Have I Seen you Before? Measuring the Value of Tracking for Digital Advertising*

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Abstract

Privacy regulation aiming to reduce the ability of ad platforms to aggregate user data can decrease the quality of ad display and thus challenge data-driven business models. We investigate the effect of privacy protection rules on the market for ads. We leverage a change in Apple's privacy policy, the *App Tracking Transparency*, to compare ad campaigns targeting iOS users versus Android users. To assess the effect of the policy, we use an original database of estimated ad outcomes on a social network in the US market. The results suggest a relative reduction in targeting efficiency and ad prices.

1 Introduction

Data collection has raised significant privacy concerns among consumers. These concerns have resulted in regulatory initiatives, not only by regulators aiming to protect consumers, but also by digital companies increasingly trying to attract consumers

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with privacy-friendly products or services. Although reassuring at first glance, these initiatives may have an adverse effect on economic outcomes (Goldfarb and Que, 2023; Johnson, 2022; Choi et al., 2022). In particular, limiting the collection and/or aggregation of data may hinder the efficiency of targeted advertising and deteriorate advertising revenues. This may in turn prevent firms from developing and maintaining qualitative internet services, hence reducing consumer surplus. It is important to examine this side of the trade-off, to be able to design efficient policies. This paper intends to shed light on how a change to privacy regulation impacts targeting efficiency, and to interpret the associated shift in equilibrium ad prices. More precisely, we look at how the *App Tracking Transparency* (*ATT*)—an initiative by Apple to offer more control over app tracking on iOS—affects predicted ad outcomes on Meta's social network.

To conduct our study, we use an original database of estimated ad performances collected via Facebook Marketing Application Programming Interface (Facebook Marketing API). This tool is used by practitioners to run real ad campaigns. We collect outcomes for a wide range of ad audiences from mid-March 2021 to mid-July 2021 and construct measures of the conversion rate (CR) and of the cost-per-mille (CPM). We use the CR as a proxy for targeting efficiency and the CPM as an indicator for price. Our empirical design exploits the fact that the *ATT* policy involves only iOS users and not Android users. The ability of firms to profile Android users hence does not change in the short run. We use a difference-in-differences design, using ads targeting iOS users as the treatment and ads targeting Android users as the control. We interpret the change in the conversion rate as the causal effect of the policy on the ability of Facebook to efficiently target consumers. We cannot, however, claim causality regarding prices, because of their highly strategic nature. Nonetheless, as we restrict the period of study around the introduction of the policy, the change

in prices can be interpreted as a combination of the effects on quality, on demand, and on strategic market interactions. It hence provides rich intuitions on the market forces at play after the change in privacy policy.

We find that the introduction of Apple's privacy scheme has been followed by a decrease in the effectiveness and prices of ads targeted at iOS users relative to Android users. Ads targeted at iOS users triggered 7.5% fewer actions per impression after the introduction of the *ATT* policy. At the same time, the CPM to target iOS users decreased by 10% compared to the CPM to target Android users. Note that this decrease in prices is only relative, as our results suggest a general upward trend in prices during the period of study.[1] We find that the effect on CR strengthens over time. This trend aligns with the growing number of users adopting the new operating system iOS 14.5, which allows them to opt-in to *ATT*. The effect also intensifies when ads aim for an action harder to trigger. Indeed, we find that ads optimizing distribution with respect to app installs are more affected than ads optimizing on link clicks. Moreover, our robustness checks validate that the observed effect varies with respect to audience sizes. This suggests that the decline in ad targeting effectiveness cannot be attributed to technical difficulties in measuring conversions, as there is no reason for the technical ability to observe conversions to depend on audience sizes. As a consequence, we do capture a genuine decrease in targeting efficiency.

Our article contributes to two streams of literature. First, it contributes to the general empirical literature documenting the effects of privacy regulations on ad outcomes. Goldfarb and Tucker (2011) studied the impact of privacy regulation on ad effectiveness. Our paper distinguishes itself by analyzing publicly available data, used by advertisers for marketing purpose. Additionally, we study a privacy

[1]This is consistent with official figures of Meta, suggesting an overall increase in the ad revenues in the US. See the Q3-2021 Earnings Presentation slides, p.10: `https://s21.q4cdn.com/399680738/files/doc_financials/2021/q3/FB-Earnings-Presentation-Q3-2021.pdf`, November 2023.

policy enforced in the market of mobile apps, characterized by pervasive data collection. A large strand of empirical studies look at the effect of privacy policies on publisher revenues in the context of open display advertising (Marotta et al., 2019; Ravichandran and Korula, 2019; Johnson et al., 2020; Alcobendas et al., 2021; Laub et al., 2022). Our article complements these, as we look at ad outcomes in another segment of display advertising: the social media owned and operated channel. Indeed, as opposed to publishers in the open channel, social media platforms such as Facebook have a fully integrated digital advertising system and hence control over the full value chain. This represents a large share of display advertising: according to practitioners, Facebook and Instagram accounted for about 24% of total digital ad revenues in the US in 2021.[2] Some of the existing studies focus on smaller players, but studying the largest player in the ad display market brings a different perspective. Our article explains how ad networks with important market power may be affected by privacy policies. Using data from Meta, Wernerfelt et al. (2022) show that limiting access to users' offsite data on a social media platform reduces ad campaign effectiveness. While they use experimental data on ad campaigns, we look at largely aggregated ad outcomes at the audience level with an exogenous policy change. Moreover, the *ATT* policy permits us to investigate the effects of an *opt-in* policy: it offers privacy by default to consumers and does not request that they make an extra effort to do so. Most of the above-mentioned articles, on the contrary, look at *opt-out* privacy policies with a rather low rate of pro-privacy choices. Aridor et al. (2020), for example, document that the introduction of the GDPR resulted in a 12.5% drop in total cookies. In the same way, Johnson et al. (2020) find that consumers' privacy preferences result in a 0.23% increase in ad impressions among those who opted out of behavioral advertising through the self-regulatory AdChoice program.

[2] https://www.insiderintelligence.com/content/google-facebook-amazon-account-over-70-of-us-digital- November 2023.

Compared to these previous empirical works, the proportion of consumers making a pro-privacy choice in the case of *ATT* is estimated to be much higher, and therefore much less subject to selection biases.

Second, our article contributes to the nascent empirical work investigating the impact of Apple's recent privacy-friendly moves. Most papers of this strand of literature have studied the market consequences of a drop in targeting efficiency and/or ad revenues following the introduction of privacy labels (Bian et al., 2021) and the *ATT* (Li and Tsai, 2022; Kesler, 2022; Cheyre et al., 2023). They document the effect of *ATT* on the structure of the app market or on app revenues and business models. Like Kraft et al. (2023) and Ahmadi et al. (2023), we complement these analyses by providing evidences that the *ATT* had a negative effect on ad performances. We show that it affected ad outcomes for one of the most prominent players in the advertising market.

Additionally, observing jointly the effect on quality and changes in prices contributes to shaping some general hypothesis on the determinants of ad prices. It provides leads regarding competition intensity in the market for ads and the value of targeting quality for ads.

2 Context and Data

2.1 The *App Tracking Transparency* (*ATT*)

In April 2021, Apple introduced a feature on its new Operating System (OS), iOS 14.5, offering more control to consumers: the *App Tracking Transparency*. This feature is included in version 14.5 and all subsequent versions.[3] It requires all apps to collect

[3]We will denote 14.5 and later versions by 14.5+ throughout the paper.

users' explicit consent before tracking them, with a simple yes-or-no form.[4] As such, the *ATT* sets privacy by default, as the simplicity of the form makes it equally costly for consumers to choose tracking or no tracking.

More precisely, the policy requires app developers to ask users for their consent to access Apple's *Identifier For Advertisers* (IDFA). The IDFA is a unique code assigned to mobile devices that allows data brokers and advertisers to track a given user across apps and to aggregate his data. Although ID tracking is not the only way to profile consumers (Jeon, 2021), it was expected that without the users' consent, companies (including Meta) would be less efficiently able to match a given consumer to a precise ad content.[5]

iOS users account for almost 50% of mobile users in the US.[6] While we do not have official statistics provided by Apple, the figures provided by practitioners measuring the rate of adoption of iOS 14.5+ and the rate of opt-in for tracking show high rates of adoption and pro-privacy choice. During the time span we studied (mid-March to mid-July 2021), adoptions of versions 14.5+ increased to around 75% (See evolution in Appendix A.2). Moreover, practitioners indicated a low rate of consent to tracking—between 12% and 25%—in September 2021.[7] The change could hence concern roughly 1/3 of consumers' privacy settings in the US mobile market.

2.2 Ad Outcome Estimate

We use Facebook *Ad Campaign Delivery Estimate* data, collected using Facebook Marketing API. This API is a tool developed by Meta, used by advertisers to plan massive

[4] See Figure 3 in the Appendix.

[5] `https://www.facebook.com/business/help/331612538028890?id=428636648170202` March 2023.

[6] According to Kantar, iOS had a market share of 46.8% in the US in September 2021 `https://www.kantar.com/campaigns/smartphone-os-market-share`, September 2021.

[7] `https://9to5mac.com/2021/07/23/app-tracking-transparency-opt-in-snap/` and `https://www.flurry.com/blog/att-opt-in-rate-monthly-updates/`, September 2021.

ad campaigns. It works through requests and allows advertisers to obtain estimates of ad outcomes—depending on a specified target audience—before running ad campaigns. A request returns estimates on the number of *impressions*, the number of *people reached* by an ad, the number of *actions* (e.g., clicks, app installs) taken by people exposed to the ad. More precisely, each request returns three times 15 points forming three full supply functions—called the Ad Set Delivery Estimate—which includes estimated *impressions*, *reach*, and *actions* for any possible daily budget (see a sample request output on Figure 5 in Appendix A.3).[8] Requests also give the size of the target audience on the day or month of the request (*DAU: Daily Average Users* and *MAU: Monthly Average Users*[9]). These estimates depend on the specified audience's demographics, on the platform used to reach the audience (e.g. Facebook or Audience Network) and on what action the ad placement should maximize, i.e. which "optimization goal" (e.g. clicks, app installs). The estimates provided by the API are computed with data from Facebook Ad Manager (Facebook's Demand Side Platform) and data from ads of thousands of outside publishers (apps and websites).
[10]

2.3 Main Outcomes of Interest

With the data provided by Facebook Delivery Estimates based on real ad performance, we build two indicators that measure *targeting efficiency* and *ad prices*. To be able to compare delivery estimates across audiences, we arbitrarily fix our daily budget to 100 €[11] and compute *impressions* and *actions* for each of the audiences. We

[8]The supply functions are always concave in spending, putting a cap on the performance of an ad with too high a budget.

[9]We express these measures in million users.

[10]See `https://fr-fr.facebook.com/business/help/1438142206453359?id=561906377587030`, March 2023.

[11]The Delivery Estimates are not all provided for the same range of budgets. Hence, increasing the daily budget reduces the number of audiences for which the ad outcome estimates are available.

compute the CR and CPM according to

$$CR_{100€} = \frac{Actions_{100€} \times 100}{Impressions_{100€}} \qquad \text{and} \qquad CPM_{100€} = \frac{100€ \times 1,000}{Impressions_{100€}}$$

The CR denotes the proportion of *impressions* that trigger an *action* by consumers. We multiply it by 100 so that it could be expressed in percentage points. This variable measures targeting efficiency in our analysis. The CPM denotes the ratio between our arbitrary budget of 100 € and the number of *impressions*, expressed in thousands. It is a measure of the price of impressions.[12]

We use the CR and CPM as our main outcome variables to measure the effect of Apple's new privacy policy on targeting efficiency and on the price of ads, respectively. Given the claims that privacy protection prevents firms from offering relevant advertising, we expect the *ATT* scheme to have a negative impact on conversion rates. The effect on prices, however, may be subject to different market effects. Indeed, a change in the conversion rate could have a direct quality effect on prices. It could also induce a change in total demand for ads on Meta's different platforms, depending on the performances of competitors. Finally, it can readjust the balance of demand between ads targeting iOS and Android users on Meta's platforms.

2.4 Data Collection

We collect daily data on estimated ad prices for target audiences in the US, from March 11, 2021 to July 11, 2021. Facebook Ad Manager provides a wide range of audiences. The advertiser can choose to include more or fewer criteria to define the

We chose a budget that allows us to get estimates for a large share of audiences, while having some economic significance.

[12]Note that with a fixed budget, what we will describe as a change in price is more precisely a shift in the supply curve of impressions.

target audience. These criteria include several socio-demographic characteristics such as age, gender, education, income, and user location. Facebook Ad Manager also provides individual interests from a list of several hundred predetermined interests, such as games or religion. An advertiser can also target users depending on their operating system. In the remainder of the paper, the word *"audience"* designates the aggregation of criteria at the exclusion of the OS, such that we observe each audience for iOS and for Android. Our requests use a combination of the audience criteria in Table 1, using one criterion per column, or not specifying (*Not spec.*) a criterion in the given category.

To use the API as in the real ad campaign, an advertiser must also specify the *optimization goal*, that is, the type of *action* that an impression should trigger. We chose to include *link clicks*[13] and *app installs*. Each request should specify a *publisher platform*. We collect data for ads published on Facebook only (Fcbk) and both on Facebook and on the Audience Network (Fcbk&AN).[14] Note that the API does not provide outcomes for ads exclusively displayed on the Audience Network.

Table 1: Targeting Criteria in Collected Audiences

Goal	Pub. Platform	Age	Gender	Education	Income	Interest/Behavior
App Install	Fcbk	18-34	Male	Bachelor degree	Top 10%	Games
Link click	Fcbk&AN	35-49	*Not spec.*	*Not spec.*	Top 10 to 25%	Fcbk page admin
		50-65			Top 25 to 50%	Religion
					Not spec.	*Not spec.*

2.5 Descriptive Statistics

Our final sample includes 203,992 observations and 1,032 different audiences. We perfectly match a given audience in the treatment and the control group. For exam-

[13]Link clicks is the default option in the API.

[14]The Audience Network is Meta's open display channel, enabling print ads on third party mobile apps.

ple, we compare the audience ad outcomes of an ad targeting a young men between 24 and 35 years using iOS with the same age and gender using Android at given point in time. To avoid biases in our estimates, we remove missing observations so that we obtain exactly the same set of audience-date couples in our treatment group (iOS users) and control group (Android users).[15] Table 2 presents the descriptive statistics of our sample. Figure 1 displays the mean of our two dependent variables over time.

Table 2: Summary Statistics of the Overall Sample

Variable	Mean	Std. Dev.	Min	Max
$CR_{100\,e}$	0.58	0.35	0.055	2.82
$CPM_{100\,e}$	5.23	2.13	1.31	19.22
$Impressions_{100\,e}$	22479.78	9318.65	5202.68	76319.76
$NbAction_{100\,e}$	145.42	131.71	11.47	848.65
iOS	0.5	0.5	0	1
Pub. Platform Fcbk	0.499	0.5	0	1
App Install	0.497	0.5	0	1
DAU (in M)	1.68	2.65	0.044	21.65
MAU (in M)	2.11	3.45	0.001	30

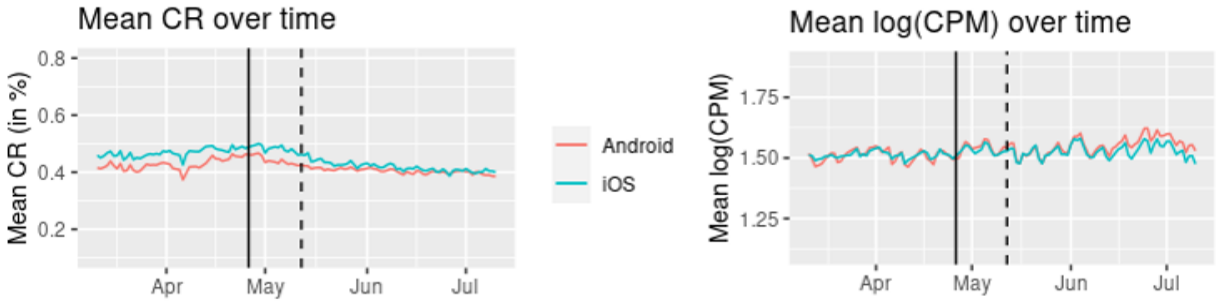


Figure 1: Mean CR and log(CPM) over time

[15] We also remove 9 dates in which, for technical reasons, the number of observations is significantly lower than the number of requests made.

3 Empirical Strategy

3.1 Econometric Identification

Our empirical strategy aims to estimate the effect of a change in the ability of an ad network to track consumers on ad outcomes. We exploit the introduction of Apple's *ATT* policy. This policy should result in a negative exogenous shock to Facebook's ability to aggregate data on iOS 14.5 and its later versions without affecting data aggregation on Android users. To obtain the causal effect of the *ATT* policy, we use a difference-in-differences design that exploits the fact that the policy applies to iOS users but is not expected to affect Facebook's ability to target consumer audiences on Android (see Goldfarb et al. (2022) for methodological issues related to policy change).

Note that we claim identification of the causal effect on CR, as we do not detect any heterogeneous pre-treatment trend that might bias our estimates (Angrist and Pischke (2009), see Appendix B). However, we cannot make this claim for the effect on CPM, as some anticipation is seen in the price. Due to their highly strategic nature, prices are indeed affected by factors other than quality, including market concentration and (anticipatory) demand shifts. Nevertheless, given the relation in time around the introduction of the policy and the coherence between our results and Facebook's Q3 earning reports, we are confident that the observed changes are related.

In the main analysis, our *treatment* group consists of all iOS users, and our *control* group consists of Android users. Because only a proportion of iOS users adopted the latest versions of the iOS and are thus exposed to the new privacy policy, our analysis measures Intention-To-Treat and we identify a lower bound for the treatment effect. To take into account the lag in adoption of the new OS, we introduce a time lapse of

about two weeks between the *before* and *after* periods. The *after* period starts on May 12, on which approximately 13% of iOS users had adopted the iOS 14.5.[16] We then interact our treatment variable with several others to understand more precisely which subgroups of audiences are affected the most.

3.2 Baseline Empirical Strategy

The baseline equation estimates the change in our two main outcomes of interest: targeting efficiency and ad prices. In the main analysis, we compare the simplest specification to one including a set of fixed effects and controls. We use the following baseline specification. We denote o the OS, a denotes the audience, and t denotes the observation date:

$$\mathbf{y_{oat}} = \alpha + \mathbb{1}_{\text{After}} + \mathbb{1}_{\text{iOS}} + \delta(\mathbb{1}_{\text{iOS}} \times \mathbb{1}_{\text{After}}) + \epsilon_{oat} \tag{1}$$

$\mathbb{1}_{\text{iOS}}$ is a dummy equal to 1 if the ad targets iOS users and 0 if it targets Android users. $\mathbb{1}_{\text{After}}$ is equal to 1 for requests made after May 12. Our robust standard errors are clustered at the audience level. We add to the baseline specification a set of control variables that include an audience-OS fixed effect, a day fixed effect, and the log of the average daily and monthly audience size (the Daily and Monthly Active Users), denoted respectively $log(DAU)$ and $log(MAU)$.

[16] To check the robustness of this choice, see Appendix A.6.

4 Baseline Results

4.1 Effect of the App Tracking Transparency

The results of the main estimates are presented in Table 3. Columns (1) and (2) report the estimates of the change in targeting efficiency proxied by the *CR*. The estimates suggest that the privacy policy change has a negative impact on targeting efficiency. In other words, preventing an ad platform from aggregating its own data on consumers with third party data seems to have a negative impact on its ability to propose relevant ads to consumers. More precisely, comparing the shift in conversion rate to the average conversion rate in the before-period on iOS indicates a decrease of 7.5% in Facebook's ability to transform impressions into actions. In column (2) of Table 3, we include date and audience-OS fixed effects, as well as a control for the audience size. The R^2 improves greatly; the difference-in-differences coefficient, however, does not vary, suggesting robustness in our estimate.

Columns (3) and (4) display the evolution of relative ad prices— measured by the CPM—after the introduction of *ATT*. In column (4), we add a set of fixed effects and covariates. The result suggests that the introduction of the *ATT* was followed by a drop of 10% of the relative price of ads targeted at iOS users, compared to those targeted at Android users.

Note that the coefficients displayed in column (3), while not as robust as those of the two-way fixed-effect model, suggest—through the combination of the *After*, *iOS*, and *After*iOS* coefficients—that, even if the relative price of iOS decreased, there was a general increase in prices both for iOS and Android after the introduction of the *ATT*.[17] The negative coefficient is therefore probably due to a transfer of

[17]Note that this is coherent in sign and magnitude—if we consider that ad space is relatively constant on Facebook—with the 12.3% growth in ad revenues in the US&Canada between Q1 & Q2-2021 (see Facebook's earnings report mentioned in a previous footnote).

demand from ads targeted at iOS users to ads targeted at Android users.[18] Note that this transfer does not seem to be fully justified by performances, as coefficients in column (1) show that in absolute value targeting is still more precise on iOS. The global increase in CPM seems to indicate that—even if hit in terms of targeting quality—Meta managed to keep a competitive advantage on the ad market and somehow reinforced it in the short run.

Table 5 in the Appendix allows us to decompose the effect on ad prices and targeting efficiency. This table reports the effect of Apple's policy on impressions and actions offered for a budget of 100€, mechanically increasing the CPM. We observe an increase both in the number of impressions and in the number of actions. The result suggests the following dynamic: an upward shift in the supply curve of impressions, hence an increase in price, triggering an upward shift in actions, but of lower magnitude.

[18]This seems to be corroborated by practitioners: `https://metrictheory.com/blog/apple-ios-14-5-update-facebook-ads-shifting-toward-android-devices/`, November 2023.

Table 3: Difference-in-Differences Estimates for Targeting Efficiency and Prices

	Dependent variable:			
	CR		log(CPM)	
	(1)	(2)	(3)	(4)
After*iOS	-0.05^{***}	-0.05^{***}	-0.10^{***}	-0.10^{***}
	(−0.06, −0.04)	(−0.06, −0.04)	(−0.11, −0.09)	(−0.11, −0.09)
After	0.004		0.15^{***}	
	(−0.002, 0.01)		(0.15, 0.16)	
iOS	0.14^{***}		0.05^{***}	
	(0.13, 0.15)		(0.05, 0.06)	
Constant	0.53^{***}		1.49^{***}	
	(0.51, 0.55)		(1.46, 1.51)	
log(DAU)		0.03		-0.34^{***}
		(−0.05, 0.10)		(−0.39, −0.28)
log(MAU)		-0.02^{***}		0.002^{*}
		(−0.03, −0.02)		(0.001, 0.004)
Clustered SE	Y	Y	Y	Y
Audience-OS FE		Y		Y
Date FE		Y		Y
Mean on iOS before	0.67	0.67	/	/
Observations	203,992	203,992	203,992	203,992
Adjusted R^2	0.03	0.91	0.02	0.97
Residual Std. Error	0.35	0.10	0.40	0.08

Note: *p<0.05; **p<0.01; ***p<0.001

The robust standard errors are clustered by audience.

Treatment group: Facebook Access iOS device.

Control group: Facebook Access Android device.

4.2 The Negative Effect on Targeting Efficiency and Price Strengthens over Time

To check the robustness and better understand the dynamics of our effect, we regress the difference in outcomes between iOS and Android on the set of date dummies. More formally, we perform:

$$CR_{iOS,at} - CR_{Android,at} = \beta \mathbb{1}_t + \epsilon_{at} \tag{2}$$

$$log(CPM)_{iOS,at} - log(CPM)_{Android,at} = \beta \mathbb{1}_t + \epsilon_{at} \tag{3}$$

In the estimation, we add an audience-OS fixed-effect as well as a control for the log of the daily audience size $log(DAU)$ and the log of the monthly audience size $log(MAU)$. Figure 2 plots the resulting time trend coefficients. At first glance, we see that the results are in line with the aggregate effect found in the previous analysis. After the introduction of the policy, the targeting ability of Facebook on iOS sharply decreases compared to that on Android. This translates into a difference in CPM that also increases over time, but in several successive phases. There seems to be some anticipation regarding the evolution of relative prices. However, there is, as for targeting efficiency, a visible difference between the average coefficients before and after. At least two possible effects are at play to rationalize such dynamics. First, the adoption of versions 14.5 and above increases over the time-period.[19] Although this may be somewhat mitigated by the increase in the tracking opt-in rate,[20] the proportion of effectively treated people in the pool of iOS users increases over time. Hence, our time dummies capture the increased intensity of treatment in the intended-to-treat group. As expected, this translates into a stronger effect

[19] See adoption graph in the Appendix.

[20] *ATT* opt-in rate, Flurry Monthly updates. `https://www.flurry.com/blog/att-opt-in-rate-monthly-updates/`, March 2023.

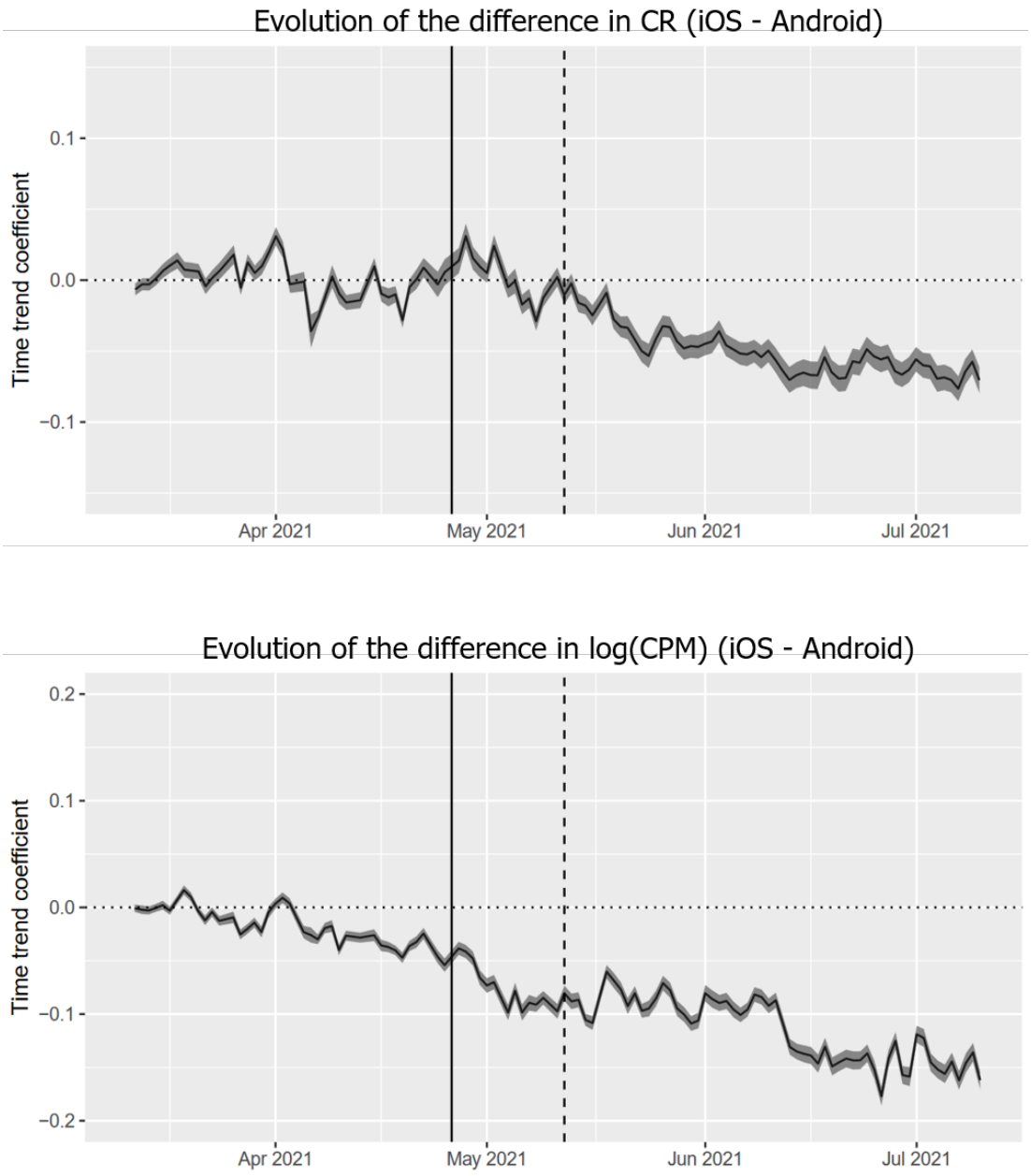


Figure 2: Evolution of the difference (iOS-Android) in CR and $log(CPM)$. Estimates include OS-audience fixed-effects, as well as $log(DAU)$ and $log(MAU)$

as more people adopt the privacy-friendly OS. Second, the negative trend in price difference also captures the demand and expectations of advertisers regarding the negative effect of the *ATT* on targeting efficiency. The trend uncovers some elasticity of demand, most probably between ads targeted at Android versus ads targeted at

iOS, as seen in the previous results.

5 Intensity of the Effect on Harder to Reach Audiences

In this section, we explore how the change in the ability to aggregate consumer data may have affected audiences differently. More precisely, we focus on three sources of heterogeneity that could change the intensity of the effect. First, we investigate whether the policy differently affects ad effectiveness with large audiences versus small audiences. Second, we study whether the change in privacy policy differently affects ads with optimization goals that are harder to achieve, namely installing an app versus clicking on a link. Finally, we look at the heterogeneity of the effect with respect to the ad placement, comparing ads displayed on Facebook only versus ads displayed both on Facebook Social Network and on the Facebook Audience Network. Table 4 shows all estimates.

5.1 Are Smaller Audiences more Affected by Apple's New Privacy Policy?

For each audience we observe in our data, we obtain an estimated daily audience size: the *Daily Active Users*. In this section, we explore whether the introduction of the *ATT* policy has a differentiated impact on targeting efficiency and prices for ads targeting different audience sizes. To this end, we interact our difference-in-differences coefficient with a factor variable classifying the audience into five quantiles, according to their size. The first quantile contains the smallest audiences, whereas the fifth quantile contains the largest audiences.

Columns (1) and (4) of Table 4 display the estimates. Column (1) shows that the effect on the conversion rate is negative overall, whatever the size of the audience.

However, surprisingly, the introduction of *ATT* seems to have had a more intense effect on targeting efficiency towards large audiences than on targeting efficiency towards small audiences.

A potential explanation is that despite the *ATT*, it is still possible to target a precise audience. While ATT affects tracking-induced targeting, it is not supposed to affect contextual targeting.[21] This requires having a relevant group of individuals with a set of characteristics that can be matched with contextual ads. On the other hand, ads with broad audiences can hardly be matched with the right individuals via contextual ads. Indeed, a wide audience will contain a much lower density of relevant users for a given ad. One complementary conjecture is that third party data is used, not only to identify the audience requested, but also to identify who, in this audience, is more likely to generate a conversion. The wider the target audience, the more data aggregation demanded.

Column (4) of Table 4 shows that the decrease in ad prices follows the same logic. It is more important for audiences that seem to have a larger decrease in quality. Interestingly, this suggests again that relative quality is a determinant of relative price.

Additionally, this result strongly supports our claim that the measured effect is attributed to the change in targeting efficiency, rather than to mere technical difficulties in obtaining conversion feedback. Indeed, there is no reason for the ability to observe conversions to depend on the size of the target audience.

[21] Practitioners provide insights into this intuition. `https://www.adexchanger.com/mobile/how-facebook-is-overhauling-its-attribution-standards-to-deal-with-apples-att/`, November 2023.

5.2 Are Ads Differently Affected by Apple's new Privacy Policy, Depending on their Objective?

We collect ad price data based on two optimization goals: *app installs* and *link clicks*. The latter is the default optimization parameter of the API. All audiences include one or the other optimization goal. However, identifying a consumer ready to download an app may require much more third-party data compared to pushing a consumer to simply click on a link. As a consequence, we expect the *ATT* policy to have a larger impact on ad campaigns using the *app install* optimization goal.

Columns (2) and (5) of Table 4 present the estimates of the difference-in-differences changes where the baseline is the treatment effect for the goal *link click*. The second line displays the marginal treatment effect on ads promoting *app installs*.

First, we observe that the change in Meta's ability to aggregate data has a negative effect on its ad effectiveness, mainly for ads aiming to trigger *app installs*. The results display significant heterogeneity between the two goals. In column (2), the ad effectiveness of ads looking for *link clicks* increases slightly after the introduction of the *ATT*, possibly due to the increased use of contextual ads. In contrast, the effectiveness of ads promoting *app installs* decreases sharply, more than twice as much as the main estimate.

The limitation in the ability to aggregate data across apps seems to have had an impact only on ads promoting an action that is "more difficult" to trigger. This is probably because identifying consumers willing to download an app is more data-intense and relies more on having access to different sources of data. Column (5) of Table 4 suggests a drop in the price of ads with both goals after the introduction of the *ATT*. It also indicates a greater price drop for ads aiming to trigger app installs. However, the heterogeneity in effect is lower than with the CR, all types

of ads being negatively affected. This introduces one interesting fact: although we have previously seen the correlation between the drop in prices and the drop in targeting quality, it seems here that prices are significantly affected by demand shifts, indicating demand elasticities.

5.3 Are ads Distributed on Facebook only more or less Affected?

In our data, ads can be distributed either only on Facebook (Fcbk) or both on Facebook and Audience Network[22] (Fcbk&AN), Meta's open display ad network. In both cases, only first-party data remains accessible if users opt out of tracking. However, the nature of this first-party data is very different on the two platforms. For ads on Facebook, logged-in user data can still be used for targeting. For ads on the Audience Network, only contextual data is easily available if users opt out of tracking. This may translate into heterogeneous effects, depending on which type of data remains available. Columns (3) and (6) of Table 4 introduce this variable.

Note that the API estimates for ads published on Fcbk&AN do not disclose the splitting rule between the two publisher platforms. Hence, these estimates have to be interpreted as weighted averages of outcomes on each of the two platforms separately. Consequently, the comparison in treatment effect between ads published on Fcbk versus on Fcbk&AN is hard to interpret. Only the sign is indicative, as the magnitude depends on the unobserved share of ads displayed on the Audience Network in the joint Fcbk&AN sample. Moreover, not observing any difference in the treatment effect is hard to interpret as well. It can reflect a true homogeneity in effects, or/and a small weight put on the Audience Network in the joint outcomes.

Column (3) of Table 4 displays the result of our regressions. We interact the

[22]The option to display an ad only on the Audience Network was not available on Meta's API during the data collection process.

difference-in-differences term with a dummy equal to 0 for ads on Fcbk, and 1 if the predictions requested are for ads displayed on Fcbk&AN. We observe no difference in the effect on targeting efficiency between the two display options. However, the price of ads on Fcbk&AN seems to be more affected than the price of ads on Fcbk. This second non-zero difference in effect also indicates that the Audience Network is sufficiently represented in the joint Fcbk&AN statistic provided by the API. Observing no difference in targeting efficiency between Fcbk and Fcbk&AN can be surprising. Indeed, this result suggests that ads on the Audience Network are not more affected than ads displayed on Facebook. At least two rationales explain this. First, ads on Facebook may be more affected than we think. Indeed, despite its already prolific data-generating social networks, Meta is among the companies collecting the most third-party data.[23] Interestingly, our result seems to indicate that this complementary third-party data plays an important role in the social network's ability to build relevant advertising profiles. Second, ads on the Audience Network may be less affected. Indeed, the use of contextual advertising and alternative targeting techniques may replace tracking better than expected.

[23]See CMA's *Online platforms and digital advertising market study* (2020), Appendix G `https://assets.publishing.service.gov.uk/media/5fe49554e90e0711ffe07d05/Appendix_G_-_Tracking_and_PETS_v.16_non-confidential_WEB.pdf`, March 2023

Table 4: Results of triple Difference-in-Differences

	CR			log(CPM)		
	(1)	(2)	(3)	(4)	(5)	(6)
After*iOS	−0.02**	0.01***	−0.05***	−0.08***	−0.06***	−0.09***
	(−0.03, −0.01)	(0.01, 0.01)	(−0.07, −0.04)	(−0.09, −0.07)	(−0.07, −0.06)	(−0.09, −0.08)
After*iOS*quantile-2	−0.01			−0.02*		
(smallest)	(−0.03, 0.01)			(−0.04, −0.001)		
After*iOS*quantile-3	−0.03**			−0.03**		
	(−0.05, −0.01)			(−0.05, −0.01)		
After*iOS*quantile-4	−0.03**			−0.03**		
	(−0.06, −0.01)			(−0.05, −0.01)		
After*iOS*quantile-5	−0.08***			−0.05***		
(largest)	(−0.10, −0.05)			(−0.07, −0.03)		
After*iOS*App Install		−0.13***			−0.07***	
		(−0.14, −0.11)			(−0.08, −0.06)	
After*iOS*Fcbk&AN			0.01			−0.03***
			(−0.01, 0.02)			(−0.04, −0.01)
Clustered SE	Y	Y	Y	Y	Y	Y
Audience-OS FE	Y	Y	Y	Y	Y	Y
Date FE	Y	Y	Y	Y	Y	Y
log(MAU)	Y	Y	Y	Y	Y	Y
log(DAU)	Y	Y	Y	Y	Y	Y
Observations	203,992	203,992	203,992	203,992	203,992	203,992
Adjusted R^2	0.92	0.93	0.91	0.97	0.97	0.97
Residual Std. Error	0.10	0.09	0.10	0.07	0.07	0.07

Note: *p<0.05; **p<0.01; ***p<0.001
The robust standard errors are clustered by audience.
Treatment group: Facebook Access iOS device.
Control group: Facebook Access Android device.

5.4 Discussion

Only a limited empirical stream of the literature has measured the impact of privacy regulations on targeting efficiency. This makes it hard to assess the economic significance of our results. Goldfarb and Tucker (2011) find a 65% reduction in ad effectiveness after the introduction of the EU Privacy Directive in 2002. Compared to our estimates, this coefficient is much larger.

Several characteristics of our study and our data contribute to explaining the low effect we find on targeting efficiency. First, we consider as conversions actions such as link click or app installs, which are not as demanding as a purchase for example. As a result, least efficiently targeted consumers could keep interacting with the ad but not necessarily go on with a purchase. Complementary studies could try to understand the impact of *ATT* on purchases. Second, our treatment groups do not include 100% of treated people. Some iOS users may have agreed to be tracked.[24] Also, our data pools all iOS users, including users of older versions; thus, formally, our main estimates are lower bounds for the true effect. To evaluate how the effect evolves with a higher proportion of treated users in the sample, we conduct a complementary analysis in Appendix C.3 Table 6. We conduct a robustness check by fixing our *after*-cutoff to June 26, when the combined adoption of iOS 14.5 and 14.6 reached approximately 70%.Although the result is mitigated by a limited amount of *after*-data, we find that the magnitudes of coefficients do not vary. The negative effect on targeting efficiency is 10.5%, while the relative drop in price reaches 14%. In the same way, however, in absolute value, both prices seem to have increased. Finally, the low magnitude could also be attributed to Meta's dominance in the market. This idea is reinforced by the positive change in prices, in absolute value.

[24]Between 12 and 25%, according to industry estimates (`https://9to5mac.com/2021/07/23/app-tracking-transparency-opt-in-snap/`, September 2021.)

Meta could be less affected than other actors in the display advertising market, for at least three reasons. First, it generates (through its own user interface) a substantial amount of data that is linked to a user profile. This profiling has no reason to be affected by Apple's privacy policy. Second, cookie syncing, which could make up for the inability to access a user's IDFA, is subject to large network effects (Jeon, 2021). As a consequence, Meta is more able than other actors of the industry to find alternative profiling methods. Third, we consider a short time period around the change in policy. This allows us to not include effects arising from other events that may happen during the year. However, Meta's user data is likely to be of sufficient quality such that it will not be completely obsolete in such a short time period. And ad effectiveness may keep decreasing as time goes by. This idea is reinforced by the different announcements META has made in 2022 regarding lost opportunities because of the *ATT*.[25] To summarize, the effect we measure on Facebook and the Audience Network should be a lower bound for the effect that *ATT* may have on other actors in the industry.

6 Conclusion

This paper contributes to understanding the impact of privacy policies on ad effectiveness and ad prices on a social media platform. We study the introduction of the *ATT* on the iOS14.5+, which aims to give consumers a choice about being tracked by apps. We use a novel dataset collected through Facebook's Marketing API. We find that the introduction of the *ATT* scheme by Apple has had a negative impact on Facebook's ability to efficiently target consumers and trigger conversions. This change was concurrent with a decline in the relative price of ads but with an increase

[25] `https://www.businessinsider.com/facebook-blames-apple-10-billion-loss-ad-privacy\-warning-2022-2?op=1&r=US&IR=T`, November 2023.

in the overall price. This suggests that the loss in targeting efficiency is followed by a readjustment in advertisers' demand or willingness-to-pay. However, despite the loss in targeting efficiency, the global increase in ad prices suggests that Facebook has kept part of its competitive advantage. The impact of the policy strengthens with time for ads targeted to the pooled iOS group, in line with an increased proportion of users adopting the latest versions of the iOS. Surprisingly however, we find that the effect on ad effectiveness and the following adjustment of ad prices weakens with the size of the target audience. This leads us to believe that contextual advertising compensates better at the end of tracking for very well defined audiences. The effect is also stronger for ads promoting app installs compared to ads promoting link clicks. This suggests that although simple advertising with easy-to-get conversions is not much threatened, Apple's new scheme may strongly affect the ability of firms to develop more sophisticated ad campaigns with actions from consumers that are harder to trigger.

There are limitations to this research. First, our data measures only the effect of privacy policy change on one platform which is one of the biggest ad platform worldwide. It should be complemented with studies on smaller actors. Second, our estimates measure the immediate effects of this policy change and do not consider long-term effects.

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clusions expressed on this articles are those of the authors and do not necessarily represent the views of their institutions.

References

Ahmadi, Iman, Nadia Abou Nabout, Bernd Skiera, Elham Maleki, and Johannes Fladenhofer, "Overwhelming targeting options: Selecting audience segments for online advertising," *International Journal of Research in Marketing*, 2023.

Alcobendas, Miguel, Shunto Kobayashi, and Matthew Shum, "The Impact of Privacy Measures on Online Advertising Markets," *Available at SSRN 3782889*, 2021.

Angrist, Joshua D and Jörn-Steffen Pischke, *Mostly Harmless Econometrics: An empiricist's companion*, Princeton university press, 2009.

Aridor, Guy, Yeon-Koo Che, and Tobias Salz, "The Economic Consequences of Data Privacy Regulation: Empirical Evidence from GDPR," Technical Report, National Bureau of Economic Research 2020.

Bian, Bo, Xinchen Ma, and Huan Tang, "The Supply and Semand for Data Privacy: Evidence from Mobile Apps," *Available at SSRN*, 2021.

Cheyre, Cristobal, Benjamin T Leyden, Sagar Baviskar, and Alessandro Acquisti, "The Impact of Apple's App Tracking Transparency Framework on the App Ecosystem," *Available at SSRN 4453463*, 2023.

Choi, W Jason, Kinshuk Jerath et al., "Privacy and Consumer Empowerment in Online Advertising," *Foundations and Trends in Marketing*, 2022, *15* (3), 153–212.

Goldfarb, Avi and Catherine E Tucker, "Privacy Regulation and Online Advertising," *Management Science*, 2011, *57* (1), 57–71.

_ **and Verina F Que**, "The Economics of Digital Privacy," 2023.

_ , **Catherine Tucker, and Yanwen Wang**, "Conducting Research in Marketing with Quasi-Experiments," *Journal of Marketing*, 2022, *86* (3), 1–20.

Jeon, Doh-Shin, "Market Power and Transparency in 0pen Display Advertising–A Case Study," 2021.

Johnson, Garrett, "Economic Research on Privacy Regulation: Lessons from the GDPR and Beyond," 2022.

Johnson, Garrett A, Scott K Shriver, and Shaoyin Du, "Consumer Privacy Choice in Online Advertising: Who Opts Out and at what Cost to Industry?," *Marketing Science*, 2020, *39* (1), 33–51.

Kesler, Reinhold, "The Impact of Apple's App Tracking Transparency on App Monetization," *Available at SSRN 4090786*, 2022.

Kraft, Lennart, Bern Skiera, and Tim Koschella, "Economic impact of opt-in versus optout requirements for personal data Usage: The case of Apple's app tracking transparency (ATT)," Technical Report, Working Paper 2023.

Laub, René, Klaus M Miller, and Bernd Skiera, "The Economic Value of User Tracking for Publishers," *Available at SSRN 4251233*, 2022.

Li, Ding and Hsin-Tien Tsai, "Mobile Apps and Targeted Advertising: Competitive Effects of Data Exchange," *Available at SSRN 4088166*, 2022.

Marotta, Veronica, Vibhanshu Abhishek, and Alessandro Acquisti, "Online Tracking and Publishers' Revenues: An Empirical Analysis," in "Workshop on the Economics of Information Security" 2019.

Ravichandran, Deepak and Nitish Korula, "Effect of Disabling Third-Party Cookies on Publisher Revenue," *Google Report*, 2019.

Wernerfelt, Nils, Anna Tuchman, Bradley Shapiro, and Robert Moakler, "Estimating the Value of Offsite Data to Advertisers on Meta," *University of Chicago, Becker Friedman Institute for Economics Working Paper*, 2022, (114).

Appendix

A Setting and Data

A.1 App Tracking Transparency screenshots

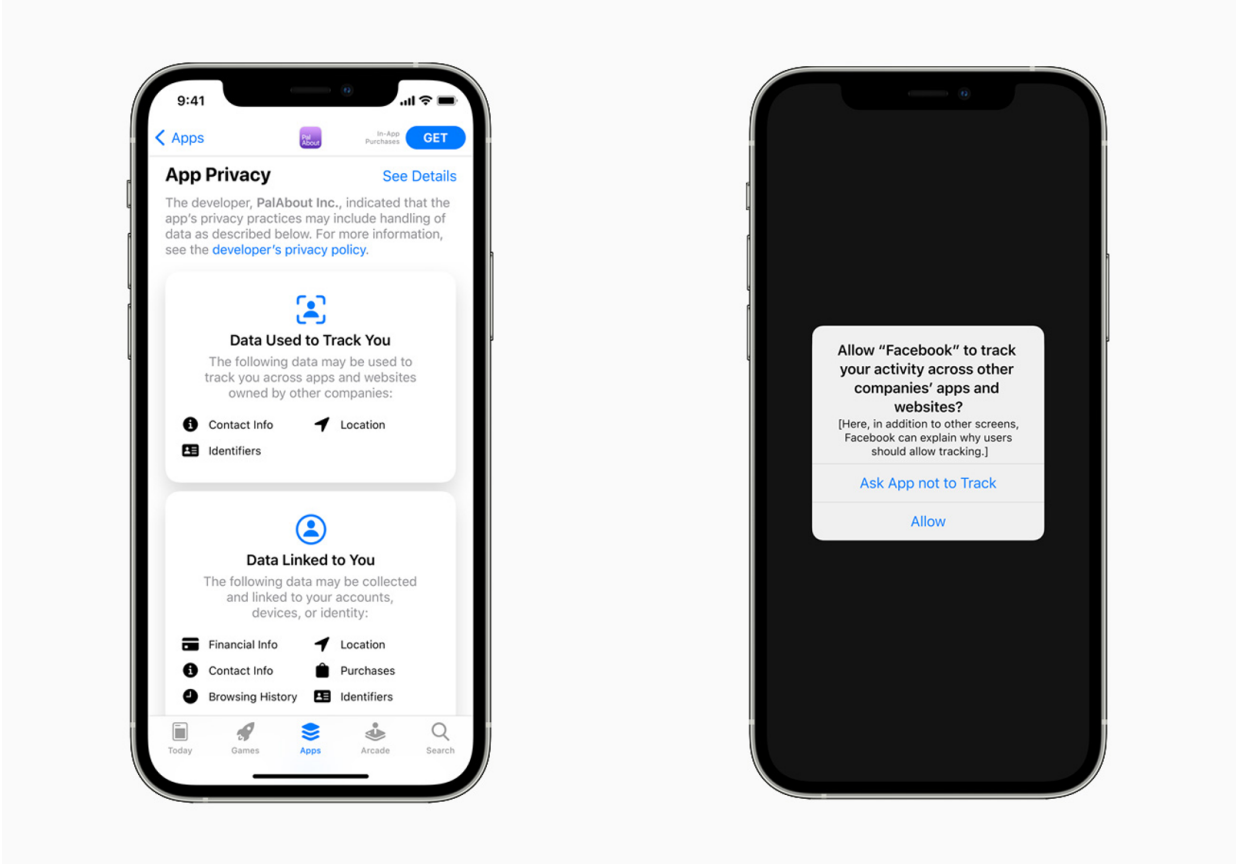


Figure 3: Apple *ATT* new features - Screenshots

A.2 Adoption of iOS14.5+

Figure 4 shows the evolution of number of iOS users in the US from March 2021 to July 2021.

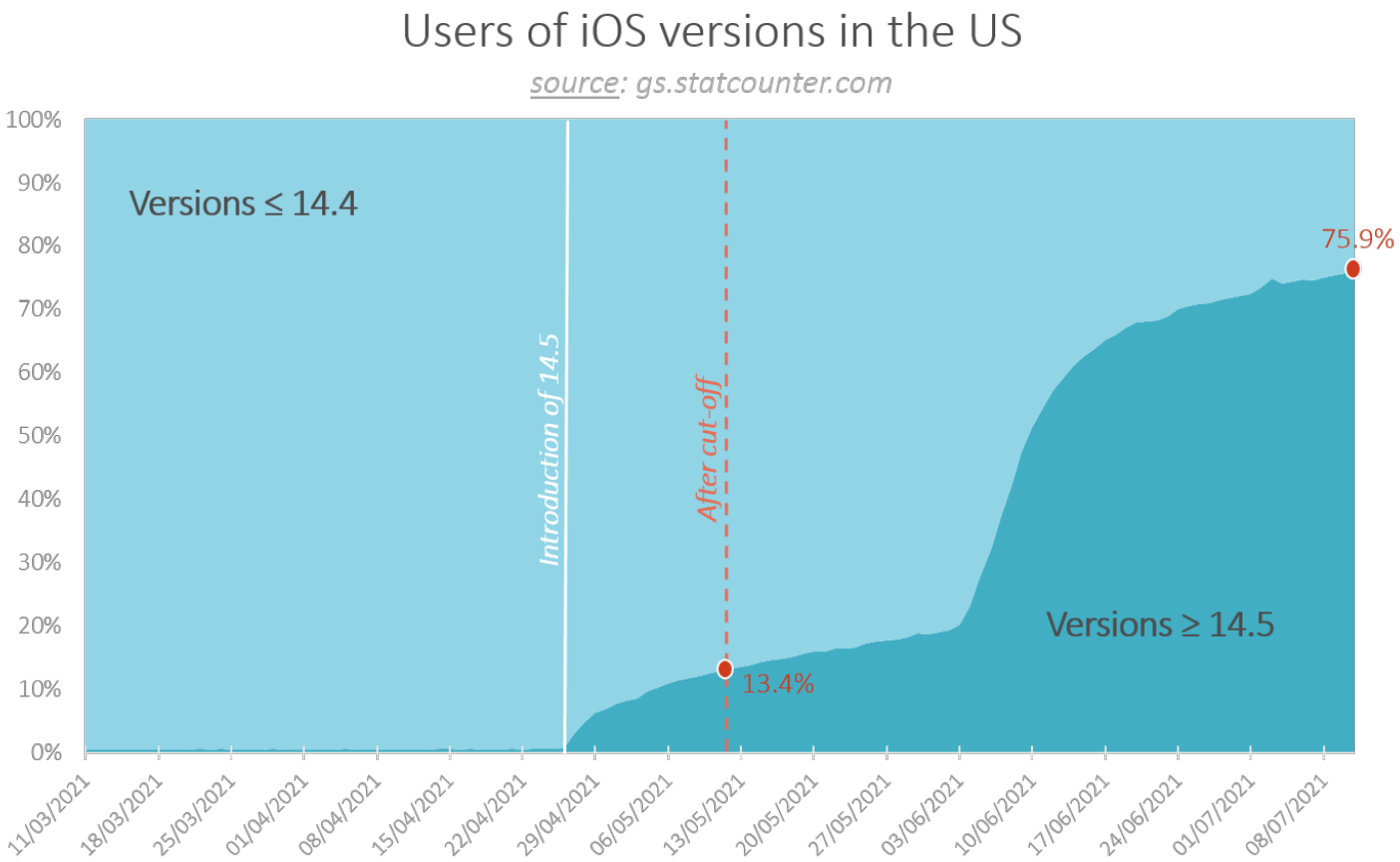
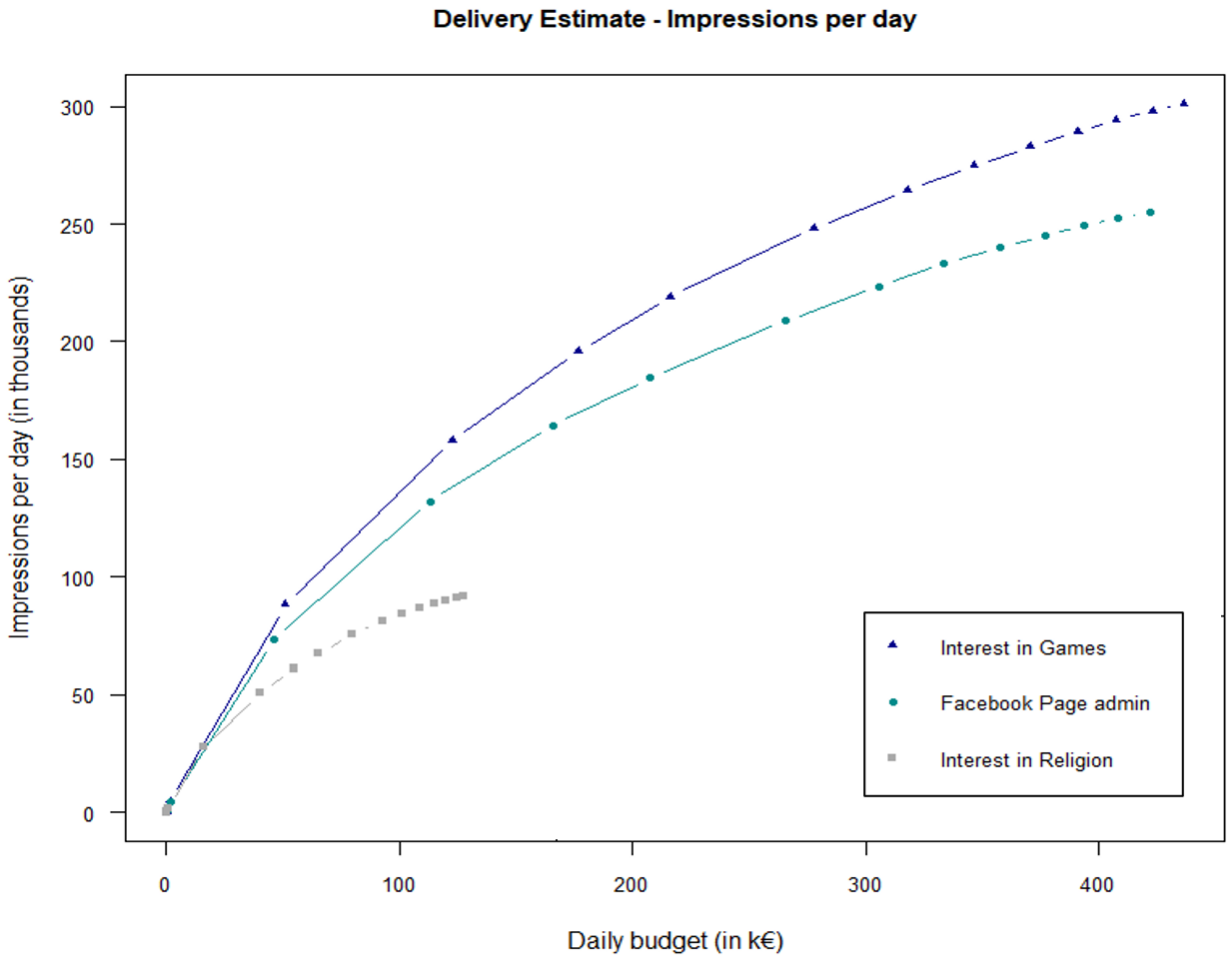


Figure 4: Proportion of Versions 14.5 and 14.6 among iOS Users during the Studied Time-Period

A.3 Sample Delivery Estimate Output

Figure 5 illustrates the curves of the delivery estimate output based on impressions for a given set of audience with a given daily budget.



Common audience characteristics: US, males, 18-34, top 10% income, bachelor degree, iOS users, publisher platform = Facebook, Optimization goal = app installs

Figure 5: Example of Delivery Estimate Output for Impressions, with three different Audiences.

B Parallel trends

The difference-in-differences methodology relies on the assumption that there are non-significant differences in pre-treatment trends. Figure 6 illustrates the trends in CR ratios, indicating that the two lines follow a parallel trend before the implementation of the *ATT*. We run the parallel trend test on a subsample to get a perfectly balanced panel. This subsample consists of precisely the same audience in both the treatment and control groups every day. The assumption holds as the statistical test does not reject the null hypothesis of parallel trends. There are no significant differences in the pre-treatment period by p-values > 0.1 (F-Stat: Parallel trends, 0.47).

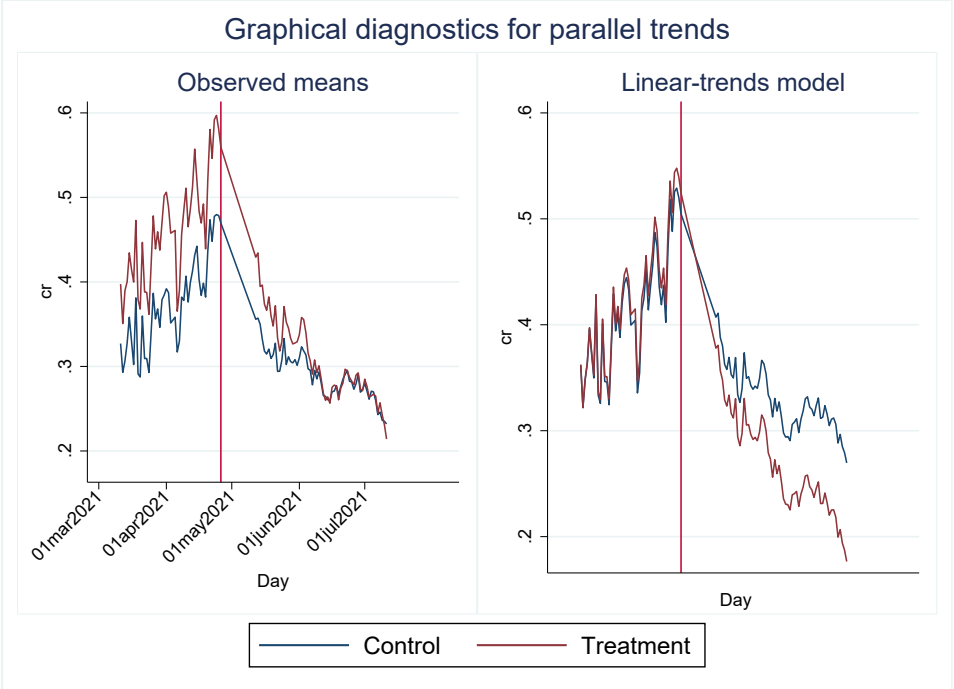


Figure 6: Graphical Diagnostic for Parallel Trends

C Complementary Analysis

C.1 Effect on Impressions and Actions

Table 5 presents estimates where we use alternative dependent variables, namely *Impressions* and *Actions*.

Table 5: Effect of the *ATT* on Impressions and Actions – Daily budget of 100 €

	Dependent variable:	
	Impressions	Actions
	(1)	(2)
After*iOS	2,110.16***	2.95***
	(1,981.71, 2,238.61)	(1.58, 4.32)
Clustered SE	Y	Y
Audience-OS FE	Y	Y
Date FE	Y	Y
log(DAU) Control	Y	Y
log(MAU) Control	Y	Y
Observations	203,992	203,992
Adjusted R^2	0.95	0.97
Residual Std. Error	2,118.22	23.55

Note: *p<0.05; **p<0.01; ***p<0.001
The standard errors are clustered at the audience level.

C.2 Robustness of *After* date

We check that the chosen *After* date does not make a significant difference on the baseline results. We run a series of regressions in which the *After* cut-off varies between May 8 and May 16. We plot the resulting difference-in-differences coefficients in Figure 7 and observe that they remain nearly unchanged as the *After* cut-off shifts.

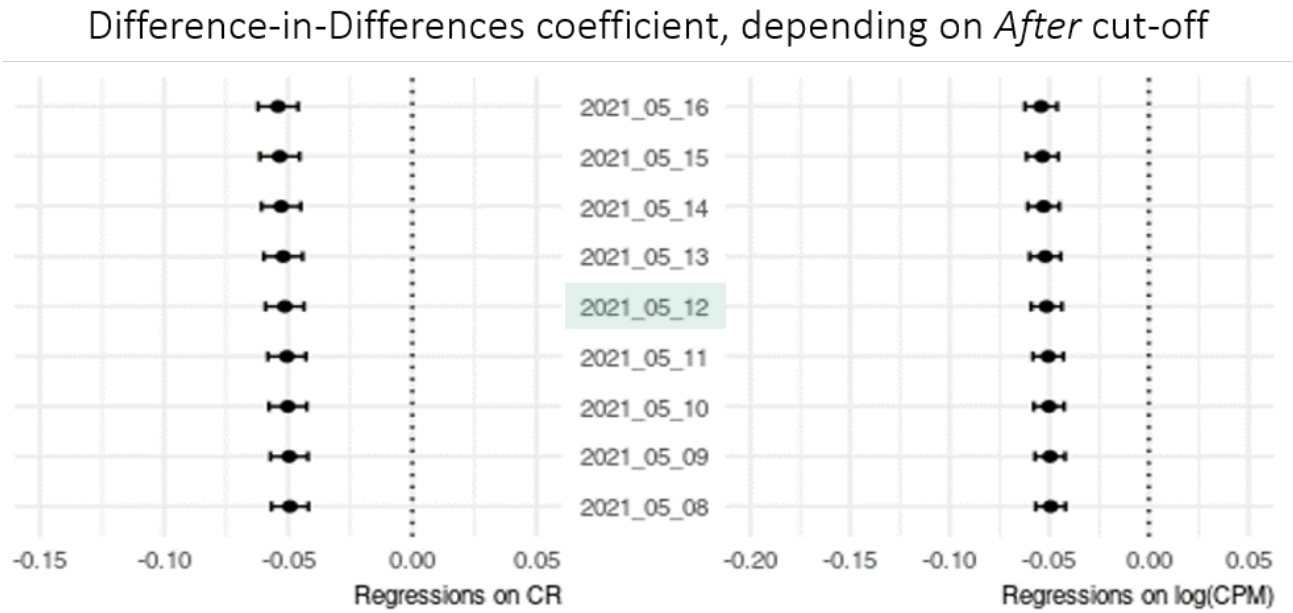


Figure 7: Results of Multiple Regressions with a different *After* Cut-off points

C.3 Analysis with High Adoption Rate of iOS 14.5-14.6

To assess how the average effect measured depends on the rate of new OS adoption in the pool of iOS users, we conduct a robustness check by fixing our *after*-cutoff to June 26, when the combined adoption of iOS 14.5 and 14.6 reached approximately 70%.[26] Columns (1) and (2) of Table 6 shows the estimates. Figure 8 shows that on this date, the income and gender compositions of the different versions of the iOS are similar. The coherence of the results alongside widespread adoption and consistent audience composition helps alleviate concerns regarding potential selection biases.

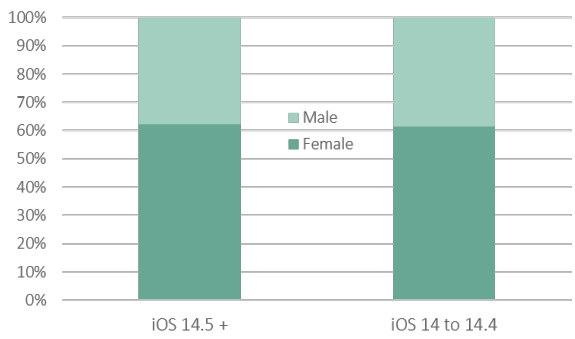
Table 6: Regression on CR and log(CPM), after June 26

	Dependent variable:			
	CR		log(CPM)	
	(1)	(2)	(3)	(4)
iOS*After_26th	-0.07^{***}	-0.07^{***}	-0.14^{***}	-0.14^{***}
	(−0.08, −0.06)	(−0.08, −0.06)	(−0.14, −0.13)	(−0.15, −0.13)
iOS	0.14^{***}		0.05^{***}	
	(0.13, 0.15)		(0.05, 0.06)	
After_26th	0.004		0.21^{***}	
	(−0.004, 0.01)		(0.20, 0.22)	
Clustered SE	Y	Y	Y	Y
Audience-OS FE		Y		Y
Date FE		Y		Y
log(DAU) control		Y		Y
log(MAU) control		Y		Y
Observations	112,122	112,122	112,122	112,122
Adjusted R^2	0.03	0.90	0.03	0.96
Residual Std. Error	0.34	0.11	0.40	0.08

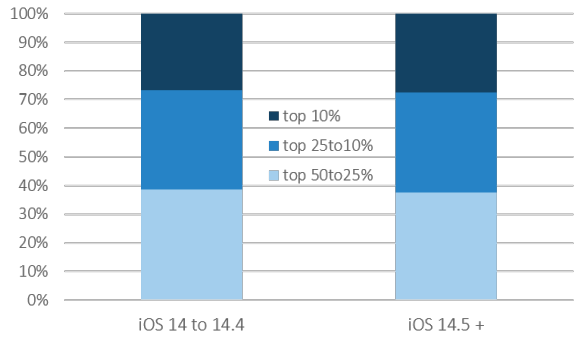
Note: *p<0.05; **p<0.01; ***p<0.001

The standard errors are clustered at the audience level.

[26] It goes up to more than 75% at the end of our time-period. `https://mediamatterssww.com/uncategorized/the-impact-of-ios14-5-and-app-tracking-transparency-att/`, November 2023.



(a) Gender Composition



(b) Income Composition

Figure 8: Sample composition iOS 14 to 14.4 vs. iOS 14.5+ on June 26, 2021, built with Facebook's DAU.