ARTICLE IN PRESS

International Journal of Research in Marketing xxx (xxxx) xxx

Contents lists available at ScienceDirect

International Journal of Research in Marketing

journal homepage: www.elsevier.com/locate/ijresmar

Economic consequences of online tracking restrictions: Evidence from cookies ☆

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A R T I C L E   I N F O

Article history:
Received 23 June 2022
Available online xxxx

Keywords:
Cookie
Privacy
Online advertising
Real-time bidding
Value of information
Consumer protection

A B S T R A C T

In recent years, European regulators have debated restricting the time an online tracker can track a user to protect consumer privacy better. Despite the significance of these debates, there has been a noticeable absence of any comprehensive cost-benefit analysis. This article fills this gap on the cost side by suggesting an approach to estimate the economic consequences of lifetime restrictions on cookies for publishers. The empirical study on cookies of 54,127 users who received ~128 million ad impressions over ~2.5 years yields an average cookie lifetime of 279 days, with an average value of €2.52 per cookie. Only ~13% of all cookies increase their daily value over time, but their average value is about four times larger than the average value of all cookies. Restricting cookies' lifetime to one year (two years) could potentially decrease their lifetime value by ~25% (~19%), which represents a potential decrease in the value of all cookies of ~9% (~5%). Most cookies, however, would not be affected by lifetime restrictions of 12 or 24 months as 72% (85%) of the users delete their cookies within 12 (24) months. In light of the €10.60 billion cookie-based display ad revenue in Europe, such restrictions would endanger €904 million (€576 million) annually, equivalent to €2.08 (€1.33) per EU internet user. The article discusses these results' marketing strategy challenges and opportunities for advertisers and publishers.

1. Introduction

Marketers are still increasing their digital marketing by allocating 53.8% of their budgets to digital marketing activities. They plan to increase spending by another 5.7% in 2024 (March edition of The CMO Survey 2023). One reason for these increased investments is the marketers' capability to track users along their customer journey, as (McKee, 2021) outlines: "Being able to accurately measure the reach and calculate the ROI of digital campaigns is hugely attractive to CMOs. Not only does this give them the information they need to optimize and improve the effectiveness of their digital spending, but it also arms them with quantifiable facts and figures to take to their boards and justify their positions."

☆ We acknowledge financial support of the NET Institute at the NYU Stern School of Business, the Hi!PARIS Center in Data Analytics & AI for Science, Technology, Business & Society, and from the European Research Council (ERC) under the European Union's Horizon 2020 Research and Innovation Program (Grant Agreement No 833714).
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https://doi.org/10.1016/j.ijresmar.2023.10.001
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Such tracking is possible because of the digital environment and the availability of tracking technologies such as (digital) cookies, digital fingerprinting, session IDs, and logins. 85% of marketers say their marketing activities are slightly to completely reliant on third-party cookies (HubSpot, 2023). Nevertheless, marketers will need to reconcile this strategy with looming changes in privacy regulations (Acquisti, 2023; Johnson, 2023).

Tracking allows firms to acquire more profound insights into user behavior, thereby improving the user experience by implementing strategies for personalizing content. Nevertheless, the gathered data also serves in deploying other marketing tactics such as attribution modeling and, notably, targeted advertising - frequency capping included. Better targeting of ads comes in many forms, but retargeting is undoubtedly one of the most remarkable (Lambrecht & Tucker, 2013; Bleier & Eisenbeiss, 2015). A typical setting for retargeting is an online shop where a user puts a product into a shopping basket but does not purchase it. The online shop can now inform a retargeting provider, such as Criteo, about this behavior. The retargeting provider then puts up ads for the online shop and the abandoned product on many other websites so that the user will observe an ad about the specific product on another website (e.g., an online newspaper), even if this website is unrelated to the online shop.

Unsurprisingly, many users are increasingly worried about their privacy in such cases (Bleier, Goldfarb, & Tucker, 2020; Beke, Eggers, Verhoef, & Wierenga, 2022). They often feel surveilled; some even find it "creepy" that a website can show them ads related to their behavior elsewhere. They may not know that (1) a tracking technology—here, cookies—enabled the online shop to track their behavior; (2) cookie matching informed the retargeting provider about the online shop's goal to target the user with ads that relate to the abandoned products; and (3) the website that showed the ad essentially had no information about what the user did in the online shop.

Policy makers are concerned and want to increase privacy. Many privacy regulations, including the European General Data Protection Regulation (GDPR) and China's Personal Information Protection Law (PIPL), emphasize obtaining a user's consent to tracking (Jin & Skiera, 2022). However, they are less focused on how long firms can store data after obtaining a user's consent, even though the duration of data storage is key for privacy protection and the security of a user's data. Therefore, regulators, such as in the EU with the upcoming ePrivacy Regulation (Council of the European Union, 2021), have discussed limiting the use of tracking technologies and data exchange between firms, among them restricting the lifetime of information collected by tracking technologies such as cookies.

Such a restriction implements the users' (human) right to be forgotten, which is implemented in several privacy laws such as GDPR and reflects that firms (or other entities) must delete certain user data after a specific period. However, evaluating the cost of such a lifetime limitation is challenging for at least two reasons. First, little knowledge exists about how long cookies even live. Many users claim they delete cookies regularly; however, the privacy paradox shows that users' stated and actual behavior can differ substantially (Gross & Acquisti, 2005; Skiera, Miller, Jin, Kraft, Laub, & Schmitt, 2022). Second, we know little about the size of the economic consequences for publishers that would result from such a lifetime restriction. Some representatives of the online advertising industry have predicted substantial losses, calling the increasing restrictions of online tracking "the single biggest change to the advertising ecosystem" (Interactive Advertising Bureau, 2021). However, other prominent voices, including Michael Zimbalist, former CMO of The New York Times, anticipate no harm to the industry (Hagey, 2019) and only a negligible impact on advertising prices. Therefore, it is unclear whether lifetime restrictions of online tracking lead to losses for the online advertising industry and how large these losses are. Unclear is also if all users and, thus, publishers are affected in the same way. For some publishers, a loss is likely to occur as the information collected via cookies enables the advertiser to target ads better. Nevertheless, it is unclear how significant the loss is.

This lack of knowledge is unfortunate because online advertising revenue ($209.7 billion (€86 billion) in 2022 in the United States (Europe) alone; Interactive Advertising Bureau, 2023a, 2023b) finances the content available to users, often free of charge or at least at a relatively low price. As a result, policy makers have no way of telling whether any benefits for consumer privacy that come with restrictions on tracking technologies are outweighed by adverse effects on publishers' profits—which policy makers have to trade off carefully.

Herein, we aim to provide an important initial step by suggesting and applying an approach for estimating the economic consequences of restricting cookie lifetimes for publishers. Specifically, we compute the lifetime value of cookies (LVC) and then determine the economic consequences (in our case, a loss) of cookie lifetime restrictions for publishers. We test which cookies live longer than a given lifetime restriction and grow in value over time. We find, for example, that only $\sim$13% of all cookies increase their daily value over time, but their average value is about four times larger than the average value of all cookies. We then derive the potential economic loss that would result from restricting cookie lifetime—for example, to 12 months as the European Union has proposed (Article 29 Data Protection Working Party, 2010; European Union, 2017a; 2017b; Council of the European Union, 2021) and the Italian DPA has already implemented or to 24 months, as the Spanish DPA and some industry stakeholders such as Facebook (Cook, 2017) have implemented.

We analyze data covering about 2.5 years collected by a large European ad exchange that serves as a programmatic marketplace to facilitate automated buying and selling of online display, mobile, and video advertising inventory. This panel enables us to use within-cookie price variations to trace the development of the value of a cookie over time, which no previous researchers have achieved.

Our results contribute to ongoing discussions in the digital advertising industry on the consequences of increasing online tracking restrictions to protect consumer privacy. They provide insights for the industry, users, and policy makers, such as determining how much users should pay for being tracked less intensively. Such knowledge could serve as a basis for regulatory decisions, industry self-regulation efforts (e.g., programs offering tracking-free digital subscriptions used by European publishers such as the Standard in Austria, Spiegel in Germany, or the premium EU subscription provided by The Washington Post), and privacy taxation. Furthermore, Chief Marketing Officers (CMOs) gain insights into the value of user data and targeting strategies. For example, restrictions on collecting user data would force firms to move away from behavioral targeting and focus on other targeting opportunities, e.g., contextual or geo-targeting. So, our results add to the literature on quantifying the value of the information generated in digital markets and determining the price of privacy.

2. Overview of online tracking technologies

In basic terms, user tracking identifies a user online via a unique identifier and records the user's behavior over time (Skiera et al., 2022). Tracking is easy if the user is willing to log in to a particular website because that login identifies the user on different browsers and devices. However, users are usually not ready to identify themselves via logins unless they benefit significantly from doing so. Social networks like Facebook provide such a benefit, but most other firms do not. As a result, they cannot rely on login data and must instead use other tracking technologies to identify users.

Mayer & Mitchell (2012) distinguish between stateless and stateful online tracking technologies. Stateless tracking does not store information but identifies the user by the (almost unique) configuration of the user's device (Besson, Bielova, & Jensen, 2013). Stateful tracking stores the information required to identify a user on the user's device (also called the user client), usually a desktop computer, tablet, or smartphone (Sanchez-Rola, Ugarte-Pedrero, Santos, & Bringas, 2016). Note that the data associated with a user's identifier, such as their consumer profile, can be stored on the user's device or the firm's server tracking the user, the latter of which is currently common.

2.1. Stateless online tracking

Stateless online tracking mainly refers to digital fingerprinting. It exploits the fact that the configuration of the user's device has many attributes (e.g., CPU type, computer clock skew, display settings, scripts, browser, operating system information, IP address, and language settings; Mayer & Mitchell, 2012). As a result, the specific combination of attribute values on a particular device is (almost) unique. Thus, observing the same configuration at multiple points makes it very likely that the configuration belongs to only one user. Behavioral biometric features—namely, dynamics that occur when typing, moving, clicking the mouse, or touching a touch screen—can provide further information to improve digital fingerprinting and, hence, user identification (Pugliese, 2015). However, a disadvantage of this tracking technology is that a firm can no longer track a user if changes in the configuration of the user's device occur.

2.2. Stateful online tracking

Stateful online tracking techniques mainly refer to cookies. In simplified terms, a cookie is a small piece of data sent from a server (i.e., a website) to a browser and stored on the user's device (Cristal, 2014). The most common are HTTP cookies (herein referred to simply as "cookies"), the focus of this study. They are stored in the user's browser, so they only identify the user if they continue using the same browser. Users can control such storage because all significant browsers enable users to prevent or delete cookies. Typically, a website is not incentivized to shorten a cookie's lifetime.

Cookies come in two main types: first-party cookies are installed by the website the user is visiting, whereas third-party cookies are installed by a server that does not belong to the website the user is visiting (e.g., a third-party ad server). First-party cookies only allow a firm to track a user on the website that initially set the cookie, whereas third-party cookies allow a firm to track a user across different websites. A cookie usually contains a unique number called "cookie-ID" that identifies the user (e.g., "179′032′342′526′846′362" in our data). Each cookie also has an expiration date that dictates when the browser will automatically delete the cookie. Table W2.1 (in Web Appendix W2) shows the maximum cookie lifetimes from a single visit to selected domains, which vary between approximately 1 and 20 years. Table W2.1 also outlines that a website often sets more than one cookie.

A cookie is typically associated with a single user. Sometimes, however, multiple users (e.g., from the same household) may share one browser on one device, such that one cookie captures the activities of multiple users. More frequently, however, a single user operates on multiple devices (e.g., desktop, tablet, smartphone) and even multiple browsers on one device (Budak, Goel, Rao, & Zervas, 2016; Yan, Miller, & Skiera, 2022). In such a case, multiple cookies store the activities of a single user. Unfortunately, those cookies are often not connected, which represents a shortcoming of this tracking technology because it leads to identity fragmentation (Lin & Misra, 2022; Tian, Hoban, & Arora, 2023).

In our study, we focus on cookies for three reasons. First, despite the availability of other online tracking technologies such as digital fingerprinting or advertising identifiers and plans to phase out third-party cookies, cookies are still frequently used to track a user on a single device on a specific website or across several websites.

Second, even if cookies are being (partially) replaced, the need for online tracking will prevail as the online advertising industry still wants to track, profile, and target online users to increase the efficiency of online advertising. As cookies work similarly to other online tracking technologies, such as digital fingerprinting, our results will likely generalize to these other tracking technologies that track users similarly to cookies.

Third, privacy regulation, e.g., the European Union's General Data Protection Regulation (GDPR; see Miller, Schmitt, & Skiera, 2023) or the upcoming ePrivacy Regulation, generally regulate online tracking technologies and are agnostic towards a specific tracking technology, such as cookies. The initiatives to restrict an online tracking technology's lifetime (see Section 3.3) could, therefore, apply to cookies (as we study in this research) but also to other online tracking technologies.

3. Initiatives to restrict online tracking

3.1. Firms' usage of online tracking

Firms primarily use online trackers such as cookies or digital fingerprints to implement two marketing strategies: First, trackers enable publishers to personalize content to benefit users' experience. For example, websites use trackers to remember users' preferences, set up personalized content, and help users complete tasks without reentering information when revisiting a website (Cristal, 2014; Tam & Ho, 2006). Usually, a first-party tracker is sufficient to accomplish this personalization (Estrada-Jiménez, Parra-Arnau, Rodríguez-Hoyos, & Forné, 2017).

Second, online trackers enable advertisers to target users with ads better, rendering their ads more effective (Goldfarb & Tucker, 2011b). Particular forms of online advertising would probably not even exist without trackers. For example, it would be challenging to attribute purchases to affiliates without trackers in affiliate marketing. Better advertising can also benefit users, who receive more relevant ads to help them make better purchase decisions (for a summary of studies, see Boerman, Kruikemeier, Zuiderveen, & Borgesius, 2017; and a recent critique that targeted ads may not always be welfare-enhancing for users from Mustri, Adjerid, & Acquisti, 2023). Summers, Smith, & Reczek (2016) have shown that targeted ads can even change how users think about themselves. Still, the decrease in privacy that comes with better-targeted ads may offset those benefits.

Advertisers usually use third-party trackers for ad targeting, allowing them to track users across websites and apps. Users may perceive such cross-site and cross-app tracking as infringing their privacy. Thus, several initiatives exist to restrict third-party trackers (cookies) but not necessarily first-party trackers (cookies). Subsequently, we will outline major privacy initiatives by policymakers and self-regulatory initiatives of the online advertising industry to restrict the usage of third-party tracking, especially cookies, and replace this form of tracking with less privacy-invasive ways of tracking. We note that although specific forms of tracking, such as third-party cookies, may lose importance, publishers will continue to benefit from their strategy of tracking users because it seems to help them better monetize their content online, as advertisers will benefit from a lower ad wastage.

3.2. Initiatives to restrict online tracking

As tracking technologies such as cookies decrease user privacy (Awad & Krishnan, 2006), policymakers and the online advertising industry have begun restricting online tracking technologies to protect users' privacy (see Fig. 1).

In Europe, online tracking is mainly governed by the ePrivacy Directive (ePD) and the General Data Protection Regulation (GDPR). The GDPR, for example, only allows the processing of personal data of internet users if one of the following applies:

OVERVIEW OF EXEMPLARY PLANNED AND IMPLEMENTED INITIATIVES TO RESTRICT ONLINE TRACKING

Initiator **Status**	**Policy Makers**	**Industry**
Implemented	• EU ePrivacy Directive (ePD) 2002 • EU General Data Protection Regulation (GDPR) 2018 (Opt-in consent) • California Consumer Privacy Act (CCPA) 2018 (Opt-out consent) • Digital Service Tax 2020	• 2018: Apple SKAdNetwork (SKAN) • 2018: netID • 2018: Tracking-free Subscriptions • 2019: Apple Intelligent Tracking Prevention (ITP) • 2021: Apple App Tracking Transparency (ATT) • 2022: Mozilla Total Cookie Protection (TCP)
Planned	• EU ePrivacy Regulation (ePR) (Restrictions of Tracking Technologies' Lifetime)	• Google Privacy Sandbox (e.g., FloC, FLEDGE, Aggregate & Conversion Measurement APIs, Trust Token API, Topics API)

Fig. 1. Overview of exemplary planned and implemented initiatives to restrict online tracking.

(a) the user has given consent to the processing of his or her personal data, (b) the processing is necessary for the performance of a contract, or (c) processing is in the legitimate interests pursued by the firm (other legal bases exist but are not applicable in the online setting).

Concerning online tracking, some European DPAs clarified that individual opt-in consent is the most appropriate legal basis for websites to process a user's personal data (Article 29 Data Protection Working Party, 2012; Data Protection Commission, 2020). Yet, the EU DPAs have signaled some openness to online trackers that exclusively use the website's own data (e.g., using first-party cookies) but remain concerned about online trackers that combine user data across websites (e.g., using third-party cookies). So, websites may deviate from using opt-in consent as a legal basis for online tracking and instead rely on another legal basis, such as legitimate interest. In contrast to GDPR, the California Consumer Privacy Act (CCPA) defaults a user into online tracking but allows a user to opt-out if she does not want to be tracked (Jin & Skiera, 2022).

In addition to initiatives of policymakers, many browsers increasingly protect online consumer privacy by restricting third-party online tracking as part of self-regulatory efforts. As early as 2013, Mozilla Firefox and Apple Safari started blocking third-party cookies from advertisers. In 2019, Apple began blocking all third-party tracking by launching its second version of Intelligent Tracking Prevention (ITP) in its Safari browser. Microsoft Edge has blocked third-party cookies since July 2020. In 2021, Apple followed suit and began preventing third-party tracking on mobile devices by introducing the App Tracking Transparency (ATT) framework (Kraft, Skiera, & Koschella, 2023).

Similarly, Google has set a 2024 deadline for preventing cross-site and cross-app tracking and announced eliminating third-party cookies in its Chrome browser (Google 2022a). Since June 2022, Mozilla has offered Total Cookie Protection (TCP), which confines third-party cookies to the site where they were created by treating them as first-party cookies. So, the trackers can see a user's behavior on the website the user visited but not the behavior on other websites.

Although the online advertising industry is moving toward a world without (third-party) cookies, the industry is also working on privacy-sensitive replacements for third-party cookies as the need for targeting ads remains, as does the need to monetize content. For example, as a substitute for device-level user tracking and advertising attribution, Apple created SKAdNetwork (SKAN) as a measurement solution to provide advertisers with coarse, time-delayed feedback on their post-ad click conversion events. Chrome's Privacy Sandbox separates the functions performed by third-party trackers into separate replacement technologies for ad targeting (FloC, FLEDGE), ad measurement (Aggregate & Conversion Measurement APIs), and other uses like fraud prevention (Trust Token API). Recently, Google introduced its Topics API for interest-based advertising, which replaced Google's earlier FloC proposal (Google 2022b). Such an approach may improve the outcome of online advertising (i.e., users are not individually targeted), but not necessarily the process of online advertising (i.e., users are still individually tracked on their devices). Raising questions of whether consumers perceive their privacy violated when their data is still being tracked, albeit anonymously (Jerath & Miller, 2023).

In addition, the online advertising industry is working on strategies to avoid third-party cookies. They increase their use of first-party cookies and other identifiers such as a user's email address or login data. They also work on privacy-preserving strategies for sharing data among companies (Schneider, Jagpal, Gupta, Li, & Yan, 2017; Kakatkar & Spann, 2019). For example, European publishers created netID, a foundation established by an alliance of publishers to increase user tracking across the associate publishers based on the user's login (Skiera et al. 2022). The basic premise of netID is that it provides a user with a single (netID) account to access different publishers and manage all permission decisions. This centralization will likely reduce users' decision costs when providing and managing permission for data processing. As netID only relies on first-party tracking, it does not fall under the above-outlined restrictions of third-party tracking. However, it recreated the functionality of third-party tracking using first-party tracking across multiple publisher websites.

We can observe similar developments in mobile advertising, where Apple's strategy with its App Tracking and Transparency (ATT) intends to hamper third-party interactions in mobile applications. Yet, some advertisers circumvent this practice and replace third-party trackers using a fingerprinting-derived identifier (Kollnig, Shuba, Van Kleek, Binns, & Shadbolt, 2022).

The online publishing industry is also innovating by offering its users the opportunity to pay to avoid being tracked. For example, in May 2018, an Austrian publisher, the news website "Der Standard", introduced a notification banner, referred to as a pay-or-consent wall, that appears for first-time users of their website. It offers the user two options: (i) pay for not being tracked and not seeing advertisements or (ii) consent to being tracked, involving the processing of their personal data for third-party advertising and seeing ads. If the user refuses to select one of the two options, accessing the publisher's content is impossible, meaning the user has to take the third option and leave the website.

Finally, another way to restrict online tracking is to introduce a Digital Service Tax. Most DSTs became effective in 2020 and most significantly affect business models that derive a high value from consumer interaction (e.g., social networks and search engines). Their tax rates vary from 2.0% to 7.5%. All DSTs apply only to those firms whose global (i.e., worldwide) and local (i.e., country-specific) revenue surpasses a substantial threshold. While all DSTs build upon revenues, they differ regarding the taxed revenue type, precisely advertising revenue. For example, the tax bases in Austria, Italy, Turkey, and the United Kingdom are online advertising revenues. In contrast, the tax base in France is only targeted online advertising revenue.

3.3. Initiatives to restrict tracking technologies' lifetime

Currently, many privacy regulations emphasize obtaining a user's consent for tracking (e.g., the GDPR; Lukic, Miller, & Skiera, 2023) and focus less on how long to store data after a user's consent has been obtained. However, the duration of data storage is vital for privacy protection and a user's data security. Therefore, EU regulators have discussed limiting the use of tracking technologies and data exchange among firms, among them the restriction of the lifetime of information collected by tracking technologies such as cookies (i.e., the right to be forgotten; Agencia Española de Protección de Datos, 2020; Article 29 Data Protection Working Party, 2010; Nationale, 2020; Garante per la Protezione dei Dati Personali, 2015; Voisin, Ruth, Assion, Nevola, & Rodriguez, 2021). For example, the Council of the European Union (2021) suggested a 12-month restriction of a tracker's lifetime in its draft for the ePrivacy Regulation. Such lifetime restrictions are already legally binding in some EU member states, such as France (6 months), Italy (12 months), and Spain (24 months). Other EU member states, such as Germany, for example, only advocate relatively shorter lifespans but do not specify precisely how long the useful life of a tracking technology should be.

Fig. 2 summarizes these planned and partially implemented initiatives of EU member states. Web Appendix W1 describes these initiatives in more detail. Some firms have already implemented a rather loose cookie lifetime restriction (i.e., two years in the case of Facebook or 18 months in the case of Google), with the notable exception of Tradelab (2019), who adopted a rather strict cookie lifetime restriction of 13 months. This voluntary industry self-regulation may prevent too strict regulation by data protection agencies and regulators. Also, big techs such as Facebook and Google may be better able to substitute an information loss from one tracking technology (e.g., cookies) with other tracking technologies such as logins, for which lifetime restrictions are currently not discussed.

We note, however, that these restrictions could, at least theoretically, apply to all tracking technologies. So, they would equally affect cookies, digital fingerprints, logins, and other tracking technologies. The different implemented and planned

PLANNED AND IMPLEMENTED INITIATIVES TO RESTRICT THE LIFETIME OF TRACKING TECHNOLOGIES (COOKIES)

Initiator / Status	Policy Makers	Industry[b]
Implemented	All cookies • France: 6 months[a] (Commission Nationale de l'Informatique et des Libertés, 2020) Italy: 12 months (Garante per la Protezione dei Dati Personali, 2015) • Spain: 24 months (Agencia Española de Protección de Datos, 2020) • UK and GER: No specification, but shorter lifetime advocated (Voisin et al.,2021)	First-party cookies • 13 months (Tradelab, 2019) • 18 months: Google (2022c) • 24 months: Facebook (Cook, 2017) Third-party cookies • Full block: Apple (Wilander, 2020), Brave (2022), Mozilla (Englehardt and Marshall, 2019), Microsoft (Barker and Murgia, 2020)
Planned	All cookies • EU: 6–12 months (European Union 2017a; 2017b) • EU: 12 months (Article 29 Data Protection Working Party, 2010) • EU: 12 months (Council of the European Union, 2021)	Third-party cookies • Full block: Google (Google, 2022a)
Notes: [a] The lifespan of analytic cookies benefiting from the CNIL consent exemption must not exceed 13 months. [b] The industry initiatives have a worldwide reach and thus apply to users from all countries.		

Fig. 2. Planned and implemented initiatives to restrict, the lifetime of tracking technologies (cookies). (See above-mentioned references for further information.)

Table 1
Observational and experimental studies on cookies.

Study	Aim	Observations			Cookie Information			
		Period	Cookies	Ad Impressions	Age	Lifetime	Value	Value over Time
Abraham et al. (2007)	Determine Impact of Cookie Deletion on Website- and Ad-Metrics	1 month	400′000	n.a.	≤ **1 month**[a]	no	no	no
Goldfarb & Tucker (2011a)	Determine Impact of Privacy Regulation on Ad Effectiveness	55 days	n.a.	n.a.	no	no	**65%**	no
Johnson (2013)	Determine Impact of Privacy Regulation on Ad Industry	1 week	n.a.	n.a.	no	no	**39%–46%**	no
Beales & Eisenach (2014)	Determine Value of a Cookie for Advertisers	2 weeks	n.a.	3.0 Mio.	**1.5 months**[b]	no	**$0.22–$0.34 premium**	↑**$0.02–$0.15 per month**
Aziz & Telang (2016)	Determine Value of a Cookie for Advertisers	1 day	115′417	1.3 Mio.	no	no	no	no
Budak, Goel, Rao, & Zervas (2016)	Determine Impact of Ad Blocking and Tracking Restrictions	1 year	13.6 Mio.	n.a.	no	no	**$2**	no
Johnson et al. (2017)	Improve Ad Effectiveness Measurement	2 weeks	566′377	n.a.	**3.5 months**[c]	no	no	no
Johnson et al. (2020)	Determine Effect of Cookie Opt-Out for Ad Industry	n.a.	n.a.	62.9 Mio.	no	no	**52%**	no
Marotta, Abishek, & Acquisti (2019)	Determine Effect of Cookies on Publisher Revenue	1 week	n.a.	n.a.	no	no	**8%**	no
Ravichandran & Korula (2019)	Determine Effect of Cookies on Publisher Revenue	96 days	n.a.	n.a.	no	no	**52%**	no
Rafieian & Yoganarasimhan (2021)	Determine Value of Mobile Targeting	30 days	7,28,340	27 Mio.	no	no	**18%**	no
Laub, Miller, & Skiera (2023)	Determine Effect of Cookies on Publisher Revenue	2 weeks	1.4 Mio.	42.4 Mio	no	no	**18%**	no
Wang et al. (2023)	Determine Effect of GDPR on Display Advertising	10 weeks	n.a.	n.a.	no	no	**6%**	no
This study	**Determine Economic Consequences of Online Tracking Restrictions**	**2.5 years**	**98,527**	**234 Mio.**	**3.5 months**[b] **16 days**[c]	**9.3 month**[b] **2.3 months**[c]	**€2.52**[b] **€.02**[c]	↑**12.807%** ↓**7.591% n.s.** **79.602%** [d]

[a] 31% of users delete their cookies within one month.
[b] Mean.
[c] Median.
[d] For 12.807% of cookies, we find a significant positive incremental effect of time on the value of a cookie. For 7.591% of cookies, we find a significant negative incremental effect of time on the value of a cookie. For 79.602% of cookies, we find a non-significant incremental effect of time on the value of a cookie.

cookie lifetime restrictions further require deleting the cookie after a specific time. That is, the activity or inactivity of a cookie does not play a role in the cookie lifetime restriction to kick-in.

4. Knowledge on cookies

4.1. Knowledge on the lifetime of cookies

Table 1 provides an overview of previous research on cookies. Primarily, it focuses on the value of cookies. Prior knowledge on cookie lifetime is limited because existing studies only report cookie age, corresponding to a cross-sectional measure of cookie lifetime at the specific time of data collection. For example, in assessing the impact of cookie deletion on website and ad metrics, Abraham, Meierhoefer, & Lipsman (2007) find that 31% of U.S. users delete their cookies within one month. Beales & Eisenach (2014) report a mean cookie age of 1.5 months, and Johnson, Lewis, & Nubbemeyer (2017) find a median cookie age of 3.5 months. Such knowledge is valuable because it serves as a lower bound for the cookie's lifetime, though not as a proxy for the lifetime itself. It also shows that the cookie age is low, with a maximum of 3.5 months.

4.2. Knowledge on the value of cookies

Many discussions on the value of cookies include debates on the economic loss to publishers that a complete ban on cookies would entail. McKinsey (2010) estimates a monthly willingness to pay to avoid advertising intrusion as high as €10 per household. Budak et al. (2016) estimate that $2 per month would be enough to offset all digital ad revenues for content publishers. Amazon (Dastin, 2019) offered users $10 in exchange for tracking them all over the web. In 2020, German publisher Spiegel introduced its "Pure" digital subscription, which charges €5 (≈$5.38) per month for an ad- and tracking-free online browsing experience (Mueller-Tribbensee, Miller, & Skiera, 2023). The Washington Post offers a similar paid and ad-free offer to its EU users for €4 per month. Finally, Deighton & Kornfeld (2020) estimate that if all online tracking were to end, absent a mitigating technology, there would be a shift of between $32 billion and $39 billion of advertising and ecosystem revenue away from the open web toward walled gardens such as Meta, Google or Apple.

However, current insights on the value of a cookie diverge greatly. Beales (2010) early survey of advertising networks suggests that tracking commands a price premium: average CPMs ("cost per 1,000 impressions") were $1.98 for untargeted "run of network" ads, $4.12 for behavioral targeting, and $3.07 for retargeting. Beales & Eisenach (2014) show a positive impact of cookies on advertisers' willingness to pay for ads; cookies result in a premium of $0.22–$0.34 for 1,000 impressions (reflected in the respective increase of CPM). Further, they quantify the positive impact of cookies' age on advertisers' willingness to pay between $0.02 and $0.15 (CPM) per month as users with older cookies accumulate more information. Goldfarb & Tucker (2011a) find that advertising was approximately 65% less effective after a European cookie restriction policy.

Johnson (2013) results indicate that a complete tracking ban (i.e., no cookies are allowed) would lead to a drop in publisher revenues by 38.5% and a 45.5% drop in advertiser surplus. Aziz & Telang (2016) find that more intrusive information makes ad targeting better but at a decreasing rate. Using an industry field experiment, Ravichandran & Korula (2019) find a decrease in publisher revenue by 52% in the absence of third-party cookies. Rafieian & Yoganarasimhan (2021) assessment of the value of mobile targeting shows that behavioral targeting leads to a 18% improvement in advertisers' targeting ability, as measured by the relative information gain of behavioral over nonbehavioral targeting. Johnson, Shriver, & Shaoyin (2020) estimate the total lost expenditure on behavioral targeting to be $8.58 per opt-out user for the U.S. desktop display industry in 2015, corresponding to a 52% loss in ad prices as paid by advertisers without a cookie, while Wang, Jiang, & Yang (2023) only find a 6% reduction in advertiser bid prices and the resulting revenues per click.

Similarly, Laub, Miller, & Skiera (2023) find an 18% decrease in ad prices paid to publishers without a cookie. In contrast, Marotta, Abishek, & Acquisti (2019) estimate an ad price loss of only 8% to publishers. Overall, the studies mentioned above show that cookies generate value, but there is considerable heterogeneity between studies on how to measure the value of a cookie and how large this value should be; losses range from 6% to 65%.

4.3. Knowledge on the development of the value of cookies

Knowledge about the development of a cookie's value over time is sparse. Some evidence in the literature indicates that a cookie's value increases over time (e.g., Beales & Eisenach, 2014; Casale, 2015). The core argument for an increase in value is that advertisers collect more information on a user's profile, and this information enables better targeting. Empirical research in the domain of targeting has primarily focused on elucidating the relationship between consumer targeting — as reflected in reliance on ad targeting (versus no targeting) — and the profits of publishers and advertisers. These studies show that targeting is more profitable for publishers and advertisers than no targeting.

More specifically, these studies find positive effects of targeting on a variety of outcome measures, including the following: click-through rates (Yan, Liu, Wang, Zhang, Jiang, & Chen, 2009), which depend on timing and placement factors (Bleier & Eisenbeiss, 2015); consumers' purchase intentions (van Doorn & Hoekstra, 2013); purchase probabilities (Manchanda, Dubé, Goh, & Chintagunta, 2006); consumers' progression through the purchase funnel (Hoban & Bucklin, 2015); ad prices and ad revenue (Beales, 2010), ad revenue per impression (Ada, Nabout, & Feit, 2022); and advertising profitability (Lewis & Reiley, 2014). These varying outcomes also explain differences in the value of users for publishers.

In contrast, prior theoretical studies on consumer targeting have identified situations in which advertisers or publishers have incentives to prevent the targeting of ads based on a large number of attributes (Badanidiyuru, Bhawalkar, & Xu, 2018). Levin & Milgrom (2010) explain the intuition behind this remarkable finding. If competition for a particular ad exposure is low—e.g., when very few advertisers wish to display an ad to a specific consumer—the publisher suffers from lower prices. The likelihood of such a "thin market" increases with the number of attribute levels in consumer profiles because some attributes can indicate that a consumer is unattractive to an advertiser. For example, knowing that someone is male keeps him in the target group for a fashion store for young people, but knowing that the person is male and 70 years old might exclude him.

Shedding further light on these ideas, a study by Board (2009) shows theoretically that, in a second-price sealed-bid auction, the number of attribute levels in a consumer profile is always positively related to the sum of the profits gained by the publisher and advertisers. However, the number of attributes does not straightforwardly affect how this profit splits between advertisers and the publisher. In some cases, as outlined above, much information about consumers can decrease prices but increase prices in other cases.

In sum, the theoretical studies cited above suggest that including more attributes in consumer profiles can often, but does not always, lead to higher prices. They also outline reasons why the effects could differ across users. For example, suppose a user belongs to a small group of users, i.e., a thin market. Little competition might exist for targeting this user, so the value of the user for the publisher is low. In contrast, suppose a user belongs to a much larger group of users. Competition for targeting these users might be much higher, as does the value of the user for the publisher.

The literature on retargeting (Bleier & Eisenbeiss, 2015) and informal discussions with industry practitioners suggest that a user may be only in the market for a specific product for a short time (e.g., renting a car for a weekend trip to San Francisco but otherwise not interested in renting a car in San Francisco). In such a case, the value of a cookie would be higher at the beginning of the cookie's life and decrease in value as the cookie ages.

Finally, other studies show reasons why cookie value remains constant over time. Recent studies by Neumann, Tucker, & Whitfield (2019), Neumann, Tucker, Subramanyam, & Marshall (2022), and Kraft, Miller, & Skiera (2023) suggest that consumer data obtained by online tracking technologies are inconsistent and sometimes even inaccurate. A study with UK managers (Weiss, 2018) confirms this result: 82% believe that consumer data are somewhat unreliable. Consequently, inconsistent and inaccurate data represent a challenge for targeted advertising, as they may lead to wrongly personalized ads, a misunderstanding of consumer habits, and an erroneous assessment of ad effectiveness (Lucker, Hogan, & Bischoff, 2017). The industry might anticipate inaccurate or inconsistent data in consumer profiles and ignore them in setting ad prices.

In summary, we know little about the value of cookies, specifically concerning cookie lifetime, cookie value, and the evolution of the value over time. Having such knowledge would make it easier to have a more thoughtful debate on the economic value of cookies and the economic consequences a restriction of cookie lifetimes might entail for the online advertising industry. Web Appendix W1 outlines the widely varying planned and already implemented initiatives to restrict cookie lifetimes currently under consideration across Europe.

5. Description of empirical study

5.1. Aim of empirical study

The goal of our empirical study is to determine the economic consequences of online tracking restrictions for publishers' revenues, specifically the following three:

1. Short cookie lifetime restriction regime (30 days, 60 days, 90 days, 120 days).
2. Medium cookie lifetime restriction regime (360 days).
3. Long cookie lifetime restriction regime (720 days).

These restrictions could be easily implemented by simply requiring the cookie owner to set the cookie's expiration date accordingly. The browser would automatically delete the cookie after this expiration date and, thus, provide a practical implementation of the right to be forgotten as outlined, for example, in Europe's GDPR.

5.2. Description of data

Our data come from a large European ad exchange that is a programmatic marketplace for online display, mobile, and video advertising. The ad exchange reaches approximately 84% of its relevant market's total monthly internet users. This exchange granted us full access to a sample of its proprietary data for 867 days between March 3, 2014, and July 16, 2016, representing ~2.5 years of data on approximately 128 million ad impressions sold in a real-time auction to 54,127 cookies. Our data include desktop and mobile browsing traffic and are anonymized, so individuals remain unidentifiable.

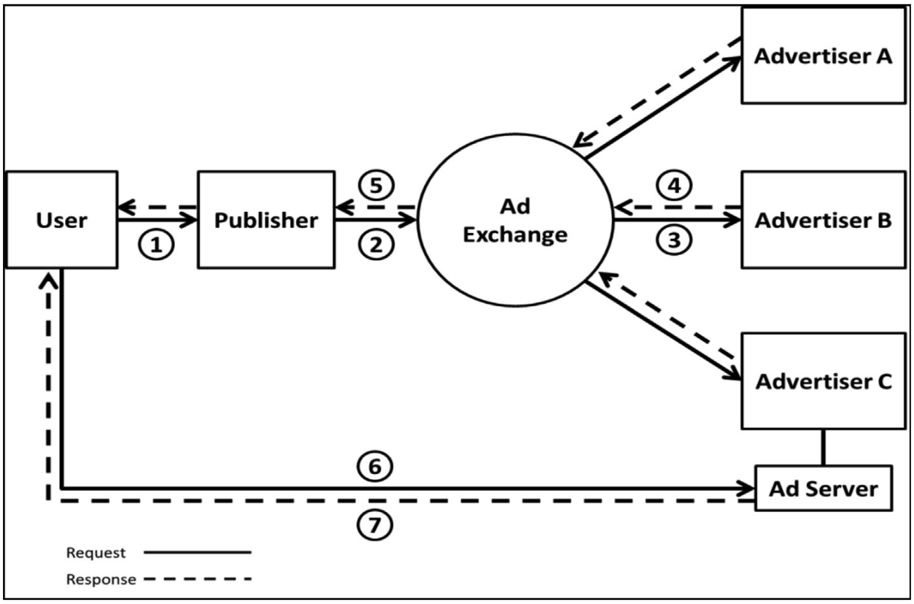

Fig. 3. Illustration of the auction process in real-time bidding. Notes: As shown in the figure, whenever a user visits a publisher's website with ad slots (1), the publisher sends an ad call to an ad exchange (2). This ad call is a request to run a real-time auction on the ad exchange and contains information about, for example, the properties of the ad slot (e.g., ad size) and a user ID, for example, a cookie ID, which we explain in more detail in Section 2.2. The ad exchange then sends a bid request to all advertisers on the ad exchange (3). Each interested advertiser submits a bid for displaying its ad to the user, including the ad server's address with the ad (4). The ad exchange determines the auction's price and winner and forwards this information to the publisher (5). The publisher then asks the user's browser to load the ad from the ad server (6) and displays the ad to the user on the publisher's website (7).

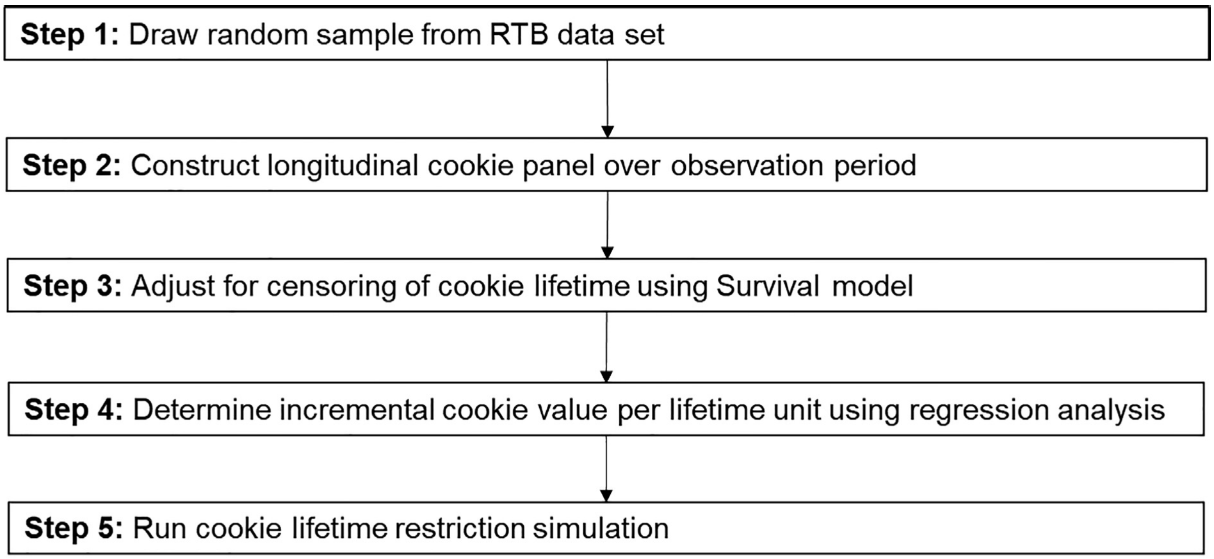

Fig. 4. Illustration of approach to derive economic consequences, of cookie lifetime restrictions from real-time bidding data.

Trading on the ad exchange occurs via real-time bidding (RTB; see Fig. 3 and, e.g., Tunuguntla & Hoban, 2020). Each observation represents an auction from a single ad impression a publisher sold on the ad exchange. We observe the third-party cookie of the ad exchange, the only cookie that the ad exchange sets. It proxies the advertiser's third-party cookie. The cookies of the ad exchange and the advertiser for a particular user overlap when the advertiser has won an auction for the particular user because serving an ad to the user allows the advertiser to place its third-party cookie in the user's browser. To our knowledge, this article is the first to exploit longitudinal auction data over ~2.5 years to gauge the value of a cookie and determine the economic consequences of cookie lifetime restrictions.

5.3. Description of approach to analyze data

Fig. 4 describes our approach to quantifying the economic consequences of cookie lifetime restrictions for publishers.

In Step 1, we draw a random sample of cookies, respectively the user behind each cookie, from the RTB data set. The sample is a random sample of 54,127 users from a randomly selected day (i.e., Wednesday, April 29, 2015) at the center of the data set. We gathered all available information for these users for our entire observational period of ~2.5 years, resulting in 128,334,068 auctions that each sell one ad impression. The random sample represents 1% of unique cookies on our sampling day. We drew a sample that covers one day to get a representative sample of cookies because it (1) draws cookies from users who access the internet at different times during the day and (2) limits the likelihood that users who often delete their cookies were included more than once in our sample. Although sampling from one randomly chosen day may oversample heavy internet users because they are more likely active on that particular day, their activity on the specific day itself did not increase their probability of being included in the sample because we drew a random sample from all users of the particular day, not from all ad impressions.

In Step 2, we construct a longitudinal cookie panel by extracting all available cookie data per unique cookie identifier over the observation period. In Step 3, we adjust for potential censoring of cookie lifetime because the cookie might have lived longer than our observation period. Using a parametric survival model, we predict the remaining (unobserved) cookie lifetime (beyond our observation period) (for validation of this approach, see Web Appendix W3). In Step 4, we use regression analysis to uncover the incremental value per day (for validation of this approach, see Web Appendix W4). In Step 5, we use the obtained information to simulate the economic consequences of the various cookie lifetime restriction regimes. This approach is easily scalable and applicable to other real-time bidding data sets using tracking technologies.

5.4. Description of sample

In the following, we describe the behavior of two selected cookies and then continue by computing summary statistics for the 54,127 cookies we observed in the sample. We describe separate analyses for cookie lifetime, cookie value per lifetime unit (e.g., days), and cookie lifetime value. Table 2 provides an overview of two selected cookies, and Table 3 gives an overview of our sample.

A detailed description of two cookies. We find a positive relationship between cookie price and cookie lifetime for the cookie with the ID 177′239′342′526′XXX'XXX (see Fig. 5). On our sampling day (April 29, 2015), the cookie was 149 days old. However, we observed the cookie in our longitudinal data from December 1, 2014, to July 15, 2016, which means that the cookie lived for another 443 days after our sampling day, yielding an observed lifetime of 592 days. During this time,

Table 2
Description of behavior of two cookies.

Row	Cookie ID	177′239′342′526′XXX'XXX	466′830′604′730′XXX'XXX
I	Date and Time of First Impression	2014-12-01 16:51:17	2015-01-15 14:41:29
II	Date and Time of Last Impression	2016-07-15 18:33:20	2015-09-11 10:49:39
III	Observed Age of Cookie on Sampling Day (in days)[a]	149	104
IV = II − I	Observed (potentially censored) Lifetime of Cookie (in days)	592	239
V = f(IV)	Predicted Residual Lifetime of Cookie (in days)	481	0
VI = IV + V	Uncensored Lifetime of Cookie (in days)[b]	1,073	239
VII = f(IV)	Observed Number of Active Days	514	150
VIII = VII/IV	Share of Observed Active Days per Observed Days	86.824%	62.762%
IX	Observed Number of Ad Impressions	9,162	3,627
X = IX/IV	Observed Number of Ad Impressions per Day	15.476	15.176
XI = XIV/IV	Observed Value of Cookie per Day (in €)	0.018	0.008
XII = XVIII/VI	Uncensored Value of Cookie per Day (in €)	0.028	0.010
XIII = XIV/IX	Observed Value of Cookie per Ad Impression (in €, CPM)	1.181	0.554
XIV = f(II, VII))	Observed (potentially censored) Lifetime Value of Cookie (in €)	10.823	2.011
XV = f(IV, XI)	Predicted Censored Lifetime Value of Cookie for Observed Lifetime (in €)	12.248	2.366
XVI = f(XIV, XV)	Absolute Percentage Error (APE) for Observed Lifetime	13.166%	17.653%
XVII = f(V, XI)	Predicted Residual Lifetime Value of Cookie for Residual Lifetime (in €)	17.687	0.000
XVIII = XV + XVII	Uncensored Lifetime Value of Cookie (in €) [c]	29.935	2.366

[a] Rounded to the next full day.
[b] We use a Weibull model to determine the predicted residual lifetime for 13.123% of the cookies with potentially censored cookie lifetime in sample 1.
[c] We determine the uncensored cookie lifetime value using the regression from Eq. (1) (i.e., model 2 in Table 6).

Table 3
Summary statistics per cookie (N = 54,127).

Category	Variable	Quantiles					Mean	SD
		Min.	25%	50%	75%	Max.		
Lifetime Unit of Cookie	Observed Age of Cookie on Sampling Day (in days)[a]	1	1	16	168	423	105	147
	Observed (potentially censored) Lifetime of Cookie (in days) [a]	1	1	68	416	867	216	268
	Uncensored Lifetime of Cookie (in days)[a,b]	1	1	68	416	1,351	279	396
	Observed Number of Active Days	1	1	8	73	836	74	138
	Share of Observed Active Days per Observed Days	0.004	0.181	0.684	1.000	1.000	0.605	0.391
	Observed Number of Ad Impressions[c]	0	4	38	771	539,264	2,371	10,569
	Observed Number of Ad Impressions per Day	0.000	0.878	2.333	9.000	4,176	12.582	55.347
Value of Cookie per Lifetime Unit	Observed Value of Cookie per Day (in €)	0.000	0.000	0.002	0.006	0.990	0.006	0.015
	Uncensored Value of Cookie per Day (in €)	0.000	0.000	0.002	0.007	0.990	0.007	0.017
	Observed Value of Cookie per Ad Impression (in €, CPM)	0.000	0.340	0.643	0.924	113.890	0.696	0.829
Lifetime Value of Cookie	Observed (potentially censored) Lifetime Value of Cookie (in €)	0.000	0.003	0.022	0.498	331.048	1.428	5.234
	Predicted Censored Lifetime Value of Cookie for Observed Lifetime (in €)	0.000	0.003	0.022	0.556	398.183	1.622	6.007
	Mean Absolute Percentage Error (MAPE[d]) for Observed Lifetime	0.000	0.000	0.000	0.091	11.222	0.082	0.229
	Predicted Residual Lifetime Value of Cookie for Residual Lifetime (in €)	0.000	0.000	0.000	0.000	238.448	0.856	5.114
	Uncensored Lifetime Value of Cookie (in €) [e]	0.000	0.003	0.022	0.610	449.403	2.522	10.603

[a] Rounded to the next full day.
[b] We use a Weibull model to determine the expected residual lifetime for 13.123% of the cookies with potentially censored cookie lifetime. The uncensored average cookie lifetime of 279 days is 29.167% larger than the average observed cookie lifetime of 216 days in the data.
[c] 202 cookies were active on our sampling day but received no ad impressions.
[d] MAPE corresponds to the in-sample absolute difference between the cookie's observed lifetime value and the cookie's uncensored lifetime value divided by the cookie's observed lifetime value.
[e] We determine the uncensored cookie lifetime value using the regression from Eq. (1) (i.e., model 2 in Table 6).

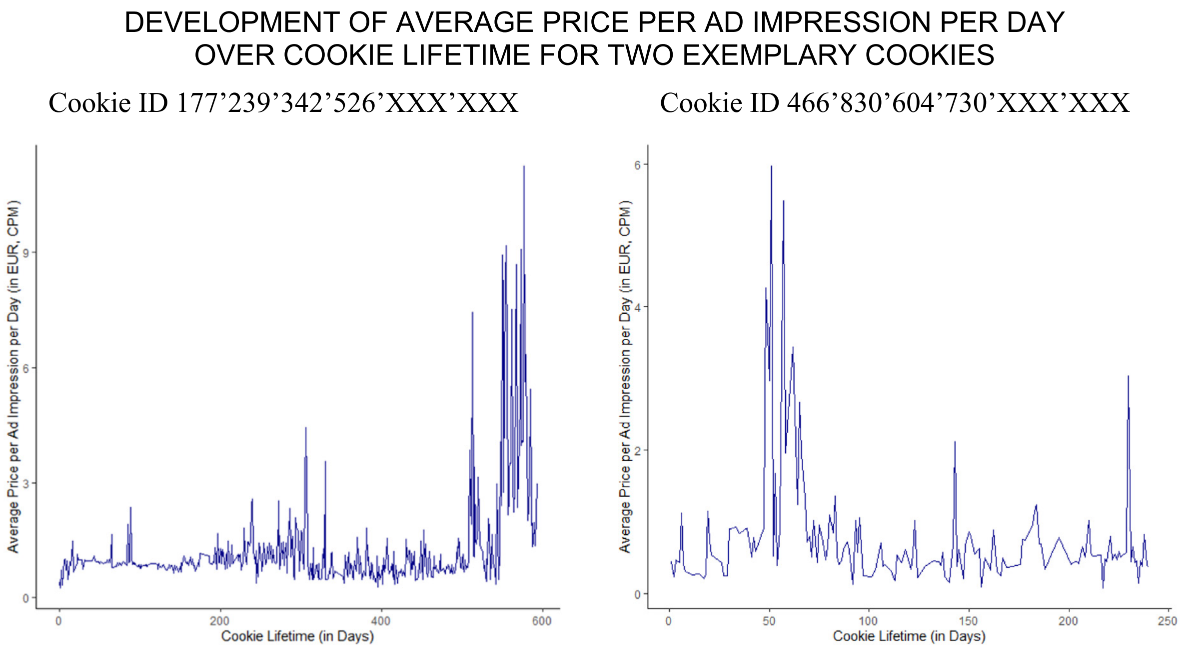

Fig. 5. Development of average price per ad impression per dayover cookie lifetime for two exemplary cookies.

the cookie was active on 514 days (86.824% of the observed days) and received 9,162 ad impressions. Thus, on average, 15.476 ad impressions per observed day.

Given that we observed the cookie last within seven days of the end of our observation period (July 16, 2016), we assume that the cookie lived longer than our observation period. Using a survival model, we predict that the cookie lived for another 481 days. Therefore, the uncensored lifetime of this cookie is 1,073 days. The observed mean price per ad impression was €1.181 CPM. The observed LVC (i.e., the sum of the prices paid by the advertisers) amounts to €10.823, giving us an observed average cookie value per day of €0.018. The predicted censored LVC is €12.248, yielding an absolute percentage error (APE) of 13.166%, which corresponds to the in-sample absolute difference between the observed and the predicted lifetime value of the cookie divided by the observed lifetime value of the cookie (=abs(€10.823 − €12.248)/€10.823)). This cookie's predicted residual lifetime value is €17.687, resulting in an uncensored lifetime value of €29.935 (=€12.248 + €17.687) and an uncensored average value of the cookie per day of €0.028 (=€29.935/1,073 days). Table 2 summarizes the descriptive statistics for this cookie.

In contrast, we find a negative relationship between cookie price and cookie lifetime for the cookie with the ID 466′830′604′730′XXX′XXX (see Fig. 5). On our sampling day (April 29, 2015), the cookie had an age of 104 days. However, we observe the cookie in our longitudinal data from January 15, 2015, to September 11, 2015, which amounts to an observed cookie lifetime of 239 days. During this time, the cookie was active for 150 days (62.762% of the observed days) and received 3,627 ad impressions (15.176 on average per observed day). Given that we observed the cookie last about ten months before the end of our observation period (July 16, 2016), we assume that we observed the entire lifetime of this cookie. The observed mean price per ad impression was €0.554 CPM. The observed LVC (i.e., the sum of the prices paid by the advertisers) amounts to €2.011, giving us an observed average cookie value per day of 0.008 (=€2.011/239 days). The predicted censored and, in this case, also uncensored lifetime value of this cookie is €2.366 (APE: 17.653%), which yields an uncensored average cookie value per day of €0.010 (=€2.366/239 days). Table 2 summarizes the descriptive statistics for this cookie.

Summary statistics of the sample. Our descriptive analysis of the data, as summarized in Table 3, shows a mean cookie age on our sampling day of 105 days (median: 16 days). We also find a mean cookie lifetime of 216 days (median: 68 days).

To account for potential censoring of observed cookie lifetime, we use a survival model to compute the predicted residual mean lifetime for those cookies that received ad impressions (and thus were active) within the first and last seven days of our observation period. Based on this cutoff criterion, 13.123% of all cookies are (potentially) censored: 5.572% are left-censored (i.e., we are only able to observe cookie death), 5.271% are right-censored (i.e., we are only able to observe cookie birth), and 2.280% are both right- and left-censored (i.e., we observe neither cookie birth nor cookie death).

We use the "flexsurv" package in R to determine the probability density for the death of a cookie at time t:

$$f(t|\mu, \alpha),\ t \geq 0,$$

where μ is the primary parameter of interest, which governs the mean or location of the underlying distribution, and α determines the variance or shape of the distribution. We do not consider any additional covariates in this analysis. Precisely, we fit a parametric Weibull and parametric Lognormal survival model to the data, consisting of the observed lifetime per cookie and an indicator variable of whether the observed lifetime per cookie is censored, as defined above.

Our main analysis uses a seven-day cut-off criterion to define whether a cookie is censored. The choice of the threshold determines the type-1 error, i.e., considering a cookie is dead although it is still alive (e.g., because it would appear again after eight days). So, choosing a low threshold, such as our seven days, yields an economic loss of cookie lifetime restrictions that is lower than if we choose a more extended threshold. However, increasing the threshold to 28 days only slightly increases our loss estimates, providing confidence that the choice of the threshold does not impact our results too strongly (see Web Appendix W3 for details).

Furthermore, we only use cookies with an observed cookie lifetime of more than seven days to fit the survival models. Otherwise, we mix up very short lifetimes with very long lifetimes, and the short lifetimes will not impact our simulation results. This restriction reduces our sample size for the survival analysis to 32,189 cookies. We report the resulting model parameters and fit measures in Table 4. We select the Weibull model for further analysis because it fits the data better (Weibull LL: −179,085.300, Akaike information criterion [AIC]: 358,174.600, Bayesian information criterion [BIC]: 358,191.400 vs. Lognormal LL: −179,653.600, AIC: 359,311.300, BIC: 359,328.000). We validate this approach in Web Appendix W3.

We find the residual mean cookie lifetime T per cookie *i* for all 13.123% censored cookies by following Meeker & Escobar (1998) approach:

$$\mathrm{T}_i(x_i) = \frac{\int_{x_i}^{\infty} S(t_i)dt_i}{S(x_i)} = \frac{\int_{x_i}^{\infty} \exp(-(t_i/\mu)^{\alpha})dt_i}{\exp((-(x_i/\mu)^{\alpha})},$$

where x_i corresponds to the observed and potentially censored lifetime of cookie *i*, $S(t_i) = \exp(-(t_i/\mu)^{\alpha})$ corresponds to the survival function of the Weibull distribution that yields the probability that cookie *i* will survive beyond a specific time t_i, μ is the location parameter and α the shape parameter of the Weibull distribution. The resulting mean cookie lifetime adjusted for censoring is 279 days (median: 68 days).

Table 4
Survival model parameters and fit measures.

Model	Shape Parameter α [95%-CI]	SE	Scale Parameter μ [95%-CI]	SE	LL	AIC	BIC
N = 54,127							
Weibull	0.979[0.969;0.990]	0.005	463.321 [457.501;469.215]	2.988	−179,085.300	358,174.600	358,191.400
Lognormal	5.633[5.617;5.480]	0.008	1.389[1.380;1.402]	0.006	−179,653.600	359,311.300	359,328.000

Notes: We only consider cookies with an observed cookie lifetime of more than seven days to fit the survival models resulting in a sample size of 32,189. CI: confidence interval; SE: standard error; LL: loglikelihood value; AIC: Akaike information criterion; BIC: Bayesian information criterion.

The cookies of our sample were active on average on 74 of the observed days (median: 8 days), yielding an average share of observed active days at the observed days of 60.500% (median: 68.400%). The cookies also differ regarding the number of ad impressions served. They reach an average number of ad impressions of 2,371 (median: 38) and an average number of ad impressions per observed day of 12.582 (median: 2.333).

We calculate that cookie values per day in our data set reach a mean value of €0.006 (median €0.002). We also compute the average uncensored cookie value per day at €0.007 (median: €0.002). Finally, the observed mean value per 1,000 ad impressions paid by the purchasing advertiser is €0.696 CPM, and the median price is €0.643 CPM. For the observed cookie lifetime value, we find a mean lifetime value of €1.428 (median: €0.022). The mean predicted censored lifetime value is €1.622 (median: €0.022). We calculate a mean APE (MAPE) of 0.082 (median: 0.000), corresponding to the in-sample absolute difference between the observed lifetime value of the cookie and its predicted lifetime value divided by its observed lifetime value. The mean predicted residual lifetime value amounts to €0.856 (median: 0.000). The uncensored cookie lifetime value yields a mean value of €2.522 (median: €0.022).

6. Simulation study

6.1. Setup of simulation study

We use a numerical example to outline the procedure of our simulation study to determine the potential economic loss associated with a restriction of cookie lifetime. In this example, we look at three cookies, each receiving one ad impression per day.

Cookie A lives for 22 (active) days. The price of the ad impression for this cookie is \$0.09 on the first day. It increases by \$0.01 on each additional day. This price measures the value of the cookie for the publisher. It is \$0.09 on day 1, \$0.10 on day 2, \$0.11 on day 3, and so forth, until \$0.30 on day 22. The LVC is thus the sum of the cookie values per day across the 22 days (\$0.09 + \$0.10 + \$0.11 + ... + \$0.30 = \$4.29).

What would be the economic loss of a restriction of this cookie's lifetime to ten days (i.e., 45% of its original lifetime)? There is no economic loss for the first ten days. After ten days, the cookie is deleted, but a new cookie is born. We assume that the user does not change her browsing behavior because of the automatic deletion of the cookie due to the cookie lifetime restriction, in line with Drèze & Zufryden (1998) finding that tracking cookies' presence or absence does not influence users' browsing behavior. Furthermore, we assume that the user consents again to being tracked.

So, the new cookie will have a value on its first day equal to the value of the old cookie on its first day—the same holds for the second day, the third day, and so forth. Thus, for the next ten days, the new cookie has a value per day that is 10 × \$0.01 = \$0.10 per day lower than the old cookie. After 20 days, including ten days of the new cookie, the new cookie is deleted and reborn with a value on its first day equal to the value of the old cookie on its first day. Thus, for the last two days of the cookie's life, days 21 and 22, the reborn cookie has a value per day 20 × \$0.01 = \$0.20 lower than the old cookie. Overall, the lifetime restriction of the cookie leads to an economic loss of 10 days times \$0.10 per day and 2 days times \$0.20 per day, or \$1.40. As a result, LVC decreases by \$1.40, from \$4.29 to \$2.89 (−33%).

This decrease diminishes publishers' revenue if the advertisers move these savings to other (more efficient) advertising media (e.g., publishers that allow targeting based on user logins). If, however, advertisers operated with fixed budgets and aimed to spend the entire budget assigned to online display advertising, they would start to spend the savings on other online display ads whose prices would increase. In such a case, the losses for publishers would be lower. Therefore, we consider our calculated values to be the upper bounds of an economic loss to publishers.

The numerical example outlines that we can easily derive the daily increase in the cookie value by estimating a regression with the value per day as a dependent variable and time (here: days) as an independent variable. The respective result for this regression is value per day = \$0.08 + \$0.01 × day. Thus, the time parameter (i.e., the parameter for the day) represents the value increase per day of a cookie, and the constant (here: \$0.08) essentially represents the value of a cookie that is independent of time (here: days). It reflects the value of a user without a cookie.

The value of the cookie beyond the constant essentially reflects the incremental value that builds over time. It reflects the cookie's value because it enables the advertiser to track, profile, segment, and target users across multiple websites and determine each impression's effectiveness. The positive value corresponds to the notion that older cookies are more valuable to the advertising industry because they contain more information, leading to higher prices in real-time bidding advertising auctions (e.g., Beales & Eisenach, 2014; Casale, 2015; Neumann et al., 2019). The value of the constant reflects that advertisers also derive value from ads that do not require tracking users over time.

Another cookie in the numerical example, Cookie B, lives for 10 days. The ad impressions for this cookie always sell at \$0.19 per day, such that the value per day is unaffected by time, and the LVC is \$1.90 (=10 × \$0.19). The regression for this cookie yields a constant of \$0.19 and a time parameter of zero. As the value of this cookie does not increase over time, restricting the cookie's lifetime will not affect the value per day and, thus, the lifetime value of the cookie. Such a case could occur when advertisers do not value a user's growing browsing history over time but are, for example, merely interested in advertising in attractive contexts.

Table 5
Economic loss of a ten-day lifetime restriction in our numerical example.

Cookie Lifetime Restriction	*Fulfillment of Condition I*[a]				*Fulfillment of Conditions I and II*[b]		*Fulfillment of Conditions I and III*[c]		*Economic Loss per Cookie that Fulfills Conditions I and II*			*Economic Loss per Cookie that Fulfills Conditions I and III*			*Economic Loss per Cookie*		
	No. Cookies	% (N = 3)	% Cond. II[d]	% Cond. III[e]	No Cookies	% (N = 3)	No Cookies	% (N = 3)	Average LVC	Average Absolute	Average % Loss	Average LVC	Average Absolute	Average % Loss	Average LVC	Average Absolute	Average % Loss
Ten days	2	67%	50%	50%	1	33%	1	33%	\$4.29	\$1.40	33%	\$3.69	−\$0.80	−22%	\$3.29	\$0.20	6%

Reading example: 2 cookies (i.e., 67% of all cookies) fulfill condition I (i.e., have a cookie lifetime that is larger than the imposed cookie restriction of ten days), and 50% of these cookies either fulfill condition II or condition III. 1 cookie (i.e., 33% of all cookies) fulfills conditions I and II (i.e., increase in value per day). One cookie (i.e., 33% of all cookies) fulfills conditions I and III (i.e., decreases in value per day). The average cookie that fulfills conditions I and II has an average cookie lifetime value (LVC) of \$4.29 and loses under a ten-day lifetime restriction an average of \$1.40 (i.e., 33% of the total average LVC). The average cookie that fulfills conditions I and III has an LVC of \$3.69 and loses under a ten-day lifetime restriction on average −\$0.80 (i.e., −22% of the total average LVC). The average cookie in our sample has an LVC of \$3.29 and loses, on average, a value of \$0.20 (i.e., 6%) under a ten-day cookie restriction policy.

[a] Condition I refers to the number of cookies with a cookie lifetime larger than the cookie lifetime restriction. Condition II refers to the number of cookies that increase in value per day. Condition III refers to the number of cookies that decrease in value per day. We consider the value increase (decrease) per day to be positive (negative) if the sign of the time parameter in our regression model is positive (negative) and the value of the parameter is significant (at a 1% level).

[b] Conditions I and II refer to the number of cookies that fulfill condition I and increase their values per day.

[c] Conditions I and III refer to the number of cookies that fulfill conditions I and decrease their values per day.

[d] Share of those cookies that also fulfill condition II (P(Cond.II | Cond. I) = P(Cond. I & II)/P(Cond. I).

[e] Share of those cookies that also fulfill condition III (P(Cond.III | Cond. I) = P(Cond. I & III)/P(Cond. I).

Our third cookie, Cookie C, has a lifetime of 18 days. The price of its ad impression on the first day is \$0.29 and decreases by \$0.01 for each additional day. Thus, the cookie generates a value of \$0.29 on day 1, \$0.28 on day 2, \$27 on day 3, and so forth, and, thus, \$0.12 on day 18. The LVC is the sum of the daily cookie values (\$0.29 + \$0.28 + \$0.27 + ... + \$0.12) = \$3.69.

In contrast to Cookie A, this cookie would not incur an economic loss but a gain due to a cookie lifetime restriction of ten days (which represents only 56% of its original lifetime). The reason could be that the advertiser learns that the user has less value (e.g., by not purchasing despite clicking on ads). The lifetime restriction of this cookie now leads to an economic loss equal to the sum of 8 days × −\$0.10 per day, thus −\$0.80. As a result, LVC is increased by \$0.80 from \$3.69 to \$4.49 (+22%).

If the study only involved those three cookies, then the overall results would be that the sum of LVC without the lifetime restriction is \$9.88 (=\$4.29 + \$1.90 + \$3.69) and \$9.28 (=\$2.89 + \$1.90 + \$4.49) with the lifetime restriction, so \$0.60 lower. The average LVC decreased from \$3.29 to \$3.09 (−\$0.20). Thus, the restriction in cookie lifetime to ten days causes a total economic loss of \$0.60 and a loss per cookie of \$0.20 (6%).

Table 5 summarizes these results, as does Table 7 for our simulation analysis of the 54,127 cookies in our sample (Panel 1). Web Appendix W5 illustrates how our simulation study accommodates that (1) the predicted lifetime is longer than the observed lifetime, (2) cookies are not active every day, and (3) eliminates differences in the daily number of impressions per cookie across time.

6.2. Results of regression analysis

We use the procedure described for the numerical example to determine the potential economic loss with a restriction of cookie lifetime ranging between 30 and 720 days. In its first step, this procedure requires running a regression for each cookie that determines the change in value per time unit (e.g., day). In its second step, we use the results of all regressions to derive the economic loss in the simulation analysis.

Setup of regression analysis. We propose the following regression to model the incremental effect of time on the value of the cookie:

$$VALUE_{i,t} = \beta_{i,0} + \beta_{i,1} DAYCOUNT_{i,t} + \beta_{i,2} ADINVENTORY_{i,t} + \varepsilon_{i,t}, \tag{1}$$

where $VALUE_{i,t}$ is the value of the cookie i on day t (here measured by the average price per ad impression on day t). $DAYCOUNT_{i,t}$ is a variable with a value of 1 on the first day that the cookie lives, 2 on the second day, 3 on the third day, and so forth. The parameter of this variable is our time parameter that reflects the incremental effect of time (here: day) on the value of the cookie (here: the average of the prices per ad impression per day). Ultimately, this parameter captures the value of behavioral targeting for advertisers because it is a proxy for the value of the information collected on a specific cookie over time. We consider the incremental effect as positive (negative) if the value of the time parameter is positive (negative) and significant (at a 1% level). If the value is insignificant, we can conclude that there is no incremental effect.

As advertisers do not only purchase ads on our ad exchange based on the capacity to conduct behavioral targeting, we add control variables for $ADINVENTORY_{i,t}$ characteristics (i.e., media type, which captures the share of video ads over regular display ads per day; fold position, which captures the share of ads displayed above the fold per day; and the share of retargeted ad impressions per day). $\varepsilon_{i,t}$ is the error term.

Given that we estimate one regression per user, our regression analysis accounts for time-invariant individual differences across users, that is, user-fixed effects (e.g., operating system, browser type, browser language). We regress separately for each cookie the value per day (measured by the average price for all ad impressions by the advertisers on that day) on the variable $DAYCOUNT_{i,t}$. Thus, we run an ordinary least-squares (OLS) regression for each cookie (54,127 cookies in our sample).

We validate this approach using the logarithmic values for our dependent variable and different sets of independent variables. Web Appendix W4 reports the estimates of our cookie-specific regressions. It shows, for example, that our preferred model 2, in which we regress the average price per ad impression per day on day count and additional ad inventory characteristics, yields the best MAPE, which corresponds to the in-sample absolute difference between the observed cookie's lifetime value and its predicted lifetime value divided by its observed lifetime value in our sample (mean: 0.175, median: 0.100). In addition, it shows that our preferred model 2 obtains a better fit than model 1 (which does not consider ad inventory characteristics), as measured by AIC (model 1 mean: 236.820 vs. model 2 mean: 230.750; model 1 median: 106.460 vs. model 2 median:101.780) and BIC (model 1 mean: 243.970 vs. model 2 mean: 240.380; model 1 median: 112.780 vs. model 2 median: 110.350). Concerning model fit, the log-linear model (model 4) and the quadratic model (model 5) have a slightly better R-squared than model 2 but have a worse (model 4) or comparable (model 5) Akaike information criterion (AIC) and Bayesian information criterion (BIC).

Linear model without additional covariates. We summarize the results of our regression analysis in Table 6. In model 1, we find a positive incremental effect for 6,719 cookies. They represent 12.413% of all cookies in our sample. They received 48.309% of all ad impressions, with an average number of ad impressions per cookie of 9,228. Their mean uncensored cookie lifetime is 628 days, and the average uncensored cookie's lifetime value is €9.965.

We find a significant negative incremental effect for 4,357 cookies, representing 8.050% of all cookies in our sample. They received 17.956% of all ad impressions, with an average number of ad impressions per cookie of 5,289. Their mean cookie lifetime is 610 days, and the average uncensored cookie lifetime value is €5.175.

For most cookies (43,051, i.e., 79.537%), the time parameter is insignificant, i.e., zero. Specifically, 10,987 cookies, or 20.299% of all cookies, have this "zero effect". Nevertheless, these cookies received 33.739% of all ad impressions, with an average number of ad impressions per cookie of 1,006. Their mean uncensored cookie lifetime is 191 days, and the average uncensored cookie lifetime value is €1.032.

Table 6
Regression results of impact of time on the average price per ad impression per day.

	Significant Positive Incremental Effect		Significant Negative Incremental Effect		Nonsignificant Incremental Effect	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Dependent Variable (in €; CPM)			Average Price per Ad Impression per Day			
Constant	0.500	0.622	1.146	1.137	0.000	0.000
[95%- CI]	[0.332; 0.674]	[0.415; 0.845]	[0.943; 1.335]	[0.887; 1.359]	[0.000; 0.000]	[0.000; 0.000]
Time Parameter	0.001	0.001	−0.001	−0.001	0.000	0.000
[95%- CI]	[0.000; 0.002]	[0.000; 0.002]	[−0.002; −0.000]	[−0.002; −0.000]	[0.000; 0.000]	[0.000; 0.000]
Additional Covariates	N	Y	N	Y	N	Y
Number of Cookies	6,719	6,932	4,357	4,109	43,051	43,086
(% of all cookies)	(12.413%)	(12.807%)	(8.050%)	(7.591%)	(79.537%)	(79.602%)
Total Number of Ad Impressions	61,996,813	68,213,838	23,043,923	19,288,148	43,293,332	40,832,082
(% of all)	(48.309%)	(53.153%)	(17.956%)	(15.030%)	(33.739%)	(31.817%)
Ad Impressions per Cookie	9,228	9,841	5,289	4,695	1,006	948
Mean (Median) Uncensored Cookie Lifetime (in days)	628 (498)	633 (504)	610 (473)	608 (468)	191(5)	190(6)
Mean (Median) Uncensored Cookie Lifetime Value (in €)	9.965(2.998)	10.530(3.078)	5.175(1.073)	4.876(1.058)	1.032 (0.009)	1.010 (0.009)
Number of Cookies with Significant Zero Effect (% of all cookies)	–	–	–	–	10,987 (20.299%)	10,951 (20.232%)

Notes: Unless otherwise noted, this table reports our sample's median estimates from 54,127 cookie-specific regressions. We consider the value increase (decrease) per day to be positive (negative) if the sign of the time parameter is positive (negative) and the value of the parameter is significant (at a 1% level). If the value is insignificant, then we conclude that there is no increase (decrease) in value over time. We apply a small Winsorization to accommodate outliers and replace the most extreme values with the 99% quantile of the respective parameter estimate. Model 1 only includes the time parameter (here: day count) as the independent variable. Model 2 includes the time parameter (here: day count) and additional covariates (i.e., ad inventory characteristics) as independent variables.

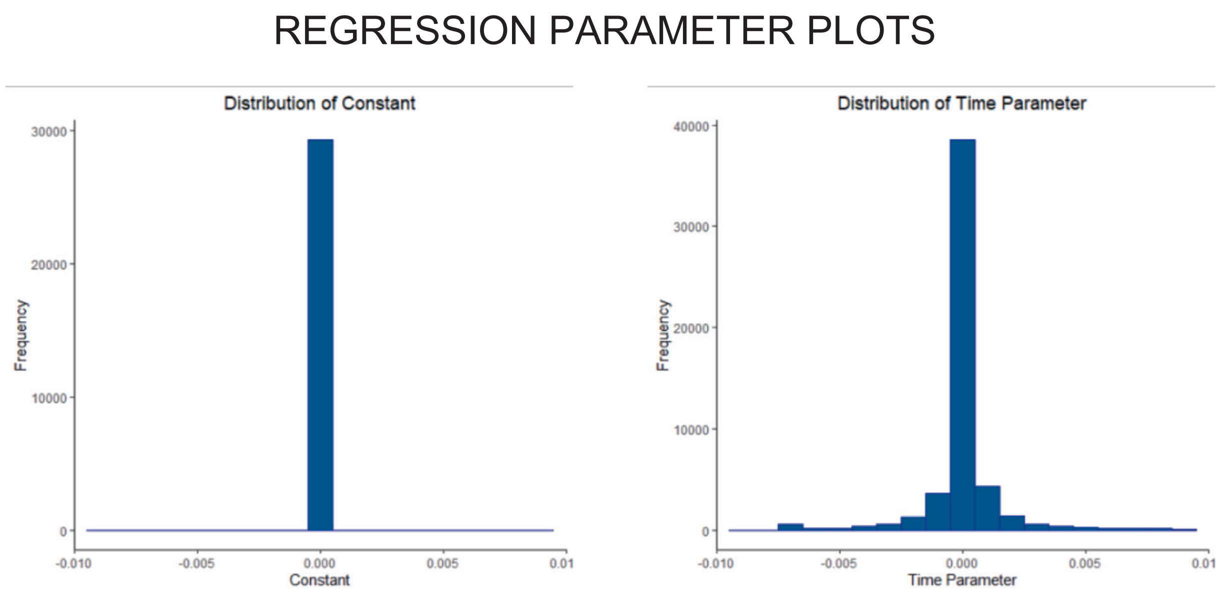

Fig. 6. Regression parameter plots. Notes: Dependent variable: average price per ad impression (in €, CPM). We apply a small Winsorization to accommodate outliers and replace the most extreme values with the 99% quantile of the respective parameter estimate. Distribution of constant: Min = 0.000, Median = 0.000, Mean = 0.409, Max = 2.220. Distribution of time parameter: Min = − 0.007, Median = 0.000, Mean = 0.000, Max = 0.016. Plots are restricted to [−0.010; 0.010] for readability.

Table 7
Economic loss of various cookie lifetime restrictions.

Cookie Lifetime Restriction	*Fulfillment of Condition I*[a]				*Fulfillment of Conditions I & II*[b]		*Fulfillment of Conditions I & III*[c]		*Economic Loss per Cookie that Fulfills Conditions I & II*			*Economic Loss per Cookie that Fulfills Conditions I & III*			*Economic Loss per Cookie*		
	No. Cookies	% of all Cookies Survived (Deleted)	% Cond. II[d]	% Cond. III[e]	No Cookies	% of all Cookies	No Cookies	% of all Cookies)	Average LVC	Average Absolute [95%-CI]	Average % Loss [95%-CI]	Average LVC	Average Absolute [95%-CI]	Average % Loss [95%-CI]	Average LVC	Average Absolute [95%-CI]	Average % Loss [95%-CI]
Panel 1: Simulation results based on Sample 1 (N = 54,127): Regression of average price per ad impression per day on day count + additional covariates (Model 2)																	
30 days	29,647	54.773% (45.227%)	22.410%	13.769%	6,644	12.275%	4.082	7.542%	€10.966	€4.135 [4.074; 4.196]	37.707% [37.149; 38.265]	€4.906	−€2.082[−2.122; −2.041]	−42.434% [−43.260; −41.609]	€2.522	€0.351 [0.340; 0.361]	13.916% [13.480; 14.312]
60 days	27,561	50.919% (49.081%)	22.662%	14.608%	6,246	11.540%	4,026	7.438%	€11.604	€4.234 [4.163; 4.305]	36.491% [35.879; 37.102]	€4.969	−€1.947[−1.986; −1.907]	−39.172% [−39.972; −38.373]	€2.522	€0.344 [0.333; 0.355]	13.638% [13.202; 14.074]
90 days	25,743	47.560% (52.440%)	23.164%	15.305%	5,963	11.017%	3,940	7.279%	€12.078	€4.209 [4.139; 4.270]	34.851% [34.272; 35.430]	€5.061	−€1.830[−1.870; −1.791]	−36.167% [−36.945; −35.389]	€2.522	€0.330 [0.320; 0.341]	13.083% [12.687; 13.519]
120 days	24,191	44.693% (55.307%)	23.600%	15.692%	5,709	10.547%	3,796	7.013%	€12.527	€4.200 [4.130; 4.270]	33.531% [32.971; 34.092]	€5.227	−€1.771 [−1.812−−1.731]	−33.890% [−34.661; −33.119]	€2.522	€0.319 [0.309; 0.329]	12.647% [12.251;13.044]
360 days	15,329	28.320% (71.680%)	28.234%	16.413%	4,328	7.996%	2,516	4.648%	€15.332	€3.785 [3.714; 3.856]	24.686% [24.226; 25.146]	€7.025	−€1.883[−1.949; −1.817]	−26.800% [−27.737; −25.864]	€2.522	€0.215 [0.206; 0.224]	8.524% [8.167; 8.881]
720 days	7,953	14.693% (85.307%)	35.986%	17.805%	2,862	5.288%	1,416	2.616%	€20.401	€3.796 [3.723; 3.869]	18.607% [18.248; 18.966]	€9.863	−€2.454[−2.569; −2.339]	−24.877% [−26.044; −23.711]	€2.522	€0.137 [0.130; 0.143]	5.432% [5.154; 5.669]
Panel 2: Simulation results based on Sample 2 (N = 44,400): Regression of average price per ad impression per day on day count + additional covariates (Model 2)																	
30 days	25,624	57.712%(42.288%)	23.127%	15.848%	5,926	13.347%	4,061	9.146%	€11.068	€4.291 [4.223; 4.359]	38.766% [38.152; 39.380]	€4.802	€-2.016 [−2.057; −1.975]	−41.989% [−42.839; −41.138]	€2.799	€0.388 [0.375; 0.401]	13.861% [13.396; 14.325]
60 days	23,830	53.671%(46.329%)	23.760%	16.513%	5,662	12.752%	3,935	8.863%	€11.542	€4.236 [4.165; 4.307]	36.703% [36.089; 37.317]]	€4.940	€-1.942 [−1.983; −1.902]	−39.319% [−40.142; −38.496]	€2.799	€0.368 [0.355; 0.381]	13.148% [12.683; 13.612]
90 days	22,358	50.356%(49.644%)	24.179%	17.014%	5,406	12.176%	3,804	8.568%	€12.022	€4.231 [4.158; 4.304]	35.191% [34.586; 35.796]	€5.078	€-1.862 [−1.902; −1.822]	−36.665% [−37.459; −35.871]	€2.799	€0.356 [0.343; 0.368]	12.719% [12.254; 13.148]
120 days	21,081	47.480%(52.520%)	24.534%	17.433%	5,172	11.649%	3,675	8.277%	€12.465	€4.225 [4.151; 4.298]	33.893% [33.302; 34.484	€5.230	€-1.789 [−1.830; −1.749]	−34.213% [−34.988; −33.437]	€2.799	. €344 [0.332; 0.356]	12.290% [11.861; 12.719]
360 days	13,313	29.984%(70.016%)	28.288%	17.832%	3,766	8.482%	2,374	5.347%	€15.859	€3.957 [3.878; 4.036]	24.951% [24.453; 25.448]	€7.198	€-1.926 [−1.994; −1.859]	−26.764% [−27.705; −25.822]	€2.799	€0.233 [0.222; 243]	8.324% [7.931; 8.681]
720 days	6,981	15.723%(84.277%)	35.625%	19.267%	2,487	5.601%	1,345	3.029%	€21.321	€3.992 [3.911; 4.073]	18.722% [18.343; 19.102]	€9.936	€-2.408 [−2.518; −2.299]	−24.239% [−25.341; −23.137]	€2.799	€0.151. [0.143; 0.158]	5.394% [5.108; 5.644]

Reading example: 29,647 cookies (i.e., 54.773% of all cookies survived the imposed cookie lifetime restriction of 30 days whereas 45.227% were deleted)) fulfill condition I (i.e., have a cookie lifetime larger than the imposed cookie lifetime restriction of 30 days), and 22.410% of these cookies fulfill condition II and 13.769% condition III. 6,644 cookies (i.e., 12.275% of all cookies) fulfill conditions I and II (i.e., increase in value per day). 4,082 cookies (i.e., 7.542% of all cookies) fulfill conditions I and III (i.e., decrease in value per day). The average cookie that fulfills conditions I and II has an average cookie lifetime value (LVC) of €10.966 and loses under a 30-day lifetime restriction on average €4.135 (or 37.707% of the total average LVC). The average cookie that fulfills conditions I and III has an average LVC of €4.906 and loses under a 30-day lifetime restriction on average −€0.2.082 (i.e., −42.434% of the total average LVC). The average cookie in our sample has an LVC of €2.522 and loses, on average, a value of €0.351 (or 13.916%) under a 30-day cookie lifetime restriction policy.

[a] Condition I refers to the number of cookies with a cookie lifetime larger than the cookie lifetime restriction. Condition II refers to the number of cookies that increase their values per day. Condition III refers to the number of cookies that decrease their values per day.

[b] Conditions I and II refer to the number of cookies that fulfill condition I and increase their values per day.

[c] Conditions I and III refer to the number of cookies that fulfill condition I and decrease their values per day.

[d] Share of those cookies that also fulfill condition II (P(Cond.II | Cond. I) = P(Cond. I & II)/P(Cond. I).

[e] Share of those cookies that also fulfill condition III (P(Cond.III | Cond. I) = P(Cond. I & III)/P(Cond. I).

Linear model with additional covariates. In model 2, our preferred model specification (see Eq. (1)), we find a positive incremental effect for 6,932 cookies. They represent 12.807% of all cookies in our sample. They received 53.153% of all ad impressions, with an average number of ad impressions per cookie of 9,841. Their mean uncensored cookie lifetime is about 633 days, and the average uncensored cookie's lifetime value is €10.530.

We find a significant negative incremental effect for 4,109 cookies, representing 7.591% of all cookies in our sample. They received 15.030% of all ad impressions, with an average number of ad impressions per cookie of 4,695. Their mean uncensored cookie lifetime is 608 days, and the average uncensored cookie lifetime value is €4.876.

The time parameter is insignificant for most cookies (43,086 or 79.602%). Specifically, 10,951 cookies, or 20.232% of all cookies, have a zero effect in the sample. Nevertheless, these cookies received 31.817% of all ad impressions, with an average number of ad impressions per cookie of 948. Their mean uncensored cookie lifetime is 190 days, and the average uncensored cookie lifetime value is €1.010.

We provide the regression parameter plots for our primary model (model 2 in Table 6) in Fig. 6. We report the distribution of the constant (Min = 0.000, Median = 0.000, Mean = 0.409, Max = 2.220) as well as the distribution of the time parameter (Min = − 0.007, Median = 0.000, Mean = 0.000, Max = 0.016). In Web Appendix W6, Table W6.1, we additionally show the results of two regressions to describe which user-level characteristics explain the constants and time parameters. These descriptive regressions show, for example, that the constant is significantly larger for cookies from a national cookie (i.e., a user from the country of our ad exchange) using a mobile device, a Chrome operating system, and a Chrome browser. It also shows that the time parameter is significantly lower for cookies with a BlackBerry or Chrome operating system.

6.3. Results of simulation study

We next evaluate the impact of different restrictions on the lifetime of cookies. Such a restriction only affects the value of a cookie if the cookie fulfills two conditions. First, the cookie's lifetime is longer than the restriction of the cookie lifetime (condition I). Second, the time parameter of the regression is either significantly positive (condition II) or significantly negative (condition III). As outlined in our numerical example, cookies with a non-significant increase in value over time will not impact our loss (gains) calculations.

Table 7 reports the shares of cookies that fulfill either conditions I and II or conditions I and III under different cookie lifetime restriction policies and the share of the lost value of all cookies. A 30-day restriction will affect 54.773% of our sample cookies. Of those, 22.410% also have a positive incremental value per day (which represents 12.275% of all cookies in our sample). These cookies have an average lifetime value of €10.966, and they lose, on average, €4.135 or 37.707% of their average lifetime value. Further, 13.769% have a negative incremental value per day (which represents 7.542% of all cookies in our sample). These cookies have an average lifetime value of €4.906, and their loss is, on average, −€2.082 or − 42.434% of their average lifetime value. The respective economic loss for all cookies in our sample with an average lifetime value of a cookie of €2.522 is €0.351 or 13.916%. In Table 7, we also report the results of a 60, 90, and 120-day cookie lifetime restriction, which leads to an average percentage loss of 13.638%, 13.083%, and 12.647%, respectively.

The 360-day restriction advocated by the European Union (Article 29 Data Protection Working Party 2010) would affect 28.320% of cookies in our sample. Of those cookies, 28.234% also have a positive incremental value per day, such that the policy affects 7.996% of all cookies. These cookies have an average lifetime value of €15.332, and their loss is, on average, €3.785 or 24.686%. Further, 16.413% of cookies have a negative incremental value per day, representing 4.648% of cookies in our sample. These cookies have an average lifetime value of €7.025, and their loss is, on average, −€1.883, respectively −26.800%. The respective economic loss for all cookies in our sample with an average lifetime value of a cookie of €2.522 is €0.215 or 8.524%.

Finally, a 720-day restriction, as some industry players such as Facebook have implemented, would affect 14.693% of cookies in our sample. Of those cookies, 35.986% also have a positive incremental value per day. Thus, the policy affects about 5.288% of cookies. These cookies have an average lifetime value of €20.401, and their loss is, on average, €3.796 or 18.607%. Further, 17.805% of cookies have a negative incremental value per day, representing 2.616% of cookies in our sample. These cookies have an average lifetime value of €9.863, and their loss is, on average, −€2.454 or −24.877%. The economic loss for all cookies in our sample with an average lifetime value of €2.522 is €0.137 or 5.432%.

6.4. Robustness of results of simulation study

To examine the robustness of the results, we use the same approach as for the first sample to select a second sample. For this second sample, we randomly drew 44,400 users from another randomly selected day (i.e., Friday, June 12, 2015) at the center of the data set. We again gathered all available information for these users for our entire observational period. This selection leaves us with 105,198,803 auctions that each sell one ad impression. The random sample represents 1% of all cookies on our sampling day.

We obtain similar results for our second sample (see Table 7, Panel 2). For example, the resulting average percentage loss of a 30-day cookie lifetime restriction is 13.861%, 13.148% for a 60-day restriction, 12.719% for a 90-day restriction, 12.290% for a 120-day restriction, 8.324% for a 360-day restriction, and 5.394% for a 720-day restriction. Overall, the results of the second sample are statistically indistinguishable from the first sample, which supports the robustness of our results. The detailed results from the second sample are available in Web Appendix W7.

7. Summary of results and implications

Tracking technologies such as cookies track what users do online, making them a central concern of many privacy debates. However, little is known about cookies, particularly their lifetime, their value, and the evolution of their value over time. This lack of knowledge makes a profound discussion about cookie restrictions challenging, which is unsatisfying for regulators and the advertising industry. Methodologically, we develop an approach to quantifying the potential economic loss of lifetime restrictions to online tracking, which applies to other data sets that contain ad prices (e.g., data sets from other ad exchanges). Our approach can also apply to restrictions of other tracking technologies, such as digital fingerprinting and login data.

Our analysis of 54,127 cookies covering approximately 128 million ad impressions over ~2.5 years shows a mean uncensored cookie lifetime of 279 days (9.3 months) and a median of 68 days (2.3 months). On average, 45.227% of cookies are deleted within one month, 49.081% within two months, 52.440% within three months, 55.307% within four months, 71.680% within 12 months, and 85.307% within 24 months. This finding indicates that a restriction of cookie lifetime to 12 months, as suggested, for example, by the European Union for the upcoming ePrivacy Regulation, and is, for example, already implemented in Italy, would affect 28.320% of all cookies (as those cookies live longer than 12 months). A restriction to 24 months, as implemented in Spain and by advertising industry stakeholders (e.g., Facebook), would affect only 14.693% of the cookies.

Our simulation study reveals that the potential economic loss to publishers of restricting cookie lifetimes to one year, as the European Union proposes (Council of the European Union, 2021), is 8.524% of the cookies' total lifetime value. In light of the €10.6 billion cookie-based display ad revenues in the European Union (Interactive Advertising Bureau, 2017), such a policy could incur a yearly loss of approximately €904 million in display ad revenues, which is equivalent to a potential yearly economic loss per EU internet user of €2.082 (see Table 8 for an overview). A two-year restriction would cut 5.432% of the cookies' lifetime value. Such a restriction policy could affect €576 million of the EU cookie-based yearly display ad revenues and could incur a potential yearly economic loss per EU internet user of €1.327.

Our results contrast Chiou & Tucker (2021), who find no significant impact of a shorter data retention policy on the accuracy of search engine results. However, many searches are unique and outline precisely what the user intends to find. So, historical data may be of less value in search than in display advertising.

So, what are the implications for the marketing strategies of publishers? First, publishers learn that cookie lifetime restrictions of 12 or 24 months will not affect most users because they delete their cookies within 12 (71.680%) and 24 (85.307%) months. Therefore, any proposed or adopted regulation that provides longer lifetimes for cookies is unlikely to have any substantive impact on many publishers and users. Second, publishers learn about the size of the potential economic loss of providing more privacy, which is about a €2 yearly loss per user in case of a one-year cookie lifetime restriction. So, publishers would be indifferent between (i) a shorter lifetime of cookies and a subscription of all users at a yearly price of €2 or (ii) an unlimited lifetime and a free subscription. Publishers could also invest more decisive in alternative targeting strategies, e.g., contextual targeting. In discussions with regulators, they can use the €2 potential yearly loss per user to discuss a compensation value for providing more privacy. Such a compensation value could also be in the users' interest because it would enable publishers to provide higher-quality content (Shiller, Waldfogel, & Ryan, 2018). Alternatively, publishers could offer users a share of their advertising revenues if they consent to be tracked for a more extended (or infinite) period.

Additionally, publishers could offer users more choices when asking for their consent. Currently, if publishers ask for consent, as they must in the European Union, they usually offer two alternatives: providing or denying consent. Instead, they could ask users to consent for a specific period, e.g., 1, 3, 6, 12, or 24 months. Our results show that more extended consent periods are better for publishers, but the more granular choices might incentivize users to deny their consent less often.

Our results indicate to advertisers and publishers that about 80% of cookies do not change in value over time. So, increasing their privacy by not collecting data over time does not come with an economic loss. It might be a suitable compromise between the industry and the regulator not to track these users. Other forms than behavioral targeting, e.g., contextual targeting, might be more appropriate for those users.

The potential loss of the remaining 20% of users adds up to a yearly loss of about €2 per user. So, there is a price for privacy, and the question for the regulator is: Is this price justified, and who should pay for this economic loss? Justifying the price requires comparing the economic loss with the (non-economic) gain of more privacy. We cannot answer this question because our cost-benefit analysis only covers the costs. However, future research could study the benefits, i.e., whether users' yearly benefit, measured by their willingness to pay, is above those €2. However, it is difficult to determine the extent to which users value privacy, given that there is a significant disparity between users' stated and revealed preferences regarding privacy, a disparity referred to as the "privacy paradox".

If the regulator did not want publishers to suffer from such a potential loss, then either users or taxpayers would have to compensate for this loss. Our results also outline that cookie lifetime restrictions, or, more generally, limiting the period a tracker can track a user, could represent a compromise between a complete ban of tracking and tracking a user for an infinite period. Our study reveals that regulators should consider shorter cookie lifetime restrictions to better protect user privacy, as almost half of all cookies (45.227%) are deleted within the first 30 days. However, this would also imply larger potential losses for publishers.

Table 8
Economic loss per eu internet user due to cookie lifetime restrictions.

Cookie Lifetime Restriction		*30 days*	*60 days*	*90 days*	*120 days*	*360 days*	*720 days*
Average % Loss for all Cookies [95% Confidence Interval]	Sample 1	13.916% [13.480; 14.312]	13.638% [13.202; 14.074]	13.083% [12.687; 13.519]	12.647% [12.251; 13.044]	8.524% [8.167; 8.881]	5.432% [5.154; 5.669]
	Sample 2	13.861% [13.396; 14.325]	13.148% [12.683; 14.325]	12.719% [12.254; 13.612]	12.290% [11.861; 12.719]	8.324% [7.931; 8.681]	5.394% [5.108; 5.644]
	Average	13.889% [13.438; 14.319]	13.393% [12.943; 14.200]	12.901% [12.471; 13.566]	12.469% [12.056; 12.882]	8.424% [8.049; 8.781]	5.413% [5.389; 5.657]
Yearly EU Cookie-Based Display Ad Revenue	€10.600 billion[a]						
Affected Yearly EU Cookie-based Display Ad Revenue [95%- Confidence Interval]	Sample 1	€1.475 billion [1.429; 1.517]	€1.446 billion [1.399; 1.492]	€1.387 billion [1.345; 1.433]	€1.341 billion [1.299; 1.383]	€904 million [866; 941]	€576 million [546; 601]
	Sample 2	€1.469 billion [1.420; 1.518]	€1.394 billion [1.344; 1.518]	€1.348 billion 1.299; 1.443]	€1.303 billion [1.257; 1.348]	€882 million [841; 920]	€572 million [541; 598]
	Average	€1.472 billion [1.424; 1.518]	€1.420 billion [1.372; 1.505]	€1.368 billion [1.322; 1.438]	€1.322 billion [1.278; 1.365]	€893 million [853; 931]	€574 million [544; 600]
EU Internet Users				434 million[b]			
Yearly EU Cookie-Based Display Ad Revenue per User				€24.424			
Yearly Economic Loss per EU Internet User [95% Confidence Interval]	Sample 1	€3.399 [3.292; 3.496]	€3.331 [3.224; 3.437]	€3.195 [3.099; 3.302]	€3.089 [2.992; 3.186]	€2.082 [1.995; 2.169]	€1.327 [1.259; 1.385]
	Sample 2	€3.385 [3.272; 3.499]	€3.211 [3.098; 3.499]	€3.106 [2.993; 3.325]	€3.002 [2.897; 3.106]	€2.033 [1.937; 2.120]	€1.317 [1.248; 1.378]
	Average	€3.392 [3.282; 3.497]	€3.271 [3.161; 3.468]	€3.151 [3.046; 3.313]	€3.045 [2.945; 3.146]	€2.057 [1.966; 2.145]	€1.322 [1.253; 1.382]

[a] This value refers to the tracking-based ad revenue during the time of our study (Interactive Advertising Bureau, 2017). Very likely, today's tracking-based ad revenue is larger.
[b] This value refers to the number of EU internet users during the time of our study (Statista 2019).

Our results show that cookie lifetime restrictions could represent an economically significant loss for publishers. It also shows that, for example, a cookie lifetime restriction to 12 months could incur a yearly loss of €904 million which represents about 1 percent of the online advertising market of €86 billion in Europe. However, not all of this money flows to publishers.

The users learn from our results that denying tracking entirely or beyond a certain period reduces publishers' profit. The question is whether users should care. Our empirical study only partly enables us to answer this question. We show that potential economic losses exist and are not minor. However, we did not show whether publishers can bear them or have to react. Users could suffer from publishers' reactions, such as creating paywalls, increasing their prices, or decreasing the quality of their content.

Finally, we note that tracking technologies such as cookies may also provide value for users. Cookies enable publishers to personalize their content, which benefits users. For example, websites use cookies to identify users, remember their preferences, set up personalized content, and help users complete tasks without re-entering information when they revisit a website. Usually, a first-party cookie is sufficient for accomplishing this personalization. Furthermore, cookies enable advertisers to better target the user with ads, rendering their ads more effective. This better targeting can also benefit the user, who receives more relevant ads to help her make better purchase decisions. In some circumstances, however, targeted ads can also be associated with lower-quality vendors and higher prices for identical products than untargeted ads (Mustri, Adjerid, & Acquisti 2023).

Data availability

The authors do not have permission to share data.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Supplementary material to this article can be found online at https://doi.org/10.1016/j.ijresmar.2023.10.001.

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