The Impact of Apple's App Tracking Transparency on App Monetization*

Reinhold Kesler†

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Abstract

Recent years have been characterized by privacy regulations amid concerns of exploitative data collection and use, thereby setting boundaries to the data economy that fuels today's ad-funded Internet. An example is Apple's App Tracking Transparency (ATT), which necessitates explicit consent for tracking users outside of an app and potentially undermines advertisement revenues. This paper studies whether and how app developers turn to payments as an alternative revenue source in response to a more privacy-preserving environment. Specifically, we use rich web-scraped data to compare the monetization of more than 580 thousand apps on Apple before and after the privacy change and across platforms with apps on Google in a difference-in-difference setting. The results suggest that the ATT brings back paid apps and reinforces the industry trend toward more in-app payments. However, the small short-run effects suggest that the ATT did not shift the relative benefits much between payments and ads. Yet, more pronounced effects for apps relying on Apple and tracking as well as those newly entering the market, may shed further light on the possible long-run impact.

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†University of Zurich and ZEW Mannheim; Plattenstrasse 14, CH-8032 Zurich, Switzerland. E-Mail: reinhold.kesler@business.uzh.ch.

1 Introduction

Many products and services of today's Internet are funded by advertisements (ads) rather than, for instance, payments. The dependency on advertisements of the digital economy becomes apparent with revenue shares of more than 97 % and 80 % for Meta and Alphabet.[1] Not only is advertising hugely important but identifying, profiling, and targeting individual users makes it even more valuable. At the same time, regulatory efforts aim to better protect user privacy and, by this, set boundaries to the current data economy, especially to mitigate the tracking of users. Besides legislation like the European General Data Protection Regulation (GDPR) or the California Consumer Privacy Act (CCPA) already in place, platforms have begun to set rules preserving user privacy. This raises the question of how businesses respond in terms of monetizing digital products and services in an increasingly privacy-preserving environment that may erode revenues from ads.

Previous research provides evidence that losing track of users or making it more costly to track undermines monetization through (targeted) advertisements. The studies look at privacy changes that range from mandating privacy policies (Tucker, 2012, 2014), disabling cookies (Goldfarb and Tucker, 2011; Johnson et al., 2020; Marotta et al., 2019), banning ad targeting for children's mobile games (Kircher and Foerderer, Forthcoming), to more wide-ranging privacy regulations like the GDPR. For the latter, empirical evidence suggests that the regulation led to fewer page views or visits and lower revenues for e-commerce firms (Goldberg et al., 2022; Schmitt et al., 2021), while the ability to collect data has also been mitigated (Aridor et al., 2022; Godinho de Matos and Adjerid, 2022).[2]

Rather than the potentially lower advertisement revenues, this paper's contribution is to study whether and how businesses that provide digital products and services turn towards alternative revenue sources with a privacy-preserving change on a platform. The

[1]See firms' annual reports, https://investor.fb.com/investor-news/press-release-details/2022/Meta-Reports-Fourth-Quarter-and-Full-Year-2021-Results/default.aspx and https://abc.xyz/investor/static/pdf/2021Q4_alphabet_earnings_release.pdf.

[2]Further studies suggest other unintended consequences of the GDPR, comprising a rise in market concentration for web technology services (Batikas et al., 2022; Johnson et al., 2022b), a decrease in venture investments (Jia et al., 2021) and entry (Janssen et al., 2022), along with frictions in search (Zhao et al., 2021), and a larger burden on profits as well as sales of small and medium-sized enterprises (Chen et al., 2022).

context of our study is the market for mobile applications (apps), where targeted advertisements are an important revenue source, and the so-called money-privacy tradeoff (Acquisti et al., 2016) has been documented in the past.[3] We specifically consider Apple's privacy-preserving change called App Tracking Transparency (ATT) which necessitates explicit consent by users to track them outside the app, thereby worsening the targeting and attribution of advertisement campaigns in case of opt-outs by users (see Section 2.2). Indeed, anecdotal evidence suggests the ATT to have a negative impact on the profitability of advertisements. For instance, Facebook made headlines by reporting losses of $10 billion in advertisement revenues in the year following the change.[4] App developers also report ad revenue losses because of the ATT of about 25 to 30 percent and more (CMA, 2022), thereby confirming forecasted losses before the enactment in the range of at least 15 to 20 percent.[5]

In this paper, we study whether and how app developers turn to payments as one alternative way to earn money with apps in a quasi-experimental setting, where apps on Google's Play Store serve as a control group with rich web-scraped data on both platforms. Specifically, we have monthly data for apps on both Apple and Google around Apple's privacy change and look at app developers' change in monetization to pay upfront or inside the app. The empirical strategy involves several steps. First, it compares apps on Apple before and after the ATT. Second, we study this change across platforms with apps on Google's Play Store in a difference-in-difference setting. Third, effect heterogeneity is considered to study whether Apple's privacy change is indeed the underlying mechanism, thereby also shedding light on which app developers are affected the most. Finally, descriptive analyses explore further implications of the ATT.

The results suggest that apps become more often for pay and have more frequently in-app payments on Apple's app store following the platform's privacy change. Interestingly, when compared to Google's Play Store, the evidence suggests that the ATT reverses the preceding negative trend for the presence of paid apps while it reinforces the existing trend toward more in-app payments. Although the impact is small on average, it is

[3] Kummer and Schulte (2019), and Cecere et al. (2020) provide correlational evidence for the market of mobile applications. Bian et al. (2022) study the introduction of Apple's privacy labels to document app developers' data collection and show decreasing demand as a reaction by users to the disclosure.

[4] See https://www.cnbc.com/2022/02/02/facebook-says-apple-ios-privacy-change-will-cost-10-billion-this-year.html.

[5] See https://venturebeat.com/2021/07/13/brian-bowman-apples-idfa-change-has-triggered-15-to-20-revenue-drops-for-ios-developers/.

more prevalent among apps relying on Apple, as measured by single-homing apps and developers, as well as for apps that employ or rely on user tracking targeted by the policy change. Moreover, apps belonging to younger cohorts adopt payments more often after a continuous decline for years, while the trend for more in-app payments accelerates. All of these results provide insights on what to expect in terms of monetization by digital businesses with the coming privacy-centric regulations and policies that may necessitate revisiting our understanding of digital marketing (Johnson et al., 2022a).

The remainder of the paper is structured as follows. Section 2 provides information on app monetization and how Apple's ATT may affect this. Section 3 introduces the empirical strategy, while Section 4 provides information on the data and shows descriptive statistics. Section 5 presents the main analyses, explores the underlying mechanism, and provides further implications. Section 6 concludes.

2 Background

2.1 App Monetization

The primary revenue sources for mobile app developers are in-app advertisements and in-app payments. Ads are more frequent among apps on Google, while on Apple, in-app payments are almost as prevalent as ads.[6] The share of apps that are for (upfront) pay is in a continuous decline over the last ten years, in the single digits, and especially low for Google.[7]

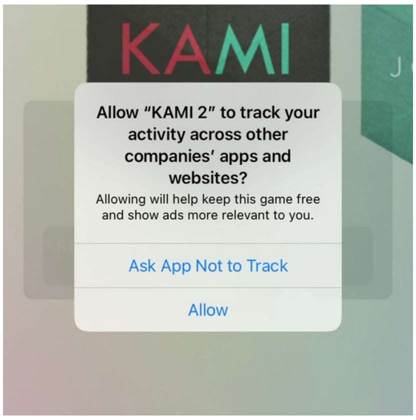
While money from payments for or inside an app is obvious, monetization through advertisements is related to the success of an advertisement campaign. This success heavily depends on the ability to target and attribute. While the former means to use the information on a user's behavior to tailor ads, the latter is the measurement of the effectiveness of ads through matching, often through a third-party, a user's ad interaction with desired conversions like a purchase afterward (CMA, 2022). For both of these key elements, identifying the users and their characteristics is of the essence, thereby making ads more valuable.

[6]See https://www.flurry.com/blog/are-app-developers-shifting-revenue-models-as/.
[7]See, for example, the archived snapshots over time, https://web.archive.org/web/2021*/https://42matters.com/stats.

2.2 Apple's App Tracking Transparency (ATT)

With the iOS update 14.5 on 26th April 2021, Apple introduced the App Tracking Transparency (ATT) as part of the company's self-declared push to strengthen users' privacy.[8] This privacy change involves a one-time prompt within the app that explicitly asks for the consent by the user, in case the app wants to track the user outside the app. Apps cannot make the functionality dependent on the user's decision. Thus, one can still use the app after opting out. Apps can briefly write what users can expect in return for allowing tracking. Some apps describe the tradeoff between (targeted) advertisements and payments already in the prompt (see Figure 1).

Figure 1: Exemplary Consent Prompt



Notes: This is an actual ATT prompt for the app KAMI 2 reported by a user on attprompts.com, see https://www.attprompts.com/details/kami-2/r/recYa8lBW6ykbmhwT.

If a user chooses to disallow tracking, the app cannot retrieve the user's identifier for advertising (IDFA). Hence, one cannot attribute the success of an advertisement to a specific user. Moreover, conversions cannot enrich user profiles, while even creating a user profile becomes more difficult without a common identifier across apps. This reduces the accuracy of measuring returns to ads, and one can target ads less effectively. As a result, this is a privacy change that potentially undermines monetization from advertisements (CMA, 2022). Lin and Misra (2022) model the fragmentation of identities by users with a policy change like the ATT as an example and find difficulties to measure advertising

[8] Although Apple's privacy changes were announced at WWDC in June 2020, the actual launch of the ATT has been delayed several times, with a vague final date of early spring 2021. In the end, the announcement of the actual version release came with the introduction of Apple's AirTag less than one week before. See https://web.archive.org/web/20210420171331/https://www.apple.com/newsroom/2021/04/apple-introduces-airtag/.

effects as a result.

This matters for businesses if many users do not allow tracking.[9] While surveys before the introduction of the ATT already suggested this,[10] actual data from user decisions by a range of mobile analytics companies and with different metrics shows that 60 to 80 percent of users do not allow tracking outside of the app.[11] This pattern remained stable over time until the end of 2021.[12]

As a consequence, tracking many users is not possible, and this not only restricts monetization from ads but also acquiring (new) users and attracting sufficient demand through ads may become more difficult (CMA, 2022).[13] Indeed, Li and Tsai (2022) find a larger decrease in rankings for top apps following the ATT, but also a decrease in new app entries. Our contribution is to study whether and how app developers may adapt their monetization strategy following Apple's privacy change.

Although the ATT came live at the end of April 2021, only users with the new iOS version got the prompt asking for consent. As the adoption of iOS updates takes time and depends on whether Apple notifies users proactively, the impact for app developers is not necessarily immediate. As suggested by mobile analytics companies, the vast majority of users had iOS 14.5 (or newer) by the end of June.[14]

Even though different kinds of tracking by means of other identifiers, so-called fingerprinting, are also prohibited under the ATT, news reports suggest enforcement by Apple to be weak in this regard. Empirical studies reveal a change in tracking following the privacy change (Kollnig et al., 2022).[15] This possible circumvention would weaken the impact of the ATT for the respective app developers, which is further discussed in the empirical setup (see Section 3.2.1).

[9]Users that opt-in may become more predictable and thus more valuable, thereby potentially offsetting losses of opt-out users as shown by Aridor et al. (2022). However, the distinctively higher amount of opt-out users with the ATT compared to those found in research on GDPR may suggest this offsetting to be less important.

[10]See, for instance, https://www.tapresearch.com/insights_platform/results/420d80ccc2b93c7a1cf0b694243ed070/IDFA.

[11]See, for an overview, https://www.adexchanger.com/data-driven-thinking/att-opt-in-rates-the-picture-so-far-and-the-ugly-truth-behind-why-the-numbers-vary-so-widely/ and https://twitter.com/alexdbauer/status/1440542344034414598.

[12]See https://twitter.com/alexdbauer/status/1489429120266084354.

[13]Wernerfelt et al. (2022) study the value of offsite data for ad targeting on Meta and find costs of acquiring new customers to increase by 37 percent without access to such.

[14]See https://twitter.com/alexdbauer/status/1410073980283748355.

[15]See an exemplary news report, https://www.ft.com/content/9cb52394-f95f-4b07-a624-89c47439aa16.

3 Empirical Setup

3.1 Hypotheses

Based on previous research showing the impact of tracking restrictions making advertisements less profitable (see Section 1), we primarily study whether Apple's privacy change may make app developers choose other revenue sources. Given the different ways of app monetization (see Section 2.1), an obvious revenue source would be payments, although the possibility of changing to such a business model may differ across apps. Alternatively, app developers may reduce the maintenance or development of apps when faced with reduced revenues.

While the focus of the analyses is on app developers' potential decision to adopt payments and its possible heterogeneity across app characteristics, we also employ auxiliary analyses to understand the impact on advertisement revenues and, ultimately, to test alternative hypotheses regarding app development.[16] Hence, for our main hypothesis, the presence of payments for the app or inside the app is compared across time and platforms to examine the impact of the ATT for the universe of apps. For this, the empirical strategy is primarily two-fold.

3.2 Empirical Strategy

Before-after: First, apps before and after the privacy change on Apple are compared as outlined in equation (1). The binary dependent variable $Y_{i,t}$ denotes pay and in-app payments as a way to monetize app i in period t. Our coefficient of interest is β_1, where $Post_{i,t}$ is a dummy variable equal to one for periods following Apple's privacy change. Additionally, we include the presence of the alternative payment option along with further control variables ($X_{i,t}$), while app fixed effects (η_i) are also employed to rule out time-constant unobserved heterogeneity.

$$Y_{i,t} = \beta_0 + \beta_1 Post_{i,t} + X_{i,t} + \eta_i + \varepsilon_{i,t} \tag{1}$$

Difference-in-difference: Second, the before-after comparison is extended by a further comparison with apps on Google, which gives a difference-in-difference setup. For

[16] App developers may also change their advertising strategy or turn to other means of identifying users across apps and websites, which is touched upon in the auxiliary analyses.

this, in equation (2), we augment the baseline with an additional subscript p indicating the platform, as the unit of observation becomes an app on a certain platform in a given period. Our coefficient of interest remains β_1, which is now composed of an interaction between a dummy variable indicating the platform $Apple_{i,p}$ and the variable $Post_{i,p,t}$ denoting the post-period. This makes it a variable equal to one only for apps on Apple in the periods following the enactment of the ATT. Having both platforms makes it possible to disentangle whether the impact is particular to one platform and thus causal or part of an industry-wide trend over time, as the market is very dynamic. For this, time fixed effects (η_t) are included. Further control variables ($X_{i,p,t}$) have to be comparable across platforms, making the set of variables more limited.

$$Y_{i,p,t} = \beta_0 + \beta_1 Apple_{i,p} \times Post_{i,p,t} + X_{i,p,t} + \eta_i + \eta_t + \varepsilon_{i,p,t} \tag{2}$$

Discussion: The difference-in-difference setup hinges on assumptions that need to be addressed.

First, related policy changes on Google's Play Store may invalidate the counterfactual. Yet, there is no privacy change like the ATT on Google's Play Store during the observation period. Relatedly, we formally need to test that in the absence of Apple's policy, apps on both platforms would have experienced the same trend, though allowing for different levels. In general, there should not be policy shocks, either from the platforms or regulatory authorities, that are relevant for monetization around the enactment. Table A.1 shows a chronology of events around the observation period and suggests no relevant changes happened at the same time as the ATT. However, it also shows the difficulty of a longer observation period. While it allows studying a longer-lasting impact, the results may be confounded by other policies.

Second, spillovers for app developers active on both platforms from Apple to Google are possible.[17] However, this would only underestimate the impact found in β_1 as apps are either less likely to change on Apple when there is enough compensation from Google or change on both platforms right away as it is hard to maintain multiple business models.

[17] For instance, there are reports of fewer bid requests for ads on iOS, and apps report lower ad prices for opted-out iOS users (see https://www.adexchanger.com/mobile/verve-group-launches-atom-targeting-by-cohort-for-ios/). Moreover, there is also anecdotal evidence of advertiser spending to be allocated more towards Google and less towards Apple (see https://digiday.com/marketing/as-att-hits-critical-mass-media-spending-see-saw-from-ios-to-android-continues/).

Furthermore, we run the analyses without multi-homing apps so that the difference-in-difference setup can rest on the stable unit treatment value assumption (SUTVA).

Finally, the anticipation of Apple's privacy change may be a concern in light of the early announcement, though the exact release date was not known until one week before. Furthermore, we will look into patterns before and around the ATT enactment. In that regard, the staggered adoption of the iOS update helps us to infer when app developers felt the 'real' impact of the privacy change.

3.2.1 Effect Heterogeneity

Having established causal evidence on the impact of the privacy change in equation (2), we try to further corroborate that the ATT is the underlying mechanism found in equation (1) and look into apps presumably affected the most by Apple's privacy change in more detail. By doing this, we also relax the assumption of a homogenous effect felt across all app developers alike. Instead, some may be more vulnerable to a possible loss both in data collected from tracking users outside the app and in advertisement revenues. In turn, these are also more likely to change their monetization and turn towards alternative revenue sources, one of them involving payments for or inside an app. Unless, of course, app developers can compensate (or live through) the losses in either user data or advertisement revenue.

In the following, we try to conceptualize the extent to which app developers may or may not compensate for the impact of the ATT. We then differentiate between the two groups. For this, we approximate (i) the reliance on Apple as a platform where the privacy change happened and (ii) the reliance on tracking users via the identifier prohibited under the privacy change without user consent. In order to do this, we augment the equation (1) by interacting the dummy variable denoting the post-ATT period with the following different indicators. For (i), we look into apps only active on Apple. These single-homing apps do not receive revenues from Google's Play Store, where no privacy change happened. Taking this a step further, one may look at the share of apps by a developer that is only active on Apple. Both approaches provide suggestive evidence about the presence and extent of spillovers. For (ii), apps are considered that collect outside data to track users, as stated by the app developers. Furthermore, we argue apps are more affected if they are part of a category that relies more heavily on advertisements (and thus tracking).

4 Data and Descriptive Statistics

4.1 Data

4.1.1 Sampling

In order to measure the impact of Apple's privacy change, we need information about apps on Apple before and after the introduction of the ATT, with apps on Google serving as a control group. The observation period spans from February 2021 to December 2021, and the unit of observation is an app that is observed monthly on the respective platform. Based on all monthly crawls, we keep apps in our panel that are observed in the last month of the observation period. Observations of an app that are missing in-between, which comprise only 1.52 percent of the sample due to technical crawl-related issues, are imputed by carrying forwarding the value of dummy variables, while an average between two periods with values is constructed for cumulative measures.[18] This results in a balanced panel.

For Apple, the panel comprises 583,834 apps based on scraping top rankings from AppAnnie (now: data.ai) to retrieve all the relevant apps (40,894), followed by gathering other apps by the developer and similar apps suggested by Apple on each app's page (542,940).[19] For Google, the panel consists of 901,182 apps, where the sample is based on a panel from Janssen et al. (2022) that ended in October 2019 and is extended by scraping every following quarter the similar apps of previously found apps until January 2021. In order to verify that the sample contains all the relevant apps, we compare the distribution of installations by apps with Androidrank (see Section A.2 for a detailed comparison). The relatively higher number of available apps on Google's Play Store resonates well with aggregate statistics provided by mobile analytics companies.[20]

4.1.2 Measures

For both platforms, the goal is to retrieve comparable information on the app developer's monetization and further characteristics. However, for some of the more detailed analyses, there is only information available for apps on Apple as the platform of interest.

[18] In case an app happens to miss in the last period, we look at whether it is present in the month afterward and impute accordingly. This approach leaves us without the latest month crawled (January 2022) to rule out random missings.

[19] See Section A.2 for more details.

[20] See https://42matters.com/stats.

Monetization: Both Apple and Google show information on the app's page, whether the app is for pay or contains in-app payments giving us dummy variables, respectively.

Measures related to advertisements and data collection are hard to compare across platforms. On Google, one can observe a field on the app's page whether it contains ads, while there is also information on requested permissions by an app that can be classified into ones enabling data collection. On Apple, there is no such information. However, Apple introduced so-called privacy labels in December 2020, the presence of which for an app we can indicate with a dummy variable. For the subgroup of apps on Apple that provided such, measures can be derived that relate to advertisements and data collection (see below and Appendix A.3).[21]

Reliance on Apple: For all apps found on Apple, we looked in February 2021 whether apptopia, an app analytics company, also links to a version of the same app on Google's Play Store. Based on this, we can identify apps that are single-homing on Apple and create a corresponding dummy variable that is assumed to be time-constant. Having the information for each app, whether it is single-homing, we can also compute the share of apps only active on Apple for each developer in the sample.

Reliance on Tracking: For apps providing privacy labels, we can infer whether they report collecting data to track users outside the app (see Appendix A.3), which is the target of Apple's policy change making the IDFA only available whenever a user gives consent. Furthermore, we define ad intensive categories, following Li and Tsai (2022), as those 10 out of the 26 categories that send the most advertisements according to App Growing.[22] This gives us dummy variables equal to one for apps that track users in such a way and which belong to ad intensive categories.

Finally, there is a rich set of further characteristics. First, there are measures similar across platforms, for which the presence (website, privacy policy) or magnitude (size in KB, description length in characters) can be indicated. Others are, however, time-

[21] Only in mid-2022, Google introduced somewhat similar privacy labels (with a so-called Data Safety section) necessitating apps to disclose collection, sharing, and handling of data. See `https://blog.google/products/google-play/data-safety/`.

[22] These comprise Books, Education, Entertainment, Finance, Games, Health & Fitness, Lifestyle, Navigation, Photo & Video, and Shopping.

constant (category, age rating, age). Second, the data includes measures for which either the observation period is shorter (updated last month)[23] or variables across platforms are harder to compare (number of ratings and average rating)[24]. Finally, there are platform-specific variables that are used selectively in the analyses (Apple: reliance measures and being a 'top' app, i.e., gathered from rankings; Google: number of installations).

4.2 Descriptive Statistics

Summary statistics in Table 1 confirm that there is a level difference in monetization through payments between the two platforms, with only 6 percent and 13 percent of apps on Google making money through pay or in-app pay, while on Apple the shares are 11 percent and 22 percent, respectively.

Table 1: Summary Statistics

	Apple			Google		
	Mean	Median	N	Mean	Median	N
Pay Dummy	0.11	0.00	6420216	0.06	0.00	9266851
In-App Pay Dummy	0.22	0.00	6421393	0.13	0.00	9886910
Size (in KB)	76447.27	40448.00	6421371	19657.84	10137.60	9058621
Description Length	955.97	685.00	6421393	1233.36	859.00	9886701
Website Dummy	0.48	0.00	6421393	0.79	1.00	9887020
Privacy Policy Dummy	1.00	1.00	6421393	0.82	1.00	9887020

	Apple		
	Mean	Median	N
Single-Homing Dummy	0.58	1.00	6422174
Privacy Label Dummy	0.29	0.00	6422174
Tracking Dummy	0.07	0.00	6421393

Notes: Numbers are based on the whole panel. Size (in KB) is missing on Google mostly due to 'varies by device' as a value. Not all variables are present on both platforms. As Apple is the platform of interest, we focus on more detailed measures available there.

While apps on Apple are greater in size and almost all have a privacy policy compared to Google, apps on Google present themselves with a longer description and a website more likely. We find 58 percent of apps on Apple in our sample to single-home, i.e., only to be available on Apple. As further outlined in Appendix A.3, the majority of apps do

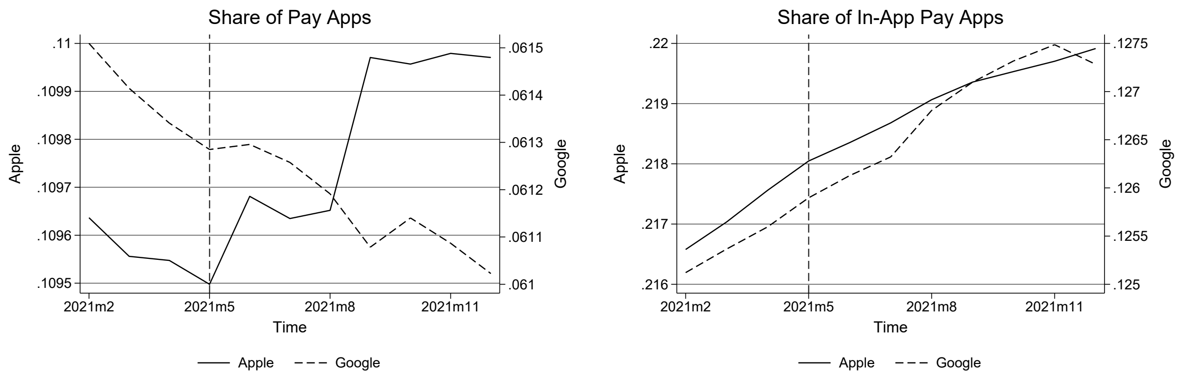
[23] On Google, we know the exact date of the last update, while on Apple, we compare the version number between months.

[24] There is a common problem of having no average rating in the absence of ratings. Furthermore, on Apple, the ratings are country-specific (here: US) and can be reset, whereas on Google, the ratings changed from global to country-specific towards the end of the observation period (see https://android-developers.googleblog.com/2021/08/making-ratings-and-reviews-better-for.html).

not provide privacy labels, while only one in four of those providing such labels use data to track users.

For both platforms, the share of pay (left) and in-app pay (right) apps over time is depicted in Figure 2. For pay, there is first a negative trend over time. But, following the ATT, there is an increase in the prevalence of paid apps on Apple, although it is very modest. This is not present on Google, which suggests a certain platform-specific divergence. Interestingly, the largest increase in the share of paid apps coincides with the period after the vast adoption of the iOS update containing the ATT. For in-app pay, there is a positive trend present on both platforms without a specific discontinuity around the privacy change.

Figure 2: Share of Apps with Payments



Notes: The first post-ATT month, May 2021, is denoted by the vertical line.

5 Results

5.1 Baseline Analyses

Table 2 shows the baseline regressions with pay and in-app pay dummy variables as dependent variables. We include the alternative payment option and the presence of a privacy label (for Apple-only samples) as explanatory variables and employ app fixed effects. Additionally, we include the size and description length of an app along with the presence of a website and privacy policy on the app's page as control variables.[25] We start with a sample comprising apps on Apple in columns 1-2 and 4-5. In order to

[25]Table A.3 includes further control variables accounting for the quality and demand of apps, which are not included in the baseline regressions as they restrict the estimation sample and/or limit the comparability of measures across platforms. The results, however, are qualitatively similar.

track the development over time, we first have time dummy variables as our coefficients of interest. These are positive and statistically significant for apps that are for pay with and after the enactment of the ATT, while for in-app payments, the periods following the ATT become positive and statistically significant. A Post dummy variable indicating the post-period confirms this and suggests a statistically significant increase of 0.055 and 0.09 percentage points for apps to be for pay and to have in-app payments following Apple's privacy change.

In columns 3 and 6 of Table 2, we add apps on Google to the sample, which enables a comparison of app monetization between platforms while controlling for common period-specific shocks. For this, we basically repeat the baseline specification[26] and include time dummy variables and have an interaction of the Post dummy variable with a variable indicating Apple as the platform, which is equal to one only for apps on Apple following the privacy change. For both pay and in-app pay, there is a positive and statistically significant coefficient, especially suggesting the increase in pay to be something peculiar to the Apple platform. Accordingly, the time dummy variables suggest a negative time trend for pay, although there seem to be slowdowns following the periods when the adoption of the respective iOS update is almost fully reached. In contrast, for in-app pay, the time dummy variables reveal a positive and statistically significant trend over time that makes up much of the increase in the Post dummy variable shown in column 5, which suggests this move towards in-app pay is common across platforms.

In order to account for spillovers between apps active on both platforms, Table A.4 repeats the baseline estimations but excludes multi-homing apps. While in columns 1 and 4, the sample contains no multi-homing apps on Apple, columns 2 and 5 only include apps by developers that do not multi-home at all. In contrast, columns 3 and 6 show results when multi-homing apps on Apple and Google are both excluded from the combined dataset. As expected, across all specifications, the positive and statistically significant coefficients denoting the before-after and difference-in-difference setup become larger. This suggests the presence of spillovers that are further studied in Section 5.2.

Turning toward the parallel trends assumption, although Figure 2 may suggest parallel trends in the pre-ATT period for both pay and in-app pay on both platforms, we employ

[26]We exclude the variable indicating the presence of privacy labels as this information is Apple-specific.

Table 2: Baseline Regressions

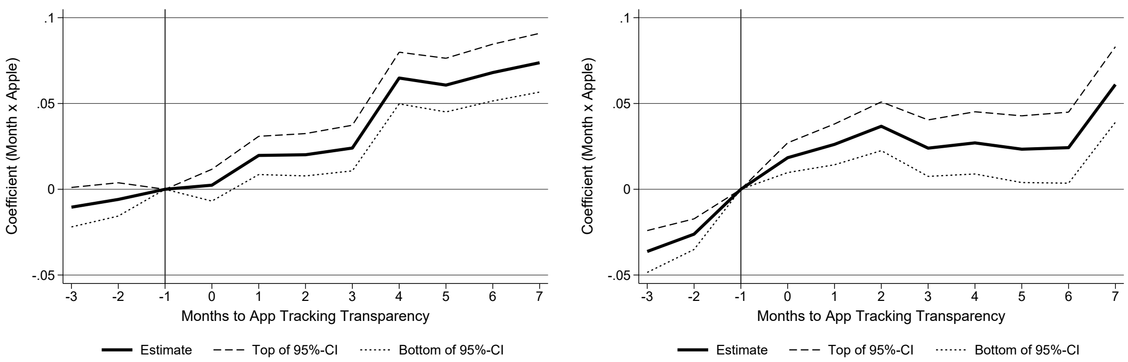
	Pay			In-App Pay		
	(1)	(2)	(3)	(4)	(5)	(6)
Post Dummy		0.055***			0.090***	
		(0.005)			(0.005)	
Post Dummy × Apple Dummy			0.047***			0.051***
			(0.006)			(0.008)
In-App Pay Dummy	-0.101***	-0.101***	-0.048***			
	(0.006)	(0.006)	(0.003)			
Pay Dummy				-0.087***	-0.087***	-0.084***
				(0.005)	(0.005)	(0.005)
Privacy Label Dummy	-0.142***	-0.121***		0.603***	0.627***	
	(0.025)	(0.025)		(0.037)	(0.037)	
Mar '21 Dummy	0.003		-0.007***	-0.024***		0.025***
	(0.005)		(0.002)	(0.004)		(0.002)
Apr '21 Dummy	0.012**		-0.009***	-0.009		0.056***
	(0.006)		(0.003)	(0.006)		(0.003)
May '21 Dummy	0.015**		-0.033***	0.021***		0.068***
	(0.006)		(0.003)	(0.007)		(0.005)
Jun '21 Dummy	0.039***		-0.022***	0.038***		0.094***
	(0.007)		(0.003)	(0.007)		(0.005)
Jul '21 Dummy	0.040***		-0.026***	0.057***		0.117***
	(0.007)		(0.003)	(0.007)		(0.005)
Aug '21 Dummy	0.047***		-0.024***	0.082***		0.160***
	(0.007)		(0.003)	(0.007)		(0.006)
Sep '21 Dummy	0.084***		-0.014***	0.103***		0.188***
	(0.008)		(0.003)	(0.008)		(0.006)
Oct '21 Dummy	0.086***		-0.012***	0.109***		0.206***
	(0.008)		(0.003)	(0.008)		(0.006)
Nov '21 Dummy	0.091***		-0.013***	0.116***		0.220***
	(0.009)		(0.003)	(0.008)		(0.007)
Dec '21 Dummy	0.093***		-0.016***	0.128***		0.218***
	(0.009)		(0.003)	(0.008)		(0.007)
Constant	12.597***	12.574***	8.985***	12.125***	12.093***	13.775***
	(0.261)	(0.261)	(0.069)	(1.280)	(1.281)	(0.156)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
App Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var.	10.974	10.974	7.993	21.857	21.857	16.676
No. of Clusters	583654	583654	1354799	583654	583654	1354799
No. of Obs.	6420194	6420194	14902789	6420194	6420194	14902789

Notes: In order to ease interpretation, pay and in-app pay are multiplied by 100 to have coefficients displayed in percentages. Feb '21 Dummy is the reference category in columns 1, 3, 4, and 6. Other Controls comprise Size (in KB), Description Length, Website Dummy, and Privacy Policy Dummy. Heteroskedasticity-robust standard errors clustered on app-level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

an event study to systematically provide further evidence on the validity of the difference-in-difference approach. For this, we adjust our baseline in columns 3 and 6 of Table 2 to have monthly indicators around the ATT release (rather than a Post dummy variable) interacted with a dummy variable denoting Apple as the platform. They show whether apps on Apple and Google were already on different trajectories before Apple's privacy change, thereby possibly complicating the counterfactual for the post-ATT period. Figure 3 displays the coefficients of these interactions. Accordingly, for pay, these are insignificant for the pre-ATT period, whereas for in-app pay, they are negatively and statistically significant, suggesting a different development already before the ATT on Apple compared to Google.

Figure 3: Event Study

(a) Pay (b) In-App Pay



Notes: The last pre-ATT month, April 2021, is denoted by the vertical line and serves as the reference category. The figures show the coefficients of the interaction between monthly indicators and a dummy variable denoting Apple as the platform.

As a summary, the results provide evidence that with Apple's privacy change, apps on Apple adopted payments for the app or within the app more likely. These short-run effects seem to be small on average, with increases of 0.047 (0.051) percentage points or 0.6 (0.3) percent in the likelihood of a pay (in-app pay) app. Interestingly, the ATT reverses the preceding negative trend for the presence of paid apps while it reinforces the adoption of in-app payments that seems to be common in the market for apps.

5.2 Effect Heterogeneity

Having established an impact of the ATT in the difference-in-difference setup, we now turn to testing the underlying mechanisms. Specifically, we ask whether it made those app developers change their business model expected to be affected the most, thus driving the results. For this, we focus on the sample consisting of apps on Apple as the platform of interest for which the before-mentioned reliance measures are also available.

We start by taking a closer look into app developers relying on Apple. For this, Table 3 augments the baseline regressions for both pay and in-app pay as the dependent variables by an interaction of the Post dummy variable with an indicator of the app to be only active on Apple in columns 1 and 3 and a variable corresponding to the share of Apple-only apps by a developer in columns 2 and 4. The impact of Apple's privacy change can be mainly attributed to single-homing apps as the base coefficient of the Post dummy variable becomes distinctively smaller in size, whereas the interaction term is positive and statistically significant, even surpassing the relationship found in the baseline estimates. Similarly, apps belonging to a developer single-homing largely or completely (35 percent of obs.) are more likely to adopt pay and in-app pay following the ATT. In fact, the results suggest no impact (pay) or even a slight decrease (in-app pay) following the ATT for apps of developers that multi-home completely (21 percent of obs.).

Table 3: Effect Heterogeneity: Reliance on Apple

	Pay		In-App Pay	
	(1)	(2)	(3)	(4)
Post Dummy	0.017***	0.002	0.003	-0.035***
	(0.006)	(0.006)	(0.008)	(0.009)
Post Dummy × Single-Homing Dummy	0.065***		0.150***	
	(0.010)		(0.012)	
Post Dummy × % Apple-Only Apps		0.090***		0.215***
		(0.013)		(0.015)
In-App Pay Dummy	-0.101***	-0.101***		
	(0.006)	(0.006)		
Pay Dummy			-0.087***	-0.087***
			(0.005)	(0.005)
Privacy Label Dummy	-0.117***	-0.116***	0.636***	0.639***
	(0.025)	(0.025)	(0.037)	(0.037)
Constant	12.578***	12.580***	12.101***	12.105***
	(0.261)	(0.261)	(1.281)	(1.281)
Other Controls	Yes	Yes	Yes	Yes
App Fixed Effects	Yes	Yes	Yes	Yes
Mean Dep. Var.	10.974	10.974	21.857	21.857
No. of Clusters	583654	583654	583654	583654
No. of Obs.	6420194	6420194	6420194	6420194

Notes: In order to ease interpretation, pay and in-app pay are multiplied by 100 to have coefficients displayed in percentages. Other Controls comprise Size (in KB), Description Length, Website Dummy, and Privacy Policy Dummy. Heteroskedasticity-robust standard errors clustered on app-level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

In Table 4, we turn towards studying a differential impact of the ATT for apps relying on tracking. In columns 1 and 3, we include a dummy variable equal to one if the app is tracking users outside of the app, as reported in the privacy label. Additionally, we interact this indicator with the Post dummy variable to study a possible effect heterogeneity. While the coefficients for the variable denoting tracking are statistically significant for both payments, the signs suggest tracking to be a substitute to pay and a complement to in-app pay. The positive and statistically significant coefficients for the interaction term suggest that apps collecting data to track users are more likely to adopt payments following Apple's privacy change than those who aren't, suggesting a possible compensation of lost revenues. In columns 2 and 4 of Table 4, we interact the indicator of the post-ATT period with a dummy variable denoting apps in ad intensive categories (56 percent of obs.). Apps belonging to such categories are more likely to adopt upfront payments than apps in the remaining categories, while for in-app payments, there is no statistically significant difference.

Table 4: Effect Heterogeneity: Reliance on Tracking

	Pay		In-App Pay	
	(1)	(2)	(3)	(4)
Post Dummy	0.052***	0.030***	0.046***	0.086***
	(0.006)	(0.008)	(0.005)	(0.009)
Post Dummy × Tracking Dummy	0.046**		0.752***	
	(0.018)		(0.045)	
Post Dummy × Ad Intensive Dummy		0.043***		0.007
		(0.011)		(0.012)
In-App Pay Dummy	-0.101***	-0.101***		
	(0.006)	(0.006)		
Pay Dummy			-0.087***	-0.087***
			(0.005)	(0.005)
Tracking Dummy	-0.086**		0.488***	
	(0.035)		(0.079)	
Privacy Label Dummy	-0.111***	-0.120***	0.438***	0.628***
	(0.027)	(0.025)	(0.037)	(0.037)
Constant	12.572***	12.575***	12.265***	12.093***
	(0.262)	(0.261)	(1.279)	(1.281)
Other Controls	Yes	Yes	Yes	Yes
App Fixed Effects	Yes	Yes	Yes	Yes
Mean Dep. Var.	10.974	10.974	21.857	21.857
No. of Clusters	583654	583654	583654	583654
No. of Obs.	6420194	6420194	6420194	6420194

Notes: In order to ease interpretation, pay and in-app pay are multiplied by 100 to have coefficients displayed in percentages. Other Controls comprise Size (in KB), Description Length, Website Dummy, and Privacy Policy Dummy. Heteroskedasticity-robust standard errors clustered on app-level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.3 Further Implications

Given the evidence on payments for or inside the app becoming a more likely way to monetize following Apple's privacy change, it is also informative to look at further implications. Specifically, this subsection shall better characterize apps adopting payments, look at the impact on (ads) revenue, and give a glimpse into how new apps cope with the newly privacy-preserving environment.

Describing Payment Adopters: Summary statistics in Table 5 shall provide further information on the characteristics of apps changing to pay and in-app pay following Apple's privacy change, which in turn may corroborate that the ATT is the underlying mechanism and also shed light on the relevance of the affected app developers. We restrict to apps that changed to the respective payments for the whole remainder of the observation period. Table 5 shows differences between the types of apps that choose to adopt pay and those including in-app payments. Compared with the whole sample, apps with in-app payments are larger in size and description length, have a website more likely, and track more often. In contrast, paid apps are older, single-home more often, collect data rarely, and update less frequent. In terms of ratings, the two groups are close to the sample average and include apps with several thousand ratings, thus being economically relevant. In that regard, 5 (19) percent of those adopting pay (in-app pay) were part of the top rankings in the sampling. Finally, the categories Education and Games contain most of the apps adopting payments following the ATT, which were also the ones with a higher share of paid apps before the enactment.[27] This complements news reports showing examples of games implementing new in-app payments amid Apple's privacy change.[28]

Impact on Advertisement Revenue: To provide evidence on whether the ATT had an actual impact on tracking and advertisements, we leverage Apple's privacy labels outlined in Section A.3. Figure A.3 suggests that following Apple's privacy change, apps are less likely to request data to track users across other apps and websites, while Figure A.4 also shows a decrease in data collection for ads, especially related to third-party ads.

[27]See https://web.archive.org/web/20210121120741/https://42matters.com/stats.

[28]See https://venturebeat.com/games/apples-idfa-changes-are-already-changing-game-design-and-monetization/.

Table 5: Summary Statistics of Payment Adopters

	Pay			In-App Pay		
	Mean	Median	N	Mean	Median	N
Size (in KB)	50824.06	27699.20	1226	97360.31	57548.80	1871
Description Length	750.41	546.00	1226	1339.48	1086.00	1871
Website Dummy	0.37	0.00	1226	0.66	1.00	1871
Privacy Policy Dummy	1.00	1.00	1226	1.00	1.00	1871
Single-Homing Dummy	0.86	1.00	1226	0.69	1.00	1871
Privacy Label Dummy	0.27	0.00	1226	1.00	1.00	1871
Tracking Dummy	0.04	0.00	1226	0.40	0.00	1871
Age in Years	5.95	6.00	1224	4.99	4.00	1867
Update Dummy	0.13	0.00	1175	0.91	1.00	1860
Average Rating	3.89	4.30	742	4.14	4.50	1429
Number of Ratings	40.05	1.00	1226	7422.21	6.00	1871

Notes: The observations are based on the period of the payment adoption. The total number of apps adopting the respective payments is lower than the previous results suggest as we restrict to those apps not changing to a free version during the remainder of the observation period (once or several times). Update Dummy measures a change in the version number compared to the preceding month. Average Rating is missing if there are no ratings.

This is suggestive evidence that apps indeed turn away from this sort of data collection for tracking and ads. Interestingly, the collection of data linked to users and of data not linked to users is distinctively less affected by the ATT, although the data might also contain valuable information for tracking users outside the app.

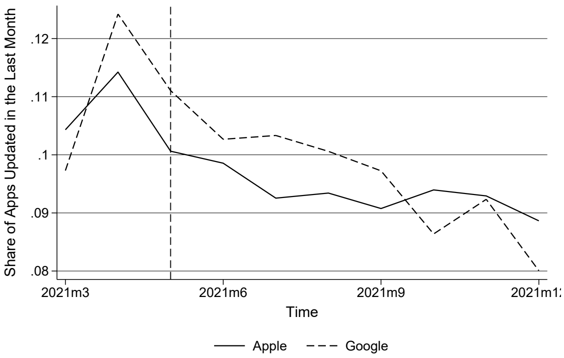
Lower advertisement revenues may also result in the abandonment of apps by app developers since the costs of maintaining may exceed the 'new' revenues following ATT, which in turn may serve as an indirect measure of an impact. The share of apps updated each month serves as a first indicator. Specifically, Figure 4 shows the share of apps that were updated the preceding month on both platforms, respectively. There seems to be a common downward-sloping trend with an uptick sometime before the ATT enactment.[29]

Another, more drastic, indicator of abandonment may involve a complete exit from the app store by an app developer. While this cannot be considered with the panel data at hand, according to Pixalate, the quarter of the ATT enactment saw the largest amount of delisted apps on Apple's app store during 2021, whereas on Google, the number of delisted apps was stable over the year.[30] While there is no suggestive evidence of decreased maintenance because of the ATT, complete abandonment of app development around the time of the enactment seems to increase.

[29] Li and Tsai (2022) find a reduction in version updates on Apple following the ATT, but instead of apps on Google, they have apps on Apple not collecting identifiers as a control group.

[30] See https://www.pixalate.com/blog/q2-2022-delisted-mobile-apps-report.

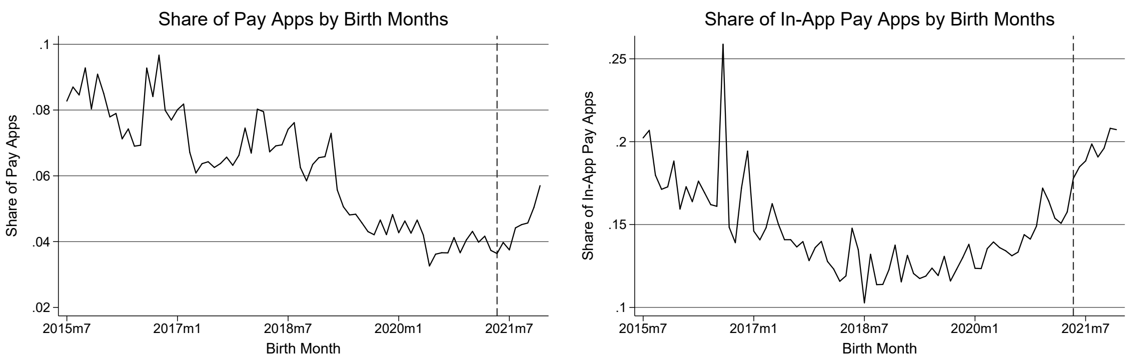
Figure 4: Share of Apps Updated



Notes: The first post-ATT month, May 2021, is denoted by the vertical line.

Monetization of New Apps: Besides a balanced panel of apps already active on Apple before the shock, apps entering after the ATT may give an even better reflection on whether monetization changed for app developers. As the sampling process outlined in Section 4.1 went on continuously throughout the year of 2021, we successfully web-scraped 1,450,688 apps on Apple at least once during the observation period. This enables us to look into the share of apps having pay and in-app pay by birth month. Figure 5 shows the corresponding graphs, where the share of paid apps increases among the cohorts born after the ATT, while for in-app pay, the increase started earlier, though picking up speed with the ATT.[31]

Figure 5: Share of Pay Apps and In-App Pay Apps by Birth Months



Notes: The first post-ATT month, May 2021, is denoted by the vertical line.

[31]This reemergence of paid apps on Apple after a continuous decline for many years can also be seen in data provided by 42matters. See the archived snapshots over time, https://web.archive.org/web/2021*/https://42matters.com/stats.

6 Conclusion

In this paper, we study how a privacy-preserving change by a platform affects the monetization of businesses providing digital products and services with mobile applications and Apple's App Tracking Transparency in a quasi-experimental setting. The evidence of the difference-in-difference analysis suggests that apps on Apple compared to ones on Google increasingly often turn towards payments following Apple's privacy change. While it seems that the ATT had an impact, it is arguably small. However, these are admittedly immediate short-run effects around the time of enactment, while longer-lasting impacts that may better reflect decisions to change business models are becoming complicated to assess due to confounding policy shocks (see Section A.1).[32] In that regard, the relatively larger increase found in the share of apps having payments among those newly entering the store post-ATT may shed further light onto the possible long-run impact.

Moreover, the results also show that the impact is more pronounced for apps relying on Apple as a platform and on tracking restricted by the regulation, which are affected the most by the change. While this suggests the presence of possible spillovers for developers also active on Google, the small effect may also be due to circumventions of the anti-tracking policy through fingerprinting users by means of other identifiers.[33] For instance, Kollnig et al. (2022) show evidence that apps resort to other kinds of tracking following the ATT, while Apple itself is able to use identifiers others have no access to. As a consequence, these results can be seen as a lower bound. However, they also suggest that Apple's privacy change does not shift the relative benefits of payments well enough, e.g., out of fear that demand drops, over less valuable advertisements.

The reliance on Apple, its rules and the corresponding enforcement, while also being a possible competitor, is met with concern. It is argued that Apple may use this update in a self-serving fashion. First, Apple provides its own apps in its ecosystem, holding them to a different standard regarding the tracking of users (CMA, 2022). Second, while Apple provides app developers a more privacy-centric replacement to analyse advertisement

[32] There is anecdotal evidence showing that more and more companies running 'free' apps announced plans for paid features during 2022. See https://www.theverge.com/2022/8/31/23331342/meta-plans-paid-features-facebook-instagram-whatsapp.

[33] See an exemplary news report, https://www.ft.com/content/9cb52394-f95f-4b07-a624-89c47439aa16.

campaigns, there are multiple indications that Apple itself is pushing its own, more superior, ads business.[34] Finally, Apple takes a revenue cut of the payments that become more prevalent, as shown before. By this, the evidence of this paper contributes to the debate of self-preferencing by Apple through the ATT that is at the heart of complaints by publishers and investigations at, for example, competition authorities in Germany and France.[35]

More broadly, it sheds light on the possible winners from such privacy changes like the ATT. These may comprise app developers that can compensate or live through losses in (ad) revenue and, more importantly, through losses in third-party data. In this respect, the importance of first-party data to create so-called content fortresses has been described as a key consequence of the newly privacy-preserving environments.[36] As for app developers adopting payments, the results suggest that the possibility of switching monetization is not evenly distributed among different types of apps. As a result, the long-run impact may involve a different composition of apps and is left for future research.

[34]The evidence ranges from an increase in reported and forecasted revenue from advertisements, multiple ad placements added, and numerous ad-related job listings posted (see https://www.ft.com/content/db21685b-d4dd-421d-95ac-980e9d40c05c).

[35]See the respective complaints, https://www.ft.com/content/0a48d9aa-244b-4945-b2a0-01c68683544a and www.geste.fr/le-geste-depose-une-nouvelle-plainte-a-lautorite-francaise-de-la-concurrence-contre-apple-centree-cette-fois-sur-les-effets-anticoncurrentiels-de-latt/amp/, as well as investigations, https://www.bundeskartellamt.de/SharedDocs/Meldung/EN/Pressemitteilungen/2022/14_06_2022_Apple.html and https://www.autoritedelaconcurrence.fr/en/article/targeted-advertising-no-urgent-interim-measures-against-apple-autorite-continues.

[36]See https://mobiledevmemo.com/content-fortresses-and-the-new-privacy-landscape/.

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A Appendix

A.1 Overview of Policy Shocks

Table A.1 shows the chronology of policy shocks related to monetization on both platforms and from regulatory authorities in order to rule out that no other relevant event coincided with Apple's privacy change.

Table A.1: Chronology of Policy Shocks

Year	Month	Policy
2020	Oct	Apple appeals Epic Games ruling to allow developers pointing users to other payment systems (A, R).
2020	Nov	Small Business Program introduced reducing commissions to 15 % (A).
2020	Dec	Privacy Labels disclosing data collection are mandated (A).
2021	Jan	Dutch competition authority starts fining Apple for failing to provide fair conditions for alternative payments (R).
2021	Feb	N/A
2021	Mar	N/A
2021	Apr	**The App Tracking Transparency (ATT) is enacted (A).**
2021	May	N/A
2021	Jun	Introduction of American Choice and Innovation Online Act (R).
2021	Jul	Commissions are reduced to 15 % for small developers (G).
2021	Aug	South Korea to allow third-party payments via apps (R). Introduction of Open App Markets Act (R).
2021	Sep	Agreement with Japan FTC by Apple to allow reader apps to provide links to external websites to make purchases (R).
2021	Oct	Allows communication with users about alternative payments (A).
2021	Nov	N/A
2021	Dec	Ad ID is not available if opt-out by user of personalized ads (G).
2022	Jan	N/A
2022	Feb	N/A
2022	Mar	The Digital Markets Act (DMA) by the European Union is agreed upon to regulate gatekeepers (R).
2022	Apr	A Data Safety section on an app's page about the collection, sharing, and handling of data is announced (G).

Notes: A, G, and R in parentheses denote whether the shock is by Apple, Google, or regulatory authorities.

A.2 Details on Sampling

Apple: From 15th December 2020 to 31st January 2021, the app rankings of the top 50 paid, free, and grossing by 16 countries[37] and 28 categories[38] were scraped daily.[39] This resulted in 40,894 unique apps, which can be considered to be the most relevant apps. For each of these apps, other apps by the developer ('more by this developer') and similar apps ('you may also like') suggested by Apple are retrieved from an app's page, which resulted in additional 542,940 apps.[40]

Google: Table A.2 compares the sample with data from Androidrank (AR) as an external source regarding the number of apps by installations.[41] In order to show that the comparability remains over time, the comparison is made for the first and last observation period. It suggests the sample in both periods to contain all top apps, almost all popular and semi-popular apps, and even distinctively more apps towards the bottom of the distribution compared to Androidrank (column '%' denotes the share of coverage).

Table A.2: Comparison of Google Sample

No. of Installations	No. of Apps (Feb '21) Sample	AR	%	No. of Apps (Dec '21) Sample	AR	%
10B - 50B	1	1	100.00	6	6	100.00
5B - 10B	13	13	100.00	10	10	100.00
1B - 5B	48	49	97.96	66	66	100.00
500M - 1B	58	61	95.08	61	68	89.71
100M - 500M	467	498	93.78	595	613	97.06
50M - 100M	735	770	95.45	882	903	97.67
10M - 50M	5494	5841	94.06	6397	6729	95.07
5M - 10M	5669	6222	91.11	6488	6886	94.22
1M - 5M	27,441	31,123	88.17	30,242	32,387	93.38
500k - 1M	20,606	24,165	85.27	22,354	23,629	94.60
100k - 500k	77,854	90,684	85.85	84,421	82,074	102.86
50k - 100k	49,193	51,506	95.51	52,571	42,902	122.54
10k - 50k	147,097	82,105	179.16	155,880	66,481	234.47

[37] These comprise 'united-states, france, germany, united-kingdom, italy, netherlands, spain, canada, sweden, switzerland, australia, japan, singapore, china, south-korea, and russia'.

[38] These comprise 'overall, kids, business, weather, utilities, travel, sports, social-networking, reference, productivity, photo-and-video, news, navigation, music, lifestyle, health-and-fitness, games, finance, entertainment, education, books, medical, magazines-and-newspapers, catalogs, food-and-drink, shopping, developer-tools, and graphics-design'.

[39] See, for instance, https://web.archive.org/web/20210225202034/https://www.appannie.com/en/apps/ios/top/united-states/overall/iphone/.

[40] The total number of apps from both steps of this process was even higher, but some apps could not be scraped or dropped out until the end of the observation period.

[41] See https://www.androidrank.org/.

A.3 Apple's Privacy Labels

Since 14th December 2020, Apple has required new or to-be-updated apps to disclose their data collection through privacy labels.[42] These can be thought of as nutrition labels with respect to how much data is collected from users. They are categorized into data used to track, data linked to users, and data not linked to users. For these three categories of data, there are 14 types describing the theme of data collected, like the contacts or location as displayed in Figure A.1. Finally, as the purpose for data used to track is given, there is another layer describing the purpose of data collection only for data linked to users and data not linked to users. These purposes comprise ads (developer or third-party), analytics, functionality, product personalization, and others. Based on this information, one may infer permissions, as some data, like location, can only be collected with the corresponding permission. Of course, this only gives a lower bound because apps may ask for permissions without collecting data. Similarly, given the presence of an 'ads purpose' for data collection, the app is likely to include ads.

Figure A.1: Privacy Labels

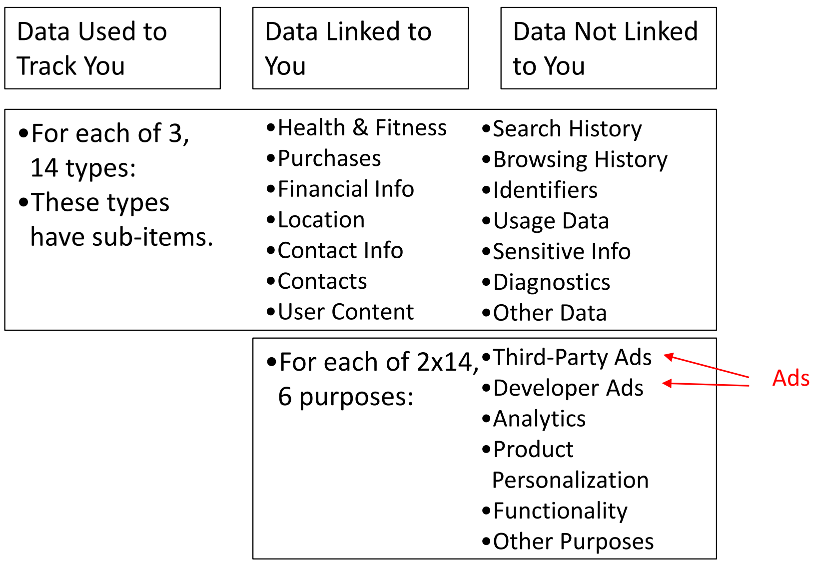
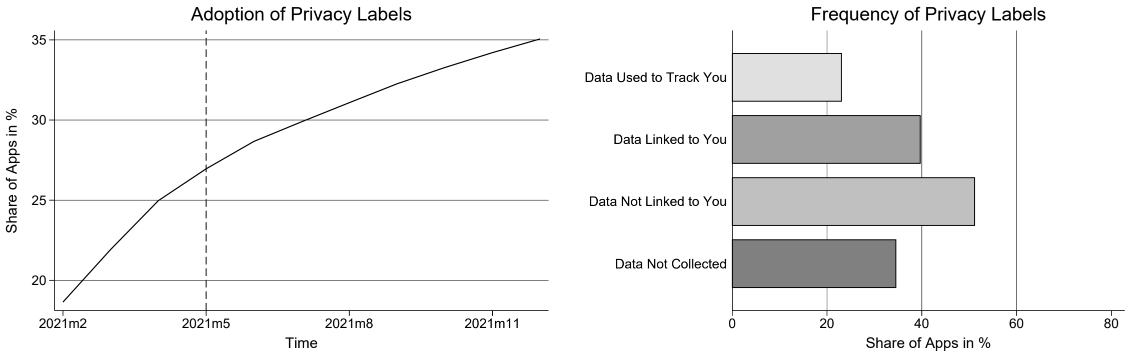


Figure A.2 provides an overview of the prevalence of privacy labels. One observation from the left panel is that the majority of apps in the sample has not provided any details

[42] See Apple's help page for more information, https://developer.apple.com/app-store/app-privacy-details/.

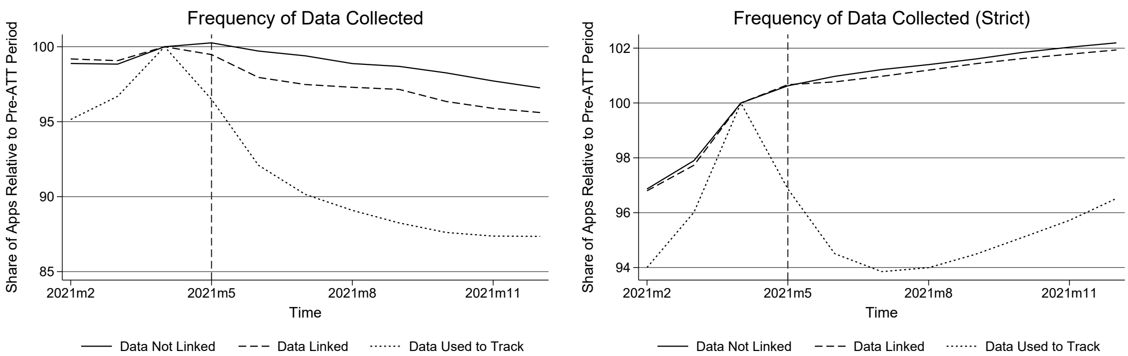
Figure A.2: Adoption and Frequency of Privacy Labels



Notes: The first post-ATT month, May 2021, is denoted by the vertical line. The right panel is based on the last cross-section (Dec '21).

by the end of 2021, as it is only necessary if developers update the app or launch a new app. Over time, one can see the share of apps with privacy labels to increase. It also shows that the ATT did not really affect the diffusion of privacy labels. For apps that provide privacy labels, two-thirds collect data, as shown in the right panel of Figure A.2. Data not linked to users is the most frequent category of data collected, followed by data linked to users and data used to track. These shares are considerably higher for free and popular apps, the latter measured by surpassing 1,000 or 10,000 user ratings. Identifiers are by far the most important type, followed by usage data, diagnostics, and location.

Figure A.3: Frequency of Data Collected

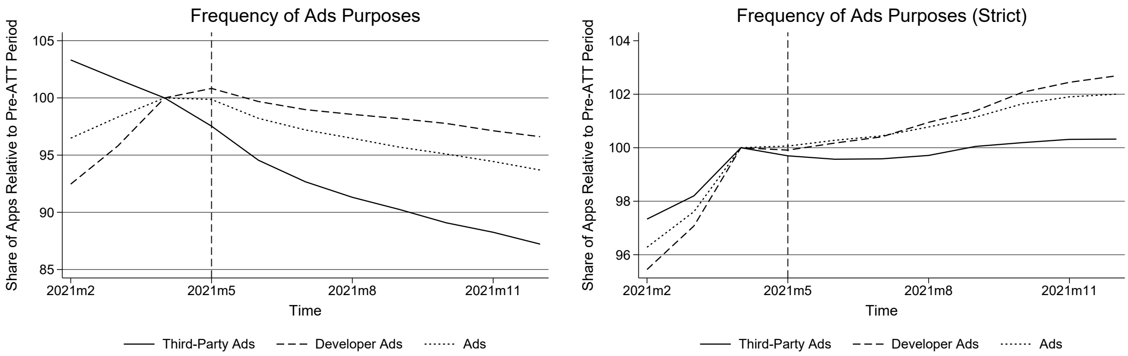


Notes: The first post-ATT month, May 2021, is denoted by the vertical line. The right panel only comprises apps that provide privacy labels at all times during the observation period.

In order to see whether Apple's privacy change reduced tracking, we look at the development of the respective data collection as stated by the app developers. Focusing on apps that provided privacy labels, the left panel of Figure A.3 shows the share of apps collecting data to track relative to the last pre-ATT period being April 2021. The share falls after the ATT, especially in comparison to data linked and data not linked to users. Restricting to apps that provided privacy labels throughout the time of the observation period in the right panel of Figure A.3, the decrease in data used to track remains, but is less pronounced and even gets smaller following some months.

As the privacy change potentially undermines monetization through ads, Figure A.4 looks at the development for purposes of data collection related to advertisements as stated in the privacy labels. The left panel considers all apps that provided such labels at the point in time and shows third-party ads as a purpose of data collection to decline stronger than developer ads. For apps with privacy labels throughout the observation period, this decrease is distinctively smaller and very short-lived, though the ATT seems to slow down the momentum of advertisements being a purpose of data collection.

Figure A.4: Frequency of Ads Purposes



Notes: The first post-ATT month, May 2021, is denoted by the vertical line. The right panel only comprises apps that provide privacy labels at all times during the observation period.

The descriptive evidence suggests Apple's privacy change to reduce data collection both to track users outside an app and, to a lesser extent, for third-party ads. However, all of this is limited to apps' stated privacy labels.

A.4 Additional Tables

Table A.3: Additional Control Variables

	Pay		In-App Pay	
	(1)	(2)	(3)	(4)
Post Dummy × Apple Dummy	0.044***	0.018**	0.052***	0.104***
	(0.006)	(0.008)	(0.008)	(0.011)
In-App Pay Dummy	-0.048***	-0.043***		
	(0.003)	(0.003)		
Pay Dummy			-0.084***	-0.091***
			(0.005)	(0.006)
Mar '21 Dummy		-0.005*		0.032***
		(0.003)		(0.003)
Apr '21 Dummy	-0.001	-0.010***	0.028***	0.063***
	(0.002)	(0.003)	(0.002)	(0.005)
May '21 Dummy	-0.023***	-0.021***	0.044***	0.068***
	(0.003)	(0.004)	(0.004)	(0.006)
Jun '21 Dummy	-0.013***	-0.015***	0.072***	0.100***
	(0.003)	(0.003)	(0.005)	(0.007)
Jul '21 Dummy	-0.017***	-0.022***	0.097***	0.127***
	(0.003)	(0.003)	(0.005)	(0.007)
Aug '21 Dummy	-0.015***	-0.022***	0.140***	0.174***
	(0.003)	(0.003)	(0.006)	(0.008)
Sep '21 Dummy	-0.004*	-0.012***	0.169***	0.210***
	(0.003)	(0.003)	(0.006)	(0.008)
Oct '21 Dummy	-0.003	-0.011***	0.187***	0.234***
	(0.003)	(0.003)	(0.006)	(0.009)
Nov '21 Dummy	-0.004	-0.010***	0.201***	0.255***
	(0.003)	(0.004)	(0.007)	(0.009)
Dec '21 Dummy	-0.007**	-0.004	0.200***	0.294***
	(0.003)	(0.006)	(0.007)	(0.011)
Update Dummy	-0.029***		0.200***	
	(0.004)		(0.010)	
Average Rating		-0.004		-0.004
		(0.017)		(0.027)
Number of Ratings		0.000		0.000
		(0.000)		(0.000)
Constant	8.933***	8.552***	13.879***	17.684***
	(0.071)	(0.107)	(0.168)	(0.238)
Other Controls	Yes	Yes	Yes	Yes
App Fixed Effects	Yes	Yes	Yes	Yes
Mean Dep. Var.	7.968	7.490	16.836	21.560
No. of Clusters	1302697	919936	1302697	919936
No. of Obs.	13026970	9485809	13026970	9485809

Notes: In order to ease interpretation, pay and in-app pay are multiplied by 100 to have coefficients displayed in percentages. Mar '21 Dummy is the reference category in columns 1 and 3 due to the update variable on Apple being based on a change in the version number compared to the preceding month, while Feb '21 Dummy is the reference category in columns 2 and 4. Missing information for the ratings reduces the estimation sample in columns 2 and 4. This is due to the average rating missing in the absence of ratings and ratings missing in general more frequently towards the end of the observation period for Google due to a policy change. Other Controls comprise Size (in KB), Description Length, Website Dummy, and Privacy Policy Dummy. Heteroskedasticity-robust standard errors clustered on app-level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.4: Excluding Multi-Homing Apps

	Pay			In-App Pay		
	(1)	(2)	(3)	(4)	(5)	(6)
Post Dummy	0.088***	0.053***		0.108***	0.139***	
	(0.008)	(0.011)		(0.007)	(0.010)	
Post Dummy × Apple Dummy			0.063***			0.068***
			(0.007)			(0.009)
In-App Pay Dummy	-0.122***	-0.128***	-0.051***			
	(0.008)	(0.009)	(0.003)			
Pay Dummy				-0.085***	-0.102***	-0.080***
				(0.005)	(0.007)	(0.005)
Mar '21 Dummy			-0.008***			0.027***
			(0.003)			(0.002)
Apr '21 Dummy			-0.008***			0.059***
			(0.003)			(0.003)
May '21 Dummy			-0.038***			0.066***
			(0.004)			(0.005)
Jun '21 Dummy			-0.024***			0.094***
			(0.003)			(0.006)
Jul '21 Dummy			-0.026***			0.119***
			(0.003)			(0.006)
Aug '21 Dummy			-0.024***			0.166***
			(0.003)			(0.006)
Sep '21 Dummy			-0.009***			0.193***
			(0.003)			(0.007)
Oct '21 Dummy			-0.008**			0.212***
			(0.003)			(0.007)
Nov '21 Dummy			-0.008**			0.225***
			(0.003)			(0.007)
Dec '21 Dummy			-0.010***			0.225***
			(0.004)			(0.008)
Constant	16.438***	15.981***	9.442***	12.829***	12.627***	13.102***
	(0.394)	(0.578)	(0.074)	(1.619)	(1.852)	(0.163)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
App Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var.	14.358	14.024	8.448	23.814	22.330	15.861
No. of Clusters	336652	204267	1099371	336652	204267	1099371
No. of Obs.	3703172	2246937	12093081	3703172	2246937	12093081

Notes: In order to ease interpretation, pay and in-app pay are multiplied by 100 to have coefficients displayed in percentages. Feb '21 Dummy is the reference category in columns 3 and 6. Other Controls comprise Size (in KB), Description Length, Website Dummy, and Privacy Policy Dummy. Heteroskedasticity-robust standard errors clustered on app-level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.