The Commodification of Consent

Daniel W. Woods and Rainer Böhme
University of Innsbruck, Austria

May 2020

Abstract

In the *commodification of consent*, a legal concept designed to empower users has been transformed into an asset that can be traded across firms. Users interact with a consent dialogue offered by one coalition member. The default setting allows any other coalition member, including both publishers and third-party vendors, to use this consent as a legal basis for processing personal data. This paper considers how this legal innovation could change the distribution of revenues among firms. Our model shows coalitions create the most value for firms with large consent deficit, which describes the proportion of users who the firm does not directly obtain consent from. The market leader in consent can capture all of the coalition fees by forming a series of 2-firm coalitions. Finally, a model extension shows how consent coalitions shift users towards providing consent to the coalition against the users' wishes even though the probability of erroneously providing consent in a given dialogue remains unchanged.

1 Introduction

Privacy advocates call for humanist principles like personhood [1], dignity [2] or the "right to be let alone" [3] at the same time as other scholars [4, 5] document the (sometimes alarming) reality of markets for personal data. This state of affairs is justified using the paradigm of privacy self-management [6], in which the "legal fiction of consent" [7] functions to establish a legal right to collect, store, process, and share personal data. Thus, obtaining consent has become an economic activity.

Historically, consent has been relatively easy to obtain due to structural and behavioural factors. Individuals using multiple sites must process information about differing access controls, data processing practices, and privacy policies across sites [8]. Decisions are further limited by behavioural factors like information asymmetries, bounded rationality, and cognitive biases [9]. A 2015 user

Daniel W. Woods and Rainer Böhme. The Commodification of Consent. *In Proceedings of The 19th Workshop on the Economics of Information Security (WEIS 2020)*, 2020

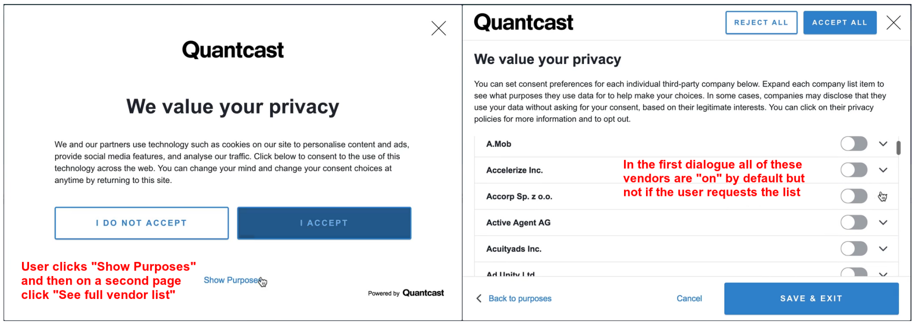

Figure 1: Users provide consent to all coalition members as default unless they navigate to the vendor list with two additional clicks. (Red text added.)

survey called into question how voluntarily consent was given and suggested 90% of users demand an alternative system [10].

Large fines associated with the European Union's General Data Protection Regulation (GDPR), which came into effect in 2018, could lead to systemic change. The nature of that change is an open question. Initial evaluations show that GDPR has had global effects [11, 12], although tracking is still ubiquitous [13]. Less obvious effects should be investigated, such as the potential for "consent management" start-ups celebrated in an EU report [14, p. 9].

This paper investigates one such innovation—the emergence of consent coalitions in which firms share the consent obtained by other coalition members. The Technical Implementation Guide [15] of a consent management provider (the most popular in one sample [16]) describes how publishers can choose the "global consent" option in which

> if a user sets consent preferences on another site using global consent, those preferences will apply to your site and the user will only see the consent window again if there are new vendors [17, p.20]

Consent being shared across publishers has been observed in the wild [18].

The *commodification of consent* describes how a legal concept designed to empower users has been transformed into an asset that can be traded across firms. The bundled service offering and opaque business practices obscure how commodifying consent creates value by allowing the firm to direct the user's initial attention towards content or advertising rather than consent dialogues. We ask how this changes the distribution of revenues among firms and the implications for users.

This is a question of privacy economics. Such questions need not detract from the humanistic principles of privacy [4]. Rather, economic analysis explains the source and nature of market power undermining user autonomy. For example, Campbell et al. [19] analyse an economic model of opt-in consent, in which users incur a one-time sunk cost for each new website they visit. These costs are shown to increase market concentration when users accept low quality services offered

	Publishers		3^{rd} Party vendor
	Consent leader	Consent laggard	No direct consent
Theory	Receive *all* coalition fees subject to competition.	Pay coalition fees to inherit consent and reduce user friction.	Pay largest fees as there is no other way to obtain consent.
Reality	No evidence the leader gets coalition payments. Coalition broker retains the value.	Fees are bundled into the consent management service fee using 3^{rd} degree price discrimination.	Pay just €1200 to establish a legal basis for data processing.

Figure 2: The winners and losers of consent coalitions.

by dominant firms to avoid the fixed cost of consenting to a niche provider. Our contribution differs by modelling consent as a factor of production that can be shared with other publishers and third-party trackers.

We first sketch the economic properties of consent. Consent is collected once and re-used each time the user visits at no additional cost. It is similar to an information good with high fixed costs and zero-marginal cost of reproduction. The value depends on the user's propensity to consent, the value of her personal data, and the purposes for which consent was collected. For example, the consent of a user who leaves the page when presented with a dialogue is more valuable than the consent of a user who consents to every dialogue.

On the demand side, commodified consent is more useful to publishers with relatively larger *consent deficits*, which describes the proportion of users who leave the site when presented with a consent dialogue. Third party trackers cannot enter into consent dialogues and rely on publishers to obtain consent. On the supply side, the value of consent for a given user and contract is independent of which firm collected it. Thus, coalitions value firms who can collect consent from many users who would not otherwise provide it.

This paper explores these properties and intuitions by defining an economic model. Section 2 identifies related literature in both the economics of privacy and empirical user studies. These findings justify our model of the commodification of consent, which is defined and analysed in Section 3. Section 4 provides model extensions and outlines directions for future work. The implications for firms, policy development, and privacy research are discussed separately in Section 5. Section 6 offers conclusions.

Summary Figure 2 summarises our contribution in terms of the winners and losers of the commodification of consent. When sharing revenues according to Shapley value, no coalition member loses when firms increase the proportion of users whose personal data can be monetised (Proposition 1). Whereas, an increase in consent share causes a drop in revenue for some coalition members unless the increase accrues to the market leader (Proposition 2). Coalitions create more value when members have greater consent deficits.

Theoretical results suggest the leader in consent share can entice every other firm into a 2-firm coalition and receive all the coalition fees (Proposition 3). We have not observed any evidence firms receive coalition fees for obtaining consent, possibly because competition among firms with large consent shares erodes all bargaining power (Proposition 4). Proposition 5 shows how consent coalitions shift users towards providing consent to the coalition against the users' wishes even though the probability of erroneously providing consent in a given dialogue remains unchanged. This effect grows with the size of the coalition.

2 Related Work

Investigating consent decisions narrows our conception of privacy to the control of personal data within the paradigm of privacy self-management [6, 20]. In doing so we import the concept of personal data as a form of property and consent as the legal basis for firms to collect, store or process it [7]. This set of assumptions is particularly suited to economic analysis and we identify similar works in Section 2.1. Section 2.2 covers empirical studies of consent to motivate and justify our modelling assumptions. Finally, Section 2.3 introduces the actors and technical standards involved in sharing consent.

2.1 Economics of Privacy

An economic lens suggests firms respond to incentives when deciding how to use personal data. In terms of the benefits, Spiekerman et al. [5] suggest collecting personal data allows firms to improve their offering via user customisation [21] or increases revenues by price discrimination [22]. In terms of the costs, personal data can be stolen causing reputation damage [23, 24] or litigation [25]. The cost of cyber incidents in general have been shown to be lower than non-cyber risks [26, 27], but more research is needed to focus on privacy related incidents.

The costs most relevant to this paper relate to how consent is managed. The Federal Trade Commission in the US established that a lack of notice to consumers constituted "unfair or deceptive" [28, p.5] trade practice and began issuing fines as early as 1999. For legal risk to spur behavioural change, the expected cost in terms of the likelihood and impact of legal action must outweigh the benefits from continuing the activity [29]. Firms weigh the inconsistently enforced and relatively small fines against the costs of consent dialogues.

The firm's cost of managing the infrastructure is often negligible, the information load upon the user is considered more significant [30, 31]. Campbell et al. [19] conclude that these costs increase market concentration as users prefer to provide consent for one dominant firm offering many services than to multiple niche providers offering one service. Choi et al. [32] introduce a model in which consent dialogues allow users to differentiate firms based on their privacy practices, which is the intended goal of the notice and consent regime. Nevertheless, the equilibrium is characterised by "excessive collection of personal information" [32, p.26] due to the information revelation of similar consumers. Justifying whether consent dialogues are better modelled as mechanisms that correct information asymmetries or as sunk-costs that transfer no information is an empirical question.

2.2 Empirical Studies of Consent Dialogues

Opt-in consent dialogues present the user with information and require the user to accept or reject the terms. This was shown to reduce enrolment in medical trials [33]. Dialogues vary along many dimensions including the amount [34] and framing [35, 36, 37] of information presented to users. This motivates normative studies aiming to design consent dialogues to empower users [38, 39]. However, firms are satisfied with a status quo in which users provide consent without reading policies [40, 41, 42]. This is often attributed to habituation [43], whereby dismissing or accepting notices without processing the particulars becomes routine [44].

Nouwens et al. [16] investigated the impact of GDPR on consent dialogues using multiple methods. They scraped the top $10,000$ websites in the UK and discovered only 11.8% met the study's compliance requirements, which were not based on court decisions but regulatory guidance [45, 46]. A user study provides evidence that "anything not immediately visible to the user, anything requiring interaction to access, might as well not exist" [16]. This finding suggests most users do not know which firms they actually provide consent to, given this information requires multiple clicks to reveal (Figure 1).

Empirical studies of consent dialogues focus on how users interact with consent dialogues taking the firm's motivation to obtain consent as a given. Similarly, studies [47, 48, 49] measuring the prevalence and techniques of third-party tracking do not explore how third-parties gather consent, which the UK Information Commissioner's Office says is "one of the most challenging areas in which to achieve compliance" [45]. Our contribution is to model the value created when consent is obtained and transferred to other publishers and third-parties, but first we describe the technical standard that makes this possible.

2.3 Standardising Consent

Standardisation is necessary to share consent across firms and the resulting standard structures the consent ecosystem. Levin and Milgrom [50] describe how seemingly unique diamonds can be sold wholesale using a classification of nineteen categories of stones. In much the same way, the Internet Advertising Bureau (IAB) Europe[1] defined standard purposes and functions that users

[1]The IAB is an industry body representing firms involved in internet advertising. They develop standards, provide legal support, and publish reports aiming to influence the industry and regulatory bodies. IAB Europe's corporate board members include representatives from technology companies (Google, Microsoft), AdTech firms (QuantCast, Xander), and media

consent to as part of the "GDPR Transparency and Consent Framework". For example, Purpose 3 allows firms to create a "personalised ads profile" by collecting information about the consenting user and combining this with existing data [51].

Matte et al. [18] describe how this standard can be implemented technically. Publishers must either build a system matching the technical specification and register as a consent management platform (CMP), or outsource this function. Vendors can register with the IAB to join the "Global Vendor List", which contains over 400 firms as of January 2020. The standard allows CMPs to collect consent for all vendors in this list, with the publisher's permission [52]. Matte et al. [18] use this standard to audit consent dialogues at scale, finding that 12% of websites store a positive consent before the user has made any choice and 8% even if the user has explicitly opted out.

Consent management platforms can further innovate on this standard. QuantCast are the CMP for 41% of the sites in [16] and one of their employees is on the IAB board. Their implementation guide [15] highlights the choices available to publishers. Users can choose between obtaining consent from every visitor or choosing the global option, in which user preferences are inherited from "all IAB framework sites" [17, p.20]. The latter means the user is not presented with a dialogue unless one of the publisher's vendors is not on the list. This proviso motivates the Global Vendor List [52] as the list increases the likelihood that each owners' vendors already have consent. In effect, the set of "all IAB framework" sites who select the global option form a consent coalition. We take this as inspiration for a generic model of consent coalitions, which we outline in the next section.

3 Modelling Consent Coalitions

Our aim is to model the economic implications of firms sharing consent in an accessible way. We define our model in Section 3.1. Section 3.2 analyses how revenues are shared in coalitions formed exogenously. Section 3.3 considers competitive coalition formation. Alternative assumptions and model extensions are discussed in the next section.

3.1 Model Definition

We consider a model in which each firm F_i has an economic relationship with a fraction U_i of the total user base $U = [0, 1]$. All firms comply with a regulation requiring consent to be obtained in order to derive revenue from this economic relationship. Each firm F_i can obtain consent from a fraction $C_i \leq U_i$ of the users. Both the user share U_i and the consent share C_i are given exogenously. The i-th firm operating alone can extract revenue equal to

$$R_i = v_i C_i \tag{1}$$

companies (BBC, RTL Group).

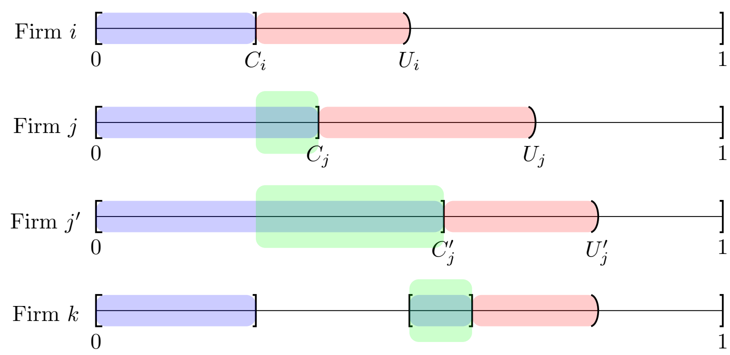

Figure 3: Each firm obtains consent from the blue region, no consent from the red region, and no visit from the uncoloured region. Firm k does not fulfil the partial ordering. Green shading indicates the share of the market who consent to tracking by the $j/j'/k$-th firm but not the i-th firm.

where v_i is a constant determined by the value to F_i of each consenting user.

This set-up describes both first-party firms (e.g publishers) and third-party vendors (e.g trackers or data analytics). For first-party firms, U_i can be interpreted as the share of users who visit the site and C_i is the fraction of users who provide consent. The *consent deficit* describes the fraction of users $(U_i - C_i)$ that the site does not have consent to extract revenue from. For third-party firms, U_i can be interpreted as the user-share that the firm collects personal data about. Third-party trackers have complete consent deficits $(C_i = 0)$ since they cannot directly obtain consent.

We define a transferrable utility (TU) game G in which coalitions enable additional revenue to be collected. Consent obtained by any single firm can be used as consent by the other firms in the coalition. The grand coalition $N = \{1, ..., n\}$ is formed when all n firms join the same coalition.

Our first assumption, motivated by empirical studies [16, 41, 42], is that users are unaware they are providing consent to the other firms in the coalition.

Assumption 1 (User indifference) *The share of users C_i provide consent to F_i regardless of which coalition it is part of.*

A firm cannot monetise consent inherited via coalition unless an economic relationship with the user exists. This partitions the user base $U = [0, 1]$ along $\sum_{i=o}^{n} \binom{i}{n} 2^{n-i}$ possible combinations of parameter values satisfying $C_i \leq U_i$. To avoid calculations involving all of these combinations, firms receive visits and consent from the users with the following partial ordering:

Assumption 2 (Partial ordering) *If $C_i \leq C_j$, the non-consenting market share $[C_i, U_i]$ of F_i either contains or is contained in the share of the market $[C_i, C_j]$ who consent to tracking by the j-th firm but not the i-th firm.*

This assumption suggests users are homogeneous in which firms they visit or consent to, differing only in the threshold for doing so. This is more relevant to popular sites. In Figure 3, the collection of the first three firms fulfils the partial ordering, whereas adding the firm k does not.

Under this ordering, the coalition's consenting share of the market is

$$C_S = \max_{i \in S} C_i. \tag{2}$$

The effective consent share for the i-th firm is

$$C_{i,S} = \min(C_S, U_i), \tag{3}$$

since the user needs to both have an economic relationship and provide consent to the coalition S.

Intra-coalition competition is not possible because U_i and C_i are given exogenously. In reality, firms obtaining consent via the coalition may cause other firms to lose revenue as vendors compete to sell insights about specific users and publishers compete for user attention. We state the assumption to make a cursory reader aware of this limitation.

Assumption 3 (No intra-coalition competition) *Whether a user's consent is inherited via the coalition does not change that user's economic relationship with any other firm.*

In this TU game, the characteristic function $\curlyvee : 2^n \to \mathbb{R}_+$ specifies the value of each coalition. Under Assumptions 1–3, the total value captured by a coalition $S \subseteq N$ is

$$\curlyvee(S) = \sum_{i \in S} v_i C_{i,S}. \tag{4}$$

If the coalition has no members, then this sum is empty so that $\curlyvee(\emptyset) = 0$. The total value of the commodification of consent to the coalition S is

$$v(S) := \curlyvee(S) - \sum_{F_i \in S} \curlyvee(\{F_i\}) \tag{5}$$

$$= \sum_{F_i \in S} v_i (C_{i,S} - C_i). \tag{6}$$

Superadditivity, convexity and balance are important properties of coalitional games. Social welfare is maximised by the grand coalition in a superadditive game [53]. Convexity and balance have consequences for coalition stability [54].

Definition 1 (Superadditivity) *A game $G(N, \curlyvee)$ is superadditive if for all $S, T \subseteq N$*

$$(S \cap T = \emptyset) \implies \curlyvee(S) + \curlyvee(T) \leq \curlyvee(S \cup T). \tag{7}$$

Definition 2 (Convexity) *A game $G(N, \curlyvee)$ is convex if for all $S, T \subseteq N$*

$$\curlyvee(S) + \curlyvee(T) - \curlyvee(S \cap T) \leq \curlyvee(S \cup T). \tag{8}$$

Definition 3 (Balanced weights) *A vector of non-negative numbers* $\lambda \in 2^N$ *is a balanced collection of weights if*

$$\sum_{S \subset N | i \in S} \lambda_S = 1, \forall i \in N. \tag{9}$$

Definition 4 (Balanced game) *A game* $G(N, \Upsilon)$ *is balanced if*

$$\sum_{S \subset N} \lambda_S \Upsilon(S) \leq \Upsilon(N) \tag{10}$$

for every balanced collection of weights $\lambda \in 2^N$.

In our model, superadditivity results from how consent accrues across firms. The following inequality holds since $C_S, C_T \leq C_{S \cup T}$

$$\sum_{i \in S} v_i C_{i,S} + \sum_{j \in T} v_j C_{j,T} \leq \sum_{i \in S} v_i C_{i,S \cup T} + \sum_{j \in T} v_j C_{j,S \cup T} \tag{11}$$

so that

$$(S \cap T = \emptyset) \implies \Upsilon(S) + \Upsilon(T) \leq \Upsilon(S \cup T). \tag{12}$$

Convexity would imply the following inequality holds

$$\sum_{i \in S \cap T} v_i C_{i,S} + \sum_{j \in S \cap T} v_j C_{j,T} - \sum_{i \in S \cap T} v_i C_{i,S \cap T} \leq \sum_{i \in S \cap T} v_i C_{i,S \cup T}. \tag{13}$$

This does not hold if, for example, $S = \{F'_s, F_k\}$ and $T = \{F'_t, F_k\}$ such that $C_k < C'_s = C'_t$. In this case, inequality 13 implies

$$v_j(2C'_s - C_k) \leq v_j C'_s \implies (C'_s - C_k) \leq 0, \tag{14}$$

which shows the game is not convex.

The game is balanced. Suppose $\lambda \in 2^N$ is a balanced collection of weights, then

$$\sum_{S \subset N} \lambda_S \Upsilon(S) = \sum_{S \subset N} \lambda_S \sum_{i \in S} v_i C_{i,S} \tag{15}$$

$$\leq \sum_{S \subset N} \lambda_S \sum_{i \in S} v_i C_{i,N}, \tag{16}$$

since $C_{i,S} \leq C_{i,N}$ as $S \subseteq N$. Now re-arranging the order of the summation

$$\sum_{S \subset N} \lambda_S \sum_{i \in S} v_i C_{i,N} = \sum_{i \in N} \sum_{S \subset N | i \in S} \lambda_S v_i C_{i,N} \tag{17}$$

$$= \sum_{i \in N} v_i C_{i,N} \sum_{S \subset N | i \in S} \lambda_S \tag{18}$$

$$= \sum_{i \in N} v_i C_{i,N} = \Upsilon(N) \tag{19}$$

with the penultimate equality following from the definition of a balanced set of weights. Thus, G is a balanced game.

3.2 Cooperative Solutions

This section considers how to distribute revenues among a coalition $N = \{1, ..., n\}$ given exogenously. Solutions consist of a payoff vector $x \in \mathbb{R}^n$ in which the i-th firm receives x_i. The solution concept known as Shapley value [55] is efficient (all revenues are paid out), symmetric (equal payments to players who contribute the same amount to every sub-coalition), linear (payoffs when two sub-games are combined is equal to the sum of the payoffs in each sub-game), and satisfies monotonicity (payoffs do not decrease if the marginal contribution of a player increases).

Definition 5 (Shapley Value) *Shapley value specifies the average marginal contribution that the i-th firm brings to a coalition $N = \{1, ..., n\}$*

$$\varphi_i(\Upsilon) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(n - |S| - 1)!}{n!} (\Upsilon(S \cup \{i\}) - \Upsilon(S)). \tag{20}$$

The rest of this section considers revenue distributed according to Shapley value because it uniquely satisfies all of these properties and is widely used.

When just two firms $\{F_1, F_2\}$ enter into coalition with $C_1 \leq C_2$, any revenue derived from the increased effective consent share relies on both firms joining the coalition and so it is divided evenly. Thus, the i-th firm receives

$$\varphi_i(\Upsilon) = v_i C_i + \frac{1}{2} v_1 (\min(U_1, C_2) - C_1). \tag{21}$$

For coalitions with $n > 2$ members, the revenue share is complicated by the possible orderings and coalitions involving $\{C_1, ..., C_n, U_1, ..., U_n\}$.

The main contribution of this subsection is two propositions that describe how changing consent and market shares affects the distribution of revenue in an n-firm coalition. First we prove two lemmas about how the revenue extracted by one firm from one subset of users is divided among firms in the coalition. The linearity of Shapley value [55] means we can aggregate these lemmas across the revenue extracted from all users by every firm to give the overall division of revenues. The lemmas concern how firms joining the coalition affects the distribution of coalition fees.

Lemma 1 *If consent can be inherited from a greater number of firms, F_i retains a greater share of the revenue extracted from the user share $[a, b] \subseteq [0, 1]$ by using inherited consent.*

Proof Each term in Shapley value represents the marginal value of F_i to the coalition S. F_i can only extract revenue $v_i(b - a)$ from the user share $[a, b]$ if at least one coalition member F_j has $b < C_j$. We can use the indicator

$$I(S) = \begin{cases} 1 & \text{if } (\exists F_j \in S)(b < C_j) \\ 0 & \text{otherwise} \end{cases} \tag{22}$$

to re-write the Shapley value

$$\varphi_i(\Upsilon) = v_i(b-a) \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(n-|S|-1)!}{n!} I(S). \tag{23}$$

The sum is increasing in the number of firms consent can be inherited from. ■

Lemma 2 *If F_i extracts revenue from the user share $[a, b]$ using inherited consent and consent can be inherited from a greater number of firms, then the firm F_j with $b < C_j$ retains a smaller share of the coalition fee.*

Proof The indicator is different in this case. The marginal benefit of F_j joining a sub-coalition is only non-zero if F_i is in the coalition and there is no other member of the coalition that consent can be inherited from. This condition can be represented as the indicator

$$I(S) = \begin{cases} 1 & \text{if } (F_i \in S) \wedge (\forall F_k \in S)(C_k < b) \\ 0 & \text{otherwise} \end{cases} \tag{24}$$

to re-write the Shapley value

$$\varphi_i(\Upsilon) = v_i(b-a) \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(n-|S|-1)!}{n!} I(S). \tag{25}$$

This sum is decreasing in the number of firms consent can be inherited from. ■

Proposition 1 *For a coalition $N = \{1, ..., n\}$ sharing revenue according to Shapley value, then no coalition members lose (gains) revenue from a marginal increase (decrease) in the unconsenting user share U_i.*

Proof Let ΔU_i be the change in unconsenting user share. A change in U_i only changes how the revenue extracted by F_i via inherited consent is shared. Suppose the consent deficit grows ($\Delta U_i > 0$), then any firm F_j with $C_j \leq U_i$ is indifferent because there is no coalition to which F_j joining affects whether F_i derives revenue from $[U_i, U_i + \Delta U_i]$ and so F_j receives no coalition fee. If $C_j > U_i$, then F_j joining a coalition with just F_i enables revenue extraction from $[U_i, U_i + \Delta U_i]$ so that there is at least one non-negative term in the Shapley value sum. Consequently, F_j receives a positive fraction of $v_j |\Delta U_i|$. This fraction is at least $\frac{1}{n(n-1)}$, which occurs when all other members of the coalition F_j have $C_j > U_i + \Delta U_i$ apart from F_i. Consequently, no firm loses revenue if U_i increases. If ΔU_i is negative, then similar reasoning shows some F_j receives less but none gain. ■

Proposition 2 *For a coalition $N = \{1, ..., n\}$ sharing revenue according to Shapley value, a marginal increase (decrease) in consent share C_i leads to: (i) a marginal increase (decrease) in the revenue of firms it lends consent to; and (ii) a marginal decrease (increase) in the firms it receives consent from.*

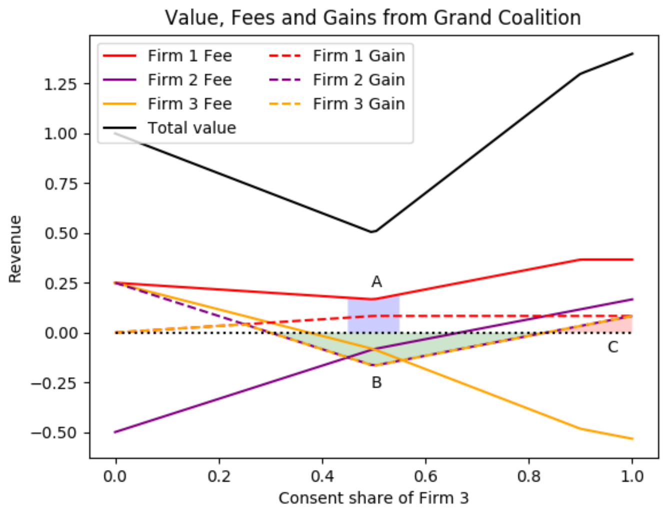

Figure 4: A 3-firm coalition sharing revenue according to Shapley value with a third-party tracker ($C_1 = 0, U_1 = 0.9$), a publisher ($C_2 = 0.5, U_2 = 1$), and a third firm ($C_3, U_3 = 1$) with all v_i equal to 1. Gain is relative to the best 2-firm coalition.

Proof Let $C_i + \Delta C_i$ be the consent share after the change and assume it is small enough that it does not change the ordering of U_j and C_j. We first consider the effect on a firm F_j who inherits consent from F_i. If ΔC_i is positive, then F_i becomes an additional firm that F_j can inherit consent from to monetise $[C_i, C_i + \Delta C_i]$. By Lemma 1, the revenue of F_j will increase if $U_j > C_i$ and stay the same otherwise. If ΔC_i is negative, then the same reasoning shows the revenue of F_i either decreases or stays the same. So (i) follows because the share of all other revenues remains the same.

We now consider firms F_j who lend consent to F_i. If ΔC_i is positive, then F_i no longer shares the revenue extracted from $[C_i, C_i + \Delta C_i]$ with F_j causing a decrease in its revenue. Additionally, there is a decrease in the fees that F_j receives from all other firms F_k who extract revenue from $[C_i, C_i + \Delta C_i]$ via inherited consent. This follows by Lemma 2 because F_i represents an additional firm that F_k can inherit consent from. The same reasoning when ΔC_i is negative completes the proof of (ii). ■

Proposition 1 shows that coalition members establishing more economic relationships without directly obtaining consent are favoured. Doing so either has no effect or sees firms who collected consent receive higher fees. Proposition 2 shows that increases in consent share negatively impact those firms who receive fees from the firm who increased their consent share. However, the firm with the most consent pays no fees and so coalition members lose when its consent share increases.

Figure 4 illustrates the two propositions by showing how coalition revenues are shared as a publisher (F_3) goes from being a consent laggard (low C_3) to a leader (high C_3). The other coalition members are a third-party tracker (F_1) and another publisher (F_2). The third-party tracker pays the lowest fees when the two owners are in competition (Region A). The publisher (F_2) receives less from the coalition as the third firm's consent share increases. The gain line becoming negative shows F_2 prefers a 2-firm coalition over the grand coalition when F_3 has intermediate consent shares and the two firms are in direct competition (region B). When F_2 and F_3 compete to receive fees from F_1, a rational firm would break from the grand coalition and instead form a two-firm coalition. For high enough C_3, the second firm becomes a net contributor *and* prefers this situation to being the receiver in a 2-firm coalition (region C). The next subsection considers these competitive dynamics.

3.3 Non-Cooperative Solutions

Coalition members need not accept a given revenue sharing agreement and can break away to form their own coalitions. This notion is formalised [56] by the core of a coalition

Definition 6 (The Core) *The core of a coalition $N = \{1, ..., n\}$ is the set of payoff vectors for which no sub-coalition achieves a greater total pay-off by leaving the coalition*

$$C(v) = \left\{ x \in \mathbb{R}^n : \sum_{i=1}^{n} x_i = \Upsilon(N); \sum_{i \in S} x_i \geq \Upsilon(S), \forall S \in N \right\} \tag{26}$$

The following proposition shows the core of the grand coalition is equivalent to a series of pairwise coalitions including the firm with the highest consent share. In other words, only the dominant firm receives coalition fees.

Proposition 3 *Label F_n such that $C_n = \max_{1 \leq i \leq n} C_i$. Suppose the commodification of consent creates value $v(N) > 0$, then the core of the grand coalition N is non-empty and can only be achieved with a series of pair-wise coalitions with F_n.*

Proof Since we showed the game was balanced earlier, the core is non-empty by the Bondareva–Shapley theorem [57, 58]. This theorem states that the core of a game is non-empty if and only if the game is balanced.

Suppose a payoff vector $x \in \mathbb{R}^n$ is in the core of the sub-game describing how the revenue of F_i is shared among the grand coalition, symbolically $x \in C(\Upsilon)$. Since $C_n = \max_{1 \leq i \leq n} C_i$, the effective consent share for F_i is the same in the coalition $\{i, n\}$ as in the grand coalition N. Consequently, the pair-wise coalition generates as much revenue as the grand coalition for the sub-game describing how the revenue of F_i is shared, which means

$$\Upsilon(\{F_i, F_n\}) = \Upsilon(N). \tag{27}$$

Combining the definition of the core and $\{i,n\} \in N$, we have

$$\sum_{j\in\{i,n\}} x_j \geq \Upsilon\left(\{F_i, F_n\}\right) \tag{28}$$

$$= \Upsilon(N). \tag{29}$$

This inequality proves that the revenues extracted by F_i are entirely shared between itself and the dominant firm F_n in the core of the grand coalition. The proposition follows by aggregating each sub-game describing how the revenue of F_i is shared for $i \in N$. ■

This proposition suggests consent coalitions display the same winner-takes-all dynamics as other technology markets. Consent (at least under current legal conceptions) can be 'transported' across firms instantaneously and has zero-marginal cost of reproduction. However, it differs from software because the quality of consent is identical across firms. For a given contract, it does not matter if the consent was obtained by firm i or firm j, which motivates the following proposition.

Proposition 4 *Label F_n and F_{n-1} such that $C_n = \max_{1\leq i\leq n} C_i$ and $C_{n-1} = \max_{1\leq i\leq n-1} C_i$. Then the maximum fee P_j that C_n can extract from the firm C_j is*

$$v_j(\min(U_j, C_n) - \min(U_j, C_{n-1})). \tag{30}$$

Proof Suppose that F_n charges more than this, then F_{n-1} can charge a fee satisfying

$$0 < P_j' < P_j - v_j(\min(U_j, C_n) - \min(U_j, C_{n-1})). \tag{31}$$

Then firm F_j derives revenue

$$v_j \min(U_j, C_{n-1}) - P_j' > v_j \min(U_j, C_{n-1}) + v_j(\min(U_j, C_n) - \min(U_j, C_{n-1})) - P_j \tag{32}$$

$$= v_j \min(U_j, C_n) - P_j. \tag{33}$$

Since the RHS is the revenue F_j receives from the coalition with F_n, a firm F_j gains by defecting and entering into a 2-firm coalition with F_{n-1}. A rational firm F_{n-1} would offer this to receive the additional fee P_j'. ■

Whereas the previous proposition suggested fees will flow to the firm with the largest consent share, this result suggests competition among consent collectors drives the gains from coalition formation towards those with large consent deficits. Intuitively, the economic relationship to the user generates value, whereas commodified consent merely enables the activity to occur. Any firm can provides this enabler. This means the firm with the consent deficit can retain more of the value of commodified consent.

4 Model Extensions

Unpacking the previous model's assumptions is important to explore complexities. Each firm's consent share C_i is given exogenously in our model so that it is independent of coalition members, the order in which users visit sites, and user error. The latter is relevant in light of the empirical finding [16] that many users do not communicate their ideal privacy settings due to interface design, even though the option was available. The "dark patterns" paradigm [16, 59] suggests consent dialogues are designed so that these errors asymmetrically skew towards users providing consent against their wishes. We need not assume asymmetric errors (by design or otherwise) to prove the Proposition 5.

Assumption 4 (Symmetric errors in consent preferences) *The result of a given consent dialogue matches the user's preferences with probability* $1-\epsilon$ *and does not match with probability* ϵ*.*

Firms treat users differently depending on whether consent has already been obtained. Modelling the order in which users arrive at sites is necessary to understand the implications for first-parties. This is less complicated for data analytics providers who already hold the personal data and only require consent for processing. Such a vendor is indifferent about which publisher obtains consent, in which case the following proposition applies

Proposition 5 *Consider a third-party firm* F_i *who only requires consent to enable an economic relationship with a user* U*. If different members of* F_i*'s consent coalition present* U *with* m *consent dialogues under Assumption 4, then where* I *is the indicator of whether* F_i *inherits consent from the coalition*

$$P(I=1) = \begin{cases} 1-\epsilon^m & \textit{if the user intends to consent,} \\ 1-(1-\epsilon)^m & \textit{if the user does not intend to consent.} \end{cases} \tag{34}$$

Proof If U has already consented, then no further dialogue takes place. Otherwise, the coalition members will continue to ask for consent. Consequently, U cannot make any errors if U intends to deny consent. Making no errors across all m dialogues has probability $(1-\epsilon)^m$. In every other case, the user consents against her wishes so that

$$P(I=1) = 1-(1-\epsilon)^m. \tag{35}$$

Similar reasoning gives the result when the user intends to consent. ■

This uncovers a dynamic that user interface studies cannot. Even when individual consent dialogues have the property that erroneously rejecting consent is as likely as erroneously accepting it, the system-wide effects of consent coalitions continually re-requesting consent leads to an asymmetrical increase in the amount of consent obtained by firms. Any increases in m, such as by increasing the size of the coalition, make coalition members more likely to obtain consent independent of the user's preferences. Section 5.2 discusses the implications for compliance to the GDPR.

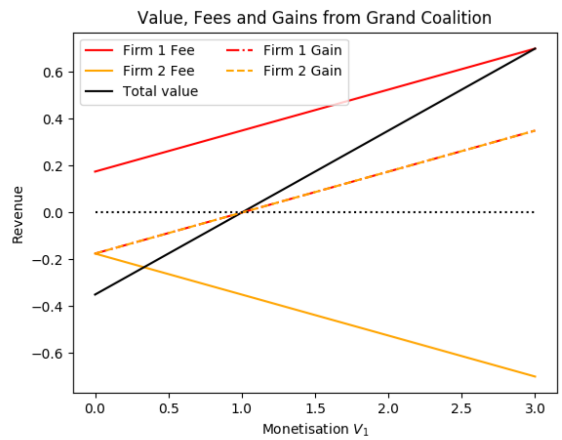

Figure 5: A 2-firm coalition sharing revenue according to Shapley value with a third-party vendor F_1 ($C_1 = 0, U_1 = 0.9$) and a publisher F_2 ($C_2 = 0.7, U_2 = 0.9, V_2 = 1$). Gain is relative to operating alone.

Introducing consumer born privacy costs (CBPCs) into the model could explain why firms have begun offering batch consent to consumers. These coalitions provide standardised contracts so that users can economise on the decision load. Turning to inter-firm competition, one could conceive of CBPCs as sunk costs that prevent users switching to an alternative, as in [19]. In this case, consent coalitions reduce switching costs between firms in the coalition creating more intra-coalition competition. Assumption 3 would have to be relaxed to capture this.

Coalitions do more than simply standardise contracts, reputation is transitive across coalition members. Less trusted coalition member inherit trust by associating with more trusted coalition members. Introducing a relationship between each firm's consent share and the other firms in the coalition could capture this and the reality that some users do read the terms of a consent dialogue [16, 41, 42]. Estimating this relationship is an empirical question. For illustrative purposes, the coalition's consent share in our model could change from the maximum to the average consent share of all firms in the coalition

$$C_S = \max_{i \in S} C_i \quad \rightarrow \quad C_S = \frac{1}{|S|} \sum_{i \in S} C_i. \tag{36}$$

Figure 5 illustrates the trade-off between coalitions eroding reputation and generating new revenue. Forming a coalition causes a drop in total revenue creation unless the third-party vendor can monetise users ($V_1 > 1$) more effectively than the publisher.

Finally, we suggest two directions for future models. Modelling the cost of forming coalitions (infrastructure and reputation risk) would provide insights into the consent management platforms who manage coalitions at present. A second direction would be to capture heterogeneity between users, which is the motivating purpose for collecting personal data after all. Firms may collect consent from disproportionately many valuable users, such as users with disposable income or who rarely provide consent, and receive high fees despite collecting small absolute amounts of consent. Modelling more fine-grained payment structures targeting heterogeneous users is an interesting future extension given similar models in advertising lead to thinner, less competitive markets [50].

5 Discussion

We conclude by drawing out considerations regarding the commodification of consent for specific stakeholders.

5.1 Managerial Implications

Our model predicts that firms with a comparative disadvantage in obtaining consent will pay coalition fees. The IAB charge an annual "membership fee" [51] of €1200 to third-party vendors. The Global Vendor List consisted of 497 firms as of January 2020. This global coalition is analogous to the grand coalition, which creates the most value in our superadditive theoretical model. Vendors might ask whether the coalition fee is reasonable. If regulators accept that commodified consent establishes a legal right to process personal data, this fee is small compared with the potential fines for non-compliance. If it is not, then joining a global coalition reduces the likelihood that one firm will be singled out by regulators.

Proposition 5 suggests bigger coalitions lead to higher consent shares for vendors. However, achieving cooperative solutions is often difficult in reality. The IAB framework has taken advantage of network effects to grow. Publishers are told to "ask their partners (advertising vendors, DMPs, analytics vendors, etc.) to register" [52]. Consent Management Providers pay one annual registration fee (€1200) regardless of how many of their clients adopt the standard [51]. To summarise, third-party vendors pay a small fee for a (growing) coalition of publishers to request consent on their behalf.

For publishers, using a global consent option means even less consent dialogues are presented to users, which reduces user friction to the site's benefit. Proposition 3 suggests that a concentrated number of firms would receive coalition fees or other benefits. Such firms would likely be trusted by users, lack competitors, and capture a significant proportion of the user base. We tentatively suggest that DoodlePoll—a seemingly innocuous event planning website—represents such a candidate. However, it is also possible that Proposition 4 has eroded all bargaining power as many firms can obtain consent at scale. These questions relate to the supply side of advertising. Marotta et al. [60] call for an empirical approach, though answers are difficult to obtain.

Propositions 1–4 predict coalition fees will vary based on how much consent is used and collected. We only observe crude third-degree price discrimination by charging a registration fee per vendor but not per publisher. First and second degree price discrimination has not been observed. For example, QuantCast state that global consent is free "to make sure the existing ad ecosystem can continue to exist." CMPs differentiating prices for publishers would make the value proposition explicit. This may instead be kept to informal discussions with potential clients to avoid regulatory scrutiny.

The lack of price discrimination could result from market immaturity. Perhaps publishers who create value by collecting consent should demand a greater share of coalition revenues. Alternatively, the industry chooses not to track each firm's contribution to a fight against the existential threat posed by GDPR to business models based around targeted adverts. In this view, commodified consent represents a unified effort to reduce user frictions and preserve a legitimate basis to collect personal data.

Establishing standards changes the distribution of power among firms. The IAB's framework allows for publishers to self-implement. However, the IAB's list[2] of firms who have passed compliance checks shows just 60 firms opted to do so. In fact, more service providers are registered as compliant (75). This suggests the majority of publishers have to purchase CMP as a service. Although ENISA may celebrate such entrepreneurialism [14] (even if many of these CMPs are not European), we worry about the unseen effects like raising barriers to earning advertising revenues for niche websites. These firms now face lock-in to a standard developed by "10 National IABs and 55 organisations, and EU-level associations, publishers, media owners, technology providers, and media agencies" [51].

Reputation damage and legal risk will be relevant going forward, given the noted opposition to third-party vendors [47]. One of our model extensions (Figure 5) illustrated how publishers trade-off the fees received from coalition members against the reputation damage resulting from associating with less trusted partners. The risk was demonstrated when Facebook provided a platform for firms like Cambridge Analytica [61].

5.2 Policy Implications

The traditional policy question is whether commodified consent is "freely given, specific, informed and unambiguous indication of the data subject's wishes" and empirical user-interface research suggests users cannot do so at present [16]. However, this work uncovers a system-wide dynamic that such research designs cannot. Proposition 5 shows larger coalitions increase the likelihood of obtaining consent, regardless of the user's preference. This has relevance to a regulatory guidance noted in [16], which states "[a] consent mechanism that emphasises 'agree' or 'allow' over 'reject' or 'block' represents a non-compliant approach" [45], and formalises Privacy International's argument that coalitions

[2] `https://iabeurope.eu/cmp-list/`

"nudge consumers into consenting" [17, p31] .

Beyond the question of legality, consent coalitions provide a model for reducing consumer born privacy costs. Even if a minority read the terms of a consent coalition, standardised terms allow this minority to make many consent decisions in one dialogue. Standardising and automating privacy dialogues has a long history, including movements like mechanized privacy [62, 63] and more recently "Do Not Track" [47]. This is curiously reminiscent of a Hegelian dialectic in which standardised privacy was resisted by AdTech for over a decade and then suddenly adopted after the passing of GDPR—however, it was adopted on terms drafted by AdTech's industry body.

Finally, consent coalitions have implications for firm structure. Campbell et al. [19] suggest market concentration results from the ability of generalist firms to re-use consent from one service to reduce user friction related to another service. Our model suggests niche providers can compete by forming coalitions and purchasing commodified consent from firms who have already collected it. If coalitions did not exist, the same value could be captured via horizontal expansion into consent generating offerings. In this sense, consent coalitions might curb consent-induced concentration identified in prior work. This would be a desirable effect that merits consideration in potential policy responses.

5.3 Privacy Theory Implications

The social desirability of consent coalitions turns on the applicability of privacy realism or rational-choice as an abstraction of user decisions. Assuming users provide consent with little care as to who is in the coalition (privacy realism) concludes that consent coalitions are an innovative way to deceive users at scale (and potentially open a novel revenue stream). Assuming rational users make decisions based on the members of the coalition (rational-choice) means the innovation reduces consumer born privacy costs by standardising contracts and collecting many decisions into one consent dialogue. Justifications for the former (and against the latter) assumption are plentiful [9, 40, 16].

If privacy realism holds, consent coalitions should not be understood as a novel direction for privacy, but rather as an intensification of the absurdity of consent. Publishers collecting consent for third-party tracking is not a new phenomena and was always opposed by users [47]. Why is sharing consent across sites any more absurd than sharing it with third-party trackers? It is not meaningfully given by the user in either case.

In the face of regulatory neutrality on the "merits of particular forms of data collection" [6], firms will simply re-design the system of consent, which they control, in their own interest. This supports Schwartz's critique of the "legal fiction of consent" [7] as the ordering principle of a regime in which personal data constitutes property. The commodification of consent shows how even the legal abstractions used to empower user autonomy have become economic assets. Expecting users to govern what constitutes reasonable data processing is still unrealistic, despite the threatened sanctions of GDPR.

6 Conclusion

The commodification of consent sees user consent notices re-purposed and shared between coalitions of publishers and vendors. This paper modelled the value created by such coalitions and showed that firms running consent deficits retain most of this value when there is no leader in consent share. In effect, the Internet Advertising Bureau developed a standard [52] by which publishers collect commoditised consent in a format that can be transferred across firms.

This represents yet another instance of technology companies exposing themselves to legal uncertainty in order to monetise personal data. The Becker model of crime [29] suggests the increased sanctions from GDPR would, at the margin, deter privacy eroding practices. The research picture is complicated with post-GDPR findings including: more cookie banners [12], longer privacy policies [11], deceiving information [13], violating data protection by design [16], simply ignoring user consent notices [18], and by commodifying consent—the contribution of this paper.

This kind of analysis should have informed policy design, which means being accessible to policy makers and not only lobbyists. Further research into the economics of privacy should continue to monitor the development of this standard [52] and the ecosystem of firms collecting and using consent notices. However, such studies are limited by the lack of representative data for empirical research into the supply-side of the advertising industry. This leaves research overly focused on user studies and legal opinions.

Acknowledgements

The authors would like to thank Daniel Arce, Paulina Pesch and the anonymous reviewers for the valuable comments.

References

[1] Stanley I Benn. Privacy, freedom, and respect for persons. In *Privacy and personality*, pages 1–26. Routledge, 2017.

[2] Edward J Bloustein. Privacy as an aspect of human dignity: An answer to dean prosser. *NYUL Rev.*, 39:962, 1964.

[3] Louis Brandeis and Samuel Warren. The right to privacy. *Harv. L. Rev.*, 4(5):193–220, 1890.

[4] Alessandro Acquisti, Curtis Taylor, and Liad Wagman. The economics of privacy. *Journal of Economic Literature*, 54(2):442–92, 2016.

[5] Sarah Spiekermann, Alessandro Acquisti, Rainer Böhme, and Kai-Lung Hui. The challenges of personal data markets and privacy. *Electronic Markets*, 25(2):161–167, 2015.

[6] Daniel J Solove. Introduction: Privacy self-management and the consent dilemma. *Harv. L. Rev.*, 126:1880, 2012.

[7] Paul M Schwartz. Internet privacy and the state. *Conn. L. Rev.*, 32:815, 1999.

[8] Joseph Bonneau and Sören Preibusch. The privacy jungle: On the market for data protection in social networks. In *Economics of information security and privacy*, pages 121–167. Springer, 2010.

[9] Alessandro Acquisti and Jens Grossklags. Privacy and rationality in individual decision making. *IEEE Security & Privacy*, 3(1):26–33, 2005.

[10] Masooda Bashir, Carol Hayes, April D Lambert, and Jay P Kesan. Online privacy and informed consent: The dilemma of information asymmetry. In *Proceedings of the 78th ASIS&T Annual Meeting: Information Science with Impact: Research in and for the Community*, pages 43–52. American Society for Information Science, 2015.

[11] Thomas Linden, Rishabh Khandelwal, Hamza Harkous, and Kassem Fawaz. The privacy policy landscape after the GDPR. *Proceedings on Privacy Enhancing Technologies*, 2020(1):47–64, 2020.

[12] Martin Degeling, Christine Utz, Christopher Lentzsch, Henry Hosseini, Florian Schaub, and Thorsten Holz. We value your privacy... now take some cookies: Measuring the GDPR's impact on web privacy. *Network and Distributed System Security Symposium (NDSS2019)*, 2019.

[13] Iskander Sanchez-Rola, Matteo Dell'Amico, Platon Kotzias, Davide Balzarotti, Leyla Bilge, Pierre-Antoine Vervier, and Igor Santos. Can I opt out yet?: GDPR and the global illusion of cookie control. In *Proceedings of the 2019 ACM Asia Conference on Computer and Communications Security*, pages 340–351. ACM, 2019.

[14] European Union Agency for Network and Information Security. Challenges and opportunities for EU cybersecurity start-ups. 2019.

[15] QuantCast. Technical Implementation Guide. `https://help.quantcast.com/hc/en-us/articles/360003814853-Technical-Implementation-Guide`, 2019. [Online; accessed 22-Feb-2020].

[16] Midas Nouwens, Ilaria Liccardi, Michael Veale, David Karger, and Lalana Kagal. Dark patterns after the GDPR: Scraping consent pop-ups and demonstrating their influence. In *Proceedings of the ACM SIGCHI Conference on Human Factors in Computing Systems (CHI 2020)*, 2020.

[17] Privacy International. Request for an assessment notice / complaint of adtech data brokers. *Submission to the UK Information Commissioner*, 2018.

[18] Célestin Matte, Nataliia Bielova, and Cristiana Santos. Do cookie banners respect my choice? Measuring legal compliance of banners from iab europe's transparency and consent framework. In *IEEE Symposium on Security and Privacy*, 2020.

[19] James Campbell, Avi Goldfarb, and Catherine Tucker. Privacy regulation and market structure. *Journal of Economics & Management Strategy*, 24(1):47–73, 2015.

[20] Daniel J Solove. Conceptualizing privacy. *Calif. L. Rev.*, 90:1087, 2002.

[21] Joachim Henkel and Eric Von Hippel. Welfare implications of user innovation. *Journal of Technology Transfer*, 30(1-2):73–87, 2004.

[22] Alessandro Acquisti and Hal R Varian. Conditioning prices on purchase history. *Marketing Science*, 24(3):367–381, 2005.

[23] Katherine Campbell, Lawrence A Gordon, Martin P Loeb, and Lei Zhou. The economic cost of publicly announced information security breaches: empirical evidence from the stock market. *Journal of Computer Security*, 11(3):431–448, 2003.

[24] Huseyin Cavusoglu, Birendra Mishra, and Srinivasan Raghunathan. The effect of internet security breach announcements on market value: Capital market reactions for breached firms and internet security developers. *International Journal of Electronic Commerce*, 9(1):70–104, 2004.

[25] Sasha Romanosky, David Hoffman, and Alessandro Acquisti. Empirical analysis of data breach litigation. *Journal of Empirical Legal Studies*, 11(1):74–104, 2014.

[26] Sasha Romanosky. Examining the costs and causes of cyber incidents. *Journal of Cybersecurity*, 2(2):121–135, 2016.

[27] Christian Biener, Martin Eling, and Jan Hendrik Wirfs. Insurability of cyber risk: An empirical analysis. *The Geneva Papers on Risk and Insurance-Issues and Practice*, 40(1):131–158, 2015.

[28] Travis D Breaux and David L Baumer. Legally "reasonable" security requirements: A 10-year FTC retrospective. *Computers & Security*, 30(4):178–193, 2011.

[29] Gary S Becker. Crime and punishment: An economic approach. In *The economic dimensions of crime*, pages 13–68. Springer, 1968.

[30] Rainer Böhme and Jens Grossklags. The security cost of cheap user interaction. In *Proceedings of the 2011 New Security Paradigms Workshop*, pages 67–82. ACM, 2011.

[31] Catherine E Tucker. The economics of advertising and privacy. *International Journal of Industrial Organization*, 30(3):326–329, 2012.

[32] Jay Pil Choi, Doh-Shin Jeon, and Byung-Cheol Kim. Privacy and personal data collection with information externalities. *Journal of Public Economics*, 173:113–124, 2019.

[33] Cornelia Junghans, Gene Feder, Harry Hemingway, Adam Timmis, and Melvyn Jones. Recruiting patients to medical research: double blind randomised trial of "opt-in" versus "opt-out" strategies. *Bmj*, 331(7522):940, 2005.

[34] Aleecia M McDonald and Lorrie Faith Cranor. The cost of reading privacy policies. *Journal of Law and Policy for the Information Society*, 4:543, 2008.

[35] Idris Adjerid, Alessandro Acquisti, Laura Brandimarte, and George Loewenstein. Sleights of privacy: Framing, disclosures, and the limits of transparency. In *Proceedings of the ninth symposium on usable privacy and security*, page 9. ACM, 2013.

[36] Rainer Böhme and Stefan Köpsell. Trained to accept? A field experiment on consent dialogs. In *Proceedings of the SIGCHI conference on human factors in computing systems*, pages 2403–2406. ACM, 2010.

[37] Dominique Machuletz and Rainer Böhme. Multiple purposes, multiple problems: A user study of consent dialogs after GDPR. *Proceedings on Privacy Enhancing Technologies*, (2), 2020.

[38] Julio Angulo, Simone Fischer-Hübner, Erik Wästlund, and Tobias Pulls. Towards usable privacy policy display and management. *Information Management & Computer Security*, 20(1):4–17, 2012.

[39] Florian Schaub, Rebecca Balebako, Adam L Durity, and Lorrie Faith Cranor. A design space for effective privacy notices. In *Eleventh Symposium On Usable Privacy and Security (SOUPS 2015)*, pages 1–17, 2015.

[40] Helen Nissenbaum. *Privacy in context: Technology, policy, and the integrity of social life*. Stanford University Press, 2009.

[41] Tony Vila, Rachel Greenstadt, and David Molnar. Why we can't be bothered to read privacy policies models of privacy economics as a lemons market. In *Proceedings of the 5th International conference on Electronic commerce*, pages 403–407. ACM, 2003.

[42] Jonathan A Obar and Anne Oeldorf-Hirsch. The biggest lie on the internet: Ignoring the privacy policies and terms of service policies of social networking services. *Information, Communication & Society*, 23(1):128–147, 2020.

[43] Nathaniel S Good, Jens Grossklags, Deirdre K Mulligan, and Joseph A Konstan. Noticing notice: a large-scale experiment on the timing of software license agreements. In *Proceedings of the SIGCHI conference on human factors in computing systems*, pages 607–616. ACM, 2007.

[44] Anthony Vance, Jeffrey L Jenkins, Bonnie Brinton Anderson, Daniel K Bjornn, and C Brock Kirwan. Tuning out security warnings: A longitudinal examination of habituation through fMRI, eye tracking, and field experiments. *MIS Quarterly*, 42(2):355–380, 2018.

[45] United Kingdom Information Commisioner's Office. Guidance on the use of cookies and similar technologies. `https://ico.org.uk/for-organisations/guide-to-pecr/guidance-on-the-use-of-cookies-and-similar-technologies/`, 2019. "[Online; accessed 22-Feb-2020]".

[46] Article 29 Working Party. Guidelines on Consent under Regulation 2016/679, 2018.

[47] Jonathan R Mayer and John C Mitchell. Third-party web tracking: Policy and technology. In *IEEE Symposium on Security and Privacy*, pages 413–427. IEEE, 2012.

[48] Steven Englehardt and Arvind Narayanan. Online tracking: A 1-million-site measurement and analysis. In *Proceedings of the 2016 ACM SIGSAC conference on computer and communications security*, pages 1388–1401. ACM, 2016.

[49] Jannick Sørensen and Sokol Kosta. Before and after GDPR: The changes in third party presence at public and private european websites. In *World Wide Web Conference*, pages 1590–1600. ACM, 2019.

[50] Jonathan Levin and Paul Milgrom. Online advertising: Heterogeneity and conflation in market design. *American Economic Review*, 100(2):603–07, 2010.

[51] IAB Europe. Transparency & Consent Framework — Policies, 2019.

[52] IAB Europe. Transparency and Consent Framework Implementation Guidelines, 2019.

[53] Yoram Bachrach, Edith Elkind, Reshef Meir, Dmitrii Pasechnik, Michael Zuckerman, Jörg Rothe, and Jeffrey S Rosenschein. The cost of stability in coalitional games. In *International Symposium on Algorithmic Game Theory*, pages 122–134. Springer, 2009.

[54] Lloyd S Shapley. Cores of convex games. *International journal of game theory*, 1(1):11–26, 1971.

[55] Lloyd S Shapley. A value for n-person games. *Contributions to the Theory of Games*, 2(28):307–317, 1953.

[56] Martin J Osborne and Ariel Rubinstein. *A course in game theory.* MIT press, 1994.

[57] Olga N Bondareva. Some applications of linear programming methods to the theory of cooperative games. *Problemy kibernetiki*, 10:119–139, 1963.

[58] Lloyd S Shapley. On balanced sets and cores. *Naval Research Logistics Quarterly*, 14(4):453–460, 1967.

[59] Christine Utz, Martin Degeling, Sascha Fahl, Florian Schaub, and Thorsten Holz. (un) informed consent: Studying GDPR consent notices in the field. In *Proceedings of the 2019 ACM SIGSAC Conference on Computer and Communications Security*, pages 973–990, 2019.

[60] Veronica Marotta, Vibhanshu Abhishek, and Alessandro Acquisti. Online tracking and publishers' revenues: An empirical analysis. In *Proceedings of the 18th Workshop on the Economics of Information Security (WEIS 2019)*, 2019.

[61] Carole Cadwalladr and Emma Graham-Harrison. Revealed: 50 million Facebook profiles harvested for Cambridge Analytica in major data breach. *The Guardian*, 17:22, 2018.

[62] Lorrie Faith Cranor. P3p: Making privacy policies more useful. *IEEE Security & Privacy*, 1(6):50–55, 2003.

[63] Ponnurangam Kumaraguru, Lorrie Cranor, Jorge Lobo, and Seraphin Calo. A survey of privacy policy languages. In *Workshop on Usable IT Security Management (USM 07): Proceedings of the 3rd Symposium on Usable Privacy and Security, ACM*, 2007.