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Privacy Management in Service Systems

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Abstract. ***Problem definition*:** We study customer-centric privacy management in service systems. ***Academic/practical relevance*:** We explore the consequences of extended control over personal information by customers in such systems. ***Methodology*:** We adopt a stylized queueing model to capture a service environment that features a service provider and customers who are strategic in deciding whether to disclose personal information to the service provider—that is, customers' *privacy or information disclosure strategy*. A customer's service request can be one of two types, which affects service time but is unknown when customers commit to a privacy strategy. The service provider can discriminate among customers based on their disclosed information by offering different priorities. ***Results*:** Our analysis reveals that, when given control over their personal data, strategic customers do not always choose to withhold them. We find that control over information gives customers a tool they can use to hedge against the service provider's will, which might not be aligned with the interests of customers. More importantly, we find that under certain conditions, giving customers full control over information (e.g., by introducing a privacy regulation) may not only distort already efficiently operating service system but might also backfire by leading to inferior system performance (i.e., longer average wait time), and it can hurt customers themselves. We demonstrate how a regulator can correct information disclosure inefficiencies through monetary incentives to customers and show that providing such incentives makes economic sense in some scenarios. Finally, the service provider itself can benefit from customers being in control of their personal information by enticing more customers joining the service. ***Managerial implications*:** Our findings yield insights into how customers' individually rational actions concerning information disclosure (e.g., granted by a privacy regulation) can lead to market inefficiencies in the form of longer wait times for services. We provide actionable prescriptions, for both service providers and regulators, that can guide their choices of a privacy and information management approach based on giving customers the option of controlling their personal information.

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1. Introduction

There is an ongoing debate among industry leaders, regulators, and increasingly, more privacy-aware consumers (Pew Research Center 2019) about who should be given control over consumer data (*New York Times* 2015). Recently introduced privacy laws and regulations, such as the European General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA), have shifted control over data from firms and platforms to consumers. The GDPR, for instance, requires that a consumer gives her explicit consent to a firm to collect and process any of the consumer's data.[1] The CCPA allows consumers to opt out of the sale of their information.[2] Although the European Union and California were early adopters of the most stringent data protection regulations, many other governments remain more conservative (*New York Times* 2019a) (https://www.cnil.fr/en/data-protection-around-the-world).

The goal of this paper is to study the consequences of providing consumers with control over their personal information. In particular, we study consumer privacy management as well as its implications for firms, for the consumers themselves, and for society in general. Although this question is a pressing issue in all the industries, in this paper, we focus on service systems, which routinely employ user data not only to offer better goods and services to their customers (e.g., through personalization) but also, to profile and discriminate among the latter and their requests. For example, call centers exploit social media (and history of interactions) data when determining a customer's call priority, wait time, and quality of service (*Forbes* 2017, *Wall Street Journal* 2017, Hathaway et al. 2020); in retail, customers are assigned data-driven shopper scores, which determine the level of service customers obtain as well as the priority with which they obtain this service (*Wall Street Journal* 2018). Given such increasing reliance on individual-level data, the GDPR and data protection regulations alike have a direct and significant impact on service systems by requiring the latter to cede control of personal information to their customers (Contact Center Pipeline 2018). In this paper, we investigate the impact that such a shift of control over information to consumers has on different stakeholders.

We build a stylized model of a service environment that features customers who (i) are granted control over their data and (ii) are strategic in deciding whether to disclose these data to the service provider—customers' *privacy or information disclosure strategy*. Customers' information disclosure strategy can take the form of giving a service provider explicit consent for using their data (i.e., customer's opt in decision under GDPR regulation), configuring privacy and/or information sharing settings or, for instance, buying and starting to use one of the numerous smart-home devices such as Alexa or Nest—hardware products of Amazon and Google, widely known for their excessive and intrusive data collection and processing (*New York Times* and *Wirecutter* 2019). A customer's request for service can be one of two types: long or short in service time. The request type is not realized at the time when a customer is choosing privacy strategy and is only observed later when the need for service arises. This is aligned with the observation that customers usually choose their privacy strategy when registering on the platform and not yet being informed about their future service needs (e.g., a customer's opt-in choice under the GDPR is made during the time of the first interaction of the customer with the firm before any service request). The service provider can infer customers' contingent request type from their latest personal data (e.g., voice recordings done by Amazon Alexa, web search queries, or activity on the platform; see more examples of how such inferences can be made in Section 3) if they are disclosed. Consequently, the service provider can discriminate among customers based on the inferred request types and can prioritize them by giving preference to either the shortest or the longest processing time, whichever suits the service provider's needs. For example, the former can be preferred when a service reward is given for each completed job regardless of its service time, and the latter can be preferred when rewards are paid out proportionally to the service time.

We start by deriving the customer's equilibrium information disclosure strategy and discover that individual customers, when given control over information disclosure, are not always incentivized to withhold their information. Instead, customers strategically choose between disclosing and withholding information by weighing the upsides against the downsides of service providers having their information; in some cases, customers will choose full (or partial information) disclosure as being in their best interest. We show that customers choose to withhold personal information only if they believe that their service requests tend to have low priority and will likely be deprioritized by the service provider. In all other cases, we find that customers choose to partially or fully disclose their personal information. Interestingly, if customers' service requests have an intermediate probability to be prioritized so that neither the benefit nor the harm of information disclosure are high, then customers employ either "follow the crowd" or "avoid the crowd" types of information disclosure behavior. In other words, customers are better off either following or *reversing* the information disclosure strategies of others.

Our analysis compares equilibrium information disclosure (i.e., customers controlling their personal information) with the scenario in which all information must be involuntarily disclosed (i.e., no control over personal information). We find that there exist scenarios under which full information disclosure is already socially optimal, and granting customers control over their personal information (e.g., through regulation) can actually reduce total customer surplus by increasing their expected wait time in the queue. That could happen, for instance, if short service requests are prioritized (e.g., when a fixed piece rate is paid for each task completed regardless of the time spent on it—a scenario often observed in healthcare applications) (e.g., see Ibanez et al. 2018)—a priority policy that is *aligned* with collective incentives. In contrast, society benefits from customers being in control over their information when the incentives of the service provider are *misaligned* with collective incentives, as when long service requests are prioritized (e.g., when a service provider is paid per unit of time spent on the task and there is a fixed setup cost associated with switching tasks). These results caution against reflexively heeding the public outcry to give customers full control of their information because such control might not benefit either the individual or society as a whole and may distort already efficient systems.

Overall, our analysis highlights that giving customers control over their personal information need not result in an efficient outcome from their collective perspective as a society and/or necessarily benefit customers individually; in other words, the service system does not necessarily achieve the state of *privacy self-synchronization* (Popa 2012). In fact, if most customers' service requests are of the long type, then—regardless of which priority rule is followed by the service provider—customer control of information backfires in the sense of leading to inferior performance of the service system (i.e., longer average wait times), which reduces customer surplus. We establish that such inefficiencies in personal information disclosure can be remedied by providing monetary incentives to customers to disclose (withhold) information when the service provider prioritizes short (long) service requests. We also show that the increase in customer surplus because of adopting a socially optimal information disclosure policy may outweigh the expense of inducing a privacy self-synchronization regime; we identify the region of model primitives in which this occurs and consequently, in which such monetary incentives are an efficient instrument to achieve a socially optimal outcome. In addition to remedies for correcting information disclosure inefficiencies (from the societal perspective), we also characterize the *price of information*; the payment customers are willing to receive to fully disclose their personal information to the service provider. These two results provide a basis for building an *information market* (see, e.g., Bergemann and Bonatti 2019, Bimpikis et al. 2019, Drakopoulos and Makhdoumi 2020), in which the service provider can pay customers for disclosing or withholding their personal information. This concept has long been a subject of discussion by regulators.

We further explore many variants of our base model. In particular, we examine models with more than two types of customer service requests, heterogeneous waiting costs, customers deciding on their information disclosure strategy after learning their request types, no information disclosure as a benchmark scenario, alternative priority policies, and social planner's imperfect knowledge of the service provider's priority discipline. Finally, we also study how providing customers with control over their information affects the service provider itself and find that the regulation granting customers control over their personal information benefits those service providers that prioritize long requests. Overall, our base model and the analyses of the alternative model formulations reinforce our main findings—the existence of scenarios under which control over information is put in customers' hands may distort service systems that have been set to customer surplus maximization.

As far as we know, our paper is the first to explore the impact of privacy regulation, such as the GDPR or the CCPA, and granting control over information to customers on service systems through investigation of *customer-centric* information and privacy management in such systems. This study extends the existing literature on service systems by considering control over information and its disclosure by customers—that is, in lieu of the traditional provider-centric approach. We also bring to this literature a particular "customer privacy" angle that has not been explored previously. The analysis reported here yields actionable prescriptions for service providers operating in the information economy and for the regulators of such markets.

2. Related Literature

This paper contributes to three active streams of literature: (i) queueing systems with strategic customers, which dates back to Naor (1969) (see Hassin and Haviv 2003, Hassin 2016 for comprehensive surveys) (we omit the discussion here); (ii) information-related issues in service systems; and (iii) information operations and economics that focus on consumer privacy.

Research into the information-related issues of service systems explores how a service provider's various information strategies affect the strategic behavior of customers. One widely studied topic is the effect of delay announcements on customer behavior. Whitt (1999) explains why customers are less likely to be blocked if delays are announced, yet Guo and Zipkin (2007) show that having more information about the wait time need not improve customers' social welfare. Allon et al. (2011) demonstrate that "cheap talk"—in the form of *unverifiable* delay announcements—may benefit the service provider and its customers alike. Li et al. (2017) identify conditions under which it is socially optimal to disclose queue-length information to customers who are not aware of the service provider's information disclosure policy. Hu et al. (2018) establish that, if only some customers are informed of the service system's congestion level, then both throughput and social welfare may be unimodal in the fraction of such customers. Wang and Hu (2020) consider a setting in which customers observe lagged, user-generated queue length information shared by fellow customers; these authors show that such information may benefit customers more than real-time queue length information does. Yu et al. (2018) explore how providing customers with the delay information can help the firm distinguish (imperfectly) their types and what the value of this information is. Huang et al. (2013) consider a service system with boundedly rational customers who cannot accurately estimate their expected waiting time. Interested readers are referred to Ibrahim (2018), who comprehensively surveys this stream of work.

The service operations literature also considers disclosure of other types of information in queues. For example, Veeraraghavan and Debo (2009) explore how customers infer service quality from their observation of the queue length, which may lead to herding behavior. Cui and Veeraraghavan (2016) show that customers' doubts about service rate information can increase the service provider's revenue but may degrade individual or social welfare.

To the best of our knowledge, most of previous research in this stream focuses on the sharing of system information such as the queue length and service quality and assumes that such information is shared with customers—either by the service provider or by fellow customers—or not. However, there are exceptions. First, the literature on priority auctions (see, e.g., Hassin and Haviv 2003, section 4.5; Kittsteiner and Moldovanu 2005; Hassin 2016, sections 5.3.1 and 6.6.3) and the literature on priority pricing (which is outcome equivalent to priority auctions) (see, e.g., Mendelson and Whang 1990; Hassin 2016, section 6.6 and references therein) assume that customers hold private information, which is not accessible by the service provider (a scenario becoming less realistic without privacy regulation in today's online environment), and they consider information sharing of customers' private information (e.g., delay sensitivity or service time information) *indirectly* through, for instance, their bids for priority in the queues. Second, there is a stream of literature in healthcare studying triage—a practice of obtaining information of patients' conditions and categorizing them into different priority levels (see, e.g., Argon and Ziya 2009, Sun et al. 2018, Bren and Saghafian 2019). This stream of literature does not usually assume strategic information disclosure by the patients as we do in this study. Finally, the stream of literature on mechanism design in the queueing context considers a setting where customers report their types strategically and not necessarily truthfully to maximize their utility (see, e.g., Su and Zenios 2006, Rodriguez et al. 2021).[3] Our paper studies both *strategic* and *direct* information sharing by customers and the *opposite* (as compared with the delay announcements literature) direction of information flow: information shared *by* customers directly and truthfully *with* the service provider (also, as opposed to information revealed through a mechanism designed by the service provider). In particular, our study assumes that customers could be in control of their information (e.g., through privacy regulation) and are strategic with regard to whether to disclose it to the service provider.

More broadly, our paper also relates to the work that addresses consumer privacy and information management. Studies in the fields of operations management, marketing, and economics examine the ways in which (i) customers voluntarily disclose their private information to firms as a strategic choice (see, e.g., Huang and Van Mieghem 2013, Ali et al. 2019) or involuntarily through product selection, product reviews (Yu et al. 2016), and other types of user-generated content and (ii) firms infer customer information from their actions—such as past purchases (Conitzer et al. 2012, Bimpikis et al. 2021), platform usage (Fainmesser et al. 2019; Ichihashi 2020a, b), and social network activity (Acemoglu et al. 2017). Although assuming that customers' information has been obtained, another stream of literature investigates how firms can exploit that information for the purpose of personalized pricing (Candogan et al. 2012, Fainmesser and Galeotti 2016, Valletti and Wu 2020), targeted advertising (Galeotti and Goyal 2009, Shen and Miguel Villas-Boas 2018, Kucukgul et al. 2021), selective selling (Momot et al. 2020), and quality discrimination (Li 2021) as well as for public opinion and engagement manipulation (Candogan and Drakopoulos 2020, Mostagir et al. 2022); Acquisti et al. (2016) provide an excellent survey of this literature. Firms using data-driven decision making can protect consumer privacy through applying privacy-preserving algorithmic mechanisms (Lei et al. 2020).

Much as in the literature on privacy and information management, we consider customers who are strategic in their private information disclosure commitments and who know that the information they reveal can be used by the service provider in their interests yet possibly also against their interests. However, we focus on a service system with negative externalities among customers and more specifically, on investigating *customers' strategic information disclosure* and its effects not only on the service provider but also, on the collective surplus of all customers as a society as well as on customers themselves individually.

3. Base Model Setup

3.1. Overview

A unit mass of time-sensitive customers arrives at a single-server queue. Upon arrival, each customer chooses her information disclosure strategy. For instance, she gives a service provider her explicit consent for using her data or not (e.g., making an opt-in decision under the GDPR), configures her privacy and/or information sharing settings, or voluntarily signs up for one of the provider's services, which gathers and processes her data (e.g., Alexa of Amazon). If a customer chooses to disclose information, this information allows the service provider to infer the type of service that the customer requires in a future interaction. For instance, advances in machine learning allow companies to predict their customers' intent by leveraging both individual- and aggregate-level data (e.g., see Bloomberg 2017, 2018; Hackernoon 2019). Similarly, Amazon's Alexa can be programmed not only to map certain spoken phrases to customer's intent[4] but also, to analyze voice recordings to predict such future intent based on the "hunch" of the hardware (*The Verge* 2018). We assume that a customer's service request can be one of two types: long or short in service time, and it is realized *after* the information disclosure strategy is chosen (see Section 3.4 for discussion). If a customer chose to disclose her information, the service provider can infer the length of her service request based on the information collected up to the point of the interaction.

3.2. Customers

Customers' service requests follow a homogeneous Poisson process with rate λ. The service time of a high-priority type-H (a low-priority type-L) request follows an independent and identically distributed exponential distribution with mean $1/\mu$ ($1/\sigma\mu$ for the parameter $\sigma \in (0,\infty) \setminus \{1\}$).[5] We relax the assumption of two customer types in Section 6.1. Note that if $\sigma < 1$ ($\sigma > 1$), then type-H requests require a shorter (longer) time, on average, to complete. A customer faces a type-H (type-L) request with an exogenous probability α $(1-\alpha)$, where $\alpha \in [0,1]$. The average service time of all requests is $(1+\alpha(\sigma-1))/\sigma\mu$, so the capacity of the service facility is $\overline{\mu} \equiv \sigma\mu/(1+\alpha(\sigma-1))$ (we assume that the arrival rate $\lambda < \overline{\mu}$; otherwise, customers have to wait infinitely long for service). Customers receive a service reward R upon completion of service, yet they incur a linear waiting cost (with a marginal rate c) as long as they remain in the system. The service reward is lower bounded ($R \geq c/\overline{\mu}$), so customers are willing to join an empty queue. The base model assumes that service reward is sufficiently large (assumption relaxed in Section 6.6).

3.2.1. Actions. Customers first choose whether to *disclose* or rather, to *withhold* their private information. If a customer chooses to disclose information, then the service provider can perfectly infer the type of the customer's *future* service request (and expected service time).

In Sections 4 and 5—where we examine the incentives of individual customers to disclose or withhold information as well as how these incentives are aligned (or misaligned) with those of the service provider or society as a whole—we assume that the service reward R is high enough that all customers avail themselves of the service. This simplifying assumption helps us isolate the effect of private information disclosure on customer surplus without the interference of an endogenized throughput through customers' joining or balking behavior. Section 6.6 extends the base model and allows for balking decision of customers. In that section, we study how customer control of information affects the service provider itself in the case of an endogenized throughput.

3.2.2. Privacy and Information. As mentioned before, information disclosed to the service provider might be the request type itself or other forms of private information—for instance, customers' individual characteristics or activity patterns (e.g., web search or platform activity history, voice recordings done by Amazon Alexa, etc.) that could enable the service provider's inference of a customer's request type. For simplicity, in the remainder of the paper, we assume that information disclosed by a customer is the type of her service request.

In contrast to most previous research, we consider a situation in which each customer has full possession and control over this information and can therefore choose whether to share it with the service provider. This choice of whether information is disclosed to the service provider determines a customer's *privacy strategy*.

3.3. Service Provider

3.3.1. Information. We model a service facility as a single-server queue with capacity $\overline{\mu}$. The single-server queue assumption is common in the queueing economics literature to gain tractability when studying information exchange (see, e.g., Allon et al. 2011) and priority schemes (see, e.g., Gurvich et al. 2019) in service systems. If arriving customers disclose information, then the service provider has perfect knowledge of the type and expected service time of their future requests. However, if arriving customers choose to withhold their information, then the provider will be unable to deduce their service request types. So, from the service provider's perspective, the service time of these type-neutral (type-N) requests from customers who withhold information follows a hyperexponential distribution with mean $(1+\alpha(\sigma-1))/\sigma\mu$, which lies between the average service times of type-H and type-L requests—that is, between $1/\mu$ and $1/\sigma\mu$.

3.3.2. Priority Policy. Using the information provided by customers and/or its knowledge that some customers are withholding information, the service provider implements a preemptive "priority queue discipline" that establishes a pecking order for type-H, type-N, and type-L requests. Two remarks are in order. First, the assumption of preemptive priority is used for technical convenience and highlights the value of privacy management in service systems. We do not expect our main qualitative results to change under the nonpreemptive priority discipline. Second, we assume the natural ranking order of $H > N > L$ as given, which is usually determined exogenously by the incentive scheme of the service provider offered to the service workers (see below). Although other priority schemes may be preferred by the service provider, we discuss in Section 6.5 that all of such alternative schemes could be linked to discrimination of customers based on their information disclosure decision (i.e., customers who disclose information are prioritized or deprioritized over all the customers who withhold information)—a practice prohibited by most recent data regulations such as the CCPA.[6] We leave the in-depth study of the choice of the optimal priority scheme when customers can protect their privacy to future research and refer an interested reader to Gurvich et al. (2019) for the analysis of the optimal priority scheme by a revenue-maximizing firm or a social planner under *full knowledge* about customers.[7]

If $\sigma < 1$, then the provider operates under the shortest processing time first (SPT) policy. This can be the case when individual service workers are paid at a per-piece rate, so they cherry-pick shorter jobs to maximize their individual revenue. For instance, Ibanez et al. (2018) find that radiology doctors prioritize tasks with a shorter expected processing time. If, on the contrary, $\sigma > 1$, then the service provider operates under the longest processing time first (LPT) policy. This could apply when individual service workers are paid according to their work time, so they prioritize longer jobs to minimize the unproductive idle time in between jobs. For example, taxi drivers could prefer longer trips to the airport rather than shorter trips within the downtown area. In other words, the parameter σ is linked to the service provider's *revenue model*. As mentioned before, we use the single-server approximation to model such service systems for tractability reasons. This approximation could work very well for many of today's online service environments with crowdsourced service workers (rather than a fixed number of agents) who arrive following a random Poisson process, select a job out of the queue, and sign off if there is no job waiting in the queue (and may come back later).

To better implement its priority policy, the service provider prefers more information on the request types of its customers. Under full information disclosure, for example, the service provider can accurately classify all requests into the type-H or type-L category and so, can prioritize them accordingly. Yet, if all customers withhold information, then the service system essentially operates under a first come, first served policy; that is, the priority rule becomes void. This outcome reduces the service provider's ability to discriminate among customers based on their types, which runs counter to its intentions.

3.4. Sequence of Events and Equilibrium

The game consists of two stages: the disclosure and service periods. In the disclosure period, all customers simultaneously choose their information disclosure strategy. In particular, each customer can either disclose or withhold information. In the service period, customers' service requests are realized, and the service provider prioritizes customers (in the order $H > N > L$) based on the information in its possession (i.e., withholding customers—type N—and disclosing customers—either type-H or type-L priority—depending on their realized and observed service request). Formally, a customer's expected utility takes the following form:

$$U = \begin{cases} U_d \equiv R - c(\alpha W_H + (1-\alpha) W_L) & \text{if the customer discloses information,} \\ U_w \equiv R - c W_N & \text{if the customer withholds information,} \end{cases} \tag{1}$$

where W_H, W_N, and W_L are expected waiting times in each of the corresponding priority classes.

In setting up the model, we make two assumptions. First, we assume that customers choose the disclosure strategy once and *before* observing the types of their requests. Such an assumption captures the reality that although more and more companies comply with data protection regulations (e.g., with the European GDPR) and ask for their customers' explicit consent for collecting/processing their data (i.e., data disclosure choice) before customers start to use the service, the mechanisms for *revoking* or *changing* such consent are typically poorly accessible. In fact, most companies' privacy policies describing, among other things, the ways how consent can be withdrawn by a customer are less comprehensible, and revoking consent often requires directly contacting the company (e.g., see *New York Times* 2019b as well as the privacy policies of Helpware, Blue Cross Blue Shield, Airbnb, and Tinder for an illustration[8]). Furthermore, companies often intentionally make it more difficult for their users to access privacy settings (e.g., see *The Verge* 2021). For all other applications in which the choice of information disclosure can be done on a regular basis after observing the types of requests (e.g., app-enabled privacy settings), in Section 6.2, we investigate an alternative scenario in which customers choose the information disclosure strategy after they observe the types of their requests. Second, we assume that in the disclosure period, all customers are aware of the priority rule employed by the service provider. This assumption can also be relaxed, and the model can accommodate a fraction of customers who are unaware of the service provider's priority rule—our structural results do not change.

We let $\gamma \in [0, 1]$ be the probability with which customers disclose information. Note that we can capture both mixed and pure disclosure strategies by this probability. Because all customers are homogeneous in the disclosure stage (i.e., they have the same service rewards and probabilities of service request types, and they expect the same waiting time in each of the priority classes), it is natural to search for a symmetric equilibrium in which all customers disclose information with the same probability γ^*. We note that the previous literature (see, e.g., Edelson and Hilderbrand 1975, Hassin and Haviv 2003) also focuses on a symmetric type of equilibria. Among all the arriving customers, $\alpha\gamma\lambda$ customers have type-H requests, whereas $(1-\alpha)\gamma\lambda$ have type-L requests; finally, $(1-\gamma)\lambda$ have type-N requests.

Naturally, information disclosure strategy γ along with the arrival rate λ affects expected waiting times W_H, W_N, W_L, and consequently, any individual customer's expected utility. With slight abuse of notation, we denote by $U_d(\gamma,\lambda)$ ($U_w(\gamma,\lambda)$) an *infinitesimal* customer's expected utility when disclosing (withholding) information given her expectation on the information disclosure strategy γ played by all other customers and their arrival rate λ. The technical Lemma 1 derives closed-form expressions for these expected utilities.

Lemma 1. *Given an infinitesimal customer's expectation of the arrival rate λ and the population's disclosure probability γ, this customer's expected utility from disclosing information, $U_d(\gamma,\lambda)$, or from withholding information, $U_w(\gamma,\lambda)$, is given by*

$$U_d(\gamma,\lambda) = R - c\left(\frac{\alpha}{\mu-\alpha\lambda\gamma} + \frac{\sigma(1-\alpha)(\mu+\lambda\alpha(\sigma-1))}{(\sigma\mu-\lambda(1+\alpha(\sigma-1)))(\sigma\mu-\lambda(\alpha\sigma+(1-\gamma)(1-\alpha)))}\right),$$
$$U_w(\gamma,\lambda) = R - c\frac{\sigma(1+\alpha(\sigma-1))\mu-\lambda\alpha(\alpha-1)(\sigma-1)(\sigma+\gamma-1)}{\sigma(\mu-\lambda\alpha\gamma)(\sigma\mu-\lambda(\alpha\sigma+(1-\gamma)(1-\alpha)))}. \tag{2}$$

Proof. Proofs for all results are given in Online Appendix A. □

We define an equilibrium disclosure strategy γ^* to be such that no individual customer has incentives to deviate from playing equilibrium strategy γ^* given that all other customers also choose their information disclosure based on this strategy (here, individual incentives are defined by Equation (2)). Formally, $\gamma^*=0$ (full withholding) if $U_d(0,\lambda) < U_w(0,\lambda)$. Similarly, $\gamma^*=1$ (full disclosure) if $U_d(1,\lambda) > U_w(1,\lambda)$. Finally, $\gamma^*\in(0,1)$ (partial disclosure) if γ^* solves $U_d(\gamma^*,\lambda)=U_w(\gamma^*,\lambda)$ and $U_d(\gamma,\lambda)-U_w(\gamma,\lambda)$ is a decreasing function of γ in the neighborhood of $\gamma=\gamma^*$ (the latter ensures that the chosen equilibrium is stable). In case there are multiple equilibria, we select the Pareto-dominant one for all customers.

4. Control over Information

In this section, we explore the consequences of customers having full control over their information. In other words, we investigate a scenario in which customers control whether the service provider has access to their data (e.g., control granted by a privacy regulation such as the GDPR). After deriving customers' equilibrium information disclosure strategy γ^*, we compare it with the *full-disclosure* and *socially optimal* information strategies.

4.1. Individual Incentives to Disclose Information

We start by characterizing the equilibrium information disclosure strategy of customers.

Proposition 1. *When they are in control of their information, customers disclose* (*withhold*) *information if there is a high* (*low*) *probability that they can obtain top priority in the service system. If this probability is intermediate, then customers* (i) *avoid the crowd and disclose with probability $\hat{\gamma}\in(0,1)$ in an SPT service system that is not too busy or alternatively,* (ii) *follow the crowd and either all disclose or all withhold information in a sufficiently busy SPT service system or in any LPT service system. Formally, there exists a symmetric equilibrium information disclosure strategy γ^* such that*

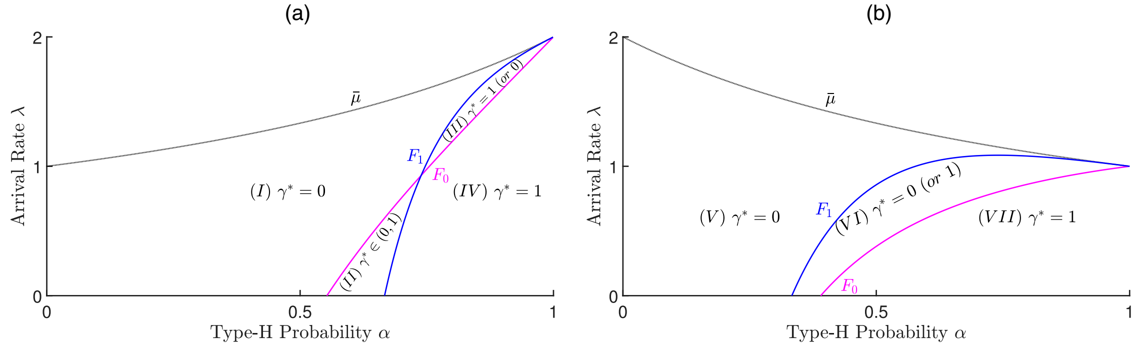
$$\gamma^* = \begin{cases} 0 & \text{if } \alpha \le \underline{\alpha}(\lambda), \\ 1 & \text{if } \alpha \ge \overline{\alpha}(\lambda), \\ \hat{\gamma}\in(0,1) & \text{if } \alpha\in(\underline{\alpha}(\lambda),\overline{\alpha}(\lambda)),\ \sigma<1,\ \lambda<\tilde{\lambda}, \\ 0 \text{ or } 1 & \text{otherwise;} \end{cases} \tag{3}$$

here $\underline{\alpha}(\lambda)=\min(F_0(\lambda),F_1(\lambda))$, $\overline{\alpha}(\lambda)=\max(F_0(\lambda),F_1(\lambda))$, and $\tilde{\lambda}$ satisfies $F_0(\tilde{\lambda})=F_1(\tilde{\lambda})$. (*Expressions for $\hat{\gamma}$ are given in Online Appendix A, where the increasing functions $F_0(\lambda)$ and $F_1(\lambda)$ are also characterized.*)

According to this proposition, customers opt to withhold personal information only if they believe there is otherwise a high chance of their service requests being assigned low priority by the service provider once it learns their realized types. If this is the case, then customers prefer to withhold information and keep the types of their requests undisclosed (i.e., keep them as an N type from the service provider's standpoint). Figure 1 illustrates the equilibrium information disclosure strategy γ^* depending on the probability α that a customer's request is of type H as well as on the arrival rate λ and the priority discipline (i.e., SPT or LPT) chosen by the service provider.[9]

There are two "extreme" cases. If α is high (i.e., $\alpha\ge\overline{\alpha}(\lambda)$) in regions IV and VII in Figure 1—that is, if the customer's request is most likely to be of type H—then all customers choose to disclose information. Any reduction in α makes disclosing information less attractive, and so, if α is low (i.e., $\alpha\le\underline{\alpha}(\lambda)$) in

Figure 1. (Color online) Customers' Equilibrium Information Disclosure Strategy γ^* as a Function of the Arrival Rate λ and the Probability α of a Type-H Request



Notes. (a) SPT discipline, $\sigma < 1$. (b) LPT discipline, $\sigma > 1$.

regions I and V in Figure 1, then all customers withhold information.

The thresholds $\underline{\alpha}(\lambda)$ and $\overline{\alpha}(\lambda)$ are both increasing in the arrival rate λ. The reason is that, the busier the service system becomes, the longer that deprioritized type-L requests must wait to be served (i.e., after the type-N and type-H requests); then, for any given α, customers' incentives to withhold information (and thus, to remain in the type-N class) increase. The result is an expansion of the range of α for which customers prefer to withhold information (an increase in $\underline{\alpha}(\lambda)$) and a shrinkage of the α range for which customers prefer to disclose information (an increase in $\overline{\alpha}(\lambda)$).

For the intermediate range of α, i.e., $\alpha \in (\underline{\alpha}(\lambda), \overline{\alpha}(\lambda))$, the equilibrium disclosure strategy is more intricate. Proposition 1 states that—depending on the service system's level of congestion as defined by the arrival rate λ and the service provider's priority rule—customers might commit to either *follow the crowd* or *avoid the crowd* behavior (cf. Hassin and Haviv 2003, chapter 1).

Consider customers who withhold information. There are two effects that information disclosure by other customers brings on them. (i) The benefit is that some of these disclosing customers will be moved to the L priority class and be deprioritized as compared with withholding customers; (ii) the downside, however, is that the rest of the disclosing customers will be moved to the H priority class and be prioritized over the withholding customers, which will lead to the longer wait times of the withholding customers.

In the LPT system (region VI in Figure 1(b)), the second effect dominates because long jobs are moved to the H priority class. In the SPT system (region III in Figure 1(a)), the second effect dominates only if there is a large number of type-H requests (i.e., if λ is high). In both of these cases, customers' incentives to disclose information, thus, increase with the number of other customers who disclose information—customers *follow the crowd*. Mathematically, $U_d(\gamma,\lambda) - U_w(\gamma,\lambda)$ is higher when more *other* customers also disclose information (i.e., when γ is higher).[10]

Customers *avoid the crowd* in SPT systems that are less congested (i.e., $\lambda < \tilde{\lambda}$); see region II in Figure 1(a). In this case, the first effect of other customers' information disclosure dominates because the arrival rate is sufficiently small—only a handful of requests are prioritized over the (type-N) requests of information-withholding customers, and the wait time caused by the H priority class is therefore only slightly longer. Thus, an increase in the population's disclosure of information leads to a decrease in $U_d(\gamma,\lambda) - U_w(\gamma,\lambda)$—that is, in the individual customer's incentive to withhold information. That behavior leads to a unique mixed equilibrium $\gamma^* \in (0,1)$ where customers randomize and where γ^* fraction $(1-\gamma^*$ fraction) of them disclose (withhold) their information.

Observe that, in all cases where customers follow the crowd, two equilibria are possible; either all customers disclose information ($\gamma^* = 1$), or all of them withhold information ($\gamma^* = 0$). One can always select a Pareto-dominant equilibrium γ_P^* from these two equilibria (see Online Appendix A.2 for the formal derivations). So, $\gamma_P^* = 0$ (all withhold) is Pareto dominant in an LPT system, whereas conversely, $\gamma_P^* = 1$ (all disclose) Pareto dominates in an SPT system. For the rest of this paper, we select the Pareto-dominant equilibrium, $\gamma^* = \gamma_P^*$.

4.2. Consequences for Society

Customers' strategy concerning whether to disclose or withhold information has definite implications for all customers collectively as a society as well as for themselves individually. In particular, an information disclosure strategy affects the average wait time in the service system, and consequently, total customer surplus. An inquiry on the implications of an information disclosure strategy on customer surplus is in line with the recent literature, which studies consumer surplus in service systems (see, e.g., Cui et al. 2020, Feldman and Segev 2021).

Having established the customer information disclosure strategy in Proposition 1, we are now in a position to compare total customer surplus under *full* control of their personal information (where the equilibrium information disclosure strategy is γ^*), $\mathrm{CS}_{\mathrm{control}} = \lambda(\gamma^* U_d(\gamma^*, \lambda) + (1-\gamma^*)U_w(\gamma^*, \lambda))$, with the surplus under *no* control of information (i.e., full information disclosure), $\mathrm{CS}_{\mathrm{discl}} = \lambda U_d(1, \lambda)$. Thus we obtain our next result as follows.

Theorem 1. *Whether self-control over personal information is less or more beneficial to society than full information disclosure depends on the priority rule adopted by the service provider. If the provider prioritizes short jobs (i.e., under the SPT discipline, $\sigma < 1$), then self-control over information leads to weakly lower total customer surplus (i.e., $\mathrm{CS}_{\mathrm{control}} \leq \mathrm{CS}_{\mathrm{discl}}$); otherwise, if the service provider prioritizes long jobs (i.e., under the LPT discipline, $\sigma > 1$), then $\mathrm{CS}_{\mathrm{control}} \geq \mathrm{CS}_{\mathrm{discl}}$. The inequalities are strict if given control over personal information, some customers choose to withhold it (i.e., $\gamma^* < 1$), which is misaligned with the service provider's preference for full information disclosure.*

When comparing the equilibrium behavior of customers who control their personal information with the scenario in which they have no control over that information (and so, it is all disclosed), we find that granting customers control over their personal information can in some cases reduce their total surplus by increasing their expected wait time in the queue, which hurts customers individually. The latter is because all homogeneous customers join the service, and hence, the impact on total surplus of all customers is equivalent to that on each individual one of them.

In particular, Theorem 1 clarifies that customers' control over information—and their consequent self-interested strategic decisions—necessarily reduces total customer surplus *only* if the service provider prioritizes short service requests (i.e., under the SPT priority rule). To develop intuition, note first that in this case, a service provider's SPT policy would be aligned with collective incentives because owing to the $c\mu$ rule (Van Mieghem 2000), it would shorten customers' expected wait time. This favorable outcome would be achieved if information was fully disclosed and if customers had no opportunity to withhold it. In contrast, a service provider's LPT policy would be misaligned with the interests of society because it lengthens customers' expected wait time.

Suppose the service provider has adopted the SPT priority (e.g., is being paid at a piece rate). In that case, if a customer's service request is likely to be long and thus, to fall into the type-L class, then that customer will withhold personal information—thereby keeping the request in the type-N class—rather than disclosing information and likely ending up in the lowest-priority class. Thus, long requests of the type-N class might be processed before short requests of the type-N class, which reduces overall customer surplus. Figure 2(a) illustrates that this effect is more pronounced when the service system is more congested, so prioritizing short service requests (over long ones) becomes even more important for society.

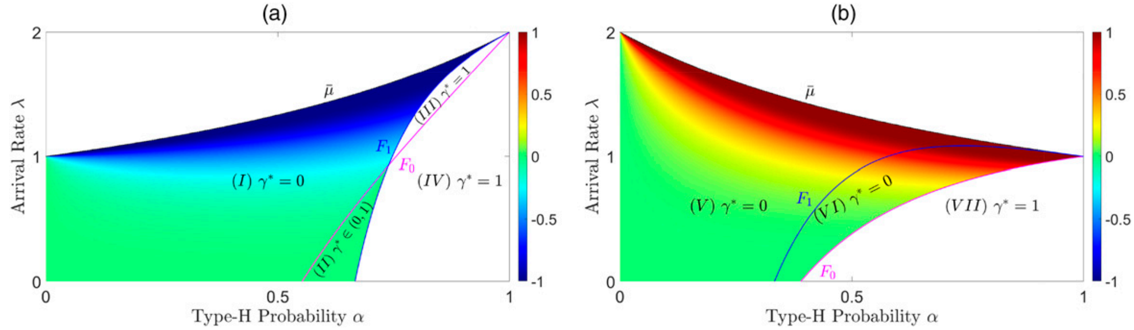
Yet, if the service provider prioritizes long service requests—the LPT policy as adopted, for instance, by service providers paid per unit of time spent on the task with fixed setup costs—then society benefits from individual customers having control over their personal information. Here, the service provider's prioritization scheme reduces total customer surplus because it lengthens customers' expected wait time. In this case, if the requests of customers are likely to be short (i.e., if α is low), then they withhold all personal information; doing so prevents long requests from being prioritized over short ones. Therefore, self-control of information disclosure reduces the average wait time and increases total customer surplus. Just as under an SPT policy, the magnitude of the difference in total customer surplus with and without self-control depends on the arrival rate and is higher when the system is more congested; see Figure 2(b).

In short, Theorem 1 offers a cautionary tale about the widely held opinion that customers always benefit from having more control over their data (*Financial Times* 2017, *New York Times* 2019a). Our analysis reveals that in our context, this statement holds only when the service provider's incentives are misaligned with collective incentives (i.e., under the LPT policy). In that event, allowing customers to control their information enables those who were deprioritized by the service provider to advance in the priority rank by *strategically* withholding information; this development is beneficial from the societal perspective because it increases customer surplus. Yet, if the service provider's incentives are aligned with collective incentives (i.e., under the SPT policy), then customers the provider had deprioritized are also those who should—from the societal perspective—be treated so. Then, control over information allows customers who are "undeserving" (from both the service provider's and society's perspective) to move up in priority rank, which lengthens expected wait times; thus, it reduces customer surplus and hurts customers themselves. In the latter case, individual customers are trapped in a version of the prisoner's dilemma, competing with their peer customers when taking control of their privacy setting.

4.3. Privacy Self-Synchronization

When choosing an information disclosure strategy, each customer makes a rational decision by comparing utilities $U_d(\gamma, \lambda)$ with $U_w(\gamma, \lambda)$—that is, given expectations about the level γ of information disclosure

Figure 2. (Color online) Difference Between Total Customer Surplus Under Customers' Full Control of Information and That Surplus Under No Control of Information, $CS_{control} - CS_{discl}$, as a Function of the Arrival Rate λ and the Probability α of a Type-H Request



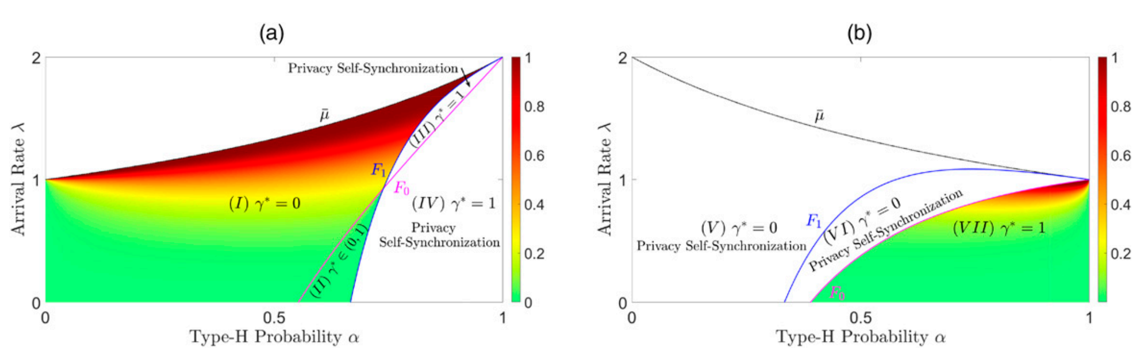
Notes. In all of our colored graphs, for better contrast we plot the *normalized* value of x: $\text{sign}(x)(1 - e^{x\cdot\text{sign}(-x)})$. (a) SPT discipline, $\sigma < 1$. (b) LPT discipline, $\sigma > 1$.

in society. As we observed in Section 4.2, such individually rational behavior is not always optimal from the societal perspective because it does not always lead to the efficient outcome with the highest possible total customer surplus. Our next proposition formalizes the following question. Under what conditions are each customer's incentives to disclose information aligned with the collective incentives? We wish to know, in other words, when the service system achieves the state of *privacy self-synchronization* (Popa 2012). Let $CS_{social} = \max_\gamma[\lambda(\gamma U_d(\gamma,\lambda) + (1-\gamma)U_w(\gamma,\lambda))]$, where the socially optimal customer information disclosure strategy is denoted by γ^{SO} (which is derived in Online Appendix A.4).

Proposition 2. *A service system reaches the state of privacy self-synchronization when a sufficiently high fraction of its customers' service requests are short. In all other cases, customers choose a suboptimal information disclosure strategy from the societal standpoint; that is, privacy self-synchronization is not achieved. Formally, there exists a threshold* $\alpha^{p.s.}(\lambda;\sigma)$ *such that* $\gamma^* = \gamma^{SO}$ *and* $CS_{control} = CS_{social}$ *iff either* (i) $\alpha > \alpha^{p.s.}(\lambda;\sigma)$ *when* $\sigma < 1$ *or* (ii) $\alpha < \alpha^{p.s.}(\lambda;\sigma)$ *when* $\sigma > 1$. *In all other cases,* $\gamma^* \neq \gamma^{SO}$ *and* $CS_{control} < CS_{social}$. *Furthermore,* $\alpha^{p.s.}(\lambda;\sigma)$ *increases with* λ *and is equal to* $F_1(\lambda)$ *if* $\sigma < 1$ *or to* $F_0(\lambda)$ *if* $\sigma > 1$.

According to this proposition, customers choose a socially suboptimal information disclosure strategy when their service requests are likely to be long, regardless of which priority rule the service provider adopts. In this case, individual incentives are misaligned with collective incentives; see Figure 3 for an illustration of the difference $CS_{social} - CS_{control}$. Recall, on the one hand, that control over information allows customers to manipulate their information disclosure (by either disclosing or withholding information) in such a way that moves them up in priority, which is each customer's goal. On the other hand, collective incentives are such that the best requests to be prioritized are short ones; serving those first leads to a shorter average wait time (based on the $c\mu$ rule) and hence, to higher total customer surplus. Yet, if service requests are likely to be long, then customers' individually

Figure 3. (Color online) Difference Between Total Customer Surplus Under the Socially Optimal Information Disclosure Strategy and That Surplus When Customers Have Full Control of Their Information, $CS_{social} - CS_{control}$, as a Function of the Arrival Rate λ and the Probability α of a Type-H Request



Notes. (a) SPT discipline, $\sigma < 1$. (b) LPT discipline, $\sigma > 1$.

rational actions will push those long requests up in priority—an outcome that society as a whole does not favor. The busier the service system (i.e., the higher the arrival rate λ), the greater the gap between the decentralized equilibrium and socially optimal customer surplus (see Figure 3). In the opposite case, when service requests are likely to be short, customers' individual incentives are synchronized with what society prefers—namely, short requests being processed first.

Note that regions III and VI in Figure 3 are such that both full disclosure and full withholding are equilibria (see Proposition 1). As discussed before (see the discussion of the "follow the crowd" type of equilibria toward the end of Section 4.1), we adopt the Pareto-dominant equilibrium selection rule to refine an equilibrium (i.e., $\gamma^* = 1$ in region III and $\gamma^* = 0$ in region VI). If, on the other hand, the other equilibrium was to be chosen, control over information in these particular regions would lead to a worse outcome for the customers.

The results presented in this section (Theorem 1 and Proposition 2) constitute a word of caution to regulators and should enrich public discussion of the most beneficial privacy and information disclosure regulation. There are two key messages. First, individual customers do not always have incentives to withhold information even when they have control over it. Customers choose strategically between disclosing and withholding information, and in some cases, full or partial information disclosure may be in their best interest. Thus, personal information disclosure becomes a useful tool for customers to navigate under a service provider's priority policy. Our second and more important message is that a regulation providing customers with full control of personal information could in some cases backfire by distorting the service system that is already operating efficiently and could lead to inferior performance—that is, longer average wait times in the service system. We show when this is the case, and whether control over information hurts or benefits the society depends on the service provider's priority policy, which is usually linked to its business or revenue model and determines the alignment (or misalignment) between customer and collective incentives. In the next section, we explore what a regulator could do to align these incentives and achieve privacy self-synchronization and whether such actions are feasible and cost-effective.

5. Inducing Information Disclosure and Privacy Self-Synchronization

In Section 4.1, we established that customers, when they have control over their personal information, do not always choose an information disclosure strategy that is optimal either for society or for the service provider. In this section, we seek to explain how customers who choose the individually optimal information disclosure can be offered monetary incentives in order to achieve either full information disclosure (the service provider's preference) or privacy self-synchronization (the regulator's societal goal).

5.1. Inducing Full Information Disclosure: The Price of Information

Paying users for their information has long been discussed by regulators and other concerned parties (*New York Times* 2018). Whereas some argue that users are already paid for their information via access to the platform's free services (e.g., Facebook's social network, Google's search engine), advocates of the "data as labor" perspective (*The Economist* 2018) point out the conflict inherent to that perspective; users are not only the platform's customers but also, its "product" (*New Yorker* 2015). Yet, as far as we know, our study is the first to pinpoint the *price* of users' personal information in a service system. Thus, we advance the following proposition, which characterizes a payment P_d that must be made to strategic users so they will switch from withholding information to fully disclosing it. (Note that P_d is the payment to all customers per unit of time, and so, the payment to an individual customer is P_d/λ.) In other words, P_d is a monetary incentive offered—by the service provider or by a regulator—to users that induces them to disclose information. This payment P_d could be offered at the stage before customers consent to information disclosure and could be in a form of a discount code. The payment should also ensure that full information disclosure becomes an equilibrium and also, that it is the Pareto-dominant one.

Proposition 3. *So that information-withholding customers will fully disclose their personal data, they must be paid the price of information*:

$$P_d = \begin{cases} \lambda(U_w(1,\lambda) - U_d(1,\lambda)) & \text{if } \sigma < 1, \\ \max(\lambda(U_w(1,\lambda) - U_d(1,\lambda)), \Delta S) & \text{if } \sigma > 1; \end{cases} \quad (4)$$

here, $\Delta S = \mathrm{CS}_{\mathrm{withhold}} - \mathrm{CS}_{\mathrm{discl}} = \frac{c\alpha(1-\alpha)(\sigma-1)}{\sigma\mu}\frac{\lambda^2}{\Theta(\lambda)}$, *with* $\Theta(\lambda) = \frac{(\mu-\alpha\lambda)(\sigma\mu-\lambda(1+\alpha(\sigma-1)))}{\mu-\alpha(1-\sigma)\lambda}$, *is the gap—in total customer surplus—between full information withholding* ($\mathrm{CS}_{\mathrm{withhold}} = U_w(0,\lambda)$) *and full information disclosure*.

The *price* of information defined in this section differs from the *value* of information discussed in the literature of operations management, economics, and marketing. The value of information is defined as the increase in a *firm's profit* stemming from its use of that information. In the literature, "information" often includes customer characteristics such as product preferences and social network position. A firm that possesses such information can boost its profits by making better operational decisions: prioritizing customers (see, e.g., Yu et al. 2018), setting personalized prices, and/or targeting particular customers to whom its product can be offered or sold (see, e.g., Fainmesser and Galeotti 2016, Momot et al. 2020). Yet, such operational decisions, which benefit the firm, may not be favored by customers—whose surplus is naturally depleted by price discrimination, service deprioritization, or selective selling. Thus, there is a potential discrepancy between the firm's gain from using customer information and customers' evaluation of that information. So, our question now becomes the following. How much utility would *customers* be willing to forgo when disclosing their personal data while knowing that the firm's use of this information might run counter to their own interests?

To the best of our knowledge, this analysis constitutes one of the first attempts to place a price on the customers' information. The customers in our model are strategic with regard to whether to disclose or withhold information, and they are fully aware of their actions' upsides and downsides. Hence, the price of information characterized in Proposition 3 (depicted in Figure 5 in the online appendix) is exactly the evaluation (from a strategic customer's standpoint) of this trade-off. Therefore, the price of information could serve as a defining variable for regulators and platforms that are contemplating privacy and data management policies.

5.2. Inducing Privacy Self-Synchronization

It is in the social planner's interest to induce a state of privacy self-synchronization for the service system. Hence, we are motivated to examine the use of a monetary incentive P_s offered to all customers (equivalently, P_s/λ to each customer) for the purpose of inducing customers to adopt γ^{SO}, the socially optimal information disclosure strategy. One must bear in mind that, because all customers are served (an assumption that we relax in Section 6.6), the strategy that maximizes total customers surplus will also maximize individual customer surplus. Therefore, the socially optimal strategy γ^{SO} is clearly Pareto dominant if it is an equilibrium. The payment P_s needs only to ensure that γ^{SO} is an equilibrium.

Proposition 4. *To induce adoption of the socially optimal information disclosure strategy γ^{SO} and to achieve privacy self-synchronization, customers should be paid an amount of P_s: either for* (i) *disclosing information when the service provider prioritizes short requests* (*i.e., under the SPT policy, $\sigma < 1$*)*; or for* (ii) *withholding information when the service provider prioritizes long requests* (*i.e., under the LPT policy, $\sigma > 1$*)*. Here,*

$$P_s = \begin{cases} \lambda(U_w(1,\lambda) - U_d(1,\lambda)) = P_d & \text{if } \sigma < 1, \\ \lambda(U_d(0,\lambda) - U_w(0,\lambda)) & \text{if } \sigma > 1. \end{cases} \tag{5}$$

Moreover, P_s is a concave function of λ under the LPT policy (*i.e., $\sigma > 1$*).

Proposition 4 characterizes the payment that must be made to customers so that they will choose the socially optimal information disclosure strategy and thus, bring the service system to a state of privacy self-synchronization. The proposition also states that customers should be rewarded differently for different actions—namely, withholding or disclosing information—depending on the service provider's priority discipline. We assume that the service provider's priority discipline is known to the social planner (we relax this assumption at the end of the section). By Proposition 2, the service system does *not* achieve privacy self-synchronization if a sufficiently high fraction of its customers' service requests are long. In that event, customers have the incentive to rise on the priority ladder via their information disclosure strategy and so, will choose either to withhold information if the service provider prioritizes short requests (i.e., under the SPT discipline) or to disclose information otherwise (i.e., under the LPT discipline). In both cases, such self-interested customer behavior is undesirable from the societal perspective. Hence, a social planner must pay customers so as to create opposing incentives in each of these cases: incentivizing information disclosure in the SPT case (e.g., by offering customers a discount code if they disclose information—the action also preferred by the service provider) and conversely, incentivizing the withholding of information in the LPT case (e.g., by providing monetary incentives to promote the use of the virtual private network services; the platform that employs individual service workers and attempts to minimize the average service time could offer customers a discount if the latter do not disclose their information to the individual service workers). Figure 6 in the online appendix plots, for a firm's LPT policy and as a function of our usual system primitives, the amount of such a monetary incentive required to induce customers' socially optimal information disclosure and thereby, achieve privacy self-synchronization.

Note that under the SPT discipline, customers who have a large proportion of long requests (i.e., low α) usually withhold information to avoid being deprioritized in case their requests are of the long type. As discussed before, this outcome runs counter to societal preferences. So, in this case, the monetary incentive P_s for inducing privacy self-synchronization coincides with the incentive P_d (defined in Proposition 3) for inducing full information disclosure; it also increases with the arrival rate λ. A graph of P_s under the SPT discipline would be identical to Figure 5(a) in the online appendix, which plots P_d. It is interesting that in the opposite case (i.e., when the service provider prioritizes long requests; the LPT discipline), the price P_s that customers demand to withhold information is not necessarily increasing in the arrival rate λ. Rather, if the probability α is high enough, P_s first increases but then, decreases with λ (see Online Appendix A.6 for a formal derivation of this result). In what follows, we give the intuition underlying price P_s's concavity in this region with respect to the arrival rate λ.

Consider a customer's individual incentive to disclose or withhold information (i.e., the logic applied when determining the price P_s) in the case where all other customers withhold information. By withholding information, the focal customer falls into the type-N class with probability of one. By disclosing information, this customer likely (because α is high) falls into the type-H priority rank, where wait time is a small constant equal to $1/\mu$; this is the upside of disclosing information. However, there also exists a small chance $1-\alpha$ that this customer falls into type-L priority rank—that is, behind all the other customers who withhold information and are of type N (the downside of disclosing information). When the arrival rate λ is relatively high (i.e., close to $F_0(\lambda)$), then the consequences of falling into the type-L priority rank when disclosing information are devastating. Hence, the pros and cons of disclosing information tend to balance out, and so, the monetary incentive needed to induce this customer to choose information withholding (i.e., to settle in the type-N class) is not very high. Suppose now that the arrival rate λ is relatively low (i.e., close to zero). Because of the service system's underutilization, the wait time difference for type-N versus type-H customers is less significant than when intermediate or high levels of λ are involved. As before, this customer's incentive to disclose information is not much stronger than that to withhold it, from which it follows that P_s is small for low levels of λ as well. When λ is in the intermediate range, the benefit of disclosing information is more significant than the downside. As a result, the service provider needs to pay a relatively large amount for this customer to withhold information.

Finally, the monetary incentive P_s under the LPT discipline is also increasing in α. That is to say, the higher the proportion of long requests, the more incentive customers have to disclose information in order to move up to the type-H priority rank (otherwise, a customer withholding information would have a higher chance of being prioritized over and hence, the greater the monetary incentive that must be offered to change behavior and conform to the socially optimal policy).

Having derived the monetary incentive required to induce privacy self-synchronization, we must now address the following question that naturally arises. Is the payment worth the increase in customer surplus to which it leads? Our next theorem posits the existence of a region where it is economically beneficial for society to induce customers' socially optimal information disclosure (i.e., to achieve privacy self-synchronization).

Theorem 2. *There exists a nonempty set of probabilities α and arrival rates λ for which inducing privacy self-synchronization via the monetary incentive P_s (as defined in Proposition 4) is beneficial for society; that is, the benefit of switching to socially optimal information disclosure outweighs its cost, P_s. Formally,*

(i) *if $\sigma < 1$, then for all $\alpha > 1/(\sigma^{3/2}+1)$, there exists a $\xi_1 > 0$ such that $P_s < \mathrm{CS}_{\mathrm{social}} - \mathrm{CS}_{\mathrm{control}}$ for all $\lambda \in [F_1^{-1}(\lambda), F_1^{-1}(\lambda)+\xi_1)$;*

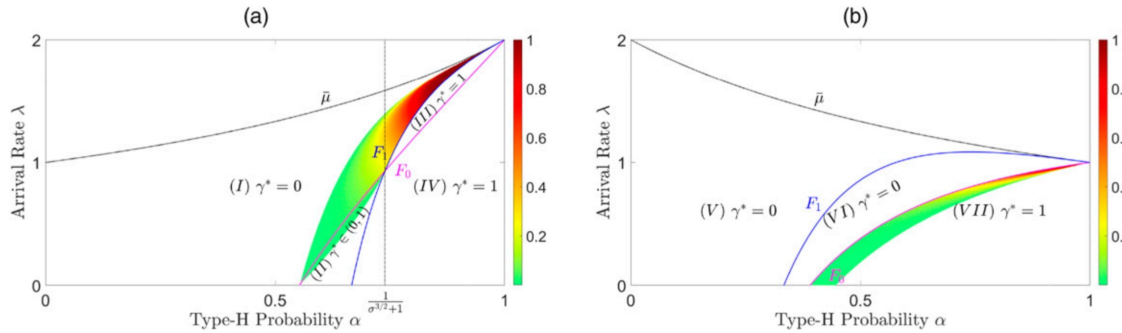
(ii) *if $\sigma > 1$, then for all $\alpha > (\sigma - 3 + \sqrt{5\sigma^2 - 2\sigma + 1})/2(\sigma^2+\sigma-2)$, there exists a $\xi_2 > 0$ such that $P_s < \mathrm{CS}_{\mathrm{social}} - \mathrm{CS}_{\mathrm{control}}$ for all $\lambda \in (F_0^{-1}(\lambda) - \xi_2, F_0^{-1}(\lambda)]$.*

The functions $F_0(\lambda)$ and $F_1(\lambda)$ are defined in Proposition 1, and the values $\mathrm{CS}_{\mathrm{social}}$ and $\mathrm{CS}_{\mathrm{control}}$ are defined in Sections 4.2 and 4.3, respectively.

Theorem 2 establishes that, irrespective of whether the service provider adopts an SPT or an LPT priority discipline, there exists a set of probabilities α and arrival rates λ (see Figure 4, which also depicts other areas where possibly $P_s < \mathrm{CS}_{\mathrm{social}} - \mathrm{CS}_{\mathrm{control}}$) for which inducing privacy self-synchronization is worth the cost—an important result from the social planner's perspective. So, in the regions characterized by this theorem, the increase in total customer surplus—when all customers switch from the individually optimal information disclosure to the socially optimal one—exceeds the monetary incentive needed to induce that switch. An outcome of considerable interest is that the benefit of privacy self-synchronization *must* outweigh the cost of inducing socially optimal information disclosure when α and λ are sufficiently high or in the region where the difference $\mathrm{CS}_{\mathrm{social}} - \mathrm{CS}_{\mathrm{control}}$ is the greatest. Yet, incentivizing individual customers to withhold their information, when doing so is socially optimal, is relatively cheap (see Proposition 4).

Observe that, from a social planner's perspective, the monetary incentive P_s amounts to a within-society transfer payment. It serves as a tool to induce adoption of the socially optimal information disclosure policy and is therefore not considered as part of total customer surplus. At the same time, that surplus is also an indicator of the service provider's profitability. Indeed, because customers are homogeneous in their service valuations and marginal waiting costs, it follows that the provider can extract all customer surplus as profit (see Hassin and Haviv 2003, chapter 3). Theorem 2 can thus also be viewed from the service provider's

Figure 4. (Color online) Difference Between the Benefit and Cost of Inducing Customers to Exhibit Socially Optimal Information Disclosure, $\text{CS}_{\text{social}} - \text{CS}_{\text{control}} - P_s$, as a Function of the Arrival Rate λ and the Probability α of a Type-H Request



Notes. (a) SPT discipline, $\sigma < 1$. (b) LPT discipline, $\sigma > 1$.

perspective; there does exist a set of parameters such that it makes an economic sense to offer customers the monetary incentive P_s in order to generate the maximum customer surplus, which translates into maximizing the service provider's profit.

Finally, recall from Proposition 4 that customers are paid to disclose information when the service provider prioritizes short requests (under the SPT discipline) and are paid to withhold information otherwise (under the LPT discipline). This dynamic when combined with Theorem 2 implies that, under the SPT discipline, giving customers control of their personal information may create an information market where (i) customers willingly sell their personal information and (ii) service providers buy that information, then use it to render better service (shorter wait times), and thus, earn higher profits. Under the LPT discipline, giving customers control over information may lead to a self-regulating mechanism in which the service provider pays customers to withhold their personal information from service contractors in hopes of ensuring a superior service.

Finally, note that when deriving the payment P_s that the customers have to be paid to induce them to adopt the socially optimal information disclosure strategy γ^{SO} in Proposition 4 and when comparing the benefit with the cost of switching to socially optimal information disclosure in Theorem 2, we assumed that the priority policy implemented by the service provider is known to the initiator of this payment. In case this payment is performed by a regulator, it may be possible that the latter does not have perfect information about a service provider's priority policy. We can show that a service provider operating under the SPT policy prefers making the priority policy visible to the regulator because then, the regulator's interest aligns with the service provider's—inducing full information disclosure to implement the SPT policy. With this rationale in mind, the regulator can treat a service provider as operating under the LPT policy if the priority policy is not visible. Thus, within our framework, the regulator knows a service provider's adoption of the LPT policy, whether the priority policy is made visible or not.

6. Discussion of Model Assumptions and Alternative Model Formulations

In this section, we relax and extend a number of assumptions of the base model. Although most of the considered scenarios lead to the insights structurally equivalent to those of the base model and we find that privacy regulation in the form of granting customers with control over their information may backfire, we were able to identify two settings in which this finding does not hold and shifting control over information to customers does not have any impact on the performance of the system.

Section 6.2 discusses one such scenario, where customers choose their disclosure strategies *after* observing the types of their requests. Although we believe that the scenario with the ex ante information disclosure decision investigated in the base model is the most realistic (because of the reasons outlined in Section 3.4), we hypothesize that ex post information disclosure may be possible if service providers do not comply with data protection regulations such as the European GDPR (or if such regulations are not imposed) or if service providers significantly facilitate customers' granting and revoking consent for collection/processing of their data (e.g., through accessible app-enabled privacy settings). Section 6.5 discusses another scenario in which the service provider deprioritizes customers who withhold information. Although as we argue, such deprioritization is prohibited by modern privacy regulations (such as the CCPA of California), such regulations are still in their infancy in most countries, and thus, there exists a possibility that service providers are able to deprioritize customers based on their information-withholding decision.

6.1. Multiple Request Types and Priority Classes (Online Appendix B.1)

We can generalize our model to a setting with M types of service requests. Each request type i is being realized with an exogenous probability α_i. The service time of request type i follows an i.i.d. exponential distribution with the mean $1/(\sigma_i \mu)$. Without loss of generality, we assume that $\sigma_1 = 1$, and types of requests are ordered $\sigma_1 > \cdots > \sigma_M$ for the SPT policy (and in reverse for the LPT policy). There exists a threshold m (see Equation (9) in the online appendix) so that the service provider puts withholding customers' requests between types m and $m+1$. Relative to those who withhold information, when choosing to disclose information, customers can expect to find themselves in either bucket H with other disclosing customers with request types $1, \ldots, m$ or in the bucket L with those with the request types $m+1, \ldots, M$. Within each bucket, requests are also prioritized according to their service times and based on the service provider's priority discipline. If a customer discloses information, with probability $\sum_{i=1}^{m} \alpha_i$ ($\sum_{i=m+1}^{M} \alpha_i$), her future request falls into the bucket H (bucket L), and if this customer withholds information, her request falls into bucket N. Online Appendix B.1 derives the expected wait times of the three priority buckets and all the customer types within them. Although we discuss how the rest of the analysis is expected to follow that of the base model, analytical expressions are cumbersome, and closed-form solutions cannot be derived (in particular, the multiple-types model cannot be converted to a two-types model with a simple redefinition of α because $\alpha_1, \ldots, \alpha_M$ enter the wait time expressions as well as that of the threshold m in a nontrivial fashion). We, thus, rely on a numerical experiment, which (i) confirms structural properties of the equilibrium disclosure strategies similar to those of the base model and (ii) confirms that there exist regimes in which privacy regulation such as granting customers with control over their information can lead to reduction in consumer surplus. We also show that the threshold m is higher for request type distributions for which more probability mass is allocated to the higher request types (i.e., more desirable request types from service provider's perspective). Bucket H is, thus, wider under such scenarios.

6.2. Ex Post Information Disclosure

Consider a scenario in which a customer observes her service request type *before* making a choice of whether to disclose this piece of information to the service provider. Customers' ex post information disclosure strategy will then be such that customers with realized type-H requests will always disclose information, whereas customers with realized type-L requests will always withhold information. This ex post information disclosure strategy is outcome equivalent to the full disclosure strategy considered in the paper (i.e., $\gamma = 1$). Therefore, granting customers control over information does not have an impact on the society or the service provider in this scenario. Similarly, in the model with more than two request types (as studied in Online Appendix B.1), ex post information disclosure is also outcome equivalent to full disclosure strategy. However, we conjecture that such outcome equivalence between the ex post information disclosure and full disclosure scenarios may not be the case when customers engage in repeated service interactions with the service provider. Under this scenario, customers with realized type-H requests may choose to withhold this information out of reciprocal consideration because they may obtain type-L requests in the future. Such behavior would be consistent with that in the setting of line cutting of Allon and Hanany (2012). There exist system configurations (e.g., the SPT policy) under which granting customers with control over their information may reduce consumer surplus because customers' information-withholding behavior prevents the service provider from applying the SPT policy to them and thus, hurts their own surplus as a whole.

Finally, we note that when comparing the ex post disclosure scenario with the one where information disclosure decision is done by the customers before they observe their request types (i.e., ex ante disclosure), one can observe that the former setting can actually hurt the customers. In particular, customers' knowledge of their request types (and consequent ex post disclosure) can lead to an inferior system performance when the service system operates under the LPT policy.

6.3. No Disclosure Benchmark (Online Appendix B.2)

We chose full information disclosure as a benchmark when studying an impact of customer control over information on service systems. Such a benchmark represents a scenario under which no personal data regulation exists and customers' information is collected by default. One could consider another extreme case as a benchmark—no information disclosure. This benchmark could correspond to a case under which data regulation is so strict that data collection is prohibited, effectively shutting down the information exchange between the customers and the service provider. Theorem 3 in the online appendix compares total customer surplus under full control of information, $\text{CS}_{\text{control}}$, with that under no information disclosure, $\text{CS}_{\text{withhold}} = \lambda U_d(0, \lambda)$. This proposition reinforces our key findings—under certain scenarios (in particular, when the service provider prioritizes short requests), it is possible that stricter privacy regulation hurts total customer surplus.

6.4. Heterogeneous Waiting Costs (Online Appendix B.3)

We studied a setting with heterogeneous marginal waiting costs c_i for type-i requests, where $i \in \{H, L\}$. The service time of requests follows an i.i.d. exponential distribution with mean $1/\mu$. Recall that α is the probability of a customer facing a type-H service request. Then, from the service provider's perspective, the waiting cost of the information-withholding customers is $c_N = \alpha c_H + (1-\alpha)c_L$, which is in between c_H and c_L. Similar to our base model, the service provider prioritizes service requests in the order of $H > N > L$. We focus on the $c_H > c_L$ case, so that the service provider effectively follows the $c\mu$ rule, which is known to minimize customers' total wait time (Van Mieghem 2000). The $c_H < c_L$ case is rare in practice, although theoretically possible. All other parameters of the model stay the same as those in the base model. The setting with heterogeneous waiting costs leads to the same results as those in the base model under the SPT policy. Proposition 5 in the online appendix characterizes customers' equilibrium information disclosure behavior, and Proposition 6 in the online appendix reaffirms our main findings from the base model: granting customers control of their private information may backfire and hurt customer surplus. Finally, we characterize the monetary incentive required to induce customers to fully disclose their information, which also happens to be the socially optimal information disclosure behavior: $P_d = P_s = \frac{\lambda^2((\alpha-1)^2\mu c_L - \alpha^2(\mu-\lambda)c_H)}{(\mu-\lambda)(\mu-\alpha\lambda)^2}$.

When choosing to disclose information, customers may face deprioritized type-L requests and suffer from higher waiting cost proportional to c_L, or on the contrary, they may face prioritized type-H requests and enjoy the benefit of waiting cost reduction, which is positively correlated with c_H. Thus, the monetary incentive, P_d, that is required to compensate customers for disclosing their information increases in c_L and decreases in c_H. Furthermore, when the probability α of facing a type-H service request increases, disclosing customers' chance of facing type-H requests and gaining priority increases, whereas the downside of facing type-L requests becomes more severe. One can prove (i.e., by deriving $\partial P_d/\partial\alpha$) that the former effect dominates the latter. Thus, the monetary incentive P_d decreases in α.

6.5. Alternative Priority Policies

The base model assumes that the service provider prioritizes customers in the order $H > N > L$. That is, information-disclosing type-H customers are treated first, whereas information-withholding customers are treated second. Finally, information-disclosing type-L customers are treated last. A possible alternative to that priority policy could be to treat information-withholding customers last—that is, the $H > L > N$ scheme (the $N > H > L$ scheme could be analyzed similarly). Under this priority scheme, all customers are incentivized to disclose information. Indeed, if withholding information, a customer will be treated after all information-disclosing customers. In this case, thus granting customers control over information does not impact the performance of the service system as compared with the benchmark of full information disclosure. Although it follows that by switching to the $H > L > N$ priority policy, the service provider could eliminate the effect of the privacy regulation, this priority scheme, however, is prohibited by major privacy regulations such as the CCPA. In particular, the CCPA prohibits providing customers with lower-quality service solely based on their information disclosure decision.[11] Notice that under the $H > L > N$ priority scheme, customers who withhold information are always provided deprioritized (i.e., lower-quality) service, in contrast to the $H > N > L$ case in which withholding customers get prioritized over by type-H disclosing customers only with a probability and experience prioritized service over type-L disclosing customers in the rest of the time.

6.6. Strategic Balking and Control over Information (Online Appendix B.4)

In Sections 4 and 5, we assume that all customers undergo service owing to a sufficiently high service reward R. In that case, the service system's throughput matches its total arrival rate and is not affected by customers' information disclosure strategy. This setup allows us to focus on how customers' control over information affects the system's performance through this control's potential to change the average wait times across customer types. In this extension, we consider another channel through which a service provider may be affected when information is controlled by customers—namely, their join or balk decisions. We relax the assumption of a sufficiently high service reward so that customers may now choose to balk at the time when committing to an information strategy if the expected waiting cost exceeds the service reward (we characterize the number of joining customers in Lemma 9 in the online appendix). All the results and conclusions derived in Sections 4 and 5 continue to hold in this extension. In addition, Theorem 4 in the online appendix establishes that the service provider itself could benefit from customers' control over information (through an increase in the number of customers who join) only in the case when it employs the long processing time first priority discipline (i.e., under the LPT discipline, $\sigma > 1$). In all other cases, customers' control over information reduces the maximum throughput and hurts the service provider.

7. Conclusion

One of the key findings of this paper is that there exist service systems that operate efficiently without data privacy regulation. In particular, in such systems customer surplus is already maximized (i.e., privacy self-synchronization is achieved) even when all of the customer information is disclosed to the service provider. Imposing a privacy regulation and granting customers control over their personal information (e.g., through a consumer privacy regulation such as the European GDPR or through a decision whether to buy a product such as Amazon Alexa or Google Nest) can actually backfire and have a detrimental effect on the performance of such service systems—which in our setting, corresponds to longer average wait times and lower utilities of individual customers. We show that, in general, whether control over information is beneficial to society or not is determined by (i) the alignment (or misalignment) between the individual and collective incentives of customers and (ii) the service provider's revenue model. Then, we demonstrate how potential inefficiencies in information disclosure can be corrected by offering monetary incentives to customers and establish that, under certain scenarios, providing such incentives is economically sensible. We finally show that the service provider itself may well benefit from customers being in control of their personal information because of potentially more customers joining the service.

More generally, this study shows a theoretical foundation for an information market in the service industry. We show that, when customers are offered appropriate monetary incentives, they can be willing to trade their personal information for a payment; at the same time, the service provider is ready to purchase and use this information for the purpose of rendering better service (here, a shorter wait time) and thereby, extracting a higher profit. From the regulator's perspective, customers can be similarly incentivized to disclose or withhold their personal information as needed to achieve service system efficiency.

Overall, our analysis contributes to the literature on service operations management and other fields on consumer privacy. This paper also speaks to different stakeholders in the information-based service economy. The findings reported here yield insights into how customers' individually rational actions concerning information disclosure can lead to market inefficiencies in the form of longer wait times for services. We also provide actionable prescriptions, for both service providers and regulators, that can guide their choices of a privacy and information management approach based on giving customers the option of controlling their personal information.

The possible future research directions related to this study include, but are not limited to, considering different types of information (e.g., information on customers' personal traits) and their interdependence among customers; intermediation of such data markets by the third parties that collect and decide which information to share with the market participants; different information structures of the service provider; and long-term reputational effects of information-based discrimination by the service providers. These and other research directions are left for future investigation.

In short, this study is a potentially fruitful starting point from which to explore customer-centric information and privacy management in service systems and more broadly, to consider consumer privacy issues in operations management. We therefore hope that our analysis not only will help inform practitioners but also, could spark new research approaches and directions in the operations community.

Endnotes

[1] See https://gdpr.eu/what-is-gdpr/.

[2] See https://oag.ca.gov/privacy/ccpa.

[3] Note that in this literature, under the revelation principle, there exist direct mechanisms such that agents are truth telling. However, the principal has to make (side) payments to the agents to make them incentive compatible to tell the truth.

[4] See https://developer.amazon.com/en-US/docs/alexa/custom-skills/create-the-interaction-model-for-your-skill.html.

[5] When $\sigma = 1$, the two types of requests are identical; we exclude this trivial case.

[6] See https://ccpa-info.com/1798-125-price-discrimination-based-upon-the-exercise-of-the-opt-out-right/ (California Civil Code 1798.125 (2018)).

[7] We also note that there are alternative priority rules in other contexts (e.g., customers can gain ahead in the queue by referring their friends, see Yang and Debo 2019).

[8] For Helpware, see https://www.helpware.com/privacy-policy. For Blue Cross Blue Shield, see https://m.bcbsm.com/home-page-links/privacy-forms.touch.html. For Airbnb, see https://www.airbnb.org/legal/privacy. For Tinder, see https://policies.tinder.com/privacy/intl/en.

[9] For illustration purposes and to ensure comparability, we assume the following parameter values for all figures in the rest of the paper: (i) $\mu = 2$ and $\sigma = 1/2$ for the SPT priority discipline and (ii) $\mu = 1$ and $\sigma = 2$ for the LPT priority discipline.

[10] Alternatively, the utility function $U(\gamma_i, \gamma, \lambda)$ of infinitesimal customers satisfies increasing differences in their respective information disclosure probability γ_i and in the population's information disclosure probability γ, where $U_d(\gamma, \lambda) = U(1, \gamma, \lambda)$ and $U_w(\gamma, \lambda) = U(0, \gamma, \lambda)$.

[11] See https://ccpa-info.com/1798-125-price-discrimination-based-upon-the-exercise-of-the-opt-out-right/ (California Civil Code 1798.125 (2018)).

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