The Platform Dimension of Digital Privacy

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Abstract

Recent advancements in economic theory explore the practices of large digital platforms in terms of data collection from individual users and their monetization strategies through targeted advertising. Of particular interest is the *platform dimension* of digital privacy, whereby the actions and behaviors of *all* users and advertisers influence the amount and the precision of the information available about each user. The acquisition of such information by platforms is facilitated by the presence of data externalities that stem from the correlation in preferences among different users. Balancing consumer privacy and product-market competition is challenging, as platforms strategically utilize their data not only to enhance the quality of matches but also to bolster advertisers' market power. These findings highlight the complex relationship between privacy, regulation, and competition.

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1 Introduction

The past two decades have witnessed an unprecedented scale of collection and dissemination of individual-level data. Large digital platforms such as Amazon, Facebook, Google, Alibaba, JD, and Tencent are at the forefront of this data collection, often through ostensibly free services offered to users. These platforms generate revenue by matching users with advertisers, merchants, and content producers, effectively selling access to a qualified consumer audience. The implications of such practices for individual privacy have raised concerns among academics and policymakers, resulting in regulatory interventions like the European Union's General Data Protection Regulation (GDPR) and the California Privacy Rights Act (CPRA).

Taking a closer look, the challenge of protecting individual privacy in today's digital markets reveals a new dimension. The equilibrium level of privacy and its welfare consequences depend on the mechanisms employed by two-sided platforms to mediate the exchange of consumer data. Notably, the presence of network effects stemming from both users (on one side) and advertisers (on the other side), as well as the potential for platform competition, collectively determine the scale and granularity of consumer data intermediation.

In this paper, I review recent advancements in economic theory that explore the platform dimension of digital privacy, examine potential sources of market failure, and suggest open areas for future research. The economic theory of privacy is decades old, beginning with the classic work of Stigler (1980) and Posner (1981), and more recently surveyed in the comprehensive work of Acquisti, Taylor, and Wagman (2016). However, the platform dimension of privacy and the dual role of digital platforms as gatekeepers of information and competition (Bergemann and Bonatti, 2023) introduce new challenges and require new modeling tools.[1]

Due to its platform dimension, privacy has evolved into a social, competition, and regulation issue. Throughout the paper, I concentrate on three key questions: (1) How do different consumers' privacy choices interact with one another? (2) Is there a tradeoff between privacy and competition? In other words, does preserving consumer data privacy also result in limited competition for the consumer? (3) How do regulatory interventions assist, and what are the potential drawbacks?[2]

I argue that data acquisition by platforms is significantly facilitated by data externalities—

[1]Huge amounts of attention have been devoted to privacy in several fields, including law, political science, and computer science. A common theme is that improvements in information and communications technology facilitate individual-level data collection and naturally introduce concerns. These concerns are not limited to big tech datasets and market power but extend to the role, for example, of government tracking and surveillance. The analysis in this chapter is highly specialized and complementary to those perspectives.

[2]The regulation dimension of privacy is examined by Johnson (2022), and I refer the reader to that paper for an in-depth analysis of the GDPR.

the impact of other consumers' data on an individual user's decision to share their own data. When consumers' characteristics are positively correlated, I demonstrate conditions under which little stands in the way of a large platform amassing vast amounts of individual data. This holds true even if consumers had full control over their privacy, as the marginal cost of acquiring each user's data is small relative to the overall value of a dataset. Additionally, I discuss whether competition among platforms for acquiring user data, given the nature of information goods, is likely to yield substantial welfare gains.

Shifting focus to data monetization, I illustrate how a digital platform with market power can transfer that power downstream to advertisers by offering exclusive access to consumers. The platform leverages its data from past and concurrent transactions to generate surplus through enhanced matching of consumers and sellers. At the same time, the possibility of awarding "de facto monopoly positions" (Cremèr, de Montjoye, and Schweitzer, 2019) to advertisers limits the diffusion of consumer data (which may be viewed as privacy protecting) but opens the door to surplus extraction through personalized offers (e.g., price discrimination and product steering).[3] The resolution of this trade-off by a monopolist seller is then critical to understanding the welfare implications of market power by digital platforms and hence the relationship between privacy and competition for access to consumers.

The welfare implications of data acquisition and data monetization by digital platforms are not straightforward. In particular, the expansion of a platform's database affects its capacity to match products to individual preferences, but it also diminishes each consumer's alternative options. This gives rise to a new form of data externality, where different consumers' privacy choices interact with one another, even in the presence of regulatory interventions like GDPR and CPRA that aim to assign formal control rights over data to individual users. Similarly, the optimal mechanisms for monetizing data create a tension between privacy and competition for the consumer.

The overall scenario that emerges depicts data externalities leading to economies of scale on the data acquisition side, while market power on the monetization side enables the sale of exclusive access to each consumer's attention. Under these circumstances, the welfare effects of privacy ultimately depend on the type of firms that gain access to the consumer—whether they primarily utilize information to generate or extract value.

To address these questions, Section 2 introduces a model of a two-sided platform as a monopolist data intermediary and examines the economics of privacy through this lens; Section 3 focuses on the data-acquisition side; and Section 4 examines the data-monetization side. Section 5 concludes and suggests open areas for future research.

[3] The availability of granular individual-level data can, of course, introduce other concerns, including government surveillance, data leakages, fraud, misinformation campaigns, and addictive social media.

2 Basic Framework

The basic role of any digital platform is to intermediate large numbers of users and producers. Here, we develop a basic data-intermediation model that captures some of the key dimensions of real-world platforms. First, any information it acquires must be obtained from multiple users. Second, any data it has acquired can be monetized through multiple producers or firms of merchants. Third, consumers and producers may have outside access opportunities or the ability to meet off the platform. As we will see, a critical determinant of the platform's bargaining power is whether it is instrumental for a match between consumers and producers or merely enables this match to occur under better complete information. Figure 1 illustrates.

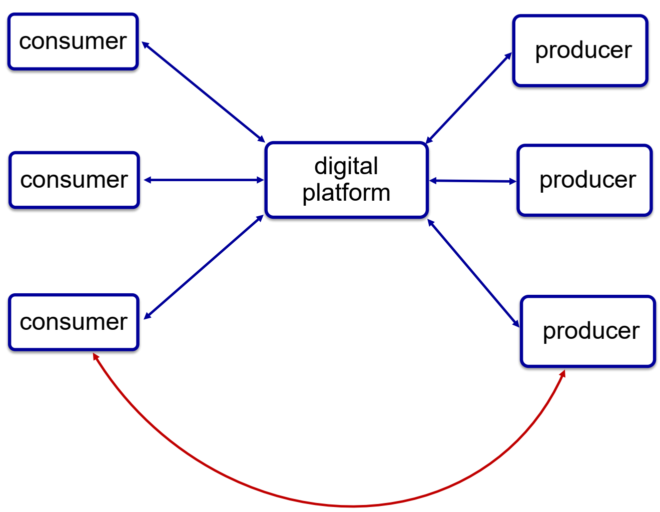

FIGURE 1: Platform Interaction with a Direct Channel

2.1 Value of Privacy

We begin this section with a simple framework to think about consumer privacy as private information about preferences. We develop a first model where a single consumer interacts with a representative producer (or "firm"). We later augment the framework by introducing multiple users, multiple producers, and potentially other agents (e.g., governments or platforms) interested in learning about the consumer.

The consumer has a preference type $\theta \in \mathbb{R}$ that parametrizes their utility function. The firm chooses an action $a \in \mathbb{R}$ (e.g., advertising message, product quality, or price) to maximize profits. When the firm chooses action a, the consumer obtains utility

$$u(\theta, a).$$

Without the need to specify the firm's preferences, we shall assume here that the firm chooses the action a to match the consumer's type:

$$a^* = \mathbb{E}[\theta].$$

Our focus is on the role of information about θ in this market. We assume that the consumer knows their true type θ, while the firm initially knows the prior distribution $F_0(\theta)$ only. In addition, the firm receives an informative signal s. Thus, the firm will be able to segment the market by choosing a different action a after observing each signal s.

It is useful to represent the signals observed by the firm as a *segmentation* (Yang, 2022). Here we follow the exposition in Bonatti and Villas-Boas (2022). A segmentation

$$\mathcal{S} = \{(\pi_s, F_s)\}_{s \in S}$$

is a mixture distribution with weights π_s over individual distributions F_s. A segmentation $\mathcal{S}$ admits two equivalent interpretations. By definition, π_s denotes probability of the signal realization s and $F_s(\theta)$ denotes the distribution of the firm's posterior beliefs upon observing s. Equivalently, the signal structure induces a partition of the consumer types (i.e., a market segmentation) where the size of each segment is given by π_s and the composition of each segment is given by $F_s(\theta)$.

Any segmentation $\mathcal{S}$ is a mean-preserving spread of the prior distribution F_0. In particular, for each θ, the distributions $F_s(\theta)$ integrate to the prior, i.e.

$$\int_s F_s(\theta)\pi_s \mathrm{d}s = F_0(\theta), \quad \forall \theta \in \Theta.$$

Furthermore, all consumers in segment s (i.e., conditional on the firm observing signal s) receive the same action, which we denote by

$$a^*(F_s) = \mathbb{E}_{F_s}[\theta] = \int_\theta \theta \mathrm{d}F_s(\theta).$$

We can then write the average surplus of consumers in segment s as

$$V(F_s) = \int_\theta u(\theta, a^*(F_s))\mathrm{d}F_s(\theta).$$

Finally, averaging over segments (i.e., taking expectations over signal realizations) yields the expected (ex ante) consumer surplus under segmentation $\mathcal{S}$,

$$U(\mathcal{S}) \triangleq \mathbb{E}_s[V(F_s)] = \int_s V(F_s)\pi_s \mathrm{d}s. \tag{1}$$

It is often useful to contrast the consumer's welfare under an informative segmentation $\mathcal{S}$ to the consumer surplus under prior information (i.e., full privacy), which is given by

$$U(\varnothing) \triangleq V(F_0).$$

This formulation for consumer surplus suggests a characterization of utility functions for which consumers unambiguously (i.e., for all segmentations) like or dislike privacy.

Proposition 1 (Value of Privacy)**.**
If $V(\cdot)$ is concave (convex), consumers like (dislike) privacy.

This result (which follows from Jensen's inequality) is spelled out in greater detail in Bonatti and Villas-Boas (2022). Under the conditions of Proposition 1, the consumer's ideal segmentation is either $\mathcal{S} = \varnothing$ or $\mathcal{S} = \mathcal{S}^*$, where $\mathcal{S}^*$ is the full information segmentation consisting of a collection of degenerate random variables ($s = \theta$).

In what follows, we shall make repeated use of the comparison between $U(\mathcal{S})$ and $U(\varnothing)$ to denote the equilibrium value of privacy for consumers. We now illustrate the usefulness of this compact representation for the value of privacy through a parametrized example.

2.2 Application

This example illustrates our model with a quadratic utility function. The firm's action a can denote either quality or price as in Argenziano and Bonatti (2021). Let the consumer's utility function be given by

$$u(\theta, a) = (\theta + \lambda a)^2.$$

The parameter $\lambda \in [-1, 1]$ intuitively captures the value creation vs. extraction role of the firm's action: when $\lambda < 0$, the firm's action resembles a price, and when $\lambda > 0$ it resembles a quality choice. Indeed, the case of $\lambda = -1$ is outcome-equivalent to the case of linear price discrimination, where a consumer type of θ facing a unit price of p obtains an indirect utility proportional to $(\theta - p)^2$.

To illustrate how this basic model yields sharp predictions on the welfare consequences of linear price discrimination, consider the surplus of segment s

$$V(F_s) = \int_\theta (\theta + \lambda\, \mathbb{E}_{F_s}[\theta])^2 \,\mathrm{d}F_s(\theta),$$

which we can write as

$$V(F_s) = \mathbb{E}_{F_s}[\theta^2] + (2+\lambda)\lambda \left(\mathbb{E}_{F_s}[\theta]\right)^2.$$

Notice that the first term (which is an expectation) is linear in probabilities, while the second term (which is a square expectation) is convex. Because $\lambda \in [-1, 1]$, we immediately conclude that $V(\cdot)$ is a concave (convex) function of F_s if and only if $\lambda < (>)0$. Therefore, if $\lambda < (>)0$, any mean-preserving spread hurts (benefits) consumers. In particular, for the fully-informative segmentation $\mathcal{S}^*$, we have $U(\mathcal{S}^*) < (>)U(\varnothing)$.

For the case $\lambda = -1$, we thus recover the classic result (Robinson, 1933; Schmalensee, 1981) that enabling market segmentation by a monopolist facing a linear demand function (and full market coverage) is detrimental to consumer surplus.

2.3 Generalizations

The model presented in this section is stylized along several dimensions. The general effect of market segmentations and the achievable combinations of consumer and producer surplus are analyzed in the seminal work of Bergemann, Brooks, and Morris (2015) and more recently by Haghpanah and Siegel (2022) and Elliott, Galeotti, Koh, and Li (2022). The consumer's type was assumed one-dimensional, but Ichihashi (2020) and Bonatti and Villas-Boas (2022) illustrate how the main logic of Proposition 1 extends to multidimensional environments such as those, for example, where the consumer has both a vertical willingness to pay attribute and a horizontal product match attribute.

Finally, the consumer was assumed entirely passive, whereas a long literature (summarized in Section 3.2 below) studied the impact of consumer actions on the equilibrium market segmentations. In the remainder of this chapter, we explore the conditions under which a platform can profitably intermediate the exchange of data in markets where consumers like (or dislike) privacy.

3 Data Acquisition

The previous section provided a language to talk about a consumer's preferences over the amount of data that a platform holds about them. We now focus on the key dimensions of the platform dimension of privacy, namely the collection and the monetization of consumer data, beginning with the former.

Why do consumers allow platforms to collect significant amounts of data? One possibility is that consumers benefit from data collection and that data intermediation is socially efficient. Another possibility is that consumers are unaware of the extent of data collection, or that their stated preferences for privacy differ from their actual preferences—the *privacy paradox* (Athey, Catalini, and Tucker, 2017). In this section, we specifically ask why platforms are able to intermediate information at little or no cost, why competition does not seem to discipline data acquisition, and whether there are limits to consumer data usage that emerge in a market context—for example, why do we see little or no personalized pricing?

3.1 Captive Consumers

Consider a single consumer and a single producer who meet on a monopolist digital platform with no alternative means to contract with each other. Figure 2 simplifies Figure 1 as follows.

FIGURE 2: "Captive" Consumer and Producer

Assume that the consumer makes a one-time participation decision. This decision takes place ex-ante, i.e., before the consumer's type is drawn. If the consumer participates on the platform, which means it uses the platform repeatedly, then it is going to reveal segmentation $\mathcal{S}$ to the platform, which observes a signal realization s and transfers it to the producer. We are going to remain agnostic as to how this transfer occurs—whether the data is effectively sold to the producer, or the producer is merely able to learn something about the consumer when it interacts with them on the digital platform. At this level of abstraction, data intermediation is equivalent to buying a database as informative as $\mathcal{S}$ from the consumer and reselling it to the producer. With one platform and one producer, it is also immediate to show that the platform will charge the producer their entire willingness to pay to access the consumer's information. Therefore, we now focus on implications for consumers.

If the consumer participates, their ex-ante surplus, aggregating across both signals and types, is going to be given by $U(\mathcal{S})$ as in the previous section. if participating and zero otherwise.[4] Why is the consumer surplus nil if they do not participate? Because in this

[4]The use of the indirect utility function $U(\cdot)$ here underscores that the value of privacy to the consumer depends on the nature of the producer's actions a and on the underlying interaction $u(\theta, a)$. This is an

setting the platform is necessary for the consumer. For example, the platform lowers search costs, offers valuable independent services and matches of higher quality. At this stage if

$$U(\mathcal{S}) \geq 0,$$

the consumer participates. In addition, if

$$U(\mathcal{S}) \geq \max\{0, U(\varnothing)\}, \tag{2}$$

data intermediation yields a Pareto improvement: the consumer gains from interacting with the platform, and so does the producer. However, the more challenging case is one in which

$$U(\varnothing) > U(\mathcal{S}) > 0. \tag{3}$$

The consumer finds it profitable to join the platform but loses relative to the case of anonymous transactions. This observation has prompted many scholars to refer to privacy loss as an unobserved price of accessing a digital platform. This occurs when the platform's services are nominally free, but consumers pay with their data.

Under these conditions, it was extremely easy for a platform to acquire the consumer's data. Let us now make the platform's problem more realistic (and a little harder) by allowing consumers and producers to meet off-platform.

3.2 Consumer Consent

Suppose now, as in Figure 3, that the consumer can choose whether to grant consent and reveal information to the platform, or deny consent and remain anonymous. If they do not reveal information, the consumer can still interact with the producer in an anonymous transaction (for example, because they can visit the producer's own website). This is akin to consent requirements in recent legislative efforts aimed at protecting consumer privacy, e.g., CPRA.

In this model, absent any form of compensation, the consumer agrees to reveal their information if and only if they dislike privacy. When consumers have a positive value of privacy, as in (3), the platform must compensate consumers to reveal their information. While direct monetary payments are quite rare, compensation can occur through better quality services and matches.

important departure from philosophy and legal approaches to privacy. Unlike in Zuboff (2019), data collection makes no first-order difference to a consumer unless of course privacy enters utility function (which may well be the correct behavioral assumption).

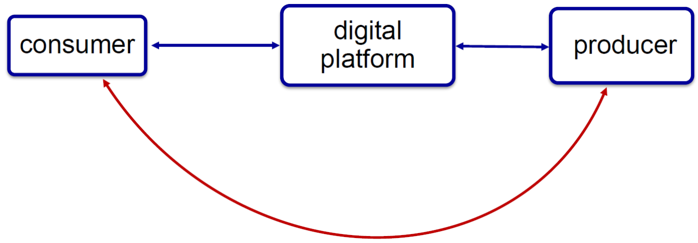

Figure 3: Consumer and Producer with Alternative Channel

To quantify those payments, let us maintain the assumption that the platform is a monopolist facing a single producer. Thus, the platform can extract the producer's entire value of information downstream. This is the setting that has prompted many scholars to appeal to the Coase Theorem (Coase, 1960) and argue that the simple assignment of property rights over data is going to yield the efficient level of information intermediation. The idea is simple and appealing: say the consumer owns the rights to their data and can sell them to the platform. In turn, the platform sells the consumer data to the producer. The three parties will be able to agree on the terms of trade—a price paid by the platform to the consumer and a price paid by the producer to the platform—if and only if the transfer of data from consumer to producer increases total surplus. In other words, if the loss in consumer privacy is worth more than the value of the information for the producer, then the platform will not be able to profitably intermediate this transaction.[5] This suggests that under well-specified property rights, the only trades of data that take place are those that satisfy condition (2).

In practice, however, there are at least two problems with the efficiency of the market for consumer information. The first problem is moral hazard: consumers do not reveal their information directly, e.g., by uploading spreadsheets with all their purchase data to an online retail platform. Instead, consumer reveal information through their online (and sometimes offline) behavior. The nature of data usage is critical for the trade of information in this setting. For instance, if consumers know their data will be used to set prices or steer their searches toward more expensive products, they have an incentive to distort their behavior. Such manipulation incentives may both bias and confound the information collected by the platform, thereby reducing its value to the producers.

These forces were first uncovered in the literature on behavior-based price discrimination and ratchet effects. The classic papers by Taylor (2004), Villas-Boas (2004), Acquisti and Varian (2005), and Calzolari and Pavan (2006) allow consumers to take actions (e.g., the level

[5]The 2020 California Privacy Rights Act also implicitly appeals to the Coase Theorem: consumers who opt out of data sharing have a *right to equal service and price*, but firms can "offer a different price, rate, level, or quality of goods or services to the consumer if that price or difference is reasonably related to the value provided to the business by the consumer's data."

of purchases) at two different times in order to manipulate the second-period firm behavior. More recently, Bonatti and Cisternas (2020) show that the applicability of these models goes beyond business to consumer relationships. For example it can be used to shed light on B2B price discrimination.[6] While business privacy is not typically an object of study, many of the same trade-offs face businesses and consumers who are aware of data collection. Argenziano and Bonatti (2021) study how consent regulation and other forms of property rights over data impact the level of trade and welfare in a signaling model.

The second problem is due to externalities, which we explore at length below.

3.3 Social Data

Unlike in the single-agent model discussed so far, many consumers make the decision as to whether to participate in the platform simultaneously. A central dimension of information intermediation is then its social aspect. The social aspect of information refers to the correlation in the underlying traits of consumers who join the same platform. Their decisions interact with one another, not directly, but indirectly through the correlation structure of their types. This may lead to a market failure, because the social nature of data generates a data externality—the phenomenon that some consumers' data reveal information about other consumers. Data externalities do not have an a priori sign like carbon emissions or vaccinations. For example, if my data is used to offer better products to others, then I impose a positive externality on them; but if others' data is used to steer me towards expensive products instead, others impose a negative externality on me.

A recent and growing literature has shown how data externalities can reduce the cost of acquiring information from consumers—see for example Choi, Jeon, and Kim (2019), Acemoglu, Makhdoumi, Malekian, and Ozdaglar (2022), Ichihashi (2021b), and Bergemann, Bonatti, and Gan (2022). The core idea is the following: when there are many consumers, even if the aggregate effect of revealing all their data might be large and negative for the surplus of any individual, the marginal impact of a single consumer's decision to participate on a digital platform is small. In the language of our basic framework, even if consumer i chooses not to participate on the platform, the producer will have now have access to a potentially very informative segmentation $\mathcal{S}_{-i}$. Figure 3.3 illustrates this scenario.

To formalize this intuition, we follow Bergemann, Bonatti, and Gan (2022), who develop a model of monopolistic data intermediation with $i = 1, \ldots, N$ consumers. In their setting, as in the previous section, a platform can compensate each consumer for their own data,

[6] For example, "Google induced advertisers to bid their true value, only to override pre-set AdX floors and [...] generate unique and custom per-buyer floors depending on what a buyer had bid in the past." (Texas vs. Google).

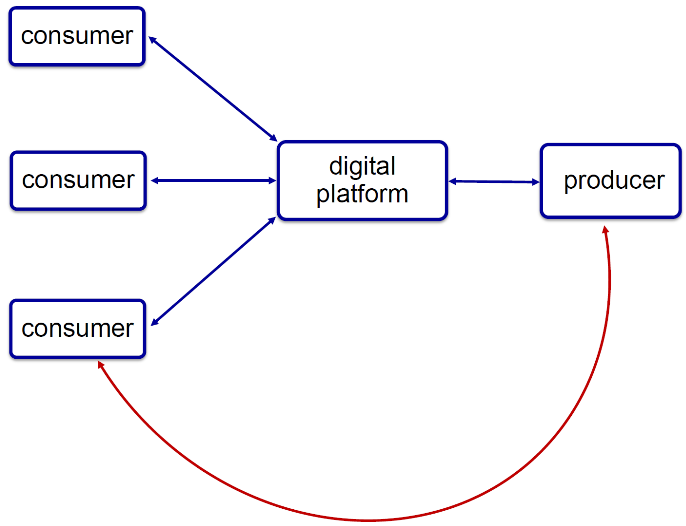

FIGURE 4: Many Consumers with Competing Channel

which it then resells to a single producer.

Suppose platform offers t_i to each consumer i for access to (data leading to) a segmentation $\mathcal{S}_i$ of i's type. Denote by $\mathcal{S} = (\mathcal{S}_1, \ldots, \mathcal{S}_N)$ the segmentation induced by every consumer's data. Consumer i makes a participation decision prior to learning their type. This consumer participates if and only if

$$t_i + U_i(\mathcal{S}) \geq U_i\left(\mathcal{S}_{-i}\right). \tag{4}$$

The interpretation of this participation constraint is that the transfer t_i must induce the consumer to prefer segmentation $\mathcal{S}$ to the alternative of withholding their data, in which case the platform collects and transmits segmentation $\mathcal{S}_{-i}$. We can then formally define a data externality as follows.

Definition 1 (Data Externality)**.**
The data externality imposed by consumers $-i$ on consumer i is given by

$$DE_i(\mathcal{S}) \triangleq U_i\left(\mathcal{S}_{-i}\right) - U_i\left(\varnothing\right).$$

The data externality DE_i captures the welfare effect for consumer i of all consumers $j \neq i$ revealing their data while i withholds theirs. We can then immediately put the data externality to work and obtain a characterization of profitable intermediation. Let $W_i(\mathcal{S})$ denote the total surplus (consumer welfare plus producer profits) generated by consumer i

when the producer is endowed with segmentation $\mathcal{S}$, and define

$$\Delta W_i(\mathcal{S}) \triangleq W_i(\mathcal{S}) - W_i(\varnothing).$$

Bergemann, Bonatti, and Gan (2022) then show the following result.

Proposition 2 (Profitability of Intermediation)**.**
Intermediation of data $\mathcal{S}$ is profitable if and only if, for all i,

$$\Delta W_i(\mathcal{S}) - DE_i(\mathcal{S}) \geq 0.$$

Intuitively, there are two channels through which a platform can potentially profit from data intermediation. A classic channel is that of surplus creation, which operates when revealing information to the producer helps (or does not excessively hurt) consumers. In particular, the transmission of information may increase total surplus ($\Delta W_i > 0$), in which case data intermediation is both profitable for the platform and socially efficient. A more novel channel operates through the social dimension of the data: if individual consumers' decisions impose negative data externalities on other consumers ($DE_i < 0$), the platform can enlist additional consumers at lower marginal cost, thereby directly increasing its profits.

The latter scenario is more likely as the number of consumers increases. It is not hard to find conditions as in Figure 5 below, where consumer surplus decreases in the number of signals the platform procures, but it does so at a decreasing rate. Thus, a negative data externality combined with a diminishing marginal impact of each consumer's signal allow data intermediation to be both profitable and socially inefficient.

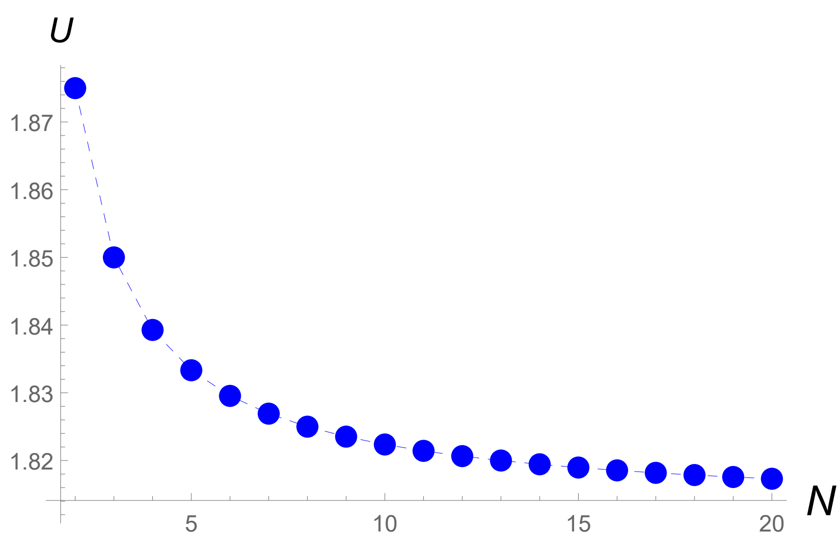

FIGURE 5: Consumer Surplus $U(\mathcal{S}^*(N))$

At this point, it may seem like this model predicts complete and unhinged data sharing. This is not always the case. Indeed, Bergemann, Bonatti, and Gan (2022) also show that the platform-optimal data sharing policy does not necessarily involve complete data sharing. In this sense, the nature of information qualifies the externality effect above and extends insights from the literature on contracting with externalities (Segal, 1999) to the case of social data. In particular, the platform finds it optimal to intermediate individual-level information when the data increases total surplus (e.g., in the case of customized product recommendations). Conversely, when this information is used for *socially inefficient* price discrimination, the platform aggregates the consumers' signals and intermediates market-level information.

To summarize, the platform-optimal data sharing policy involves socially efficient data-anonymization decisions. Nonetheless, there are very few guarantees, if any, that the allocation of data is going to be socially efficient. After all, consumers are compensated for their individual harm, but not for the social harm that they create. Finally, as the markets grow large, which is a reasonable approximation for digital platforms, the cost of acquiring the information from consumer vanishes, while the gains persist.

The social aspect of the data relates to the digital privacy paradox, whereby consumers require negligible compensation to reveal their data, in contrast with their stated preferences.[7] These results have prompted several scholars, most notably in psychology, philosophy, and law, to refer to privacy as a collective issue or public good, because the effectiveness of the tools used to monetize and leverage our information depends on our collective choices. Most notably, Zuboff (2019) argues that

> "Privacy is not private, because the effectiveness of these and other private or public surveillance and control systems depends upon the pieces of ourselves that we give up."

3.4 Regulation and Competition

The potential market failures highlighted in this section naturally pose the question of the effectiveness of regulation. The discussion of data externalities above strongly suggests that individual-level regulation is unlikely to restore efficient outcomes in data collection.[8] A market structure that might achieve a more efficient outcome, without the aid of regulatory

[7]This result appears in the randomized control trial of Athey, Catalini, and Tucker (2017), and it was also true in a recent paper on the effects of the GDPR (Aridor, Che, and Salz, 2020). In that paper, a large number of users paid no attention whatsoever to cookies and privacy-enhancing techniques even prior to the regulation. This is consistent with, even though not causally related to, the privacy paradox.

[8]Viljoen (2021) emphasizes the relational aspect of digital markets whereby data creates value by enabling people to connect and the difficulties in regulating the nexus of links created by online data.

interventions, would be one where multiple platforms compete as in Rochet and Tirole (2003) for the (ideally exclusive) engagement of every consumer.

However, several recent papers have shown that the effect of competition is not at all straightforward, and that it is not hard to imagine realistic settings where platform competition does not lead to gains in consumer surplus. Most notably, Ichihashi (2021a) develops a model of competing data intermediaries that can acquire one or more "units" of data from a single consumer. The key property of data is that it can be sold to any number of intermediaries at zero cost by the consumer. Furthermore, all copies of the data must be identical—there is no room for selling differentiated data products as in Admati and Pfleiderer (1986). Therefore, if multiple intermediaries hold the consumer's data, they compete away all profits. In this model, when revealing their data has a negative impact on consumer surplus, a single platform is able to make an offer to the consumer that leaves them exactly indifferent. In equilibrium, no other platform can then offer a positive price to the consumer for the data. Hence, the monopoly outcome obtains.

In complementary work, Casadesus-Masanell and Hervas-Drane (2015) offer an explanation for the shortcomings of competition, based on service quality; Loertscher and Marx (2020) provide an explanation for the emergence monopoly platforms based on data aggregation; and Prüfer and Schottmüller (2021) develop a dynamic model of "tipping" in data-rich industries that also supports the near-natural-monopoly theory.

Finally, even if competitive forces were strong, "privacy fixing" has emerged as a new anticompetitive concern. The idea is that, instead of fixing prices (because they are constrained to be zero), competing platforms might agree to not preserve their users' privacy. For example, the 2022 Texas v. Google complaint claims that

> "Effective competition is concerned about both price and quality, and the fact that Google coordinates with its competitors on the quality metric of privacy—one might call it privacy fixing—underscores Googles selective promotion of privacy concerns only when doing so facilitates its efforts to exclude competition."

Similarly, the United States 2010 Horizontal Merger Guidelines require that

> "When the Agencies investigate whether a merger may lead to a substantial lessening of non-price competition, they employ an approach analogous to that used to evaluate price competition."

4 Data Monetization

The mechanisms by which data is monetized are critical to understand the privacy implications of data intermediation. In this section, we consider a model where a platform has freely collected a single consumer's information, with the understanding that this is a metaphor for the equilibrium effect of data externalities. We also imagine that the platform can monetize this data by allowing any number of producers in a given industry to access the consumers' attention and target them with personalized offers.

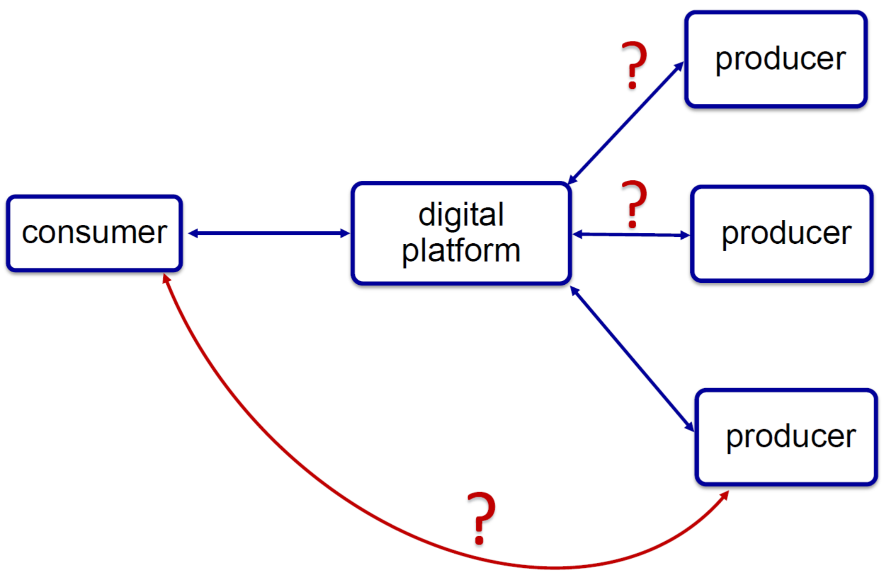

Figure 6: (Potentially) Competing Producers

Before turning to the privacy implications of such a market structure, let us think for a moment about potentially less profitable ways in which data might be sold.

4.1 Direct Sale of Information

In practice, digital platforms very rarely sell consumer data directly to advertisers and other parties. For one, the reputation backlash and the risk of leakages would be significant, but it is equally important to understand why this would be a suboptimal strategy even absent these concerns.

Indeed, there are at least five reasons why platforms would not want to sell data directly.

1. The first problem a platform would face when selling data directly would be that information about consumers' willingness to pay is likely to create negative externalities downstream: if two or more competitors are informed about the correct product or

price level to offer, each one is forced to lower prices. In this world, relative to physical goods, exclusive sales tend to be more profitable as shown in the classic contribution by Admati and Pfleiderer (1986).

2. The second problem relates to data pricing under exclusive sales. Let us entertain the possibility that a digital platform sells individual level data to a single merchant only. The value of this information is a complicated equilibrium object, which depends on the complex game between one informed firm and its uninformed competitors (Bonatti, Dahleh, Horel, and Nouripour, 2022).

3. The third problem is a classic difficulty with selling information. "Selling wine without bottles" is a famous metaphor (Barlow, 1994) that refers to the zero marginal cost of data reproduction, which might easily lead to a profitable resale market for data (Shapiro and Varian, 1999; Jones and Tonetti, 2020). In other words, any data-selling platform creates its own competition by simply letting the data flow out of its own hands.

4. The fourth problem is that data about an individual consumer becomes obsolete over time, but not very quickly. Therefore a data seller is able to charge for the incremental information that they provide over and above the data buyer's initial information (Bergemann, Bonatti, and Smolin, 2018). In other words the platform can charge for the innovation component in the data, and not for the entire value of the dataset.

5. The fifth and fundamental problem relates to how to measure the causal impact of data sales. In practice, it is difficult to prove how much a data product is worth without giving away the information contained in the data itself. This is the famous *information paradox* pointed out by Arrow (1962).

4.2 Indirect Sale of Information

While direct sales of information are problematic, targeted advertising is a superior, more profitable means to monetizing consumer information. Consider for example Google or Amazon search ads (or paid placement on Taobao.com). Advertisers buy a slot on a keyword-results page, which means they can tailor their message, the link they want to show, to the consumer's search query, which is informative of their underlying preferences. Of course, the search engine could sell data about those searches directly, but prefers to leverage the data to sell access to qualified eyeballs instead. Indirect sales of information are far more prevalent than direct sales, which is entirely consistent with what economic theory would have predicted (Admati and Pfleiderer, 1990; Bergemann and Bonatti, 2019).

Indeed, selling access to consumers directly solves all five problems we mentioned above. It solves the data exclusivity problem by offering a scarce number of slots. It solves the problem of competition under asymmetric information structures because only a few informed parties access the consumer at one time. It solves the resale and rental problem by never really giving out the data. Finally, it solves the quality measurement problem because advertisers have a number of conversion metrics available to them. Thus, it is only by bundling qualified eyeballs and advertising space that a large digital platform is able to monetize the troves of data at its disposal.[9] With these foundations in mind, we want to understand the implications of selling exclusive access to consumers through targeted advertising space.

4.3 Mechanisms for Digital Advertising

We now consider a large digital platform that matches heterogeneous buyers and sellers, running individual-level auctions for targeted advertising. A first treatment of this topic is in de Cornière and de Nijs (2016), who focus on bidding and unit pricing, and derive conditions under which the platform prefers targeting vs. a random allocation of slots. In what follows, we follow the more recent contribution of Bergemann and Bonatti (2023), who introduce the notion of a "managed campaign." Relative to that paper, we simplify the exposition by considering single-product sellers only.[10]

There are J sellers who offer horizontally differentiated products at no cost and a unit mass of consumers. Each consumer has a multidimensional type denoted by

$$\theta = (\theta_1, \dots, \theta_j, \dots, \theta_J) \in \mathbb{R}^J.$$

Each type component θ_j denotes the consumer's value for the product of firm j.

Independent of their type, a fraction $\lambda \in [0, 1]$ of these consumers use a platform that runs ads in order to find a seller. The remaining $1 - \lambda$ consumers buy directly from sellers and face unit search costs $\sigma > 0$ after the first free search as in Diamond (1971).

The platform observes all types θ while consumers have arbitrarily precise beliefs m about their valuations. The platform offers a single "sponsored" advertising slot per consumer. In allocating the slot, the consumer's type serves as a *targeting category:* the firms' ads can condition on the entire vector θ.

More formally, the platform offers a *managed campaign* mechanism, which consists of the

[9] Indirect sales of information in digital markets are not limited to search advertising platforms: the same advantages relative to direct sales apply to large display advertising networks such as Google, Meta, Criteo, and Microsoft, as well.

[10] See also Bergemann, Bonatti, and Wu (2023) for a comparison between the managed campaign model and data-augmented auctions for digital advertising with manual bidding.

following. The platform charges a fixed fee t to participating sellers. (This can be viewed as a minimum mandatory campaign budget.). The platform specifies which seller j (among those who pay the fee) obtains the slot for which consumers θ. By releasing additional information, the platform then reveals to the consumer their value θ_j for the advertised product j. Finally, the platform enables each selected seller j to advertise a personalized price $p_j(\theta)$ to the consumer.

Simultaneously to making their participation and personalized pricing decisions on the platform, the sellers also set posted prices $\hat{p}_j$ intended for the (anonymous) off-platform consumers. The two sales channels (on- and off-platform) interact because on-platform consumers can also search, and (if they find a lower price or better product) they may buy off-platform. This introduces a "showrooming constraint" as in Wang and Wright (2020) and Teh and Wright (2022) whereby each seller j must provide weakly greater utility to their on-platform consumers than their off-platform consumers. Figure 7 illustrates the model.

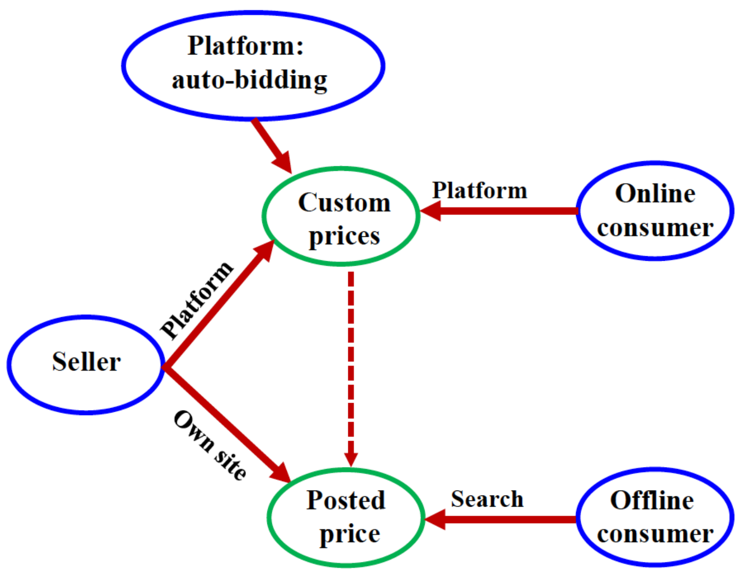

Figure 7: Model Summary (Bergemann and Bonatti, 2023)

In the Varian (1980) model of sales, consumers can be distinguished into shoppers and loyal and derive their surplus from price competition for shopping consumers. In the present model, the off platform sales channel provides the consumer's outside option. In equilibrium, consumers obtain surplus because they can act anonymously and leverage their own right to privacy, so to speak, in order to acquire a good from the seller's direct channel. More generally, the on-platform consumer's search behavior depends on the criteria by which the platform assigns a sponsored link. Bergemann and Bonatti (2023) establish the following intuitive result, which has immediate implications for the equilibrium search patterns.

Proposition 3 (Optimal Matching Mechanism)**.**
The platform maximizes revenues by matching each consumer θ to most their favorite seller $j^* = \arg\max_j \theta_j$ among those who participate in the managed campaign mechanism.

Under this matching mechanism, the platform fully exploits its informational advantage: the λ on-platform consumers infer that the displayed seller is $j^* = \arg\max_j \theta_j$, and they cannot detect any deviations by non-participating sellers. Furthermore, by showrooming, these consumers expect symmetric prices off the platform. Consequently, Bergemann and Bonatti (2023) show that these consumers only consider offers by the advertised seller.

Proposition 4 (Consideration Sets)**.** *Every online consumer θ only compares the displayed seller j^*'s personalized (on-platform) and posted (off-platform) prices, $p_{j^*}(\theta)$ and $\hat{p}_{j^*}$.*

Off the platform, consumers act as in the Diamond (1971) model. These $1-\lambda$ consumers with beliefs m face search costs $\sigma > 0$ after the first search; they expect symmetric prices and hence visit $\hat{j} = \arg\max_j m_j$ only. Figure 8 illustrates the search patterns of a consumer with beliefs m and true type θ both off platform and on platform.

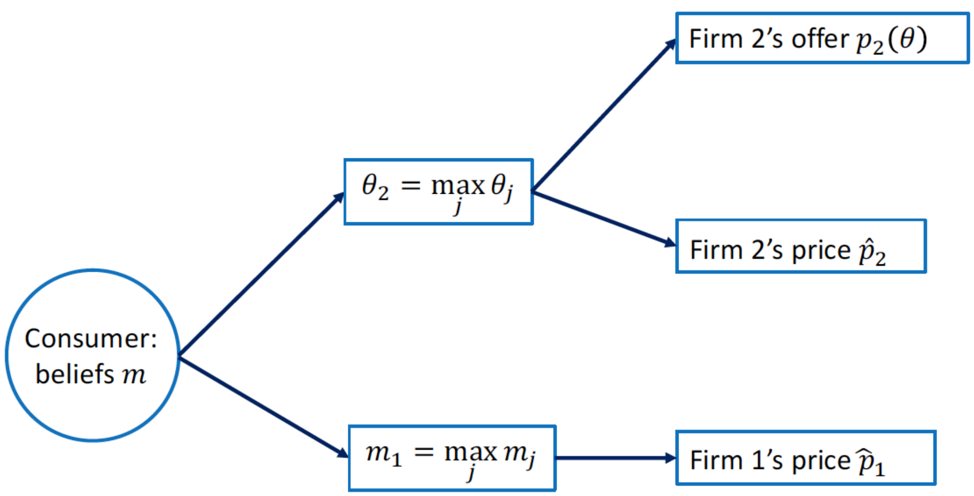

FIGURE 8: Search Patterns (Bergemann and Bonatti, 2023)

The key result is that the platform is able to completely shield the most efficient producer from competition. After a link by the highest-value firm is shown to the consumer. The consumer infers that is indeed the highest value firm. If this consumer were to showroom, they would only visit that firm's website. Indeed, the model admits an equivalent interpretation wherein each brand has an identical fraction $(1-\lambda)/J$ of loyal, imperfectly informed consumers who are already shopping off of the platform. The remaining λ consumers are not currently shopping, but they can be alerted to the existence of a brand. Once they are alerted by an ad, they contemplate shopping either on or off the platform. The equivalence with this behavioral model requires arbitrarily small amounts of search costs and informational advantages by the platform: without an informational advantage, the platform will not be able to control the consumers' outside options because the consumer's own beliefs will determine where they search first off the platform.

Finally, let us look at the results from a welfare perspective. The platform sells prominence to the highest bidder. This enables trade under symmetric information and induces higher total surplus. In this sense it has a positive social effect.[11] The platform, however, also sells market power. Indeed, the firms never compete in price, which leads to higher prices both on and off the platform. This is mostly due to the platform's informational advantage, which narrows the consumers' search options. The growth of a platform's database (through more consumers λ) reduces outside options and leads to higher prices—a different kind data externality as pointed out in Kirpalani and Philippon (2021).

If, in addition, firms were heterogeneous in their cost function or in the number of on- versus off-platform consumers, the platform would introduce a further source of inefficiency. In particular, lower-quality brands with a smaller off-platform presence might be able to generate higher bids (or be willing to invest larger budgets), and their products might generate lower value for consumers. This scenario is qualitatively consistent with the evidence in Mustri, Adjerid, and Acquisti (2022).

4.4 Privacy and Competition

The results in the managed campaign model make apparent the privacy vs. competition tradeoff. With any indirect sale of data (such as digital advertising auctions and managed campaigns), advertisers learn relatively little about consumers. The key to the success of this intermediation mechanism is that advertisers are able to use the information exactly as if they owned the data. But in practice, they only learn summary statistics on the return on their investment. With automated bidding, advertisers might not even know how much they bid for each consumer category, because the platform does so for them. Furthermore, only the platform ever holds the consumer data, which reduces the risk of leakages.[12]

However, because only a few firms (in the model, just one) are allowed to use the information at any time, the additional privacy gains can come at the cost of worse terms of

[11]Trading through the platform is inherently more efficient even if consumers know their types. This is because under symmetric information, the platform eliminates any distortions from uniform monopoly pricing—with personalized pricing, all consumers buy. See Hidir and Vellodi (2021) on the price discrimination vs. product matching tradeoff.

[12]See Fainmesser, Galeotti, and Momot (2022), Jullien, Lefouli, and Riordan (2020), Tucker (2018) for a discussion of exogenous and endogenous (equilibrium) risks of data leakages.

trade for the consumer. This is consistent with the concern in Cremèr, de Montjoye, and Schweitzer (2019) that

> One cannot exclude the possibility that a dominant platform could have incentives to sell "monopoly positions" to sellers by showing buyers alternatives which do not meet their needs.

In this sense, the optimal managed campaign mechanism is successful precisely because it restricts competition. Privacy protection sounds anti competitive in the context of this model, but this is not yet a general conclusion—a lot more work is warranted on this topic, especially as it relates to data-driven mergers (Chen, Choe, Cong, and Matsushima, 2022). I outline further critical areas for research below.

5 Conclusions

We have focused on the data that large digital platforms collect from individual users, and on the mechanisms by which they monetize the information so-gained with advertisers. Various characteristics of digital markets suggest the emergence of a novel "two-sided" dimension of user privacy, where the actions of all participants on both sides of the platform (users and advertisers) shape the level of privacy for each individual consumer.

Let us summarize the key findings. Firstly, a platform's ability to profitably collect an individual's data is not solely dependent on that individual's actions or legal rights. The social aspect of data, where others' information provides insights into my preferences, introduces a data externality that creates a gap between the profitable and efficient allocation of information, even when property rights are well-defined.

Secondly, the profitability of selling targeted advertising rises as more firms compete for exclusive access to a consumer's attention. This amplifies the incentives for data collection and potentially enhances the quality of matching between consumers and producers through stronger selection effects. However, higher-quality matches may also result in a (smaller) more homogeneous consumer population for each advertiser, enabling surplus extraction through market prices without the need for first-degree price discrimination.

Lastly, the activities of data collection and data monetization by digital platforms interact with each other. The expansion of a platform's database through increased consumer participation facilitates data acquisition while simultaneously increasing advertisers' willingness to pay for premium placement. This, in turn, diminishes the value of their private sales channels as well as the value of each consumer's outside option.

A lot of work remains to be done in this area. For example, the question of competing data platforms and data sellers is conspicuously understudied, with only recent promising initial treatments (de Cornière and Taylor, 2023; Ichihashi, 2021a). Data combination, federated learning and other privacy-preserving initiatives are also worth further study (Bergemann, Bonatti, Demirer, and Vilfort, 2023), as is the evaluation, both theoretical and empirical, of recent regulatory interventions (Ali, Lewis, and Vasserman, 2023; Argenziano and Bonatti, 2021; Chen, 2022). Finally, the information-design approach can apply to equally, if not more, important dimensions of consumer privacy, such as the political economy implications of government surveillance. Questions of algorithmic fairness, differential privacy, the tradeoff between the efficacy of industrial policy and individual liberties (Beraja, Kao, Yang, and Yuchtman, 2022), as well as the special status of health data (Miller, 2022) are all areas deserving of further treatment.

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