchases. While an increase in the number of apps with in-app payments seems to be an industry-wide phenomenon, there is evidence that the increasing adoption of paid business models is exclusive to apps affected by ATT. The results of the current paper may help explain these recent observations.

There is research on the valuation of privacy from the user's perspective, where privacy serves as a protective instrument against the disclosure of one's personal type. For instance, Taylor (2004), Acquisti and Varian (2005), and Hann et al. (2008) introduce models in which privacy acts as a tool to avoid price discrimination. Other studies investigate how user data can be used for personalized pricing and targeted advertising (e.g., Villas-Boas, 1999; Villas-Boas, 2004; Zhang and Krishnamurthi, 2004). I contribute to this body of literature by providing a theoretical model that, to the best of my knowledge, is the first to link privacy policies with business model choices in the context of addictive service design. This allows me to demonstrate that the value of privacy for consumers encompasses a new dimension. A higher level of privacy results in higher service quality.

Lastly, this article contributes to the general discussion about antitrust in connection with privacy policies and online platforms. Sticking to the example from above, there are some recent antitrust issues against Apple in connection with ATT brought up by France, Germany, Italy, and Poland (e.g., McGee, 2023). This article highlights potential benefits of privacy policies for users. It contributes to the discussion by providing evidence that a restrictive data disclosure policy leads to higher service quality and therefore, user satisfaction. In the context of social media, Montag and Elhai (2023) state that actual problems can only be solved if the providing platforms change their business model away from data and therefore attention monetization. I show that this may be induced by the implementation of privacy policies by superordinate platforms such that the user-harming free and addictive models are becoming less profitable.

3 Model

A host platform matches two parties of participants: a service provider on one side and a homogeneous group of potential users $\mathcal{I}$ on the other, with the group's mass normalized to one, while each individual has a mass of zero.

The host platform chooses a data disclosure policy which defines a framework that determines to which extent the service provider can monetize attention, represented by the variable $\gamma \in \{0, 1\}$. A restrictive data disclosure policy may prohibit the service provider from collecting user data which results in a less effective targeting. For tractability, consider γ as dichotomous. Either data usage is fully restricted (privacy policy), $\gamma = 0$, or there is full disclosure (disclosure policy), $\gamma = 1$.[3] The service provider sets an admission price $p \geq 0$ and offers its services to the group of potential users who may spend attention on it. The service provider can implement addictive features into its service design in order to boost user attention. Examples are endless scrolling, the utilization of social pressure or implementation of gambling elements (Montag, Lachmann, et al., 2019). Following Ichihashi and Kim (2023), these features are captured in the addictiveness variable $d \geq 0$. A higher level of addictiveness is associated with higher marginal utility of service consumption but lower utility it generates.[4] The combination (d, p) reflects the business model of the service provider. Each user $i \in \mathcal{I}$ simultaneously decides whether to use the service provider's service or not and how much attention $a_i \geq 0$ to spend on it.

If user i spends a positive amount of attention, her utility is

$$U_i(a_i, d, p, A_{-i}) = u(a_i, d) + \kappa \cdot b\left(A_{-i}\right) - c\left(a_i\right) - p, \tag{1}$$

where $u(\cdot)$, $b(\cdot)$ and $c(\cdot)$ represent service utility, network effects and attention costs, respectively. Her reservation utility is normalized to zero. User i enjoys utility from the service provider's service, denoted as $u_i(a_i, d)$. Since users are assumed to be homogeneous, one can write $u_i(a_i, d)$ as $u(a_i, d)$. For all $a_i \geq 0$ and $d \geq 0$, the utility function $u : \mathbb{R}^2_+ \to \mathbb{R}$ is twice-differentiable and $u(0, 0) \geq 0$. The value a service generates is monotonically increasing and concave in the attention spent, such that for all $d \geq 0$ and $a_i \geq 0$, $\partial u / \partial a_i|_{(a_i,d)} > 0$, and $\partial^2 u / \partial a_i^2|_{(a_i,d)} < 0$. Service utility is affected by the addictiveness level of the service. Adopting the modelling of Ichihashi and Kim (2023), consider $u(a_i, d)$ as a super-modular function, where a higher level of addictiveness corresponds to a lower level of utility, $\partial u / \partial d|_{(a_i,d)} < 0$, and a

[3] I discuss the implications of a positive γ under privacy in Section 6.1. Furthermore, I contend that assuming γ is dichotomous is not critical in Section 6.2.

[4] Ichihashi and Kim (2023) motivate the service utility specification based on a three-period model with habit formation of a time-inconsistent dual-self consumer. A consumer first chooses a set of service platforms to join (long-run self) and, second, an allocation of attention across them (short-run self), prior to being addicted. Third, the consumer again chooses an allocation of attention over the joined platforms, where prior attention spending negatively affects consumer utility. This negative impact is associated with service addiction, and the consumer consequently needs to increase attention in the last period to ensure the same payoff as in the second. The extent of this negative impact is scaled by an addictiveness parameter, with a higher value corresponding to a greater harm on the consumer in the last period.

higher level of marginal utility of attention, $\partial^2 u/(\partial a_i \partial d)|_{(a_i,d)} > 0$, for all $d \geq 0$ and $a_i \geq 0$. Furthermore, assume that the disutility of addictiveness increases, such that $u(\cdot)$ is concave in d, $\partial^2 u/\partial d^2|_{(a_i,d)} < 0$.[5]

User i enjoys utility from interacting with other users who make use of the service via network effects, which are scaled by an exogenous parameter $\kappa > 0$. The parameter represents various factors, such as the size of the network, mechanisms that enhance network effects, or other relevant attributes. Let $b(A_{-i})$ be a twice differentiable function indicating the extent of network effects, the strength of which depends on the attention the service provider receives by all other users except i, $A_{-i} = \int_{j \in \mathcal{I} \setminus i} a_j \, \mathrm{d}j$. I focus on positive direct network effects, such that $b(0) = 0$ and, for all $A_{-i} \geq 0$, the function $b : \mathbb{R}_+ \to \mathbb{R}_+$ monotonically increases in attention, $\partial b/\partial A_{-i}|_{(A_{-i})} > 0$. Further assume decreasing marginal utility of attention, i.e., $\partial^2 b/\partial A_{-i}^2|_{(A_{-i})} < 0$.[6,7]

Each user faces attention costs, denoted as $c_i(a_i)$, which represent, for instance, the opportunity cost of allocating attention to an online service. Because of homogeneity, we have $c_i(a_i) = c(a_i)$ for all users, where $c : \mathbb{R}_+ \to \mathbb{R}_+$ is monotonously increasing, convex, and twice differentiable in her spent attention with $c(0) = 0$. That is, $\partial c/\partial a_i|_{(a_i)} > 0$ and $\partial^2 c/\partial a_i^2|_{(a_i)} > 0$ for all $a_i \geq 0$. Each user has to pay the admission price $p \geq 0$ for access to the service. In order to ensure existence of a solution with positive attention and a finite addictiveness, assume that $\lim_{a_i \to 0} \left(\partial u/\partial a_i|_{(a_i,0)} - \partial c/\partial a_i|_{(a_i)} \right) > 0$ and that there exists a d such that $\max_{a_i} \left(u(a_i, d) + \kappa \cdot b(A_{-i}) - c(a_i) \right) < 0$.[8]

If its service is used, the service provider's profits are

$$\Pi_S = (1 - \lambda) \cdot P + \gamma \cdot v\,(A)\,. \tag{2}$$

[5]A simple function that satisfies the assumptions is $u(a, d) = \ln(a - d + 1)$ for $d < 1 + a$.

[6]An intuitive way of thinking of this assumption is to consider social networks like Facebook. A *Like* releases a positive emotion, whereby every Like goes along with a piece of attention of other users. Thus, attention of others is translated into a boost of positive emotions for oneself, or more formally, a utility increase. See e.g., Meshi et al. (2013) who investigate Facebook use in connection with reputation. According to them, spending and receiving Likes is one of the most prevalent ways of social interaction on the platform, whereby a Like is a positive social feedback and boosts reputation.

[7]This is in line with the modeling of Chen et al. (2009), where the network effects monotonically increase in platform specific variables. In this model, network effects are assumed to be independent of a user's own attention level. It is also possible to allow for dependence on a user's own attention level, as in, e.g., Candogan et al. (2012) and Fainmesser et al. (2023), by representing effects via a function $\kappa \cdot b(A_{-i}) \cdot a_i$. I have found that this feature does not alter the results, so, I omit it for reasons of simplicity.

[8]The second assumption rules out trivial situations in which it is always profitable for the service provider to increase the level of addictiveness, resulting in equal outcomes under privacy and disclosure policies and making the host always indifferent.

If not, profits are zero. Assume that all costs of the service provider are normalized to zero, such that profits consist of two streams of revenues. First, there are payments that flow directly between the user of a service and the provider. A user may pay in advance for entry to a service platform, for subscription to or to unlock additional features of a service. Throughout this work, focus on admission prices representative for payments between user and service provider. Denote $\mathcal{I}_S \subseteq \mathcal{I}$ the set of users that use the service. Each one pays p, such that total revenues from this stream are $P = \int_{i \in \mathcal{I}_S} p \, \mathrm{d}i$. For operation, the service provider has to give an exogenous share $\lambda \in (0, 1)$ of admission revenues to the host.[9] Second, there are profits generated from a third party, typically by advertisement, or more specific, targeted advertisement. The service provider basically sells user attention to advertisers and its revenue from it depends on the amount of attention users spend. The profits from targeted advertisement are captured by the function $v : \mathbb{R}_+ \to \mathbb{R}_+$ that positively depends only on the total attention the platform receives, $\mathrm{d}v/\mathrm{d}A|_{(A)} > 0$ for all $A \geq 0$. The total attention is then $A = \int_{i \in \mathcal{I}_S} a_i \, \mathrm{d}i$.[10] The success of targeting depends on the service provider's capability to track and use user data, which is, in turn, determined by the host's data disclosure policy. Thus, profits from targeted advertisement are scaled by γ.

Assume that all costs of the host are normalized to zero. The host's profits consist of the share λ of total admission fees P, i.e.,[11]

$$\Pi_H = \lambda \cdot P. \tag{3}$$

The timing of the three-stage game is as follows:

1. The host commits to a data disclosure policy $\gamma \in \{0, 1\}$.
2. The service provider chooses an addictiveness level $d \geq 0$ and an admission price $p \geq 0$.
3. The users $i \in \mathcal{I}$ simultaneously decide whether to use the service and, if they do, set an attention level $a_i \geq 0$.

[9] The standard commission on all revenues generated via the App Store, which every app provider must pay to Apple, is 30%. For example, Baggott (2023) provides a detailed overview of Apple App Store fees. A meaningful examination of the endogenous choice of λ would need to involve factors that are not investigated here. For instance, one might consider λ as a market price determined by competition among host platforms, which is beyond the scope of this paper.

[10] This simplistic approach of modeling advertisement revenues is made for tractability. A characterization of advertisement strategy is beyond the scope of this article.

[11] This model focuses on host revenues that are related to user attention and therefore to addictive service designs. In reality, there are other sources of revenues. For instance, Apple's profits in connection with iOS also include revenues from selling devices and from offering own services to users like iCloud or Apple Care.

4 Equilibrium

The solution concept is a symmetric subgame-perfect Nash equilibrium (SPNE) in pure strategies, in which users do not strategically interact.

4.1 User participation and attention

At the last stage, each user decides whether to use the service provider's service and how much attention to spend on it. The utility of user i is presented in (1). For any observed d, p and γ, the equilibrium strategy of i must satisfy two conditions: her attention choice must maximize her utility and the resulting utility level must be weakly positive. If she uses the service, she spends the amount of attention $a = a_i^*$ that solves the first-order condition $\mathrm{d}U_i/\mathrm{d}a_i = 0$, or rather

$$\left.\frac{\partial u}{\partial a_i}\right|_{(a_i,d)} - \left.\frac{\partial c}{\partial a_i}\right|_{(a_i)} = 0. \tag{4}$$

It follows from the properties of $u(\cdot)$ and $c(\cdot)$ that there exists a unique $a_i^* > 0$ that maximizes (1). (4) implies that the optimal attention level of i is a function of platform addictiveness, $a_i^*(d) = \arg\max_{a_i} U_i$.

Note that in equilibrium also her participation constraint must hold. Recall that her reservation payoff is normalized to zero. Thus, user i only uses the service if her utility maximizing behavior generates a (weak) positive utility. Her participation constraint is

$$U_i(a_i^*(d), d, p, A_{-i}) \geq 0. \tag{5}$$

As in Ichihashi and Kim (2023), addictiveness d not only affects the optimal amount of attention if the service is used, but also the decision whether to make use of it or not. It follows from the definition of $u(\cdot)$ that a higher d corresponds to a lower utility and therefore less willingness to use the service, for a given level of attention. Note that prices and network effects do not directly influence the optimal level of attention. Nevertheless, they play a role in the participation constraint (5), where higher prices correspond to less, and stronger network effects correspond to more participation. The following proposition describes the strategy of each user in the equilibrium of the last stage.[12]

[12] One can think about a strategy of user i in which she does not use the service if she is indifferent. Following the backward induction argument, this makes the profit maximizing service provider choose d in order to provide an infinitely small amount of positive utility to each user. Since d is continuous, the service provider optimizes over an open set. Like in the standard bargaining game of Harsanyi (1961) (*Ultimatum game*), this makes it

Proposition 1 *In the equilibrium of the last stage, each user i makes use of the service and spends a strict positive level of attention $a_i^*(d) > 0$ if her participation constraint* (5) *holds. Otherwise, she does not use the service, resulting in zero attention. Furthermore, $a_i^*(d)$ strictly increases in the level of addictiveness, i.e., $\partial a_i^*/\partial d|_{(d)} > 0$ for all $d \geq 0$.*

Proof. *See Appendix A.1.*

4.2 Service provider's admission price and addictiveness level

At the second stage, the service provider observes the host's data disclosure policy γ and maximizes its profits (2) by choosing a combination of an addictiveness level and an admission price, (d, p). The profits of the service provider stem from collecting admission fees and from attention monetization via targeted advertisement. The service provider solves

$$\max_{d \geq 0, p \geq 0} \Big[(1 - \lambda) \cdot P + \gamma \cdot v\,(A) \Big]. \tag{6}$$

First, observe that the service provider's multivariate problem can be displayed as an univariate one. For any level of addictiveness, denote the price that makes the user indifferent between using the service or not as $\overline{p} \geq 0$. For each d, the service provider can set a price $p \in [0, \overline{p}]$ that satisfies the participation constraint of the users. In absence of competition, profit maximization implies that the service provider extracts all user utility and chooses $p = \overline{p}$ in equilibrium, such that the participation constraint (5) holds with equality. Since $a_i^*(d)$ is uniquely determined for each d, the corresponding utility level is also unique. Denote as $\overline{p}(d)$ the profit maximizing admission price for any given d. It is

$$\overline{p}(d) = u\left(a_i^*(d), d\right) + \kappa \cdot b\left(A_{-i}^*(d)\right) - c\left(a_i^*(d)\right), \tag{7}$$

where $A_{-i}^*(d)$ is the optimal total attention level of all users except i. In equilibrium, all users make a conjecture regarding the participation and attention decisions of all other users. Since users are homogeneous and rational, users predict that all other users behave like themselves, which is true. Thus, $a_i^*(d) = a_j^*(d)$ for all $i, j \in \mathcal{I}$ with $i \neq j$ and for all d, and, as a consequence, $A_{-i}^*(d) = a_i^*(d)$.

Since the optimal price is a function of d, the service provider's problem boils down to

impossible to characterize an equilibrium strategy of the service provider. As a consequence, a strategy in which the user does not use the service if she is indifferent cannot be part of any equilibrium.

the optimal choice of the addictiveness level. The service provider prefers users to participate. Thus, it can never be optimal to choose $d > \overline{d}$, where $\overline{d}$ is the maximal amount of addictiveness such that user i makes use of the service for a price of zero. It is implicitly defined by $p(\overline{d}) = U_i(a_i^*(\overline{d}), \overline{d}, 0, a_i^*(\overline{d})) = 0$. If all users participate, the total attention the service provider receives is $A^*(d) = a_i^*(d)$. In anticipation of optimal user decisions in the subsequent subgames, the service provider's problem (6) becomes $\max_{d\in[0,\overline{d}]} \Pi_S(d,\gamma)$, or rather

$$\max_{d\in[0,\overline{d}]} \Big[(1-\lambda)\cdot\left(u\left(a_i^*(d),d\right)+\kappa\cdot b\left(a_i^*(d)\right)-c\left(a_i^*(d)\right)\right)+\gamma\cdot v\left(a_i^*(d)\right)\Big].$$

In any interior equilibrium, the service provider solves the first-order condition $\mathrm{d}\Pi_S/\mathrm{d}d = 0$ which is equivalent to

$$\begin{aligned}(1-\lambda)\cdot\Bigg[\Bigg(\frac{\partial u}{\partial d}\bigg|_{(a_i^*(d),d)} &+ \kappa\cdot\frac{\partial b}{\partial A_{-i}}\bigg|_{(a_i^*(d))}\cdot\frac{\partial a_i^*}{\partial d}\bigg|_{(d)}\Bigg)\\ &+\Bigg(\frac{\partial u}{\partial a_i}\bigg|_{(a_i^*(d),d)}-\frac{\partial c}{\partial a_i}\bigg|_{(a_i^*(d))}\Bigg)\cdot\frac{\partial a_i^*}{\partial d}\bigg|_{(d)}\Bigg]\\ &+\gamma\cdot\frac{\partial v}{\partial A}\bigg|_{(a_i^*(d))}\cdot\frac{\partial a_i^*}{\partial d}\bigg|_{(d)}=0.\end{aligned}\tag{8}$$

The service provider chooses a business model balancing benefits and losses associated with higher addictiveness. More specific, it chooses a level that balances two streams of profits, one from direct attention monetization and one from charging admission prices. The term in square brackets in (8) captures the effect that an increase in addictiveness has on the price the service provider can charge for entry. Call this the *Price Effect (PE)* of increasing addictiveness, which basically is the effect of increasing addictiveness on individual user utility. Recall Proposition 1. For any $d \leq \overline{d}$, the optimal attention level $a_i^*(d)$ solves (4), such that the term in the second line of (8) equals zero in any equilibrium. Consequently, the PE as a function of d, denoted by $\psi(d)$, is

$$\psi(d) \equiv \frac{\partial u}{\partial d}\bigg|_{(a_i^*(d),d)} + \kappa\cdot\frac{\partial b}{\partial A_{-i}}\bigg|_{(a_i^*(d))}\cdot\frac{\partial a_i^*}{\partial d}\bigg|_{(d)}.\tag{9}$$

On one hand, an increase of addictiveness corresponds to a decrease in service utility. On the other hand, it corresponds to an increase of attention, which results in increasing utility due to network effects.

The service provider additionally receives revenues from direct monetization of attention. The last term of (8) represents the effect an increase of addictiveness has on it. Call this the

Attention Monetization Effect (AME). Its function of d and γ is denoted by

$$\xi(d,\gamma) \equiv \gamma \cdot \left.\frac{\partial v}{\partial A}\right|_{(a_i^*(d))} \cdot \left.\frac{\partial a_i^*}{\partial d}\right|_{(d)}. \tag{10}$$

An increase of addictiveness triggers attention, which, in turn, increases profits from attention monetization. Note that $\xi(d,0)=0$ for all d. Adopting the notation, the first-order condition (8) is equivalent to $(1-\lambda)\cdot\psi(d)+\xi(d,\gamma)=0$. More specific, it is $\psi(d)=0$ for $\gamma=0$ and $(1-\lambda)\cdot\psi(d)+\xi(d,1)=0$ for $\gamma=1$. For any $\gamma\in\{0,1\}$, denote the interior solution of the service provider's maximization problem as $d^*(\gamma)$.

Proposition 2 *In the equilibrium of the second stage, the service provider chooses a unique combination* $(d^*(\gamma),\overline{p}(d^*(\gamma)))$*. For any* $\gamma\in\{0,1\}$*,* $d^*(\gamma)\in(0,\overline{d})$ *is a solution of* (8) *if the existence conditions*

$$\lim_{d\to 0}\left(\psi(d)\right) > 0 \tag{11}$$

$$\lim_{d\to\overline{d}}\left((1-\lambda)\cdot\psi(d)+\xi(d,1)\right) < 0 \tag{12}$$

hold, where $\psi(d)$ *and* $\xi(d,\gamma)$ *are defined in* (9) *and* (10)*, respectively. The corresponding prices are positive, i.e.,* $\overline{p}(d^*(\gamma))>0$.

Proof. *See Appendix A.2.*

The proposition characterizes conditions under which there exists a unique interior solution to service provider's profit maximization problem under both policies. (11) ensures that the profit maximizing level of addictiveness is positive even if the service provider cannot monetize attention in a direct manner, i.e., the (accepted) admission price is not maximized under zero addictiveness. (12) ensures that corresponding prices are positive under each policy, i.e., it rules out the possibility that service provider profits are maximized by only maximizing revenues from targeted advertisement by maximization of user attention. Details are presented in Appendix A.2. In what follows, focus on situations in which there exist interior solutions to the service provider's maximization problem under privacy and disclosure policies, i.e., (11) and (12) hold.[13]

[13] In Section 6.4, I discuss the scenarios in which the service provider's problem results in corner solutions rather than interior solutions, as specified in Proposition 2, and demonstrate that the main results of the paper also hold in these situations.

4.3 Host policy

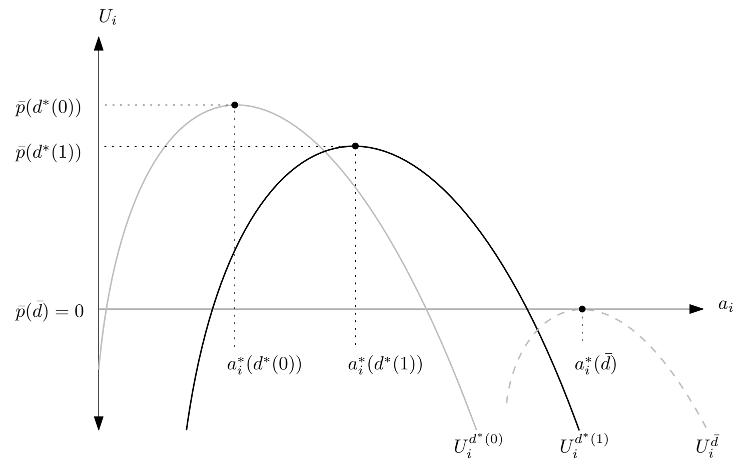
At stage one, the host chooses its policy γ in order to maximize its profits (3). Since profits strictly increase in total admission revenues of the service provider and users are homogeneous, host profits strictly increase in admission prices. In anticipation of the service provider's and the users' optimal strategies, the host problem is equivalent to

$$\max_{\gamma \in \{0,1\}} \overline{p}(d^*(\gamma)). \tag{13}$$

Proposition 3 *In the unique equilibrium, the host chooses privacy policy, i.e.,* $\gamma^* = 0$.
Proof. *See Appendix A.3.*

The proposition states that the host prefers a restrictive data disclosure policy over a less restrictive one. The reason behind this is that, in equilibrium, the host chooses a policy that induces price maximization of the service provider. Under a restrictive privacy policy, the service provider is not able to generate profits from targeted advertisement, i.e., from selling user attention. Thus, it sets a level of addictiveness that maximizes the willingness to pay of the users, or rather, the admission price.

The intuition behind this result is as follows. Under disclosure policy, the service provider has to balance revenues from both streams in order to maximize profits, i.e., it takes into consideration the PE and the AME of increasing addictiveness. Thus, it can be profitable for the service provider to forego some admission price revenues in order to generate higher direct attention monetization revenues. As long as there is a positive relationship between attention and direct monetization possibilities, i.e., $\partial v / \partial A > 0$, and addictiveness and equilibrium attention, $\partial a_i^* / \partial d > 0$, the corresponding incentives distort the service provider's decision away from price maximization. More specific, it tends to implement a level of addictiveness that is higher than the price maximizing one. By setting of privacy policy, the host snatches the possibility of direct attention monetization from the service provider. Then, the service provider maximizes its profits by maximization of admission price revenues. Thus, the equilibrium addictiveness choice leads to the highest possible price. Taken together, $d^*(0) < d^*(1)$ and $\overline{p}(d^*(0)) > \overline{p}(d^*(1))$. Regarding the price, the service provider chooses over-addictiveness under disclosure policy. It follows that implementation of privacy policy leads to a less addictive but more pricey business model of the service provider. Since equilibrium attention of each user increases in the level of addictiveness, users spend less attention under privacy than under disclosure policy, i.e.,



The figure depicts the utility of a user who anticipates the optimal attention spending of all other users, denoted by $U_i^d = U_i(a_i, d, 0, a_i^*(d))$, dependent on its own attention, for optimal levels of addictiveness under privacy, $d^*(0)$, and disclosure policies, $d^*(1)$, and under $\overline{d}$.

Figure 1: Individual user utilities under equilibrium addictiveness levels.

$a_i^*(d^*(0)) < a_i^*(d^*(1))$.

Figure 1 illustrates the results from the perspective of a user. Recall that $0 < d^*(0) < d^*(1) < \overline{d}$. The graphs show user utilities under the addictiveness levels of the equilibria of the privacy and disclosure policy subgames for an admission price of zero. The following corollary summarizes:

Corollary 1 *Service utility is higher in the equilibrium of the privacy policy subgame than in the equilibrium of the disclosure policy subgame if*

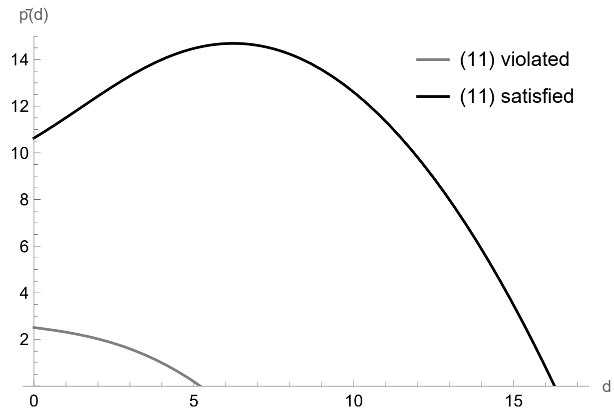
$$\frac{\partial u}{\partial a_i}\bigg|_{(a^*(d^*(0),d^*(0))} \cdot \frac{\partial a_i^*}{\partial d}\bigg|_{(d^*(0))} + \frac{\partial u}{\partial d}\bigg|_{a^*(d^*(0),d^*(0))} > 0.$$

The corollary highlights the effect of the policy-induced addictiveness choice on service utility. Service utility increases in attention and decreases in the level of addictiveness. Thus, the inequality $d^*(0) < d^*(1)$ suggests that service utility is higher under privacy than under disclosure policy for equivalent levels of attention. Thus, privacy policy corresponds to superior service quality. However, a higher level of addictiveness triggers a higher level of attention. Therefore, the overall effect of privacy policy on service utility hinges on the balance between utility gain due to decreased addictiveness and the utility loss due to decreased attention. Given that the monopoly service provider captures all user utility by setting a price that extracts all user surplus, higher prices under privacy policy correspond to higher overall utility.

5 Comparative-statics results

5.1 The impact of network effects

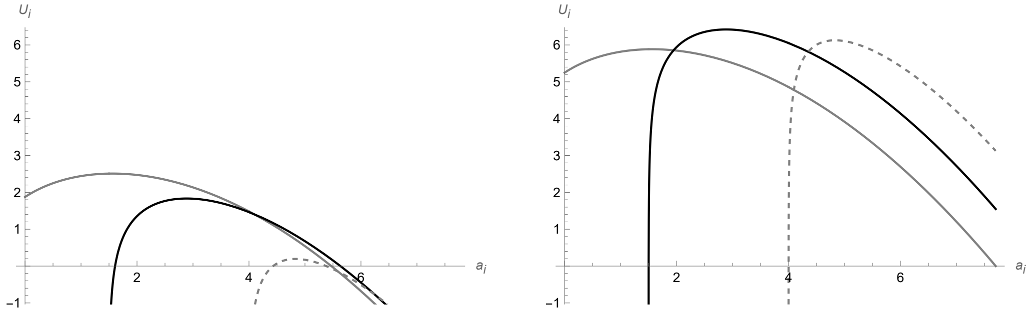
In what follows, I investigate the influence of network effects on the PE of increasing addictiveness, as defined in (9), and the decision of the service provider. Recall that κ is a parameter that scales the extent of network effects and therefore impacts the PE. Thus, one can write the PE as $\psi(d;\kappa)$.



The graphic depicts the price $\overline{p}(d)$ for varying levels of addictiveness. The parameter values and functions are based on the numerical example presented in Appendix B. The black graph shows the price for $\kappa = \kappa_2 = 8$, where the existence condition (11) holds. The gray graph represents the price for $\kappa = \kappa_1 = 1.5$, where (11) is violated.

Figure 2: Price $\overline{p}(d)$ for $\kappa_1 < \underline{\kappa} < \kappa_2$.

In the absence of network effects or if they have a negative sign, which corresponds to $\kappa \leq 0$, the service provider can never increase the price by increasing addictiveness because, in this case, the PE is strictly negative for all levels of addictiveness under which the service is used. That is, $\psi(d;\kappa) < 0$ for all $0 \leq d \leq \overline{d}$. Since the service utility strictly decreases in addictiveness and network effects do not counteract, the price is maximized under zero addictiveness. This is in line with the findings of Ichihashi and Kim (2023) who do not consider network effects. If network effects are positive like assumed in the present model, user utility increases in the total attention of other users. Then, the utility increase caused by other users' attention may exceed the service utility loss from increased addictiveness. If that is the case, (11) holds, and the service provider maximizes the price if it provides incentives to increase each user's attention. This situation corresponds to a $0 < \underline{\kappa} < \kappa$, where $\underline{\kappa}$ is a threshold value such that $\psi(0;\underline{\kappa}) = 0$. Note that, holding all else equal, condition (11) is more likely satisfied with a stronger impact of network effects, i.e., a larger parameter κ, stronger marginal network effects of attention $\partial b/\partial A_{-i}|_{(a_i^*(0))}$, or a higher marginal increase in equilibrium attention of each user $\partial a_i^*/\partial d|_{(0)}$.



(a) $\kappa < \underline{\kappa}$ (b) $\kappa > \underline{\kappa}$

The figures depict the utility of a user who anticipates the optimal attention spending of all other users, i.e., $U_i(a_i, d, 0, a_i^*(d))$, dependent on its own attention, for scenarios in which the existence condition (11) is violated (a) or holds (b). The price is zero, and the parameter values and functions are based on the numerical example presented in Appendix B. The gray solid line, black line, and gray dashed line represent level curves for d_1, d_2, and d_3, respectively, with $d_1 = 0 < d_2 = 2.5 < d_3 = 5$.

Figure 3: Utility $U_i(\cdot)$ of user i for different levels of addictiveness with correct conjectures.

Thus, network effects provide a channel to which the attention-price trade-off is altered. As a consequence, the existence of positive network effects explain why service providers implement addictive features into their platform design even under restrictive data disclosure policies.

Figure 2 illustrates the role of the existence condition from the perspective of the service provider. It shows the optimal price dependent on the addictiveness level (7) for different values of κ. The parameter κ scales the impact of network effects on user utility, where an increase goes along with a stronger impact. Holding all else equal, the parameter determines whether (11) is satisfied, or not. Note that the slopes of the graphs represent the respective PEs. The gray graph indicates a situation where the impact of network effects is not sufficiently large in order to make the condition hold, such that the PE is always negative. In this case, the price is monotonously decreasing in d. The optimal choice of the service provider is zero addictiveness. The black graph shows a situation in which the condition holds, resulting in a strictly positive price maximizing addictiveness level.

Figure 3 illustrates the situation from the user perspective. It shows the utility of a user who anticipates optimal attention spending of all other users for different levels of addictiveness. Figure (a) depicts a situation in which (11) does not hold. In this setting, the PE is always negative. Thus, an increase of addictiveness never results in an increase of user utility and therefore of the achievable price. Figure (b) illustrates the case in which (11) holds, such that the effect of addictiveness on optimal utility is ambiguous. Then, there exists an interval of addictiveness levels in which the loss of service utility is outweighed by the gain of utility from network effects, such that the effect of increasing addictiveness on user utility is positive. Optimal user utility increases as addictiveness increases from d_1 to d_2 and then decreases as addictiveness increases from d_2 to d_3. Since higher addictiveness is attention increasing, it also leads to a utility increase through network effects. This opposes the service utility loss associated with increasing addictiveness level.

As mentioned above, the parameter κ scales the impact network effects have on individual utility, with a larger value of κ corresponding to a larger effect. The following proposition illustrates its impact on equilibrium addictiveness:

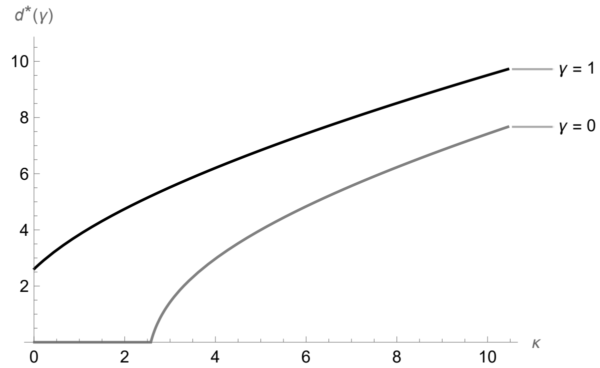
Proposition 4 *The equilibrium addictiveness level increases with stronger network effects, i.e.,* $\partial d^*(0)/\partial\kappa > 0$. *Furthermore, the maximum level of addictiveness under which users use the service increases in network effects,* $\partial\overline{d}/\partial\kappa > 0$.
Proof. *See Appendix A.4.*

The proposition states the properties of the effects of an increase of κ on the equilibrium level of addictiveness, i.e., the level that the service provider chooses under privacy policy. The effect is strictly positive. Furthermore, it states that the effect of κ on the highest possible addictiveness level that makes users use the service if entry is free, $\overline{d}$, is also positive. If users are homogeneous and network effects increase in attention, a larger κ goes along with a stronger impact of network effects on user utility. In equilibrium, every user uses the service and spends a positive amount of attention. An increasing level of κ increases the PE of addictiveness. More specific, it boosts the utility users gain from other users' attention. With a higher κ, the effect of an increase in total attention results in a utility rise which potentially compensates downsides of addictiveness increasing, leading to higher equilibrium addictiveness levels.

Figure 4 illustrates the proposition and shows the positive relationship between κ and addictiveness levels under both policies. For small values of κ, it is profit maximizing to choose zero addictiveness under privacy policy. As κ increases, the impact of network effects outweighs the utility loss from addictiveness and (11) becomes satisfied. Then, an increase of κ corresponds to an increase of equilibrium addictiveness levels under both policies.

5.2 The host's share of admission prices

The host collects an exogenous share of admission price revenues from the service provider. The following proposition examines how equilibrium strategies of the host and the service provider



The graphs show the profit maximizing addictiveness level for varying κ. Parameters and functions are according to the numerical example presented in Appendix B. The black and gray lines represent the optimal levels of addictiveness under disclosure ($\gamma = 1$) and privacy policy ($\gamma = 0$), respectively.

Figure 4: Optimal addictiveness levels under privacy and disclosure policy for varying κ.

react to changes of it:

Proposition 5 *An increase of λ has no effect on equilibrium data disclosure. Furthermore, it has no effect on the equilibrium addictiveness level and price. That is, $\partial d^*(0)/\partial\lambda = 0$ and $\partial\overline{p}(d^*(0))/\partial\lambda = 0$.*

Proof. *See Appendix A.5.*

The proposition illustrates the effect of a change of λ on equilibrium strategies of the host and the service provider. In equilibrium, the host chooses privacy for each $\lambda \in (0, 1)$. Under privacy policy, the service provider cannot generate profits from user attention. Thus, it aims at price and therefore utility maximization. The corresponding first-order condition (8) is independent from λ for $\gamma = 0$. As a consequence, its solution, namely, the optimal level of addictiveness, is also independent from it.

From this finding, one may conclude that the host would prefer privacy policy in combination with the highest possible λ in order to maximize revenue through admission fees and the share it receives from them.

6 Extensions and robustness

6.1 The host cannot fully restrict attention monetization

In the model, it is assumed that the host can fully restrict ad revenues of the service provider under privacy policy. Now consider a more realistic scenario in which $\gamma \in \{\underline{\gamma}, 1\}$ with $0 < \underline{\gamma} < 1$, such that the service provider is only capable of partially restricting service provider profits from attention monetization. The following proposition investigates the effect of λ on the equilibrium strategies of the host and the service provider in this scenario:

Proposition 6 *For $\gamma \in \{\underline{\gamma}, 1\}$ with $0 < \underline{\gamma} < 1$, an increase of λ has no effect on equilibrium data disclosure. The equilibrium level of addictiveness increases and the corresponding price decreases in λ, i.e., $\partial d^*(\underline{\gamma})/\partial\lambda > 0$ and $\partial\overline{p}(d^*(\underline{\gamma}))/\partial\lambda < 0$.*
Proof. *See Appendix A.6.*

The proposition states that an increase of λ does not change the equilibrium policy of the host. But in contrast to before, it has an effect on the equilibrium business model of the service provider. More specific, an increase of λ corresponds to an increase of addictiveness and a decrease of the price. The intuition behind this effect is as follows.

In this scenario, the AME is always positive when users participate. Consequently, the service provider's incentives are distorted away from price maximization under each policy. For any given λ, this distortion is stronger with a higher level of data disclosure, such that the host still strictly prefers privacy. The corresponding equilibrium addictiveness level $d^*(\underline{\gamma})$ solves the service provider's first-order condition (8) for $\gamma = \underline{\gamma}$ and balances the PE and the AME of increasing addictiveness for any given λ. As stated before, the service provider chooses a level of addictiveness above the price maximizing one when attention monetization is feasible. More specific, $d^*(0) < d^*(\underline{\gamma}) < d^*(1)$. The corresponding PE is strictly negative and the price is $\overline{p}(d^*(1)) < \overline{p}(d^*(\underline{\gamma})) < \overline{p}(d^*(0))$.

Profits of the service provider stem from two sources, where only the source of admission price revenues is "taxed" by the host platform and higher λ corresponds to a lower share of admission price revenues the service provider keeps for itself. Thus, the service provider becomes more interested in increasing revenues from attention monetization with higher λ, and the impact of the PE on the service provider's decision decreases with increasing λ. Consequently, the equilibrium addictiveness level increases in λ, which goes along with a decreasing price.

In the current model, λ is treated as exogenous, and the host maximizes profits by choosing its policy accordingly. Given that λ, similar to γ, is in fact determined by the terms and conditions of the host platform, it is feasible to propose a model in which both variables are endogenously chosen. In such a scenario, Proposition 6 suggests that the host is confronted with a trade-off in the selection of λ. On one side, a higher λ corresponds to a larger portion of the admission prices received by the host, which makes the host prefer a higher λ. On the other side, an increased λ induces the service provider to increase addictiveness, which, in turn, leads to a lower price. Consequently, by increasing λ, the host secures a greater share of a diminished revenue.[14]

6.2 The host chooses a continuous policy variable

In the baseline model, the data disclosure policy of the host is represented by a dichotomous variable that determines whether the service provider is able, or is not able to directly monetize attention. A more realistic approach is to model the policy as a continuous choice variable, i.e., $\gamma \in [0, 1]$, whereby a higher value of γ corresponds to a less restrictive privacy policy. In the example of iOS, a positive share of users chooses to opt-in to tracking, which could be captured by an intermediate value of γ. In such a scenario, the policy variable scales to which extent direct attention monetization is possible. The corresponding first-order condition of the service provider includes the PE and the AME, with the latter increasing monotonically in the level of data disclosure. The optimal level of addictiveness $d^*(\gamma)$ is a continuous function. Recall that the AME distorts the service provider away from price maximization. This distortion is stronger with increasing γ, and the price is maximized under the most restrictive data disclosure policy, i.e., $\gamma = 0$. Consequently, the host still chooses full privacy in equilibrium, such that the structure of the equilibrium and the results are robust to change from a dichotomous to a continuous policy variable.

6.3 Network effects depend on participation rather than on attention

Throughout the current model, the network effects a user experiences depend on the attention of all other users. An alternative approach is to consider network effects $b(n)$ as a function increasing in the mass of participating users, denoted by $n \in [0, 1]$.

The host chooses privacy in equilibrium, independent from the network effects depending on user activity (attention) or presence (mass), since privacy triggers price maximization of the service provider. Under privacy, the service provider only considers the PE for determination of the profit maximizing level of addictiveness, where the PE is affected by network effects. If network effects depend on the number of active users and not on their attention level, i.e.,

[14] For instance, Ling (2021) provides an overview of app store fees for different platforms. One can observe that shares are between 30% and 50% which indicates that there has to exist a mechanism that limits the share like e.g., a market mechanism. Proposition 6 might provide an argument why observed shares are intermediate. In order to investigate the decision and underlying mechanisms, other factors like, e.g., competition between host platforms would have to be considered, which is beyond the scope of this paper.

$\partial b/\partial A_{-i} = 0$, the service provider can only enhance network effects by ensuring participation. A boost of user attention, which is achieved by an increasing level of addictiveness, does not affect network effects. Consequently, increasing the level of addictiveness decreases user utility and, consequently, the price. Thus, user utility is maximized under zero addictiveness. The resulting equilibrium always involves privacy policy in combination with zero addictiveness.

Nevertheless, there would be non-zero network effects that influence the admission price that the service provider can charge. In equilibrium, all users make use of the service, resulting in network effects $b(1)$. Denote the price with network effects solely dependent on user mass as $\tilde{p}$ and the price without network effects as p_0. Then, $\tilde{p} = p_0 + b(1)$. It follows that if $\partial b/\partial n \lesseqgtr 0$, we obtain $\tilde{p} \lesseqgtr p_0$.

6.4 Allow corner solutions of the service provider's problem

The previous results apply to scenarios in which interior equilibria of the second game stage exist, i.e., situations in which the conditions specified in Proposition 2 hold. If this is the case, the effect of increasing service addictiveness on service provider profits is ambiguous and the profit maximizing choice of the addictiveness level is not trivial. In what follows, I discuss the implications of loosening the assumption that (11) and (12) are satisfied.

Condition (11) rules out the possibility that the price is maximized under zero addictiveness. If it does not hold, situations can occur in which user utility under optimal behavior does never increase in addictiveness. As a consequence, the service provider chooses an addictiveness level of zero under privacy and a weak positive addictiveness level under disclosure policy, $\tilde{d} \geq 0$, resulting in prices $\overline{p}(0) \geq \overline{p}(\tilde{d})$. If strictness holds, i.e., if the AME outweighs the PE for small levels of addictiveness resulting in $\tilde{d} > 0$, the host strictly prefers privacy over disclosure. Otherwise, the host is indifferent between both policies. Taken together, even if (11) does not hold, the host never prefers disclosure over privacy policy.

Condition (12) rules out the possibility of profit maximization under disclosure policy by setting an addictiveness level that makes users only use the service if it is free. If the condition does not hold, there can be situations in which the AME is stronger than the PE for all levels of addictiveness. Consequently, the service provider is only interested in maximization of revenues from attention monetization if possible, which is achieved by maximization of user attention. The corresponding level of addictiveness is $\overline{d} > 0$ with a corresponding price of zero. Under privacy, the service provider maximizes the price and achieves a strictly positive one, with a corresponding addictiveness level strictly below $\overline{d}$. Consequently, the host prefers privacy over disclosure policy, indicating the robustness of the main results.

7 Conclusion

This paper presents a theoretical model that captures features of online markets in which a service provider and users are matched on a host platform. It investigates the relationship between the data disclosure policy of the host and the pricing and service design adopted by a subordinate service provider in a monopoly environment. Within this framework, the host's policy choice influences the service provider's capabilities of making profits from targeted advertisement, and the service provider can sacrifice service quality in order to generate attention by incorporating addictive design features.

The analysis reveals that the host platform chooses a restrictive data disclosure policy in equilibrium. Under this policy, the service provider chooses a higher admission price and a lower level of addictiveness as compared to a policy involving a higher level of data disclosure. In absence of competition, the service provider sets a price that absorbs all surplus from the users. Consequently, a higher price indicates higher service utility, which also goes along with less attention spending of the users. Furthermore, network effects among users alter the price-attention trade-off in connection with the implementation of addictive service design features. If strong enough, the service provider chooses a positive level of addictiveness even when attention cannot be monetized via targeted advertisement, i.e., under a restrictive data disclosure policy. Furthermore, the equilibrium level of addictiveness increases with stronger network effects.

The findings may provide insight into shifts in corporate privacy policies recently observed in online markets, such as Apple's ATT and Google's Privacy Sandbox, as well as other privacy-focused updates, as they increase the profits of the host platforms. The results suggest that these shifts lead app providers to increase prices, which is empirically supported by Kesler (2023), who finds that apps in Apple's App Store have increasingly become chargeable and integrate in-app purchases following the ATT update. The results further suggest a positive relationship between increased user privacy and improved service quality. While earlier research has demonstrated that privacy can safeguard users from price discrimination or harmful targeting (e.g., Villas-Boas, 1999; Taylor, 2004; Villas-Boas, 2004; Zhang and Krishnamurthi, 2004; Acquisti and Varian, 2005; Hann et al., 2008), this work highlights an additional benefit: enhanced service quality for users. Considering the adverse effects of online addiction, the results suggest potential welfare benefits through increased service quality and the reduction of negative external effects amplified by the implementation of addictive design elements. Taken together, the findings imply that policymakers who are interested in decreasing the addictiveness of online services may not need to actively regulate online markets, as host platforms may be motivated to address these issues themselves.

Nevertheless, this advice should be considered with caution, as the model has certain limitations. The current model specifically focuses on corporate data disclosure policies that restrict the data usage of third-party service providers. However, it does not address the data usage practices of the host platform itself. Profits derived from the host's data usage are not examined, meaning that related topics, such as asymmetric competition and self-regulation of the host, are beyond the scope of this work. To make more general statements about regulating host platforms, other factors should be considered, such as self-preferencing, profit shifting, or market distortions. It is important to note that the advice provided here is specific to the service addictiveness and quality of third-party service providers.

Future research may explore the theoretical and empirical effects of data disclosure policies on business models, taking into account user heterogeneity, platform and service provider competition, and behavioral nuances. Analyzing platform incentives in relation to advertising strategies and content moderation could also provide valuable insights.

A Proofs

A.1 Proof of Proposition 1

If a user uses the service provider's service, she chooses her attention level according to (4). Omitting the indices, define $F(a, d) = \frac{\partial u}{\partial a} - \frac{\partial c}{\partial a}$ for this proof, such that $F(a, d) = 0$ is equivalent to (4). In order to investigate how changes in d affect the equilibrium a, consider the Implicit Function Theorem (IFT):

i.) The utility of user i, as presented in (1), is a $\mathbb{C}^2$ function and concave in a. As a consequence, there exists an $a = a_0$ that (uniquely) solves the corresponding first-order condition (4) for a given $d = d_0$. Thus, $F(a_0, d_0) = 0$.

ii.) At the point $(a, d, F(a, d)) = (a_0, d_0, 0) = A$, we have

$$\left.\frac{\partial F}{\partial a}\right|_{(a_0,d_0)} = \left.\left[\frac{\partial^2 u}{\partial a^2} - \frac{\partial^2 c}{\partial a^2}\right]\right|_{(a_0,d_0)} < 0,$$

which follows from the definitions of $u(\cdot)$ and $c(\cdot)$. Therefore, it holds that $\left.\frac{\partial F}{\partial a}\right|_{(a_0,d_0)} \neq 0$.

iii.) Since i.) and ii.) hold, the IFT is applicable. In the neighborhood of A, a can be expressed as a function of d, such that $F(a(d_0), d_0) = 0$. Furthermore, we have

$$\left.\frac{\partial a}{\partial d}\right|_{(a_0,d_0)} = -\left.\frac{\frac{\partial F}{\partial d}}{\frac{\partial F}{\partial a}}\right|_{(a_0,d_0)} = -\left.\frac{\frac{\partial^2 u}{\partial a \partial d} - \frac{\partial^2 C}{\partial a \partial d}}{\frac{\partial F}{\partial a}}\right|_{(a_0,d_0)} = -\left.\frac{\frac{\partial^2 u}{\partial a \partial d}}{\frac{\partial F}{\partial a}}\right|_{(a_0,d_0)} > 0.$$

Since $\frac{\partial^2 u}{\partial a \partial d} > 0$ for all $d \geq 0$ per definition, this is true for arbitrary $d_0 \geq 0$. Changing the notation from a_0 to a_i^* and considering d as a variable, we have $\frac{\partial a_i^*}{\partial d} > 0$. Thus, given the user has already joined the monopoly platform, her equilibrium attention increases in d. It follows from assumption $\lim_{a_i \to 0} \left(\left.\frac{\partial u}{\partial a_i}\right|_{(a_i,0)} - \left.\frac{\mathrm{dc}}{\mathrm{d}a_i}\right|_{(a_i)} \right) > 0$ that $a_i^*(0) > 0$ and therefore $a_i^*(d) > 0\,, \forall\, d \geq 0$.

■

A.2 Proof of Proposition 2

In this proof, I provide conditions under which a unique interior solution to the service provider's profit maximization problem exists. For each observed policy $\gamma \in \{0, 1\}$, the interior solution satisfies the first-order condition (8). Define, for this proof, the function from the left-hand side (LHS) of the condition as

$$G(d, \gamma; \kappa, \lambda) = (1 - \lambda) \cdot \psi(d; \kappa) + \xi(d, \gamma),$$

such that $G(\cdot) = 0$ corresponds to (8). In the subsequent analysis, I exclude corner solutions, specifically $d = 0$ and $d = \overline{d}$, and demonstrate the existence of unique interior solutions for both subgames, when $\gamma = 0$ and $\gamma = 1$.

- Consider $\gamma = 0$. Taking into account that $\xi(d, 0) = 0$ for all d, $G(d, 0; \kappa, \lambda) = 0$ is equivalent to $\psi(d; \kappa) = 0$.
  - $d = 0$ can never be a solution to the service provider's maximization problem if

$$\lim_{d \to 0} G(d, 0; \kappa, \gamma) = (1 - \lambda) \cdot \lim_{d \to 0} \psi(d; \kappa) > 0,$$

which is equivalent to

$$(1-\lambda)\cdot\left(\frac{\partial u}{\partial d}\bigg|_{(a_i^*(0),0)}+\kappa\cdot\frac{\partial b}{\partial A_{-i}}\bigg|_{(a_i^*(0))}\cdot\frac{\partial a_i^*}{\partial d}\bigg|_{(0)}\right)>0.$$

Proposition 1 implies that $\partial a_i^*/\partial d|_{(0)} > 0$. Thus, it is feasible for this condition to be both satisfied and violated. Consequently, to exclude $d = 0$ as an optimal solution, we need to introduce the following assumption:

$$\psi(0;\kappa) > 0 \tag{14}$$

If (14) is satisfied, then $d = 0$ cannot be an optimal solution to the service provider's problem under privacy policy.

– In order to exclude $d = \overline{d}$ as an optimal solution, recall that $d = \overline{d}$ corresponds to a price of zero and that $\overline{d}$ exists by assumption. Since the service provider can achieve a positive price by setting $d < \overline{d}$, this implies

$$\psi(\overline{d};\kappa) < 0. \tag{15}$$

Under privacy policy, the service provider aims at price maximization. Consequently, it can never be optimal to choose $d = \overline{d}$.

- Consider $\gamma = 1$, where $G(d, 1; \kappa, \lambda) = (1-\lambda)\cdot\psi(d;\kappa) + \xi(d, 1)$.

– $d = 0$ can never be a solution to the service provider's maximization problem if

$$\lim_{d\to 0} G(d,1;\kappa,\gamma) = (1-\lambda)\cdot\lim_{d\to 0}\psi(d;\kappa) + \lim_{d\to 0}\xi(d,1) > 0.$$

Proposition 1 implies that $\xi(0, 1) > 0$. Thus, the condition is not feasible to be violated if (14) holds. Consequently, if (14) is satisfied, $d = 0$ cannot be an optimal solution to the service provider's problem under disclosure policy.

– $d = \overline{d}$ cannot be an optimal solution of the service provider's problem if

$$\lim_{d\to \overline{d}} G(d,1;\kappa,\gamma) = (1-\lambda)\cdot\lim_{d\to \overline{d}}\psi(d;\kappa) + \lim_{d\to \overline{d}}\xi(d,1) < 0.$$

Since $\xi(\overline{d}, 1) > 0$, (15) implies that the condition is feasible to be both satisfied and violated. As a consequence, to exclude $d = \overline{d}$ as a solution, we need to impose the following assumption:

$$(1-\lambda) \cdot \psi(\overline{d};\kappa) + \xi(\overline{d},1) < 0 \tag{16}$$

If (16) is satisfied, then $d = \overline{d}$ cannot be an optimal solution to the service provider's problem under disclosure policy.

Taken together, the service provider will never choose $d = 0$ and $d = \overline{d}$ if conditions (14) and (16) are satisfied. In what follows, I demonstrate that there exists a unique interior solution to the service provider's problem under both policies for a situation in which both conditions hold.

Consider the Intermediate Value Theorem (IVT). For each $\gamma \in \{0,1\}$, we can make the following statements:

- By construction, $G(d,\gamma;\kappa,\lambda)$ is continuous over $d \in (0,\overline{d})$.
- (14) implies that the limit of $G(\cdot)$ at the lower border of its support is positive, i.e.,

$$\lim_{d \to 0} G(d,\gamma;\kappa,\lambda) > 0. \tag{17}$$

- (16) implies that the limit of $G(\cdot)$ at the upper border of its support is negative, i.e.,

$$\lim_{d \to \overline{d}} G(d,\gamma;\kappa,\lambda) < 0. \tag{18}$$

According to the IVT, it follows that there exists at least one $d_c \in (0,\overline{d})$ such that $G(d_c,\gamma;\kappa,\lambda) = 0$. Denote the set of all these critical points as $\mathcal{D}_c = \{d_{c1}, d_{c2}, d_{c3}, \dots\}$. If $\mathcal{D}_c$ is a singleton, its element characterizes a unique global maximum, i.e., the unique addictiveness level in the equilibrium of the second stage for a given policy. If not, within the scope of the model, every element characterizes a critical point of the service provider's profit function $\tilde{\Pi}^S(\cdot)$. Each critical point is either a local maximum or a local minimum of $\tilde{\Pi}^S(\cdot)$. (17) and (18) imply that $\mathcal{D}_c$ consists of an odd number of elements, where every odd-numbered element of the set characterizes an argument that locally maximizes profits. Thus, the set of critical points that correspond to local maxima is $\mathcal{D}_{c,\max} \subset \mathcal{D}_c$, with $\mathcal{D}_{c,\max} = \{d_{c1}, d_{c3}, \dots\}$. Since corner solutions are ruled out, the set of potential global maxima is $\mathcal{D}_{c,\max}$. Every global maximum characterizes an equilibrium level of addictiveness.

In addressing the issue of multiplicity of equilibria, it is crucial to acknowledge that the presence of multiple equilibria inherently depends on the existence of multiple global maxima within a given function or system. For each γ, the conditions that must be met for the existence of multiple maxima are $\overline{p}(d_{ci}(\gamma)) = \overline{p}(d_{cj}(\gamma))$ for $d_{ci}, d_{cj} \in \mathcal{D}_{c,\max}$, $i \neq j$. However, scenarios featuring multiple global maxima are highly specific, often arising within meticulously constructed functions and under particular parameter constellations that are not commonly encountered in practical applications. These instances require an exact alignment of parameters and conditions, making them somewhat theoretical and not broadly applicable. Furthermore, the delicate nature of these setups implies that even minimal variations in parameter values (e.g., marginal variation of κ) are sufficient to disrupt the existence of multiple global maxima, thereby eliminating the multiplicity of equilibria. Given the rarity and instability of such configurations, I choose to abstract from these cases in my analysis.

Consequently, exactly one element of $\mathcal{D}_{c,\max}$ characterizes a global maximum, which we call $d^*(\gamma)$, dependent on the policy.

Taken together, for every $\gamma \in \{0, 1\}$, there exists a unique $d^*(\gamma) \in (0, \overline{d})$ if conditions (14) and (16) are satisfied. These conditions correspond to (11) and (12), respectively. The corresponding prices, as defined in (7), are strictly positive, i.e., $\overline{p}(d^*(\gamma)) > 0$.

■

A.3 Proof of Proposition 3

For profit maximization, the host chooses a policy that maximizes the price the service provider sets. It solves (13). Recall the proof of Proposition 2. For $\gamma = 0$, the service provider's profit maximization problem is equivalent to a price maximization problem, i.e., $d^*(0) = \arg\max_{d \in (0, \overline{d})} \overline{p}(d)$ and $\psi(d^*(0)) = 0$. Thus, a strict privacy policy of the host induces price maximization and, in equilibrium, the host chooses $\gamma^* = 0$.

In order to show that the equilibrium is unique, i.e., to show that the host is never indifferent between $\gamma = 0$ and $\gamma = 1$, compare equilibrium outcomes of the respective subgames. Recall the proof of Proposition 2. The LHS of the first-order condition under privacy policy is

$$G(d, 0; \kappa, \lambda) = (1 - \lambda) \cdot \psi(d, \kappa).$$

The LHS of the first-order condition under disclosure policy is

$$G(d, 1; \kappa, \lambda) = (1 - \lambda) \cdot \psi(d, \kappa) + \xi(d, 1) = G(d, 0; \kappa, \lambda) + \xi(d, 1).$$

Since $\xi(d, 1) > 0$ for all $d \in (0, \overline{d})$, we can conclude that

$$G(d, 0; \kappa, \lambda) < G(d, 1; \kappa, \lambda) \quad \forall\, d \in (0, \overline{d}). \tag{19}$$

According to Proposition 2, there exist solutions to both first-order conditions if conditions (11) and (12) hold, which we assume is the case. Consequently, (19) implies that $d^*(0) < d^*(1)$.

Recall that $d^*(0)$ globally maximizes the price. Consequently, every $d^*(0) \neq d^*(1)$ implies that $\overline{p}(d^*(0)) > \overline{p}(d^*(1))$.

Thus, the host strictly prefers privacy over disclosure policy, i.e., $\gamma^* = 0$ is the unique equilibrium strategy of the host.

■

A.4 Proof of Proposition 4

In this proof, I investigate the effects of increasing κ on equilibrium addictiveness and on the maximum rationalizable level of addictiveness. In equilibrium, the host chooses $\gamma^* = 0$. Under privacy policy, the service provider solves the (8). The corresponding LHS is equivalent to the function

$$G(d, 0; \kappa, \lambda) = (1 - \lambda) \cdot \psi(d; \kappa),$$

such that $G(d, 0; \kappa, \lambda) = 0$ is equivalent to (8). Consider the IFT:

i. Denote, for this proof, the addictiveness level that solves the first-order condition under privacy policy as $d_0 = d^*(0)$. The function $G(d, 0; \kappa, \lambda)$ is $\mathbb{C}^1$, and according to Proposition 2, there exists a $d_0 \in (0, \overline{d})$ that solves $G(d, 0; \kappa, \lambda) = 0$ for any given κ_0 and λ_0, if conditions (11) and (12) are satisfied, which they are by assumption.

ii.) $\partial G/\partial d|_{(d_0,0;\kappa_0,\lambda_0)}$ is equivalent to the second-order condition of the service provider's profit maximization problem. d_0 characterizes a maximum. Consequently, the second-order condition has to be negative, i.e., $\partial G/\partial d|_{(d_0,0;\kappa_0,\lambda_0)} < 0$, or rather $\partial G/\partial d|_{(d_0,0;\kappa_0,\lambda_0)} \neq 0$.

iii.) Points i.) and ii.) imply that the IFT is applicable. In the neighborhood of the point

$(d, \kappa, \lambda, G(d, 0; \kappa, \lambda)) = (d_0, \kappa_0, \lambda_0, 0)$, d can be expressed as a function of κ, $d = g(\kappa, \lambda)$, such that $G(g(\kappa_0, \lambda_0), 0; \kappa_0, \lambda_0) = 0$. Furthermore, we have

$$\frac{\partial g}{\partial \kappa}\bigg|_{(\kappa_0,\lambda_0)} = -\frac{\frac{\partial G}{\partial \kappa}\Big|_{(d_0,0;\kappa_0,\lambda_0)}}{\frac{\partial G}{\partial d}\Big|_{(d_0,0;\kappa_0,\lambda_0)}} = -\frac{\frac{\partial b}{\partial A_{-i}}\Big|_{(a_i^*(d_0))} \cdot \frac{\partial a_i^*}{\partial d}\Big|_{(d_0)}}{\frac{\partial \psi}{\partial d}\Big|_{(d_0;\kappa_0)}}$$

Proposition 1 and Proposition 2 imply that $\partial g/\partial \kappa|_{(\kappa_0,\lambda_0)} > 0$. Changing notation, we obtain $\partial d^*(0)/\partial \kappa > 0$.

The maximum level of addictiveness under which users join, $\overline{d}$, makes the user indifferent between joining, or not. $\overline{d}$ is defined by $\overline{p}(\overline{d}; \kappa) = 0$. Define for this proof from the RHS of (7) the function

$$H(d; \kappa) = u(a_i^*(d), d) + \kappa \cdot b(a_i^*(d)) - c(a_i^*(d)),$$

where $H(d; \kappa) = 0$ is equivalent to $\overline{p}(d; \kappa) = 0$. Consider the IFT:

i.) $H(d; \kappa)$ is $\mathbb{C}^1$ and there exists a value $\overline{d} > 0$ that solves $H(d; \kappa) = 0$ by assumption for any κ_0. For this proof, denote this level as d_1.

ii.) $\partial H/\partial d|_{(d_1;\kappa_0)} = \psi(d_1; \kappa_0)$. It follows from the existence of d_1 that $\psi(d_1; \kappa_0) < 0$.

iii.) i.) and ii.) imply that the IFT is applicable. In the neighborhood of $(d, \kappa, H(d; \kappa)) = (d_1, \kappa_0, 0)$, d can be expressed as a function of κ, $d = h(\kappa)$, such that $H(h(\kappa_0), \kappa_0) = 0$. Furthermore, we have

$$\frac{\partial h}{\partial \kappa}\bigg|_{(\kappa_0)} = -\frac{\frac{\partial H}{\partial \kappa}\Big|_{(d_1;\kappa_0)}}{\frac{\partial H}{\partial d}\Big|_{(d_1;\kappa_0)}} = -\frac{b(a_i^*(d_1))}{\psi(d_1; \kappa_0)} > 0.$$

Changing the notation, we obtain $\partial \overline{d}/\partial \kappa > 0$.

■

A.5 Proof of Proposition 5

In order to investigate the effect of λ on the equilibrium outcome, consider the service provider decision under privacy policy. If the host chooses $\gamma^* = 0$, the monopolist maximizes profits by maximization of the price via choice of d. The maximization of price (7) is independent of λ, i.e., $\partial d^*(0)/\partial \lambda = 0$ for all $\lambda \in (0, 1)$. Thus, a change in λ does not affect equilibrium addictiveness. As a consequence, it also has no effect on the price, i.e., $\partial \overline{p}(d^*(0))/\partial \lambda = 0$.

The host chooses γ in order to induce price maximization, which is independent from λ. Thus, $\partial\gamma^*/\partial\lambda = 0$.

■

A.6 Proof of Proposition 6

In this proof, I investigate the effects of increasing λ on equilibrium addictiveness, where $\gamma \in \{\underline{\gamma}, 1\}$ with $0 < \underline{\gamma} < 1$. In equilibrium, the host chooses $\gamma = \underline{\gamma}$. Under such a policy privacy policy, the service provider solves first-order condition (8) for $\gamma = \underline{\gamma}$. The corresponding LHS is equivalent to the function

$$G(d, \underline{\gamma}; \kappa, \lambda) = (1 - \lambda) \cdot \psi(d; \kappa) + \xi(d, \underline{\gamma}),$$

such that $G(d, \underline{\gamma}; \kappa, \lambda) = 0$ is equivalent to (8). Consider the IFT:

i. Denote, for this proof, the addictiveness level that solves the first-order condition for $\gamma = \underline{\gamma}$ as $d_0 = d^*(\underline{\gamma})$. The function $G(d, \underline{\gamma}; \kappa, \lambda)$ is $\mathbb{C}^1$, and according to Proposition 2, there exists a $d_0 \in (0, \overline{d})$ that solves $G(d, \underline{\gamma}; \kappa, \lambda) = 0$ for any given κ_0 and λ_0, if conditions (11) and (12) are satisfied, which they are by assumption.

ii.) $\partial G/\partial d|_{(d_0, \underline{\gamma}; \kappa_0, \lambda_0)}$ is equivalent to the second-order condition of the service provider's profit maximization problem. d_0 characterizes a maximum. Consequently, the second-order condition has to be negative, i.e., $\partial G/\partial d|_{(d_0, \underline{\gamma}; \kappa_0, \lambda_0)} < 0$, or rather $\partial G/\partial d|_{(d_0, \underline{\gamma}; \kappa_0, \lambda_0)} \neq 0$.

iii.) Points i.) and ii.) imply that the IFT is applicable. In the neighborhood of the point $(d, \kappa, \lambda, G(d, \underline{\gamma}; \kappa, \lambda)) = (d_0, \kappa_0, \lambda_0, 0)$, d can be expressed as a function of λ, $d = g(\kappa, \lambda)$, such that $G(g(\kappa_0, \lambda_0), \underline{\gamma}; \kappa_0, \lambda_0) = 0$. Furthermore, we have

$$\left.\frac{\partial g}{\partial \lambda}\right|_{(\kappa_0, \lambda_0)} = -\frac{\left.\frac{\partial G}{\partial \lambda}\right|_{(d_0, \underline{\gamma}; \kappa_0, \lambda_0)}}{\left.\frac{\partial G}{\partial d}\right|_{(d_0, \underline{\gamma}; \kappa_0, \lambda_0)}} = \frac{\psi(d_0; \kappa_0)}{\left.\frac{\partial G}{\partial d}\right|_{(d_0, \underline{\gamma}; \kappa_0, \lambda_0)}}$$

Recall Proposition 2 and the proof of Proposition 3. Linearity of $G(\cdot)$ in γ implies that $d^*(0) < d^*(\underline{\gamma}) < d^*(1)$. It follows that $\psi(d^*(1); \kappa_0) < \psi(d^*(\underline{\gamma}); \kappa_0)) = \psi(d_0; \kappa_0) < \psi(d^*(0); 0) = 0$. Consequently, $\partial g/\partial \lambda|_{(\kappa_0, \lambda_0)} > 0$. Changing notation, we obtain $\partial d^*(\underline{\gamma})/\partial \lambda > 0$. It further follows that the equilibrium price strictly decreases in λ.

■

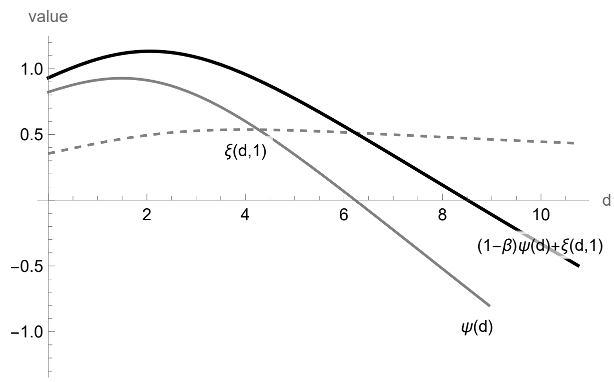


Figure 5: Service provider's first-order condition under disclosure policy (black), first-order condition under privacy policy / PE (gray), and AME (gray, dashed).

B Numerical example

Suppose service utility is $u(a_i, d) = \ln(1 + a_i - d)$, network effects are $b(A_{-i}) = \sqrt{A_{-i}}$, attention costs are $c(a_i) = 1/8 \cdot a_i^2$, and attention can be directly monetized according to $v(A) = 3 \cdot \sqrt{1+A}$. Furthermore, suppose $\kappa = 8$ and $\lambda = 0.3$ In the following, we construct the equilibrium.

At stage 3, each user i maximizes utility

$$U_i(a_i, d, p, A_{-i}) = \ln(1 + a_i - d) + \kappa \cdot \sqrt{A_{-i}} - \frac{1}{8} \cdot a_i^2 - p.$$

If she uses the service, the optimal attention level of user i is

$$a_i^*(d) = \frac{1}{2} \cdot \left(d - 1 + \sqrt{17 - 2d + d^2}\right). \tag{20}$$

Her participation constraint is

$$\begin{aligned} &\ln\left(\frac{1}{2} \cdot \left(1 - d + \sqrt{17 - 2d + d^2}\right)\right) + \kappa \cdot \sqrt{A_{-i}} \\ &\quad - \frac{1}{32} \cdot \left(d - 1 + \sqrt{17 - 2d + d^2}\right)^2 - p \geq 0. \end{aligned} \tag{21}$$

At the second stage, for any $d \in [0, \overline{d})$, the price is determined by (21) holding with equality for $A_{-i} = A_{-i}^* = a_i^*(d)$ as defined in (20), and $\kappa = 8$, i.e.,

$$\begin{aligned} \overline{p}(d) = 4 \cdot \sqrt{2} \cdot \sqrt{d - 1 + \sqrt{17 - 2d + d^2}} - \frac{1}{32} \cdot \left(d - 1 + \sqrt{17 - 2d + d^2}\right)^2 \\ + \ln\left(\frac{1}{2}\left(1 - d + \sqrt{17 - 2d + d^2}\right)\right) \end{aligned} \tag{22}$$

Note that the conditions for the existence of an interior solution to the service provider's profit maximization problem, as presented in Proposition 2, are satisfied. Condition (11) holds for $\kappa > \underline{\kappa} \approx 2.57$. Thus, the condition is satisfied for $\kappa = 8$. The maximum rationalizable level of addictiveness is $\overline{d} \approx 16.28$. Condition (12) is satisfied because $(1-0.3)\cdot\psi(16.28; 8)+\xi(16.28, 1) \approx -1.65 < 0$. Consequently, in the equilibria of both subgames, the service provider chooses addictiveness levels over the set $(0, \overline{d})$.

In the privacy subgame, i.e., for $\gamma = 0$, the service provider solves the first-order condition $\mathrm{d}\overline{p}/\mathrm{d}d = 0$, which is equivalent to $\psi(d) = 0$, or rather

$$\frac{1}{8}\left(1 - d - \sqrt{17 - 2d + d^2} + \frac{16\sqrt{2}\sqrt{d - 1 + \sqrt{17 - 2d + d^2}}}{\sqrt{17 - 2d + d^2}}\right) = 0. \tag{23}$$

$d^*(0) \approx 6.22$ solves (23). Plugging this value into (22) yields $\overline{p}(d^*(0)) \approx 14.69$. The corresponding attention level, as defined in (20), is $a_i^*(d^*(0)) \approx 5.90$.

In the disclosure subgame, i.e., for $\gamma = 1$, the service provider solves $(1-\lambda)\cdot\mathrm{d}\overline{p}/\mathrm{d}d+\mathrm{d}v/\mathrm{d}d = 0$, or rather

$$(1 - 0.3) \cdot \psi(d) + \frac{3\left(2 + \frac{2(-1+d)}{\sqrt{17-2d+d^2}}\right)}{4\sqrt{2}\sqrt{1 + d + \sqrt{17 - 2d + d^2}}} = 0, \tag{24}$$

where $\psi(d)$ is equivalent to the LHS of (23). $d^*(1) \approx 8.51$ solves (24). Evaluating (22) yields the corresponding price $\overline{p}(d^*(1)) \approx 13.92$. The attention level of each user is $a_i^*(d^*(1)) \approx 8$, as defined in (20).

Figure 5 illustrates the effects of increasing d on the second stage. The solid and dashed gray lines depict $\psi(d)$ and $\xi(d, 1)$, respectively. The black graph shows the interplay, i.e., $(1 - \lambda)\psi(d) + \xi(d, 1)$. Note that the roots of the solid gray and black lines characterize the addictiveness levels in the equilibrium of the privacy and disclosure subgame, respectively.

At the first stage, the host aims at price maximization. Thus, it follows from $\overline{p}(d^*(0)) > \overline{p}(d^*(1))$ that the host chooses $\gamma^* = 0$ in equilibrium.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author used ChatGPT-4o in order to proofread the manuscript, focusing on grammar, spell checking, and readability. After using this tool/service, the author reviewed and edited the content as needed and takes full responsibility for the content of the published article.

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