NET Institute*

www.NETinst.org

Working Paper #17-02

September 2017

Economic Damage of Cookie Lifetime Restrictions

Klaus M Miller and Bernd Skiera
Goethe University Frankfurt

* The Networks, Electronic Commerce, and Telecommunications (“NET”) Institute, <http://www.NETinst.org>, is a non-profit institution devoted to research on network industries, electronic commerce, telecommunications, the Internet, “virtual networks” comprised of computers that share the same technical standard or operating system, and on network issues in general.

Economic Damage of Cookie Lifetime Restrictions¹

*Klaus M. Miller, Bernd Skiera
Goethe University Frankfurt*

*NET Institute Working Paper
Work-in-Progress*

September 2017

Over the past few years, regulators have begun to consider restricting a cookie's lifetime or even banning cookies altogether as a way to protect consumer privacy. Most of this debate has taken place in the absence of any quantified cost-benefit analysis. To begin to fill this gap in the discourse, we estimate the potential economic damage of lifespan restrictions on cookies. Our analysis is based on an empirical study on cookies of 54,127 users who received about 130 million ad impressions over 2.5 years. Only 22% of all cookies increase their daily value over time but the value of that quantile represent 61% of the value of all cookies. This analysis suggests that restricting their lifetime to one year as the European Union proposes (two years as Google advocates) decreases cookie lifetime value by 14.8% (5.9%), which represents a decrease in the value of all cookies of about 7.4% (1.3%). Overall, we find that the average lifetime of a cookie is 215 days (median 68 days) and the average value of a cookie is €1.43 (median €02).

Keywords: Cookie; Privacy; Online Advertising; Real-time Bidding; Value of Information; Consumer Protection

¹ The results are preliminary; *please do not cite for policy purposes*. We thank the NET Institute (www.NET-inst.org) for supporting this research. All errors are our own.

1. Introduction

Since the advent of the internet 20 years ago, most content has been provided for free. Despite some digital publishers' attempts to introduce paid content, the prevalent monetization model for free content remains advertising. From 2011 to 2016 digital ad spending in the United States has increased constantly at yearly growth rates between 15%-22%, rising from \$31.7 billion in 2011 to \$72.5 billion in 2016 (IAB 2017a). This growth has been facilitated by cookies, unique digital records left behind on the internet user's browser, and other software that enables advertisers to track and target potential customers with granularity and precision that grows each time the user visits (Aziz and Telang 2016; Beales 2010).

Free content in exchange for personal data might seem like a reasonable trade but many consumers are averse to advertisers' use of highly invasive tracking technology to collect it. (Turow et al. 2009; Morales 2010; Goldfarb and Tucker 2011a; Hoofnagle et al. 2012). Almost half of U.S. adults think that online advertisers should not save records of their activity for any length of time (Pew Research Center 2015). Many consumers have become increasingly reluctant to share personal data such as income information in marketing research surveys (e.g., Goldfarb and Tucker 2012). Further, 30% of individuals delete cookies within one month (DigiDay 2013) and 59% of U.S. internet users delete cookies (Pew Research Center 2014).

In response to the largely negative public perception of user profiling and targeting in recent years, online advertisers and regulators have discussed restricting the use of cookies. Some policy-makers have proposed restricting cookie lifetimes, while others go one step further and propose banning cookies altogether. Although there are still no explicit and binding regulations on cookie lifetimes in the United States and Europe, Google, after some public pressure in 2007, made a voluntary commitment to a maximum cookie lifetime of two years. In their privacy directive, European Union (EU) legislators recommended an overall cookie lifetime of not more than one year

(EU 2009); the French data protection agency (CNIL) has endorsed a maximum of 13 months (CNIL 2013). These limits stand in stark contrast to the technical expiration date of a cookie as set by the cookie's owner. Investigators found cookies designed to last anywhere from one year to 8,000 years in a recent cookie sweep within the European Union (EU 2015).

Many discussions have included debates on the economic loss to publishers that a complete ban of cookies would entail. McKinsey (2010) estimates monthly willingness to pay to avoid advertising intrusion to be as high as €10 per household, whereas Budak et al. (2016) estimate that \$2 per month would be enough to offset all digital ad revenues for content publishers. In such a case, Google (2015) suggests a monthly subscription of \$1.99 - \$14.99 for Google Contributor, a relatively new program that allows consumers to turn ads off on a small number (5-10) of participating Google Contributor sites in exchange for the monthly payment.

Perhaps because of the emotional nature of consumer opposition, estimates about the amount of money it might take to offset privacy-intrusive advertising diverge wildly. Further, when taking a closer look it becomes clear that the estimates are not based on any empirical research. In fact, most of these discussions lack solid data on actual cookie behavior. We find little understanding in academia and even among practitioners regarding the value of cookies, specifically with regard to cookie lifetime, cookie value per day, and the evolution of that 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 damage a restriction of cookie lifetimes might entail.

In this paper, we aim to fill this void by estimating the economic damage of various cookie lifetime restriction policies. Specifically, we compute the lifetime of cookies (in days), their value per day, and their lifetime values. We then analyse the decay or growth in each cookie's value per day over time to derive the economic damage that comes with restricting the cookies' lifetime. This

analysis then allows for deriving, for example, the economic damage that would come with restricting the cookie lifetime to 24 months as Google advocates or to 12 months as the European Union proposes.

To address these questions, we analyze rich, detailed data collected by a large European ad exchange. This exchange serves as a programmatic marketplace that facilitates automated buying and selling of online display, mobile, and video advertising inventory. The ad exchange reaches approximately 50 million monthly unique users, or 84% of all monthly internet users in its relevant market. We have obtained detailed data from the ad exchange that includes information on approximately 110 billion transacted impressions over 2.5 years, the respective prices paid by advertisers for those impressions, and the resulting clicks and conversions. This time series enables us to conduct not only a mean and distribution analysis between the cross-sections of cookies, but also to use within-cookie price variations to trace the development of cookie value over time.

Our analysis of the data reveals that cookie lifetimes are highly skewed. We find a mean cookie lifetime of 215 days (7.2 months) and a median of 68 days (2.3 months). Overall, approximately 45% of the cookies are deleted within one month, 72% within 12 months, and 93% after 24 months. This finding indicates that a restriction of cookie lifetime to 12 months, for example, would affect approximately 28% of the cookies and destroy approximately 53% of the 11.7 million cookie days in our data while a restriction to 24 months would affect only 7.41% of the cookies and destroy only 11% of the available cookie days. Our analysis further reveals a highly skewed cookie lifetime value. We find an average cookie lifetime value of €1.43, a median of €02, and a maximum of €31.

Our counterfactual policy simulation of various cookie restriction policies shows that a 30-day restriction would affect 55% of the cookies and destroy an average of .266€(or 18.6%) of the cookie lifetime value, while a 180-day restriction would affect approximately 40% of the cookies

and destroy .18€ of average cookie value of (12.4%). A restriction to 360-days as the European Union proposes would affect 28% of the cookies and lead to average economic damage of .11€ per cookie (7.4%). A 720-day restriction as advocated by Google would affect 7.4% of the cookies and incur losses for the average cookie of .02€ (1.3%).

Our results contribute to the ongoing discussions in the digital advertising industry on the consequences of more cookie regulation. They provide important insights for the industry as well as users and policymakers, who can make better-informed decisions if they can quantify the economic damage that a cookie lifetime restriction can entail. Finally, our results add to the literature on quantifying the value of information generated in digital markets and determining the value of privacy.

In Section 2, we provide a short overview of the existing literature in online advertising on cookies and user privacy and our contribution to those discussions. We then describe our data and empirical methods in detail in Section 3. In Section 4, we present the descriptive results of our empirical study and in Section 5 we discuss the results of our counterfactual policy simulation. We close with a summary of our findings in Section 6.

2. Contribution to Related Literature

Our research relates primarily to two literature streams in online advertising: cookies and user privacy.

The literature on *cookies* is divided between analytical and empirical studies. We focus on the empirical studies as the analytical studies are rather silent with regard to the impact of privacy policy on cookies. For example, Mahdian et al. 2012 investigate a publisher's incentives to share

user cookies with advertisers and how these incentives change with the publisher's market structure, while Bergemann and Bonatti (2015) propose a model for cookie data provision and pricing. Neither team try to quantify the time-value of cookies.

The empirical literature on cookies is further divided into two distinct categories: survey and observation studies. The *survey studies* on cookies are produced mostly by market research firms. In aggregate, these studies show that approximately 39% to 55% of users delete their cookies at least monthly (see Song 2009 for an overview and detailed discussion). But Song (2009) finds that survey respondents do not always act in real life in the way they say they do in their survey response. In fact, Song finds significant differences between stated and actual cookie deletion behavior. For example, 46% of users who claim they delete their cookies every month have cookies that have lived longer than two months. This contradiction suggests that surveys on cookie deletion behavior can be considered indicative at best, if not simply aspirational.

Observation studies on cookies are somewhat more robust. We found four papers relevant to our research questions (see Table 1 for an overview). In assessing the impact of cookie deletion on website- and ad-metrics, Abraham, Meierhoefer, and Lispman (2007) find that approximately 31% of U.S. users delete their cookies within one month. Beales and Eisenach (2014) determine the value of a cookie to advertisers and report a mean cookie lifetime of 1.5 months. The authors confirm the positive impact of the presence of cookies on advertisers' willingness to pay a premium of \$.22 to \$.34 for 1000 impressions (reflected in the respective increase of Cost per Thousand (CPM)). Further, they are the first to quantify the positive impact of cookies' age on advertisers' willingness to pay between \$.02 and \$.15 (CPM) per month.

Aziz and Telang (2016) also deal with the question of how advertisers can calculate the value of a cookie. The authors find that more intrusive information only improves advertiser targeting up to a certain threshold and then levels off. More information makes ad targeting easier,

but with decreasing effect. Finally, Johnson, Lewis, and Nubbemeyer (2017) report cookie lifetimes in their data to have a median lifetime of 3.5 months. Although these studies document cookie lifetimes and assess the arc of the growth of their value over time, they do not address the impact of privacy regulation on cookie lifetime values or assess the potential economic damage that might do to digital advertisers.

TABLE 1
OBSERVATION STUDIES ON COOKIES

Study	Aim	Observations			Cookie Information	
		Period	Cookies	Ad Impressions	Lifetime	Value over Time
Abraham, Meierhoefer, and Lipsman (2007)	Impact of Cookie Deletion on Website- and Ad-Metrics	1 month	400'000	n.a.	yes (< 1 month ^a)	no
Beales and Eisenach (2014)	Determine Value of a Cookie for Advertisers	2 weeks	n.a.	3.0 Mio.	yes (1.5 months ^b)	yes
Aziz and Telang (2016)	Determine Value of a Cookie for Advertisers	1 day	115'417	1.3 Mio.	no	no
Johnson, Lewis, and Nubbemeyer (2017)	Improve Ad Effectiveness Measurement	2 weeks	566'377	n.a.	yes (3.5 months ^c)	no
This study	Determine Economic Damage of Cookie Lifetime Restrictions	2.5 years	54'127	130 Mio.	yes	yes

^a Unfortunately, the authors do not report whether this value represents the mean or median. ^b mean. ^c median.

In a broader context, our work relates to the literature on *user privacy* in online advertising. In this literature, Goldfarb and Tucker (2012) show that consumer privacy concerns have risen over time. Tucker (2012) discusses recent empirical research on the trade-off between the informative value of advertising and the degree of privacy intrusion. Tucker (2014) illustrates empirically that users can be more receptive to behavioural targeting when they can modify a publisher's privacy settings. Other studies show that behavioural targeting (e.g., Bailey and Farahat 2012) and retargeting (e.g., Lambrecht and Tucker 2013; Bleier and Eisenbeiss 2015) improve ad effectiveness. Goldfarb and Tucker (2011b) use the introduction of the European Union's opt-in tracking policy as a natural experiment and find that as a result of this policy, online display ads are 65% less

effective in terms of survey metrics. However, this literature is silent regarding the impact of privacy regulation on the value of a cookie.

Budak et al. (2016) use web browsing histories to show that 32% of the page views for content providers and 91% of online news pages are endangered by ad-blocking software or third-party tracking regulation. At the same time, among retailers, only 3% of the online traffic originates from display advertising. Although the authors make a back-of-the-envelope estimate that for most display ad-supported content sites ranked in the top 10,000, \$2 per month, charged to one-quarter of loyal users, would be sufficient to offset all ad revenue, they are unable to infer the economic consequences tracking restrictions might have on online display advertising.

Johnson (2013) takes the literature one step further and examines the financial impact of privacy policies on the online display advertising industry through the lens of empirical auction theory. His results suggest that online publishers' revenues drop by 3.9% under an opt-out policy, 34.6% under an opt-in policy and 38.5% under a tracking ban. Total advertiser surplus, defined as the difference between a winning advertiser's bid (which equals his valuation) and the price paid, drops by 4.6%, 40.9%, and 45.5% respectively.

Our work contributes to the research streams of cookies and user privacy in two significant ways: First, unlike prior studies, our large-scale observation study of 54,127 users who received approximately 130 million ad impressions is the first to determine cookie lifetime, cookie lifetime value per lifetime unit (e.g., per day or ad impression), and cookie lifetime value. Specifically, we depart from assessing individual auctions and construct a panel over the entire lifetime of a cookie using longitudinal data over 2.5 years. This is intended to complement the majority of prior studies that relied on time series of up to one month.

Second, while Johnson (2013) focuses on the number of users who are considered "do not track" under different policy regimes, we concentrate on the impact of privacy restrictions on those

users who allow cookie tracking (i.e., so-called opt-in users in contrast to opt-out or do not track users) and the restrictions’ implications for digital publishers and advertisers. We determine the number of cookies that would be affected by restrictions of cookie lifetimes (e.g., by reducing cookie lifetimes from two years to one year) and determine the loss in cookie days as well as cookie value under various restriction policies. Finally, we determine whether different cookie types (i.e., cookies where cookie value correlates with cookie longevity versus cookies where there is a negative or non-significant relationship between the two variables) would be affected differently by various cookie restriction policies.

Our results offer important insights for the digital advertising industry as well as consumers and policymakers concerning the actual value of user-data revealed online. Ultimately, our results contribute to the literature that quantifies the value of personal behavioral information generated in digital markets against the cost to privacy.

3. Description of Data and Methods

Our unique data set comes from a large European ad exchange that serves as a programmatic marketplace for online display, mobile, and video advertising. The ad exchange reaches approximately 50 million monthly unique users, or 84% of the total monthly internet users in its relevant market. This exchange granted us full access to its proprietary data collected between February 17th, 2014 and July 16th, 2016, which represented 2.5 years of data on approximately 110 billion individual real-time ad auctions. The total size of the data set is about 8TB. Our data includes desktop and mobile browsing traffic. All our data are anonymized so that no individual can be personally identified.

Each observation represents an auction arising from a single ad impression that a publisher sold at the ad exchange. The auctions follow hybrid rules:

- If the highest bid is greater than the soft price floor, a second-price auction takes place. The bidder with the highest bid wins the auction and pays the second-highest bid or the soft price floor if she was the only bidder.
- If the highest bid is greater than the hard price floor, but less than the soft price floor, a first-price auction takes place. That is, the winner of the auction pays the exact amount she has bid.
- If the highest bid is less than the hard price floor, the seller will not be selling her opportunity to display the ad impression at the bid price.

Each observed auction includes information about the user, the seller, the buyer, and the ad, which we describe subsequently (see Figure 1 and Appendix A for an overview). Thereby, we ignore all users that do not accept cookies or users that opted-out of cookie tracking (i.e., so called do not track users):

1. **User information:** We observe the user’s unique identifier², the location of the user (e.g., time zone, country, region, language), the device of the user (e.g., desktop browser, mobile browser, mobile app), characteristics of previous browsing behavior of the user (including a user’s socio-demographics and –economics, interests, and preferences), and the actions of the user after the ad was displayed (e.g., ad click, post-click and post-view conversion, post-click and post-view revenue).

² We acknowledge that multiple users (e.g., from the same household) may share one browser (i.e., one cookie) and that one user may use multiple browsers (i.e., multiple cookies) on one or several devices, which is also called the multi-user, multi-client (i.e., browser) problem. Still, we follow the literature by referring to each cookie as an “individual” or “user” (Budak et al. 2016; De los Santos, Hortascu, and Wildenbeest 2012; Gentzkow and Shapiro 2011). Our specific sampling strategy that is described in further detail below makes it also not too likely that a user appears multiple times in our analysis.

2. **Seller information (i.e., publisher information):** We observe the unique publisher's identifier (including site and domain information), the publisher's revenue, the publisher's placement pricing information (e.g., a publisher's reserve price, estimated clear price, and estimated average price), and the publisher's yield management settings (e.g., information on hard and soft price floors).
3. **Buyer information (i.e., advertiser information):** We observe the unique advertiser's identifier and the unique brand's identifier. Further, we observe an advertiser's recency and frequency information, as well as information regarding to the advertiser's bid as well as the price paid by the winning bidder.
4. **Ad impression information:** The ad impression combines information from the advertiser, the publisher, and the user. Specifically, we observe the ad's size (width, height), the ad's placement (e.g., above or below the fold at the publisher as well as the display channel of the user such as web, mobile or app) and the ad's unique campaign and creative identifier. Further, we observe the ad's creative information (e.g., media type such as banner, expandable, or video, frequency and recency) and the ad's viewability metrics, which allow us to determine whether and how long an ad was rendered viewable or why an ad could not be viewed).

To our knowledge, this is the first paper to exploit such rich longitudinal auction data over 2.5 years to gauge the value of a cookie and determine the economic damage of cookie lifetime restrictions.

FIGURE 1

OVERVIEW OF INFORMATION USED IN EMPIRICAL STUDY

We use a high-performance cloud-computing cluster³ to construct a cookie panel from our auction data. To do so, we draw a random sample of 54,127 users from a randomly selected day (i.e., Wednesday, April 29th, 2015) at the center of the data set and gather all available information for these users for our full observational period of 2.5 years. This selection leaves us with a total of 128,334,068 auctions.

We compute cookie lifetime (CLT_i) for each user (i.e., cookie) i as the absolute difference between the first and last observation in our data. Given that about 93% of all cookies have a lifetime of less than 2 years and our data set covers a period of 2.5 years, we are confident that the first and last observations represent for most cookies their actual birth and death date.

We compute the total cookie lifetime value (CLV_i) for each user (i.e., cookie) i as the sum of prices ($Price_{i,t}$) paid per ad impression by the winning advertiser at each purchase occasion t

³ The specific cluster consists of 16 CPU cores featuring the latest Intel Xeon high-frequency technology for super-computers and more than 5,500 GiB of memory running a high-performing enterprise class UNIX-based operating system.

($t \in \{1, 2, 3, \dots, T_i\}$) over a cookie's lifetime T_i . As the lifetime is rather short, we ignore any discounting:

$$CLV_i = \sum_{t=1}^{T_i} Price_{i,t}$$

In the following two sections, we will present the results of our empirical analysis. In Section 4, we present the results of our descriptive analysis. In Section 5, we use a counterfactual policy simulation to evaluate the damage of various cookie restriction policies.

4. Descriptive Results of Empirical Study

To analyze the data, we begin by computing summary statistics for each of the 54,127 cookies that we observe. We report the mean, standard deviation and the respective quantiles of the distribution of the variable of interest. We distinguish into an analysis of cookie lifetime, an analysis of cookie value per lifetime unit (e.g., days), and an analysis of cookie lifetime value. Table 2 provides an overview of the summary statistics.

4.1 Analysis of Cookie Lifetime

We measure a cookie's lifetime using various lifetime units. We distinguish cookie lifetime in days, in active days (i.e., days when a user was active online and received ad impressions), and the number of ad impressions (i.e., representing a specific point in a cookie's lifetime).

Our descriptive analysis of the data reveals that cookie lifetime is highly right-skewed for all lifetime units. Figure 2 displays this skewness for the lifetime unit measured in days. We find a mean cookie lifetime of 215 days (7.2 months), a median of 68 days (2.3 months), and a maximum of up to 867 days (28.9 months) with a possible maximum of 882 days, the length of our observational period. The distribution is very tight up until the median, while the 75%-quantile is about 6-times larger than the 50%-quantile, and the maximum is more than double the 75%-quantile. The

standard deviation (268 days) is larger than the mean (215 days), which also suggests a quite dispersed distribution.

Our analysis of the cumulative distribution of cookie lifetimes (see Figure 3) shows that 45% of the cookies have a lifetime of less than 30 days, 60% of the cookies die within 180 days, 72% of the cookies die within 360 days, and 93% of the cookies die within 720 days.

During their lifetime, the cookies' active life ranged from less than a full day to 836 days. On average, a cookie's activity lasted 74 days (median: 8 active days). Similar to the cookie lifetime, the distribution of active days is highly right-skewed. The 75%-quantile is more than 9-times larger than the median, and the maximum is more than 11-times larger than the 75%-quantile. The standard deviation of 137 days is almost doubled the mean, indicating a highly dispersed distribution.

53,925 users (99.6%) received at least one ad impression, while 202 users (.4%) were active but did not receive any ad impressions. The observed cookies differ with regard to the number of ad impressions served. They range from 1 to 539,264 with a mean of about 2,371 and median of 38 ad impressions. Again the distribution is highly right-skewed where the 75%-quantile is more than 20-times larger than the median, and the maximum is almost 700-times larger than the 75%-quantile. A four-times larger standard deviation (10,569 ad impressions) than the mean shows again a strong variation in the data. As a result, the average number of ad impressions per active day also ranges from 0 to 2,088, with a mean of 17.2, median of 5 and standard deviation of 54.

TABLE 2
SUMMARY STATISTICS PER COOKIE (N= 54,127)

Category	Variable	Quantiles					Mean	SD
		Minimum	25%	50%	75%	Maximum		
Cookie Lifetime Units	Cookie Lifetime (in days)	.000	.002	68.121	416.166	866.909	215.035	268.038
	Active Days	.000	1.000	8.000	73.000	836.00	73.900	137.226
	Number of Ad Impressions	.000	4.000	38.000	771.000	539,264.000	2,370.981	10,568.757
	Avg. Number of Ad Impressions per Active Day	.000	2.000	5.000	15.004	2,088.000	17.240	54.254
Cookie Value per Lifetime Unit	Cookie Value per Day (in €)	.000	.0002	.002	.006	.990	.006	.014
	Cookie Value per Active Day (in €)	.000	.001	.004	.010	.990	.009	.017
	Cookie Value per Ad Impression (in € CPM)	.000	.339	.641	.923	113.890	.694	.829
Cookie Lifetime Value	Cookie Lifetime Value (in €)	.000	.002	.023	.498	331.048	1.428	5.234

FIGURE 2
DISTRIBUTION OF COOKIE LIFETIME
(IN DAYS)

FIGURE 3
CUMULATIVE COOKIE LIFETIME
(IN DAYS)

Cookie Lifetime ($\leq$)	30 days	180 days	360 days	540 days	720 days	882 days
Cumulative Sum of Cookies	24,435	32,647	38,783	45,599	50,115	54,127
%	45.14%	60.32%	71.65%	84.44%	92.59%	100%

4.2 Analysis of Cookie Value per Lifetime Unit

We calculate that cookie values per day in our dataset range from €000 to €990 with a mean value of €006 and a median of €002. The distribution is right-skewed and shows a 75%-quantile that is 3-times larger than the median and a maximum that is 165-times larger than the 75%-quantile with a standard deviation of €014 which is more than twice the size of the mean showing a large dispersion of the data. The Pearson correlation coefficient shows only a very small positive correlation between cookie value per day and cookie lifetime ($r = .032$ $p = .000$).

We also compute the average cookie value per active day at €009 (median: €004; maximum: €.990). The distribution is slightly right-skewed with a 75%-quantile which is 2.5-times larger than the median and a maximum which is 99-times larger than the 75%-quantile. We find a standard deviation of €02, which is approximately twice the size of the mean and indicates a highly dispersed distribution. The Pearson correlation coefficient between cookie value per active day (in €) and cookie lifetime is positive but not very large ($r = .180$, $p = .000$).

Finally, we find the observed mean value per 1,000 ad impressions as paid by the purchasing advertiser is approximately €70 (CPM), the median price is €64 (CPM), up to a maximum of about €13 (CPM). Overall this distribution is more concentrated up to the 75%-quantile which is about 1.5-times larger than the 50%-quantile, but the maximum is still more than a 122-times larger than the 75%-quantile. In line with this observation, the slightly larger standard deviation (€83) than the mean indicates once more a highly dispersed distribution. The Pearson correlation coefficient between cookie value per ad impression (in €, CPM) and cookie lifetime (in days) is again positive but remains small ($r = .088$, $p = .000$).

4.3 Analysis of Cookie Lifetime Value

With regard to cookie lifetime value, we find a highly right-skewed distribution with a mean lifetime value of €1.43, a median of €02, and a maximum of €331 (see Figure 4). Interestingly, the

distribution is highly concentrated up to the median, while the 75%-quantile is approximately 23-times larger than the 50%-quantile, and the maximum is almost 665-times larger than the 75%-quantile. The almost four-times larger standard deviation at €5.23 than the mean indicates an overall highly dispersed distribution. The Pearson correlation coefficient shows a positive linear correlation between cookie lifetime value and cookie lifetime ($r = .378$, $p = .000$). Figure 5 depicts the relationship between cookie lifetime value and cookie lifetime in days.

FIGURE 4

DISTRIBUTION OF COOKIE LIFETIME VALUE (in €)

FIGURE 5

RELATIONSHIP BETWEEN COOKIE LIFETIME VALUE
AND COOKIE LIFETIME (IN DAYS)

5. Policy Simulation

5.1 Setup of Policy Simulation

We use the following numerical example to outline how we will derive the economic damage associated with a restriction of cookie lifetime in our policy simulation. We assume that a cookie lives for 22 days and the value per day increases by \$.01 per day. Thus, the cookie generates a value on the first day of \$.01, \$.02 on the second day, and so forth. The cookie lifetime value (*CLV*) of this cookie is thus the sum of the cookie values per day ($$.01 + $.02 + \dots + $.22 = \$2.53$).

How large is the economic damage of a restriction of this cookie's lifetime to 10 days, i.e., only 45.45% of its original lifetime? There is no economic damage for the first 10 days. After 10 days, the cookie is deleted but, assuming that the user does not change its behavior because of the deletion of the cookie, a new cookie is born. We assume that this cookie has a value on its first day

that is equal to the value of the old cookie on its first day. The same holds for the second day, the third day, etc. Thus, for the next ten days, the new cookie has a value per day that is $10 \times \$0.01 = \0.1 per day lower than the old cookie. After 20 days, including 10 days of the new cookie, the new cookie is deleted and reborn as a cookie that has a value on its first day equal to the value of the old cookie on its first day. Thus, for days 21 and 22, the reborn cookie has a value per day that is $20 \times \$0.01 = \0.2 lower than the old cookie. Overall, the lifetime restriction of the cookie leads to an economic damage of the sum of 10 days times \$0.1 per day and 2 days times \$0.2 per day, thus \$1.4. As a result, CLV is reduced by 55.34%, from \$2.53 to \$1.13.

We can derive this daily increase in the cookie value by running a regression with the value per day as a dependent and time (here days) as an independent variable. The respective result for this regression is $\text{value per day} = 0 + 0.1 \times \text{day}$. Thus, the time parameter, i.e., the parameter for the day, represents the incremental value per day of a cookie and the constant (here 0) represents the value of a cookie that is independent from time (here days).

It is, however, unlikely that the constant of the regression will be zero. It is more likely that it will be positive. Let us assume that it will be \$0.3. The economic damage will still be \$1.4 but the cookie lifetime value will now be $\$0.31 + \$0.32 + \dots + \$0.52 = \9.13 . As a result, the percentage reduction in value will reduce from 55.34% ($= \$1.4 / \2.53) to 15.33% ($= \$1.4 / \9.13).

In addition, it is not very likely that all cookies increase in value over time. Let us assume that another cookie has a lifetime of 10 days, a lifetime value of one-third of the first cookie, i.e., $\$3.043 = \$9.13 / 3$, and a value per day that is unaffected by time so that the value per day is \$0.304 ($= \$3.04 / 10$). Regressing the value per day on the impact of day yields a regression with a constant of \$0.304 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, cookie lifetime value.

If the study would only involve those two cookies, the overall results would be that 50% of all cookies lose value because of a restriction in cookie lifetime. The lifetime value of those 50% of cookies represent 75% of all cookie lifetime values ($= \$9.13 / (\$9.13 + \$3.04)$). Thus, the restriction in cookie lifetime to 10 days causes a total economic damage of \$1.4 and a damage per cookie of \$.7 ($50\% \times \1.4), which represents $15.33\% * 75\% = 11.50\%$ (alternatively $= \$1.4 / (\$9.13 + \$3.04)$) of all cookie lifetime values. Table 3 summarizes these results in the same way as Table 5 later summarizes the results of our counterfactual analysis of the 54,127 cookies.

5.2 Counterfactual Analysis

We use the procedure described for the numerical example to analyze the economic damage that comes with a restriction of cookie lifetime to 30-days, to 180-days, to 360-days (as the European Union proposes), and to 720-days (as Google advocates). This procedure requires in a first step to run a regression for each cookie that determines for each cookie the incremental impact of time on the value per time unit. The second step then uses these regression results to derive the economic damage.

5.2.1 Results of Regression Analysis

We select the most granular time unit, i.e., each ad impression, as the unit of our analysis. We derive a new variable called “ad impression count” that has a value of 1 for the first ad impression that was sold for the user behind the cookie, 2 for the second ad impression, and so forth. We then regress separately for each cookie the impact of the variable “ad impression count” on the value per impression (measured by the price that was paid for this impression by the advertiser). Thus, we run an ordinary least-squares (OLS) regression for each of the 53,925 cookies that received at least one ad impression. The parameter of the variable “ad impression count” is our time parameter that reflects the incremental effect of time on the value of the cookie. We consider this

TABLE 3

ECONOMIC DAMAGE OF A 10-DAY LIFETIME RESTRICTION FOR OUR NUMERICAL EXAMPLE

<i>Cookie Lifetime Restriction</i>	<i>Fulfillment of Condition I</i>			<i>Fulfillment of Conditions I & II</i>		<i>Economic Damage per Cookie that Fulfills Conditions I & II</i>			<i>Economic Damage per Cookie</i>		
	No. Cookies	% (N = 2)	% Cond.II ^c	No Cookies	% (N = 2)	Average CLV	Average Absolute	Average % Damage	Average CLV	Average Absolute	Average % Damage
10 days	1	50.000%	100%	1	50.000%	\$9.13	\$1.40	15.334%	\$6.087	\$0.70	11.500%

Notes: ^a Condition I refers to the number of cookies with a cookie lifetime larger than the cookie lifetime restriction. ^b Condition I and II refer to the number of cookies that fulfil condition I and possess a positive incremental value per day. ^c Share of those that also fulfil condition II ($P(\text{Cond. II} \mid \text{Cond. I}) = P(\text{Cond. I \& II}) / P(\text{Cond. I})$).
Reading example: 1 cookie (or 50.000% of all cookies) fulfils condition I (i.e., have a cookie lifetime that is larger than the imposed cookie restriction of 10-days) and 100% of these cookies also fulfil condition II. 1 cookie (or 50.000% of all cookies) fulfil condition I and condition II (i.e., possess a positive incremental value per day). The average cookie that fulfills conditions I and II has an average cookie lifetime value (CLV) of \$.9.13 and loses under a 10-day lifetime restriction on average \$1.40 (or 15.334% of the total average CLV). The average cookie in our sample has a cookie lifetime value (CLV) of \$6.087 and loses on average a value of \$.070 (or 11.500%) under a 10-day cookie restriction policy.

incremental effect to be positive (negative) if the sign of this time parameter is positive (negative) and the value of the parameter is significant (at a 1% level). If the value is not significant, then we conclude that there is no incremental effect.

We find a positive incremental effect for 11,813 cookies. They represent 21.91% of all cookies in our sample. They received 66.12% of all ad impressions and represent 60.6% of the total cookie lifetime value. Their mean cookie lifetime is about 397 days (median 413) and the average cookie's lifetime value is 3.97€

We find a significant negative incremental effect for 6,953 cookies. They represent 12.89% of all cookies in our sample. They received 20.72% of all ad impressions and represent 23.09% of the total cookie lifetime value. Their mean cookie lifetime is 368 days (median 355) and the average cookie lifetime value is 2.60€

For the majority of the cookies, 35,159 (65.2%), the time parameter is not significant. Yet, these cookies received only 13.16% of all ad impressions and represent only 16.31% of the total cookie lifetime value. Their mean cookie lifetime is 125 days (median .04 days) and the average cookie lifetime value is .36€

5.2.2 Results of Counterfactual Analysis

We now evaluate the impact of different restrictions on the lifetime of cookies. Such a restriction only affects the value of a cookie if two conditions are fulfilled. First, the lifetime of the cookie needs to be longer than the restriction of the cookie lifetime (*condition I*). Second, the time parameter of the regression needs to be significantly positive (*condition II*). Thus, Table 5 reports what percentage-share of cookies fulfill the first condition and which shares fulfill both conditions. Table 4 already outlined that 21.91% of all cookies fulfill condition II. It then reports the average percentage value that is destroyed for each cookie that fulfills both conditions. Finally, it reports the percentage value of all cookies that is destroyed.

Our counterfactual analysis reveals that a 30-day restriction will affect approximately 55% of all cookies in our data set. Of those, 36% also have a positive incremental value per day (which represents 20% of all cookies in our data), and their damage is on average €1.35 so that almost 31% of the average cookie lifetime value of €4.36 is destroyed. The respective economic damage for all cookies in our sample with an average cookie value of €1.43 is €27 (or 18.6%).

Approximately 40% of the cookies have a cookie lifetime longer than 180-days and 38% of those or 15% of all cookies in our data also have a positive incremental value per day. These cookies have a lifetime value of €5.38. The policy would destroy on average a value of €1.16 so that almost 22% of their value is lost. These results correspond to an average loss of €18 (12.4% of the cookie lifetime value) of all cookies in our sample.

The 360-day restriction currently advocated by the European Union would affect approximately 28% of cookies in our sample. Of those cookies, 42% also have a positive incremental value per day so that the policy affects almost 12% of all cookies. The policy reduces on average a value of €90, which is almost 15% of their average lifetime value of €6.07. These results translate to an average economic damage of €11 (7.4% of their cookie lifetime value) of all cookies in our sample.

Finally, a 720-day restriction as Google has implemented affects roughly 7% of all cookies. Approximately 50% of those or almost 4% of all of the cookies are affected because they have both a cookie lifetime longer than 720-days and a positive incremental value per day. These cookies have an average cookie lifetime value of €8.40 and almost 6% of this value (€50€) will be lost under such a restriction policy. For all cookies in our sample, this finding means that on average a value of .02€(1.3% of its lifetime value) per cookie would be destroyed.

TABLE 4

RESULTS OF OLS-REGRESSION WITH
IMPACT OF TIME ON VALUE OF COOKIE PER TIME UNIT

Parameters	Sign. Positive Incremental Effect	Sign. Negative Incremental Effect	Non-Significant Incremental Effect
Constant (SE)	.415* (.069)	1.034*** (.114)	.374** (.124)
t-value (p-value)	17.373 (.057)	19.461 (.000)	3.548 (.026)
Time Parameter (SE)	.005** (.002)	-.011** (.004)	.000 (.007)
t-value (p-value)	9.141 (.010)	-4.658 (.018)	-.007 (.229)
Adjusted R ²	.058**	.064**	-.003
F-value (p-value)	242.609 (.010)	42.113 (.018)	.763 (.229)
Number of Cookies	11,813 (21.906%)	6,953 (12.894%)	35,159 (65.200%)
Total Number of Ad Impressions	84,854,127 (66.120%)	26,587,186 (20.717%)	16,892,755 (13.163%)
Ad Impressions per Cookie	7,183.114	3,823.844	480.467
Average Cookie Lifetime (in days, SD)	397.344 (277.209)	368.030 (268.374)	124.760 (215.239)
Median Cookie Lifetime (in days)	412.892	354.960	.038
Average Cookie Lifetime Value (in €)	3.965	2.567	.359
Median Cookie Lifetime Value (in €)	1.202	.307	.005

Notes: This table reports mean estimates of 53'925 cookie-specific regressions.
Significance levels: * p < .1, ** p < .05, *** p < .01.

TABLE 5

ECONOMIC DAMAGE OF VARIOUS COOKIE LIFETIME RESTRICTIONS

<i>Cookie Lifetime Restriction</i>	<i>Fulfillment of Condition I</i>			<i>Fulfillment of Conditions I & II</i>		<i>Economic Damage per Cookie that Fulfills Conditions I & II</i>			<i>Economic Damage per Cookie</i>		
	No. Cookies	% (N = 54,127)	% Cond. II ^c	No Cookies	% (N = 54,127)	Average CLV	Average Absolute	Average % Damage	Average CLV	Average Absolute	Average % Damage
30-days	29,692	54.856%	36.007%	10,691	19.752%	4.363€	1.345€	30.841%	1.428€	.266€	18.610%
180-days	21,480	39.684%	38.333%	8,234	15.212%	5.337€	1.165€	21.825%	1.428€	.177€	12.409%
360-days	15,344	28.348%	41.809%	6,415	11.852%	6.071€	.897€	14.774%	1.428€	.106€	7.444%
720-days	4,012	7.412%	49.150%	1,972	3.643%	8.382€	.498€	5.945%	1.428€	.018€	1.271%

Notes: ^a Condition I refers to the number of cookies with a cookie lifetime larger than the cookie lifetime restriction. ^b Condition I and II refer to the number of cookies that fulfil condition I and possess a positive incremental value per day. ^c Share of those that also fulfill condition II ($P(\text{Cond. II} | \text{Cond. I}) = P(\text{Cond. I \& II}) / P(\text{Cond. I})$).

Reading example for the first row: 29,692 cookies (or 54.856% of all cookies) fulfil condition I (i.e., have a cookie lifetime that is larger than the imposed cookie restriction of 30-days) and 36.007% of these cookies also fulfil condition II. 10,691 (or 19.752% of all cookies) fulfil condition I and condition II (i.e., possess a positive incremental value per day). The average cookie that fulfills conditions I and II has an average cookie lifetime value (CLV) of 4.363€ and loses under a 30-day lifetime restriction on average 1.345€ (or 30.841% of the total average CLV). The average cookie in our sample has a cookie lifetime value (CLV) of 1.428€ and loses on average .266€ (or 18.610%) under a 30-day cookie restriction policy.

6. Summary of Results

Cookies can be used to track what users do on the web, making them a central feature of many privacy debates. Yet little is known about the lifecycle of cookies. This lack of knowledge makes a profound discussion about how to deal with cookies very difficult, which is unsatisfying for regulators and advertisers alike. We hope our analysis can lead to a more nuanced understanding of the tradeoffs between economic growth and online privacy that the restrictions of cookie lifetimes now being debated by policymakers would entail.

Our empirical analysis of more than 54,000 cookies over 2.5 years found that the economic damage of restricting cookie lifetimes to one year is 7.4% of the cookies' total lifetime value. It would cut short the economic utility of 28.3% of all cookies. A two-year restriction would cut 1.3% of the cookies' total lifetime value and cut short the useful life of only 7.4% of all cookies. A 6.1% difference might seem marginal but could represent tens of millions of euros in lost online display advertising, which in 2016 amounted to €5.2 billion in the United Kingdom, €1.8 billion in Germany, €1.4 billion in France, and \$31.7 billion in the US (IAB 2017a, IAB 2017b).

However, we cannot judge the overall economic impact of shortening cookie life. Our analysis does not include any measurement of the economic benefit of an increase in privacy due to a shorter cookie lifetime. Nor could we quantify the potential costs of a bumpier user experience to the consumer or the website owner on sites that restrict their use. Still, we are confident that our evaluation of the economic damage to the online advertising industry enriches welfare discussions of cookie regulation and complements studies that focus on the benefits users might gain through a more restricted use of cookies by the industry.

References

- Abraham, M., Meierhoefer, C., and Lipsman A. (2007), “The Impact of Cookie Deletion on the Accuracy of Site-Server and Ad-Server Metrics: An Empirical comScore Study”, *comScore*.
- Aziz, A., and Telang, R. (2016), “What is a Digital Cookie Worth?”, SSRN Working Paper, Available at https://papers.ssrn.com/sol3/Papers.cfm?abstract_id=2757325 [Retrieved May 22nd, 2017].
- Bailey, M., and Farahat, A. (2012), “Essays in Applied Economics: Evidence from Natural Experiments”, PhD Dissertation How Effective is Targeted Advertising?, Stanford University.
- Beales, H. (2010), “The Value of Behavioral Targeting”, Network Advertising Initiative, Available at http://www.networkadvertising.org/pdfs/Beales_NAI_Study.pdf [Retrieved May 22nd, 2017].
- Beales, J., and Eisenach, J. (2014), „An Empirical Analysis of the Value of Information Sharing on the Market for Online Content”, SSRN Working Paper, Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2421405 [Retrieved May 22nd, 2017].
- Bergemann, D., and Bonatti, A. (2015), “Selling Cookies”, *American Economic Journal: Microeconomics*, 7(3), 259-94.
- Bleier, A., and Eisenbeiss, M. (2015), “Personalized Online Advertising Effectiveness: The Interplay of What, When, and Where”, *Marketing Science*, 34 (5), 669-88.
- Budak, C., Goel, S., Rao, J., and Zervas, G. (2016), “Understanding Emerging Threats to Online Advertising”, SSRN Working Paper, Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2505643 [Retrieved May 22nd, 2017].
- CNIL (2013), „Site Web, Cookies et Autres Traceurs“, Available at <https://www.cnil.fr/fr/site-web-cookies-et-autres-traceurs> [Retrieved May 22nd, 2017].

- De los Santos, B., Hortascu, A., and Wildenbeest, M. R. (2012), „Testing Models of Consumer Search Using Data on Web Browsing and Purchasing Behavior“, *American Economic Review*, 102 (6), 2955-80.
- DigiDay (2013), „13 Alarming Stats About Cookies“, Available at <https://digiday.com/media/13-alarming-stats-about-cookies/> [Retrieved May 22nd, 2017].
- EU (2009), „Cookies“, Available at http://ec.europa.eu/ipg/basics/legal/cookies/index_en.htm [Retrieved May 22nd, 2017].
- EU (2015), „Cookie Sweep Combined Analysis Report“, Available at http://ec.europa.eu/justice/data-protection/article-29/documentation/opinion-recommendation/files/2015/wp229_en.pdf [Retrieved May 22nd, 2017].
- Gentzkow, M., and Shapiro, J. M. (2011), “Ideological Segregation Online and Offline”, *Quarterly Journal of Economics*, 126 (4), 1799-839.
- Goldfarb, A., and Tucker, C. E. (2011a), “Online Display Advertising: Targeting and Obtrusiveness”, *Marketing Science*, 30(3), 389-404.
- Goldfarb, A., and Tucker, C. E. (2011b), “Privacy Regulation and Online Advertising”, *Management Science*, 57 (1), 57-71.
- Goldfarb, A., and Tucker, C. E. (2012), “Shifts in Privacy Concerns”, *American Economic Review*, 102(3), 349-53.
- Google (2007), „Cookies: Expiring Sooner to Improve Privacy“, Google Blog, Available at <https://googleblog.blogspot.de/2007/07/cookies-expiring-sooner-to-improve.html> [Retrieved May 22nd, 2017].
- Google (2015), “Changing Your Contribution”, Available at <https://contributor.google.com> [Retrieved December 9th, 2015].

- Hoofnagle, C. J., Urban, J. M., and Li, S. (2012), “Privacy and Modern Advertising: Most US Internet Users Want 'Do Not Track' to Stop Collection of Data About Their Online Activities”, Amsterdam Privacy Conference.
- IAB (2017a), “IAB Internet Advertising Revenue Full-Year Report”, Available at https://www.iab.com/wp-content/uploads/2016/04/IAB_Internet_Advertising_Revenue_Report_FY_2016.pdf [Retrieved August 2nd, 2017].
- IAB (2017b), “ADEX Benchmark 2016: European Online Advertising Spend”, Available at <https://www.iabeurope.eu/research-thought-leadership/resources/iab-europe-report-adex-benchmark-2016-the-definitive-guide-to-europes-online-advertising-market/> [Retrieved August 2nd, 2017].
- Johnson, G. (2013), “The Impact of Privacy Policy on the Auction Market for Online Display Advertising”, SSRN Working Paper, Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2333193 [Retrieved July 26th, 2017].
- Johnson, G., Lewis, R., and Nubbemeyer, E. (2017), “Ghost Ads: Improving the Economics of Measuring Online Ad Effectiveness”, *Journal of Marketing Research*, Forthcoming.
- Lambrecht, A., and Tucker, C. E. (2013), „When Does Retargeting Work? Information Specificity in Online Advertising”, *Journal of Marketing Research*, 50 (5), 561-76.
- Mahdian, M., Ghosh, A., McAfee, P., and Vassilvitskii, S. (2012), “To Match or Not to Match: Economics of Cookie Matching in Online Advertising”, *Proceedings of the 13th ACM Conference on Electronic Commerce*, 741-53.
- McKinsey (2010), “Consumer Driving the Digital Uptake. The Economic Value of Online Advertising-based Services for Consumers”, White Paper, Available at https://www.youronlinechoices.com/white_paper_consumers_driving_the_digital_uptake.pdf [Retrieved May 22nd, 2017].

- Morales, L. (2010), "US Internet Users Ready to Limit Online Tracking for Ads", Gallup Polls.
- Pew Research Center (2014), "Public Perceptions of Privacy and Security in the Post-Snowden Era". Available at http://www.pewinternet.org/files/2014/11/PI_PublicPerceptionsofPrivacy_111214.pdf.
- Pew Research Center (2015), "Americans' Attitudes about Privacy, Security and Surveillance". Available at http://www.pewinternet.org/files/2015/05/Privacy-and-Security-Attitudes-5.19.15_FINAL.pdf.
- Song, Y. B. (2009), "Is the Sky Falling on Cookies? Understanding the Impact of Cookie Deletion on Web Metrics", Atlas Institute Digital Marketing Insights.
- Tucker, C. E. (2014), "Social Networks, Personalized Advertising, and Privacy Controls", *Journal of Marketing Research*, 51 (5), 546-62.
- Tucker, C. E. (2012), "The Economics of Advertising and Privacy", *International Journal of Industrial Organization*, 30 (3), 326-29.
- Turow, J., King, J., Hoofnagle, C. J., Bleakley, A., and Hennessy, M. (2009), "Americans Reject Tailored Advertising and Three Activities That Enable It", SSRN Working Paper, Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1478214 [Retrieved May 22nd, 2017].

Appendix A: DESCRIPTION OF VARIABLES (1/2)

Type	Category	Variable	Description
User Information	User Identification	user_id	The User ID.
	User Location	user_tz	The time zone of users vs. UTC.
		geo_country	The geographic country of the impression.
		geo_region	The geographic region of the impression.
		language	The ID of the language.
		latitude	The latitude of the user's location.
		longitude	The longitude of the user's location.
	User Device	operating_system	The ID of operating system version.
		browser	The ID of the browser.
		device_unique_id	The unique identifier representing the mobile device.
		device_id	The model ID of the mobile device.
		carrier_id	The ID of the carrier associated with the mobile device.
		application_id	The ID of the mobile application.
	User Tracking Information	segment_id	The ID of the segment pixel (e.g., indicating age, sex, income, interests, preferences, social media usage, click behavior, etc.).
	User Actions	is_click	Used to indicate that the creative was clicked.
		post_click_conv	Used to identify a row that is a post click conversion.
		post_view_conv	Used to identify a row that is post view conversion.
		post_click_revenue	The advertiser post click revenue.
		post_view_revenue	The advertiser post view revenue.
Seller Information	Seller Identification	seller_member_id	The member ID of the seller.
	Publisher Identification	publisher_id	The ID for the publisher of the placement.
		site_id	The ID for site associated with placement.
		site_domain	The publisher domain.
	Seller Revenue	seller_revenue_cpm	The amount the seller is paid for the impression.
		seller_currency	The currency used by the seller.
		revenue_type	The method by which the seller network was paid by the buyer network.
	Publisher Revenue	pub_rule_id	The ID for the publisher rule, which defines how the publisher is paid.
		media_cost_dollars_cpm	The dollar amount * 1000 paid to publisher.
		publisher_currency	The currency in which the publisher is paid.
		publisher_exchange_rate	The exchange rate on the day of the transaction.
		media_buy_rev_share_pct	The publisher revenue share.
		billing_period_id	The ID of the billing period under which the impression was served.
		serving_fees_cpm	The serving fees in addition to media costs to when serving ad.
		serving_fees_revshare	The revenue share in addition to media costs when serving ad.
	Seller Placement Pricing	reserve_price	The reserve price for the placement.
		ecp	The estimated clear price for placement tag.
		eap	The estimated average price for placement tag.
	Seller Yield Management Settings	ym_floor_id	The ID of the yield management floor that was applied to the buyer.
		ym_bias_id	The ID of the yield management bias that was applied to the buyer.
		total_bid_modifier	The total amount added or deducted from the bid due to yield management biases and/or modifiers.
		exclusivity_level	The higher values get precedence over bids with lower values.
		ym_auction_tier_id	The ID of the yield management auction tier into which this bid was categorized.
		hard_floor	The hard floor specified in the seller's yield management profile.
		modified_hard_floor	The floor actually applied in the auction.
		soft_floor	The soft floor specified in the seller's yield management profile.
		modified_soft_floor	The soft floor that is actually supplied in the auction.

Appendix A: DESCRIPTION OF VARIABLES (2/2)

Type	Category	Variable	Description
Buyer Information	Buyer Identification	buyer_member_id	The member ID of the buyer.
		advertiser_id	The id of the advertiser.
	Advertiser Identification	brand_id	The ID for brand of the creative.
		advertiser_frequency	The advertiser-level frequency.
	Advertiser Frequency & Recency	advertiser_recency	The advertiser-level recency in minutes.
		buyer_spend	The gross CPM amount paid by the buyer.
	Buyer Bid Price & Paid Price	buyer_bid	This value is the bid that was evaluated during the auction.
		is_winning_bid	Whether this bid won the impression.
		pricing_type	The line item pricing type.
		payment_type	The method by which the buyer is paying for the impression.
		booked_revenue_dollars	The dollar amount earned by network on impression.
		booked_revenue_adv_curr	The same amount as booked revenue dollars, but displayed in a different currency.
		commission_cpm	If commission is used.
		commission_revshare	If commission is used.
		auction_service_deduction	The dollar amount deducted from the bid to pay for auction hosting.
		auction_service_fees	The dollar amount charged for purchasing inventory from a publisher without a revshare agreement.
		creative_overage_fees	The dollar amount charged if the creative is over our size limit.
		clear_fees	The dollar amount charged for facilitating the auction for the buyer.
		buyer_currency	The currency used by the buyer.
		advertiser_currency	The currency used by the advertiser.
		advertiser_exchange_rate	The exchange rate on day of event.
		deal_id	The Deal ID associated with this impression.
		bid_payment_type	How the buyer was paid for the impression.
		is_mediated_bid	Whether this bid is coming from mediated demand.
		actual_bid_price	The actual price of the bid.
		biased_bid_price	The biased price of the bid, if yield management biases were applied to the buyer.
		bid_reject_reason	The reason a bid was rejected.
Ad Impression Information	Ad Identification	ad_profile_id	The publisher-level ad profile ID that was applied to this impression.
		auction_id	Unique auction identifier.
		datetime	The time and data of impression in YYYY-MM-DD HH:MM:SS (UTC).
	Ad Size	width	The width of the creative.
		height	The height of the creative.
	Ad Placement	tag_id	The ID of placement tag of the impression.
		fold_position	The placement position relative to fold.
		supply_type	The type of supply (Web, Mobile Web, Mobile App, Facebook Sidebar, Toolbar).
	Campaign Identification	campaign_id	The ID of the campaign.
		insertion_order_id	The ID for insertion order if used.
		campaign_group_id	The identifier of line item.
	Creative Identification	creative_id	The ID of the creative served.
		media_type	The general display style of the creative, classified by media subtype.
	Creative Information	creative_freq	The creative-level frequency.
		creative_rec	The creative-level recency.
		cadence_modifier	The cadence modifier for the impression.
		can_convert	If impression has conversion pixels associated or not.
		is_control	Whether the creative served is a control creative.
		controller_pct	The percentage of impressions that are control.
		controller_creative_pct	The ID of the control creative.
		pixel_id	The ID of conversion pixel.
		is_remarketing	Used to indicate that a new segment pixel is remarketing or not.
		imp_type	The type of impression.
	Ad Viewability	view_result	The viewability measurement result of the impression.
		view_non_measurable_reason	The reason an impression could not be measured for viewability.