Centre for Economic Performance

Discussion Paper ISSN 2042-2695

No. 2207
August 2026

Is data privacy a losing game? Evidence from Apple's App Tracking Transparency (ATT) policy

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Abstract
We study the impact of Apple's App Tracking Transparency (ATT) policy, which requires apps to obtain explicit user permission before cross-app tracking, on the mobile gaming industry. Using SensorTower US data on the top 5,000 games on iOS and Android (2020–2023) and a difference-in-differences design, we show that ATT increases iOS games' revenue and revenue per user, with little impact on user numbers. Gains arise from re-optimised in-app purchase menus and more major updates, not higher prices or paywalls. ATT raises concentration and reduces entry, benefiting Apple and incumbents while raising barriers to entry for new competitors.

Keywords: privacy regulation; digital platforms; mobile gaming industry; App Tracking Transparency (ATT); market structure and concentration
JEL codes: L11; L13; L86; K24; D18; D83

This paper was produced as part of the Growth Programme. The Centre for Economic Performance is financed by the Economic and Social Research Council.

We would like to thank Ambre Elsas-Nicolle, Andrea Enache, Christian Peukert, Patrick Rey, Steve Tadelis, Tommaso Valletti and seminar audiences at Cambridge, Mannheim, TSE and conference audiences at CRETE, EARIE, EEA and IIOC for helpful comments and discussions. We are grateful to Fanbo Kong and Ashley Wang for their excellent research assistantship. Genakos is grateful for funding received from the Cambridge Judge Business School. The authors have no conflict of interest to declare. AI tools have been used for drafting and editing. All remaining errors are those of the authors alone.

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Published by
Centre for Economic Performance
London School of Economic and Political Science
Houghton Street
London WC2A 2AE

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1 Introduction

Digital markets increasingly rely on the collection and exploitation of personal data. Mobile applications track users across apps and websites, construct detailed behavioral profiles, and monetize attention through targeted advertising and data-driven optimization. At the same time, concerns about privacy, data misuse, and opaque data practices have grown among policymakers and the public. This tension has led to a wave of privacy interventions, ranging from comprehensive regulations such as the EU's General Data Protection Regulation (GDPR) or California's Consumer Privacy Act to platform-level policies that restrict data access within particular ecosystems.

A central question in this debate is whether privacy regulation is inevitably a "losing game" for firms and, by extension, for innovation and growth in digital markets. A growing empirical literature on GDPR and related laws tends to find that stricter privacy rules reduce web traffic, advertising, revenue and even profits, with especially pronounced effects for smaller firms and data-intensive industries. These findings have fuelled concerns that privacy protection may come at the cost of weaker competition and slower innovation.

In this paper, we study a prominent and controversial privacy intervention that does not fit neatly into the standard regulatory paradigm: Apple's App Tracking Transparency (ATT) policy. Introduced with iOS 14.5 in April 2021, ATT requires iOS apps to obtain explicit user permission before tracking them across apps and websites using device identifiers such as the Identifier for Advertisers (IDFA). In practice, this change reversed the default from "opt-out" to "opt-in" for cross-app tracking, causing the share of users who consent to tracking to fall significantly from around 70% to roughly 15%. ATT thus represents a sharp, platform-imposed reduction in tracking capabilities for the majority of iOS users.

We focus on the impact of ATT on the mobile gaming industry, one of the largest and most dynamic segments of the app economy. Mobile games are heavily reliant on data-driven advertising for user acquisition and monetization, yet they also derive substantial revenue

from in-app purchases (IAPs) and paid downloads. This dual revenue model makes gaming a particularly informative laboratory for studying how firms respond when targeted advertising becomes less effective. Moreover, many games are available on both iOS and Android, allowing us to compare how the *same title* evolves across platforms that are differentially exposed to ATT.

Our empirical strategy exploits two key features of ATT. First, the policy applies to iOS but not to Android, which continued to allow the use of its advertising identifier over our sample period. Secondly, ATT was announced and implemented at clearly defined dates worldwide. These features generate a natural experiment: we can compare the evolution of outcomes for iOS games before and after ATT to the evolution of Android games over the same period, controlling for common shocks and time-invariant app characteristics. Using proprietary data from SensorTower on the top 5,000 mobile games per platform in the US from January 2020 to December 2023, we implement a difference-in-differences design at the app–platform–month level, with a particular focus on the subsample of multi-homing titles that appear on both platforms.

Our analysis yields several novel findings. First, we show that ATT is associated with a substantial increase in revenue and revenue per active user for iOS games relative to their Android counterparts, while having little effect on the number of active users. Event-study estimates reveal that these monetisation gains emerge after implementation and grow over time, with no sign of reversal by the end of 2023. This pattern contrasts sharply with prior evidence on GDPR and other privacy regulations, which typically document negative effects on firm performance.

Second, we open the "black box" of how developers adjust to the new environment. We find that the increase in revenue per user is not driven by simple price-based changes: games do not become more likely to switch from free to paid on iOS after ATT, nor do posted prices of IAP packages increase after ATT. Instead, developers respond by re-optimising their in-app purchase menus and investing more in major quality updates. Using detailed

data on IAP packages, we construct pseudo-revenue measures that capture whether menu changes increase the potential revenue generated by the menu. ATT significantly raises the probability that iOS games update their IAP menus in ways that increase pseudo-revenue. At the same time, iOS versions of games release major updates more frequently after ATT, and these updates are strongly associated with higher revenue per user. Together, these findings support a "waterbed" mechanism: as targeted advertising becomes less effective, developers shift monetization towards deeper consumer spending, supported by higher quality and more sophisticated menu design.

Third, the effects of ATT are heterogeneous across genres. Genres that traditionally rely heavily on in-app purchases and deep engagement—such as casino, card, and strategy—benefit more than casual genres. This suggests that ATT amplifies existing monetization capabilities.

Fourth, we show that ATT has important consequences for market structure. On iOS, revenue concentration rises significantly after ATT: the revenue share of the top 1,000 and 2,000 games, as well as the HHI index, increases relative to Android. At the same time, entry into the top-5,000 segment declines on iOS relative to Android. These patterns are consistent with a Sutton (1991, 1998) style mechanism in which higher returns to quality investment lead to a more concentrated equilibrium with higher barriers to entry. While users may enjoy higher privacy and higher-quality games, the industry becomes more concentrated and less open to new entrants.

Taken together, our results offer a nuanced answer to the question posed in the title: data privacy is not necessarily a losing game, but its effects are highly asymmetric. In the case of ATT, stricter privacy does not depress industry revenue; instead, it reshapes monetization, quality investment, and market structure in ways that appear favourable to the platform (assuming a 30% commission our results translate into $421 million annual revenue increase for games, or $1.98 billion for the entire app store) and to large incumbents (our estimates imply an annual increase in developers revenue of approximately $1.4 billion), while raising

challenges for smaller developers and advertising intermediaries.

The paper contributes to several strands of literature. First, it adds to the empirical literature on privacy regulation and firm performance by providing, to our knowledge, the first large-scale, systematic analysis of Apple's ATT policy in the mobile gaming industry. Unlike most prior work on GDPR, which finds negative average effects, we document positive monetization effects and show how they arise. Secondly, it contributes to the literature on platform governance and two-sided markets by showing how a platform can use privacy policy as a strategic instrument that shifts surplus between advertising and consumer payments, and by documenting the resulting changes in business models and market structure. Thirdly, it connects to theoretical work on quality investment and endogenous sunk costs, providing empirical evidence that a privacy-induced shift in monetization can increase concentration and entry barriers.

The remainder of the paper is organized as follows. Section 2 provides institutional background on digital advertising, IDFA, ATT, and the mobile gaming industry. Section 3 reviews the related literature. Section 4 develops a conceptual framework and sets out our hypotheses. Section 5 describes the data, and Section 6 outlines our empirical strategy. Section 7 presents the main results on app performance, mechanisms, and market structure. Section 8 discusses the implications for platform governance, competition, and policy, and Section 9 concludes.

2 Institutional Background

2.1 Digital advertising, tracking and the role of IDFA

Mobile applications increasingly rely on data-driven advertising technologies to monetize user attention. A large share of display and video advertising on smartphones is sold through programmatic auctions in which advertisers bid for impressions conditional on detailed information about the user and the context in which the ad will be shown. The profitability

of these ads depends critically on the ability to: (i) identify users across apps and over time, (ii) measure subsequent conversions, and (iii) attribute those conversions to particular campaigns.

On Apple's iOS ecosystem, this identification and attribution historically relied on the Identifier for Advertisers (IDFA), a device-level alphanumeric string that is unique, persistent, and accessible to all apps installed on a given device. By observing the same IDFA across multiple apps and websites, ad networks and analytics providers could construct rich profiles of user behavior, enabling granular targeting and accurate measurement of advertising effectiveness. For free-to-play mobile games, these technologies were central to two key activities.

First, on the user acquisition side, game publishers purchase ads on social media platforms, ad networks, and other apps in order to attract new users. Bidders in these markets typically optimize campaigns using performance metrics such as cost per install or cost per paying user. These metrics require tracking a user from the ad impression to the eventual installation and in-app purchase, which is greatly facilitated by a stable identifier such as IDFA.

Secondly, on the monetization side, many games display third-party ads to their own users. Here, the publisher receives revenue from ad networks, which in turn monetize the impression by selling targeted access to the user. Again, the value of these impressions depends on the ability of advertisers to target and track users across apps. In both cases, therefore, the availability of IDFA underpins a large ecosystem of intermediaries that specialize in user acquisition, attribution, and ad optimization.

In summary, these technologies support a two-sided market in which app users on the one side and advertisers on the other side are matched through the app store and ad networks. The presence of a common identifier, such as IDFA, reduces information frictions and increases the returns to scale in data: larger publishers and networks can leverage more observations per user to refine targeting, potentially reinforcing concentration.

2.2 Apple's App Tracking Transparency (ATT) policy

In 2020, Apple announced a fundamental change to the way tracking and attribution would operate on iOS. Under the App Tracking Transparency (ATT) framework, which became effective with the release of iOS 14.5 in April 2021, apps that wish to "track" users across apps and websites owned by other companies must first obtain explicit permission via a system-generated prompt. Users are asked whether they "allow" the app to track them or prefer that the app does "not track". If the user declines, the app is barred from accessing the IDFA and from using other techniques that Apple deems equivalent for cross-app tracking.

Prior to ATT, access to IDFA was effectively granted by default. Users could opt out of tracking by navigating to a relatively obscure setting ("Limit Ad Tracking"), and empirical evidence suggests that only a small minority did so. Industry estimates indicate that, in this pre-ATT environment, effective opt-in rates to tracking were around 70%. After ATT, the situation reversed: the decision to share the IDFA became opt-in rather than opt-out, and observed consent rates worldwide fell to roughly 15-20% (Kraft et al., 2024; Lukovitz, 2022; Koetsier, 2024), or even lower for the US market (Axon, 2021). For the majority of iOS users, therefore, cross-app tracking via IDFA was effectively disabled.

The ATT policy was rolled out in several stages. At Apple's Worldwide Developer Conference in June 2020, the company announced its intention to limit access to IDFA and to introduce a new transparency framework. Following a period of lobbying and technical adjustments, the full enforcement of ATT began with the release of iOS 14.5 in April 2021. Subsequent releases, such as iOS 15 in September 2021, introduced further refinements, including enhancements to Apple's SKAdNetwork (SKAN), an attribution system that supplies advertisers with aggregated and privacy-preserving information about campaign performance.

From the perspective of identification in our empirical analysis, ATT has two key features. First, the policy is platform-specific: it applies to Apple's iOS ecosystem but not to Google's

Android system, which continued to allow the use of its own advertising identifier during our sample period. Secondly, the timing of the policy is global and discrete: the announcement and the enforcement occurred at well-defined dates and were implemented simultaneously across countries. These features generate a natural experiment in which iOS apps are exposed to a sharp decline in tracking capabilities, whereas Android apps serve as a control group.

Apple's stated rationale for ATT emphasises privacy and user control. The company has repeatedly argued that "privacy is a fundamental human right" and that users should have greater transparency and choice over how their data are used. From a competition perspective, however, ATT also has important implications for the distribution of surplus within the app ecosystem. By limiting third-party access to IDFA while offering its own aggregated attribution tools (SKAN) and by taking a commission on in-app purchases, Apple may shift value away from external ad networks and towards its own platform and in-app monetization channels (Perez, 2022). Understanding how this policy affects app performance, business models, and market structure is therefore of central interest.

2.3 The mobile gaming industry

Mobile gaming is economically significant and highly dynamic. Games account for a large share of total app store revenue and downloads, and the sector has experienced rapid growth over the past decade. In 2023, global mobile game revenue were on the order of 118.5 billion of dollars (Statista, 2023), with the United States representing the highest revenue country with 76.7 billion (ASO World, 2024). Within our data, the top 5000 game apps on each platform account for more than 80% of users and revenue, indicating a relatively concentrated but still competitive landscape.

The prevalent business model in mobile gaming is freemium. Most games are free to download and monetize through a combination of third-party advertising and in-app purchases (IAPs), such as virtual currency, cosmetic items, or access to additional content. This dual revenue model makes game publishers particularly sensitive to changes in advertising

technology. A reduction in the effectiveness of targeted ads may directly reduce advertising revenue and indirectly increase the cost of user acquisition, thereby affecting the viability of free-to-play strategies.

Mobile games are characterized by high fixed costs of development and quality investment but relatively low marginal costs of distribution. Developers continuously update their games with new levels, events, and features in order to retain users and encourage further spending. These quality investments are often lumpy and can be proxied by major version updates. The interaction between such investments and changes in monetization opportunities is central to understanding how ATT reshapes the industry.

From an empirical standpoint, mobile gaming offers several advantages. The industry is well covered by third-party analytics providers, which collect detailed data on active users, revenue, and update histories. Many games are available on both iOS and Android, allowing us to observe the same title on both platforms. This multi-homing structure is crucial for our identification strategy: by comparing the evolution of an app's iOS version to its Android counterpart, we can difference out time-invariant app characteristics and common shocks that affect both platforms.

Finally, there are strong reasons to treat Apple's introduction of ATT as exogenous to the performance of individual game developers. The policy was announced and implemented uniformly across app categories and countries, and there is little evidence that mobile game publishers had any meaningful influence on Apple's decision. At the same time, the mobile gaming sector is sufficiently important for Apple's services revenue that developers had strong incentives to react promptly to the new environment. These features make the industry an ideal setting in which to study how a platform-imposed privacy policy affects firm behavior and market outcomes.

3 Related Literature

Our paper relates to several strands of research: empirical work on privacy and mobile apps, studies of privacy regulation and firm performance, and the literature on platform governance and digital business models. We discuss each in turn and then clarify our contribution.

3.1 Privacy, mobile apps, and consumer behaviour

A first line of research documents the extent of data collection by mobile applications and the information provided to users about these practices. Early work shows that many apps collect sensitive data and transmit them to third parties without adequate disclosure (Acquisti et al., 2016; Arrieta-Ibarra et al., 2018). For example, studies such as Chia et al. (2012) and Felt et al. (2011) examine privacy policies and permission requests in app stores, concluding that privacy notices are often incomplete, hard to understand, or absent. This literature highlights a substantial information asymmetry between app developers and users regarding data practices.

A second set of papers investigates how users respond when this information asymmetry is reduced. Experiments (Acquisti et al., 2012; Tsai et al., 2011) and field studies (Goldfarb and Tucker, 2011; Goldfarb and Tucker, 2012; Jin and Leslie, 2003; Luca, 2016) show that privacy prompts, labels, or ratings can affect download decisions and usage, although the magnitude and persistence of these effects vary across contexts. In the mobile environment, disclosure often takes the form of permission requests or app store privacy labels. These interventions typically increase transparency but may also impose frictions on adoption if users perceive them as intrusive.

Our paper is related to this literature in that Apple's ATT policy introduces a prominent system-level privacy prompt that directly asks users whether they wish to be tracked across apps. However, whereas most prior work focuses on user responses to privacy information at the app level, we study the industry-wide consequences of a platform-level change

that simultaneously alters tracking capabilities, advertising technology, and monetization incentives.

3.2 Privacy regulation and firm performance

A growing empirical literature documents the wide-ranging economic consequences of privacy regulation on firm behaviour and market outcomes.

Goldfarb and Tucker (2011) first established that privacy regulation reduces marketing effectiveness in the context of the EU's 2003 ePrivacy Directive, a finding subsequently corroborated in the context of the European Union's General Data Protection Regulation (GDPR) by Godinho de Matos and Adjerid (2022) and Aridor et al. (2023). Other papers find that GDPR increased compliance costs, reduced data flows, and led to consolidation in the ad-tech sector, as smaller intermediaries exited or were acquired (Campbell et al., 2015; Peukert et al., 2022; Lefrere et al., 2026). Beyond advertising markets, the GDPR has been shown to impose significant costs across multiple dimensions of firm behaviour and market structure. Goldberg et al. (2024) and Aridor et al. (2023) document adverse effects on website traffic and revenue, while Miller et al. (2024) find broader reductions in online usage behavior alongside revenue losses and increased market concentration. Demirer et al. (2024) further document that the GDPR increased cloud storage data costs to firms. This concentration effect is further corroborated by Johnson et al. (2023), who show that websites disproportionately retain top vendors following the GDPR, raising vendor market concentration.

In addition, Frey and Presidente (2024) find that GDPR regulation has imposed substantial compliance costs on firms and that these costs harm firm profitability, with the burden falling disproportionately on smaller companies, while Koski and Valmari (2020) estimate a reduction in profit margins of between 1.7 and 3.4 percentage points, with data-intensive and smaller firms suffering the largest losses. Finally, Janssen et al. (2022) show that the regulation induced the exit of approximately one third of available apps, while the rate of

new app introductions ("entry") fell by roughly 47% and led to substantial decreases in consumer surplus within the app market.

Within the mobile app ecosystem, several studies have analyzed ATT's effectiveness in reducing user tracking and the impact of "forced disclosure" requirements introduced by Apple's earlier privacy labels. On the latter, Bian et al. (2021) find that iOS versions of apps subject to these disclosures experience declines in downloads and revenue, consistent with users reacting negatively to information about data collection. On the former, ATT's introduction had a clearly negative effect on advertisers.

Kraft et al. (2024) document the immediate impact on tracking behaviour, finding that ATT reduced tracking rates in the United States by 54.73 percentage points, from 73% to 18%, and that while prices for trackable users rose by 51%, advertising revenues for Apple users nevertheless fell by 20%. The consequences for digital advertising markets were similarly pronounced. Aridor et al. (2025) find that conversion-optimised Meta advertisements, among the most exposed to ATT, experienced a 37% reduction in click-through rates, and that although firms responded by reallocating ad spend toward the Google ecosystem, those with greater baseline dependence on Meta suffered firmwide revenue declines of between 8%-40% relative to less exposed firms, with smaller e-commerce firms bearing a disproportionate share of these losses. Deisenroth et al. (2024) corroborate these findings using Meta data combined with offline administrative records, documenting that reductions in digital advertising effectiveness led to decreased advertising investment, increased market concentration, and higher product prices.

The effects of ATT on the app ecosystem itself are more nuanced. Cheyre et al. (2024) drawing on data covering every app available on both the Apple App Store and the Google Play Store in the 18 months surrounding ATT's implementation, find that the number of available apps rebounded quickly after an initial decline, driven by a temporary fall in entry rather than an increase in exit, and that freemium apps strategically shifted toward in-app purchases relative to advertising-based monetization, while paid apps were unaffected. At the

same time, Li and Tsai (2026) find that the inability of apps to use tracking for advertising reduced new downloads and new entry, while Kesler (2023) studies how app developers change their monetization strategies following the implementation of ATT, finding a small increase in the number of paid apps and apps that offer in-app purchases. Taken together, this literature has led to a widely held view that stricter privacy rules tend to harm firms' performance, particularly in data-intensive industries, and may tilt the competitive balance towards larger incumbents that can better absorb compliance costs.

Our study is closely connected to this line of work but differs in two important respects. First, we examine a platform-initiated privacy change (ATT) rather than a government regulation. The policy is implemented through Apple's governance of its own ecosystem, which potentially aligns privacy objectives with the platform's strategic interests. Secondly, we focus on a single, economically important sector (mobile gaming) and exploit detailed app-level data over a long horizon. This allows us to move beyond average treatment effects and examine the mechanisms through which firms adapt to privacy constraints.

3.3 Platform governance, two-sided markets, and business models

A third relevant literature studies digital platforms as two-sided or multi-sided markets. Classic models emphasise how platforms set prices and rules to balance participation on different sides and internalize cross-group externalities (Rochet and Tirole, 2003; Armstrong, 2006; Rochet and Tirole, 2006; Rysman, 2009). In the context of app stores, the platform intermediates between app developers and end users, but it may also act as a gatekeeper for advertising technologies and data access (Hagiu and Wright, 2015a; Cornière and Taylor, 2020).

Recent work has examined how platform policies – such as commission rates, ranking algorithms, or access to APIs – affect developer behaviour, market structure, and innovation (Belleflamme and Peitz, 2010). For example, studies of app stores show that changes in fees or ranking rules can influence entry, quality investment, and the distribution of revenue

across apps. There is also a growing literature on self-preferencing and vertical integration, where platforms simultaneously operate marketplaces and compete with third-party sellers (Hagiu and Wright, 2015b; Zhu and Liu, 2018; De Corniere and Taylor, 2019).

Our paper contributes to this literature by analyzing a particular form of platform governance: privacy policy. By unilaterally restricting access to IDFA, Apple alters the relative profitability of different monetization channels. This change has two-sided implications. On the user side, ATT increases privacy and may affect perceived trust in the platform. On the developer side, it reduces the effectiveness of advertising but leaves in-app purchases (on which Apple charges a commission) unaffected or even relatively more attractive. We show how this shift in relative returns induces developers to adjust their business models, invest in quality, and re-optimize in-app purchase menus.

3.4 Quality investment, concentration, and waterbed effects

Our analysis also relates to theoretical work on quality investment and market structure. Sutton's (1991, 1998) endogenous sunk cost framework predicts that in industries where quality or advertising expenditures are important competitive instruments, equilibrium outcomes may feature high and persistent concentration. When firms respond to competitive pressure by investing in quality, the resulting escalation of sunk costs can create barriers to entry and lead to a "natural oligopoly" (Sutton, 2007; Ellickson, 2007).

In our setting, ATT changes the profitability of different forms of investment. If targeted advertising becomes less effective, developers may find it optimal to reallocate resources towards product quality and in-app monetization. This reallocation is likely to favour larger or more established apps that can finance substantial quality improvements, potentially increasing concentration and reducing entry (Tirole, 1988; Bresnahan and Reiss, 1991; Berry and Waldfogel, 2010). We provide empirical evidence consistent with this mechanism, showing that ATT is associated with higher concentration indices and lower entry rates in the iOS gaming market.

Relatedly, the concept of waterbed effects – whereby a constraint on one side of a multi-sided business leads to compensating adjustments on another side – has been discussed in the context of telecommunications and payment cards (Evans and Schmalensee, 2005; Genakos and Valletti, 2011; Verdier, 2011; Genakos and Valletti, 2015). In our context, the waterbed operates between advertising revenue and consumer payments, as is common in other media-type platforms (Anderson and Coate, 2005; Anderson and Gabszewicz, 2006; Peitz and Valletti, 2008). ATT compresses the advertising side of the business, but we find that developers respond by extracting more revenue per user through in-app purchases, supported by quality upgrades and re-optimized pricing menus.

3.5 Our contribution

Relative to these literature, our paper makes four main contributions. First, we provide, to our knowledge, the first large-scale, systematic analysis of Apple's ATT policy in the mobile gaming industry. While prior work has studied GDPR and earlier disclosure requirements, ATT represents a qualitatively different intervention: it is a platform-level change that directly disables cross-app tracking for the majority of users, with immediate implications for advertising technology and monetization strategies.

Secondly, we move beyond documenting average revenue effects and open the "black box" of firm adjustment. Using rich data on app updates and in-app purchase menus, we show that the response to ATT is not primarily an increase in posted prices or a shift from free to paid apps. Instead, developers engage in quality investment and menu re-optimization, leading to higher in-app spending per active user. This mechanism has been largely absent from previous empirical studies of privacy regulation.

Thirdly, we connect privacy policy to market structure. By exploiting the differential exposure of iOS and Android to ATT and tracking concentration indices and entry rates over time, we show that stricter privacy can coexist with robust industry revenue but may also lead to higher concentration and lower entry. This provides a nuanced perspective on

the competitive implications of privacy-enhancing policies.

Finally, our setting allows us to speak to the broader debate on platform incentives and regulatory design. Because Apple earns a commission on in-app purchases but not on third-party ad revenue, ATT effectively shifts surplus from advertising intermediaries towards in-app monetisation and, ultimately, towards the platform itself. Our findings illustrate how a platform can simultaneously advance privacy objectives and strengthen its own position in the ecosystem, highlighting the importance of considering platform incentives when evaluating the welfare effects of privacy interventions.

4 Conceptual Framework and Hypotheses

In this section, we outline a simple conceptual framework that organizes our empirical analysis and allows us to formulate testable hypotheses. The framework is deliberately stylized: its purpose is not to provide a fully specified structural model, but to clarify the key mechanisms through which Apple's ATT policy can affect the performance and market structure of the mobile gaming industry. We focus on three key elements: (i) the app's revenue model, (ii) the platform's incentives, and (iii) the implications for quality investment and market structure.

4.1 Revenue model of a mobile game

Consider a representative mobile game j operating on an app platform $p \in \text{iOS}, \text{Android}$. The platform intermediates transactions between end-users and game developers, from which it derives commission-based revenue on sales conducted via the platform. In addition, game developers are able to monetize their applications through in-app advertising as facilitated by ad platforms. The simultaneous operation of these distinct platform markets constitutes a defining characteristic of the mobile application ecosystem.

In each platform and period, the game developer earns revenue from two main sources:

advertising revenue, R_j^{Ad}, generated when users view ads served by third-party ad networks, and, application revenue, R_j^{App}, generated from in-app purchases (IAPs), or paid downloads, or subscriptions. Total revenue is therefore

$$R_j = R_j^{Ad} + R_j^{App}.$$

Each game developer chooses an app price ($p_j > 0$), an ad "price", or nuisance, ($A_j > 0$) and a quality level ($q_j > 0$). The ad nuisance is considered to be the money-equivalent cost incurred by users due to annoying ads displayed in the app (Jullien and Bouvard, 2022; Zennyo, 2024). The quality of the game is to be broadly interpreted to include content, features, and user experience. We assume that app developers in each platform face the same demand function, $D_j(p_j, A_j, q_j)$, that is downward-sloping with respect to the total price. We assume that price and quality are complementary in demand in that higher quality makes users tolerate a higher app price or more ads. Then, we can write:

$$\begin{aligned} R_j^{Ad} &= D_j \cdot \alpha_j(A_j, q_j, \theta_p), \\ R_j^{App} &= D_j \cdot p_j, \end{aligned}$$

where $\alpha_j(A_j, q_j, \theta_p)$ is the advertising revenue per user, which depends on the level of ad nuisance, the app quality and the effectiveness of tracking technologies on targeting and attribution on platform p, summarized by a parameter θ_p.

Before ATT, tracking effectiveness is high on both platforms, so $\theta_{\text{iOS}} \approx \theta_{\text{Android}}$ and advertising revenue per user is similar across platforms, controlling for user composition. ATT reduces tracking effectiveness on iOS from θ_{iOS}^0 to $\theta_{\text{iOS}}^1 < \theta_{\text{iOS}}^0$, while θ_{Android} remains unchanged. Holding everything else constant, this shock decreases R_j^{Ad} and thus total revenue on iOS.

4.2 Developer responses: a waterbed mechanism

Developers choose the app price, the ad price and the app quality to maximize profits. Quality investment involves a sunk cost[1] $K(q)$ that is convex in q, while we assume a constant marginal cost, c, of selling a game. The design of the in-app purchase menu (bundles and prices of packages) can be adjusted at relatively low marginal cost through updates. On each platform, Apple or Google charges a commission rate r of the application revenue[2], while the ad platform takes a share τ of the advertising revenue. Hence, each developer's per-period profit on platform $p \in \text{iOS}, \text{Android}$ can therefore be written as:

$$\pi_{jp} = (1-r)R_{jp}^{App} + (1-\tau)R_{jp}^{Ad} - cD_{jp} - K(q_{jp}).$$

In this environment, Zennyo (2024) shows that the simultaneous co-existence of the app platform and the ad platform means that these platforms are substitutes for app developers. In other words, there will be a cut-off value of r and τ below which apps follow the paid business model ($A_j = 0$), while the remaining adopt the ad-funded business model ($p_j = 0$) or, for a range of intermediate values, developers also adopt a hybrid business model ($A_j > 0$, $p_j > 0$). When ATT reduces θ_{iOS}, developers face two immediate consequences: First, lower advertising revenue per user on iOS, i.e. $\alpha_j(\theta_{\text{iOS}})$ decreases. Second, higher user acquisition costs, as campaigns that previously optimized on cost-per-install or cost-per-paying-user become less precise. Absent any adjustment, these changes would reduce total ad revenue and profits for iOS games.

Developers can respond along several margins. First, they can adjust app prices at

[1]To distribute applications on the iOS App Store, developers must enrol in Apple's developer programmes, which involve an annual membership fee. The standard Apple Developer Program, which is required for publishing consumer facing apps on the public App Store, costs 99 USD per year.

[2]Apple levies a commission of 30% on paid app downloads, in app purchases, and subscriptions, with the rate on auto renewing subscriptions falling to 15% after the first year. In addition, under the Small Business Program, developers whose total App Store proceeds do not exceed $1 million in the preceding calendar year are eligible for a reduced commission rate of 15% on paid apps and in app purchases. This fee structure implies that Apple's marginal revenue from an app is tightly linked to the extent of in app monetisation rather than to user numbers per se. Google Play, similarly, charges a standard service fee of 15% for digital goods and subscriptions, which drops to 10% depending on specific programs.

the download stage by switching from free to paid apps. Second, they can re-optimize their monetization strategies by increasing the intensity of in-app monetization (e.g. more attractive bundles, more aggressive upselling) or by changing the price levels of IAPs. Third, they can invest in higher quality to support deeper engagement and spending.

From a two-sided market perspective, ATT compresses the advertising side of the business on iOS. The alternative of "going ad-funded" becomes less attractive. So for paid or hybrid apps the relative return to quality rises: you can't rely on ads, so you must make a better product users are willing to pay for. In other words, if developers can adjust their strategies, we expect a "waterbed" effect (Inderst and Valletti, 2011; Genakos and Valletti, 2011) in which revenue shifts from advertising to application payments. The extent of this shift is an empirical question and depends on the elasticity of user demand with respect to quality and prices, and on the costs of quality investment.

4.3 Platform incentives and Apple's role

Apple earns revenue from its app ecosystem through two main channels. First, it collects the commission rate r (typically 30%, or 15% for small developers) on IAPs and paid downloads. Secondly, it may earn some revenue from its own advertising products, but it does not generally take a direct cut of third-party ad revenue generated within apps. Because Apple's commission applies to R^{App} but not to R^{Ad}, the platform has an incentive to tilt the revenue mix towards consumer payments. ATT effectively makes the advertising channel less profitable relative to in-app purchases, encouraging developers to rely more heavily on R^{App}. At the same time, the policy improves the platform's privacy stance, which may be valuable for user acquisition and brand differentiation. In this sense, Apple's incentives are aligned with both stronger privacy and a greater reliance on consumer monetization, even if the policy reduces total advertising revenue in the ecosystem.

4.4 Quality investment, entry, and market structure

The shift towards in-app monetization has implications for quality investment and, consequently, for market structure. Quality upgrades in mobile games often take the form of major content updates, new game modes, or significant feature additions that involve fixed and sunk costs. These investments are costly and lumpy, and their returns depend on the size and engagement of the user base.

When ATT reduces advertising-based monetization, the relative payoff to quality investment changes. For developers with a sufficiently large existing user base, increasing quality is comparatively easier and can justify more aggressive investment, whereas smaller or newer applications may find it more difficult to finance substantial quality improvements or to amortize such investments over a relatively limited user base.

This logic is reminiscent of Sutton's (1991, 1998) endogenous sunk cost theory. In industries where quality (R&D) or advertising is a key competitive instrument, firms may engage in a "quality race" that raises equilibrium sunk costs and leads to higher concentration. In our setting, ATT can be seen as a shock that increases the marginal return to quality investment relative to advertising. If quality improvements are subject to economies of scale, we expect: a) higher concentration among top apps, as leading titles invest heavily in quality and monetization, and b) lower entry, as the minimum efficient scale required to compete profitably increases.

4.5 Testable hypotheses

The conceptual framework yields a set of testable hypotheses about the effects of ATT on app performance, monetisation strategies, and market structure. We formulate them relative to the Android platform, which serves as a control group not directly affected by ATT.

H1: Increased application revenue. If developers successfully strategically respond to the decline in advertising revenue by increasing consumer monetization, we should observe

an increase in application revenue on iOS games relative to Android.

H2: Ambiguous effect on users. The direct effect of ATT on user numbers is ambiguous. On the one hand, higher privacy may increase user trust in iOS apps; on the other hand, higher user acquisition costs may reduce the scale of ad-driven installs.

H3: Monetization adjusts. Developers have various strategic instruments available to monetize users and it is not obvious a priori which ones they are going to utilize. We should expect quality upgrades that are associated with higher in-app spending, but we cannot exclude that developers may also raise prices or convert free apps into paid ones.

H4: Effects on market structure. As quality investment becomes more important, we expect the industry to become more concentrated and to reduce the number of new game apps entering the iOS ecosystem relative to Android.

5 Data

Our empirical analysis is based on proprietary data from SensorTower, a leading mobile app analytics provider. SensorTower collects information from app stores, publishers, device panels, and other sources to estimate usage and revenue for mobile across more than 100 countries. We select the top 5,000 mobile gaming apps in the United States, ranked by their average number of active users over the period January 2018 to December 2023, with rankings constructed separately for Apple's App Store (iOS) and Google Play (Android). The long selection period ensures inclusion of the pre-COVID market and captures the most relevant apps. For these 5,000 apps on each platform, we then collect detailed data over January 2020 to December 2023 for our empirical analysis. The estimation period differs from the selection period to avoid contamination from other events. Focusing on 2020–2023 balances statistical power with pre-trend validity. As shown in Fig. 1, these 5,000 apps account for

over 80% of total active users and revenue on each platform in every year, so our sample covers the economically most relevant part of the market while remaining computationally tractable.

The basic unit of observation in our dataset is the app–platform–month triple (j, p, t), where: j indexes a distinct game title, $p \in \text{iOS}, \text{Android}$ denotes the platform, and t denotes the calendar month. The resulting panel is unbalanced, as apps enter and exit the top-5,000 ranking over time, and not all titles are present on both platforms.

For each app–platform–month observation, we observe a set of performance measures, business model characteristics, and update indicators.

Users and Revenue. We obtain the estimated number of unique active users, $Users_{jpt}$, and estimated gross revenue, $Revenue_{jpt}$, for each app j on each platform p in month t. Revenue is measured in US dollars. We use these variables to construct revenue per user, $RevpUser_{jpt} = \frac{R_{jpt}}{U_{jpt}}$, which captures the intensity of monetization conditional on having an active user base. Because the distribution of $RevpUser_{jpt}$ is highly skewed, we also consider its logarithm in some specifications, $LogRevpUser_{jpt}$.

SensorTower reports revenue derived exclusively from consumer-related transactions, and does not account for income generated through advertising activities.[3] Our analysis therefore focuses on total revenue and revenue per user, and we infer changes in monetization channels from complementary evidence on pricing, in-app purchase menus, and updates, assuming that the advertising revenue was negatively affected as a direct result of Apple's ATT policy. To understand how developers adjust their monetization strategies, we exploit detailed information on each app's business model and in-app purchase (IAP) offerings.

Free vs paid app. For each app–platform–month, we observe whether the app is free to download or requires an up-front payment, and if paid, its price. We construct three

[3]Sensor Tower estimates revenue by combining proprietary data from partner apps with app-store attributes, such as rankings, category, and number of reviews.

measures. $Price_{jpt}$ denotes the price of app j on platform p in month t. $PaidApp_{jpt}$ is a binary indicator equal to one if app j is paid on platform p in month t. When multiple price updates occur within a month, we use the last observed value. Finally, $IfChangeP_{jpt}$ equals one if at least one price update occurs during a given month, regardless of whether the change is an increase or a decrease.

In-app purchase packages. For iOS gaming apps, we also collect detailed information on in-app purchase (IAP) packages. In-app purchases are particularly popular among gaming apps and can be classified into two types. Consumable in-app purchases expire once used, such as game coins or extra lives, while durable in-app purchases provide lasting benefits, such as special weapons or premium skins. We observe the top 10 IAP packages ranked by revenue for each iOS app. For each package, we observe an anonymized IAP identifier, price, ranking, and package name when available. For example, an in-app package labeled "Buy All Content Forever" is priced at \$19.99. We observe this information whenever the top 10 IAP packages are updated, for instance due to changes in package prices or rankings. This information allows us to construct several measures of pricing behaviour. We measure net price changes in in-app packages at each update as the difference between the total price of all changed packages after versus before the update. For example, if an update adds a \$0.99 package, removes a \$4.99 package, and modifies a \$6.99 package to \$5.99, the net price change equals $(\$0.99 + \$5.99) - (\$4.99 + \$6.99) = -\$5$. We then aggregate these measures to the monthly level. We construct an indicator $IAPprice_{jpt}$, which equals 1 if the sum of net price changes across all updates in that month is positive.[4]

Pseudo-revenue measures of IAP menus. To capture changes in the structure and ranking of IAP menus, we follow a two-step procedure. First, for each app at each IAP menu update, we assign weights for each IAP package that reflect their position in the menu (for

[4]In robustenss check, we also construct an alternative dummy $IAPpriceAlt_{jpt}$, which equals one if the net price change is positive for the last update in a given month.

example, higher weights for more prominent ranks). Secondly, we compute a *pseudo-revenue index* as $\sum_{r_{pack}=1}^{10} \frac{\text{Price}_{pack}}{r_{pack}}$, which represents the weighted sum of package prices, with weights given by the inverse of each package's rank r_{pack}. Intuitively, this index approximates the potential revenue the menu could generate under a given pattern of consumer choices. Using this index, we construct a binary variable. $PseudoInc_{jpt}$ equals one if the sum of changes in the pseudo-revenue index across all updates within month t is positive.[5] We provide a detailed example illustrating the construction of this measure in Appendix Section A. This variable captures whether the application's in-app purchase menu is undergoing re-optimization, through the introduction of new offers and packages, and the extent of their popularity among consumers, as reflected in its ranking, without requiring us to observe actual purchase-level data.

Update history. We use information on apps' update histories to proxy for quality investment. SensorTower records the date and version number of each app update. For each update, we classify it as major or minor based on changes in version numbering and release notes. A major update (also called feature update) is defined as a change in the second digit of the version number (e.g., from 2.1 to 2.2), which typically indicates the introduction of new content, game modes, or significant modifications to existing functionality. In contrast, a minor (or maintenance or patch) update is defined as a change in the third digit (e.g., from 2.1 to 2.1.1), which generally corresponds to bug fixes or minor improvements. At the app–platform–month level, we construct $IfMajorUpdate_{jpt}$, an indicator equal to one if app j on platform p releases at least one major update in month t, and, $MajorUpdates_{jpt}$, which counts the number of major updates in that month.

Entry of new apps. We observe the release date of each app and use this information to construct the number of new entrants in each month. For each platform–month, we count

[5] In robustenss check, we also consider an alternative definition that looks only at the final update of the month. *PseudoIncAlt* equals 1 if the pseudo-revenue index increases between the last update in month t and the previous update, and zero otherwise.

the number of new entrants, $Entry_{pt}$. Because our data cover only the top 5,000 apps, entry is measured relative to this segment of the market; however, trends in this segment are informative about entry conditions for economically significant titles.

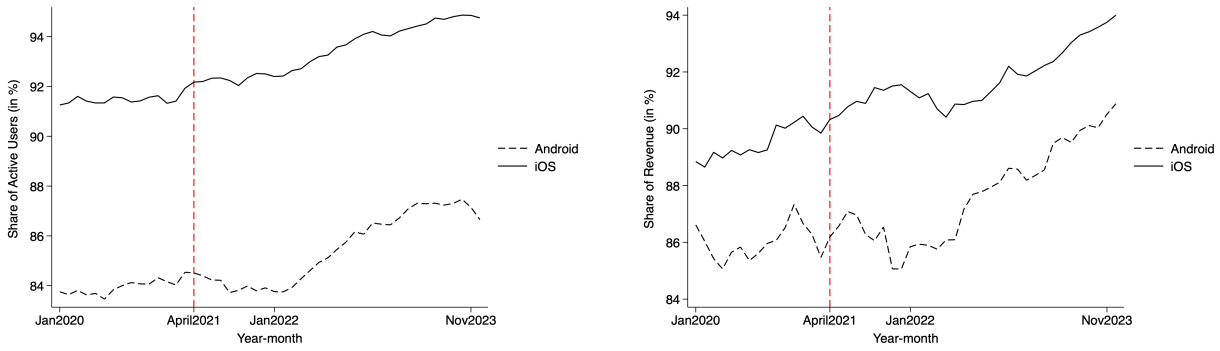
Concentration indices. For each platform p and month t, we compute the revenue share of the top n apps, with $n \in \{1{,}000, 2{,}000\}$, denoted by $CR1k_{pt}$ and $CR2k_{pt}$, respectively, as well as the Herfindahl–Hirschman Index (HHI) of revenue across all games in our sample, HHI_{pt}. These measures capture how revenue is distributed across titles and how this distribution evolves over time on each platform.

Our main analysis focuses on multi-homing apps available on both iOS and Android platform among the top 5,000 apps.[6] These apps account for over 70% of active users and revenue within the top 5,000 apps during the sample period, yielding a final sample of 2,515 apps and 148,234 app–month observations for the main outcome variables.[7]

Table 1 reports descriptive statistics disaggregated by platform. On average, iOS apps have more active users and generate higher revenue than Android apps, with 338,186 users and $435,598 in monthly revenue, compared to 266,875 users and $291,114 for Android. Revenue per user is also higher on iOS, reflecting greater monetization per user. Market concentration is broadly similar across platforms on average, indicating a moderately concentrated app market. The number of new entrants per month is also comparable, averaging around 55 apps for both platforms. App prices are low on both platforms, with very few paid apps and minimal price changes. Metrics on IAP menus are available only for iOS apps, showing that, on average, around 8% of iOS apps increase IAP prices each month, and approximately 3% experience increases in pseudo-revenue indices. While update information exists for both platforms, our analysis links updates to IAP data, which are specific to iOS. Therefore, updates are reported only for iOS apps in the table. Summary statistics show

[6] We analyze the full sample of top 5,000 apps in our robustness checks.

[7] Some secondary outcomes, such as IAP metrics and app prices, are only available for a subset of apps, so the number of observations varies across these variables. We report the exact sample size for each variable in Table 1.



(a) Share of Top 5K Apps in Active Users.

(b) Share of Top 5K Apps in Revenue.

Figure 1: Share of Top 5K apps on Android and iOS platforms.

Notes: This figure shows the share of the top 5,000 gaming apps in total active users and revenue for iOS and Android. The solid line represents iOS, while the dashed line denotes Android. The vertical red line represents the implementation of the ATT policy (April 2021).

that major updates are relatively infrequent, affecting roughly 8% of apps per month, with 13% of all updates classified as major.

6 Empirical Methodology

We study the effect of Apple's App Tracking Transparency (ATT) policy on the performance of mobile gaming apps using a difference-in-differences (DiD) approach. Our empirical strategy exploits the fact that the ATT policy applied only to iOS apps, leaving Android versions unaffected during the study period. Focusing on multi-homing apps allows us to construct within-app comparisons across platforms. As these apps offer identical content on both platforms, any differential change following the ATT policy can plausibly be attributed to the policy itself.

Our baseline specification is as follows:

$$Y_{jpt} = \beta_0 + \beta_1 \, iOS_{jp} \times Post_{pt} + \lambda_t + \lambda_{jp} + \varepsilon_{jpt} \tag{1}$$

where Y_{jpt} denotes the outcome for app j, on platform p, in year-month t, including the

Table 1: Summary Statistics Disaggregated by Platform

	(1) iOS				(2) Android			
	Mean	Median	S.D.	No. of Obs.	Mean	Median	S.D.	No. of Obs.
Revenue and Users								
Users	338186.36	119302	1115270.2	74,117	266874.73	120972	762575.09	74,117
Revenue	435597.56	4365.04	1839189.3	74,117	291114.43	1742.62	1168449.8	74,117
RevpUser	2.47	0.03	11.10	74,117	1.39	0.01	4.77	74,117
LogRevpUser	0.49	0.03	0.87	74,117	0.39	0.01	0.74	74,117
Concentration and Entry								
HHI	116.29	105.34	33.79	48	110.32	102.18	23.29	48
CR2k	82.69	82.68	0.96	48	84.73	84.64	0.84	48
CR1k	67.63	67.47	1.81	48	70.05	70.28	1.71	48
Entry	55	57.5	17.61	48	56.94	60.5	18.52	48
App Prices								
Price	0.02	0	0.33	72,609	0.02	0	0.31	73,143
Paidapp	0.01	0	0.08	72,609	0.00	0	0.05	73,143
IfChangeP	0.00	0	0.03	72,609	0	0	0	73,143
IAP Menu and Updates								
IAPprice	0.08	0	0.28	72,624				
PseudoInc	0.03	0	0.17	72,624				
IfMajorUpdate	0.08	0	0.27	72,624				
MajorUpdates	0.13	0	0.57	72,624				

Notes: This table presents summary statistics disaggregated by platform, focusing on apps common to both iOS and Android. Variable *LogRevpUser* is measured as *Log*(*RevpUser+1*). Metrics on IAP menus are available only for iOS apps. While update information exists for both platforms, our analysis links updates to IAP data, which are specific to iOS. Therefore, we report updates only for iOS apps in this table.

number of active users, revenue, revenue per user and its logarithmic form. iOS_{jp} is an indicator equal to 1 for iOS version of the app and 0 otherwise. $Post_{pt}$ equals one for periods after the policy implementation. λ_t are year-month fixed effects controlling for common time shocks affecting all apps. λ_{jp} are platform-app fixed effects accounting for all time-invariant characteristics specific to each app on each platform. Identification therefore comes from comparing how the iOS version of a given app changes after ATT relative to its Android counterpart, net of permanent differences between the iOS and Android versions of that app and common time shocks. Standard errors are clustered at the app level. The coefficient of interest, β_1, captures the causal effect of the ATT policy.

Our identification relies on the exogeneity of the ATT policy. The ATT framework was designed and implemented by Apple with the goal of improving user privacy and control over their data. Importantly, developers received only a week's notice before the actual implementation of the policy, and no similar changes were adopted by Google during our study period. Thus, any differences in outcomes between the iOS and Android versions of the same app following ATT can plausibly be attributed to the policy itself.

A key assumption of the DiD framework is the parallel trends assumption, which suggests that the difference between iOS and Android versions should follow a similar trajectory before the treatment. To test this assumption, we estimate the following event-study specification:

$$Y_{jpt} = \lambda_t + \lambda_{jp} + \sum_{k=-12}^{24, k\neq -1} \beta_k \cdot \mathbf{Day}\{t - T_{jp} = k\} \cdot iOS_{jp} + \varepsilon_{jpt} \tag{2}$$

where T_{jp} denotes the timing of ATT implementation. $\mathbf{Day}\{t - T_{jp} = k\}$ is a set of event-time dummy equal to 1 if period t is k periods from treatment, with k ranges from -12 to 24. Specifically, we group all months more than 12 months before implementation into $k = -12$, and all months more than 24 months after into $k = 24$. We omit $k = -1$, the month before implementation, as the reference period. The coefficients β_k trace the difference in outcomes between iOS and Android versions of the same app, for k months before or after implementation relative to the baseline month. Pre-treatment estimates can

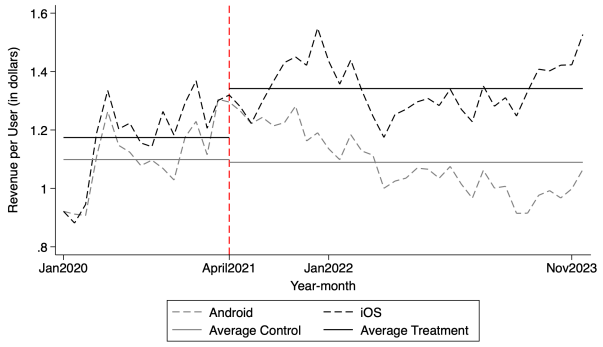
be used to test the parallel trends assumption, while post-treatment coefficients capture the evolution of the treatment effect over time.

7 Main Results: Impact of ATT on App Performance

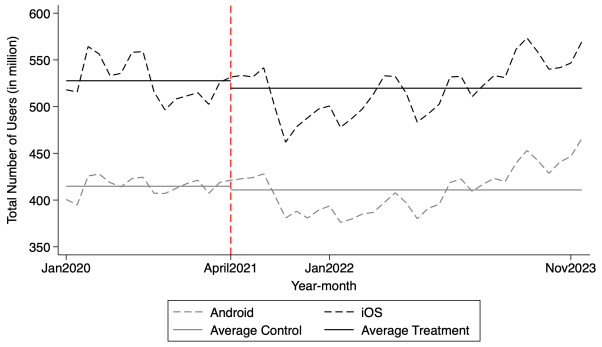
7.1 Average Effects of ATT on App Performance

We begin with descriptive evidence on the impact of the ATT policy using simple time-series plots in Fig. 2. The vertical red line represents the implementation of the ATT policy (April 2021). Panel (a) plots revenue per user for iOS and Android apps. Following the ATT policy, revenue per user increases significantly for iOS apps, while showing no change for Android. To understand this pattern, we examine active users and total revenue separately. Panel (b) plots the number of active users and shows very similar trajectory across platforms both before and after the policy. This suggests that the increase in revenue per user is unlikely to be driven by changes in the user base. Panel (c) shows that total revenue for iOS apps increases after ATT, while no comparable change is observed for Android versions. Taken together, these patterns suggest that revenue per user goes up after ATT and is mainly driven by higher revenue rather than changes in user numbers.

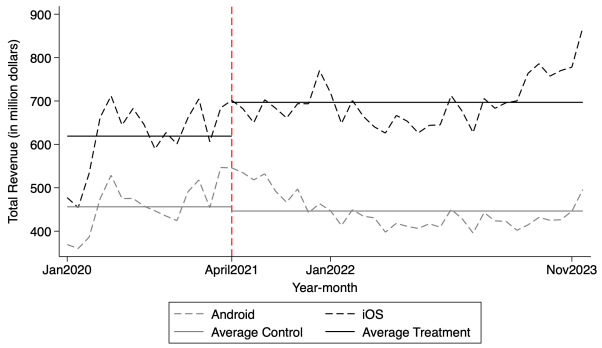
Table 2 presents the estimated coefficients from Equation (1). Column (1) shows no significant effect of ATT on the number of active users. Column (2) reveals a statistically significant increase in revenue following the ATT policy. On average, app-level revenue increases by approximately $46,802 after ATT implementation, corresponding to a 11% increase for an average iOS app. Applying the estimated effect to the approximately 2,500 multi-homing gaming apps in our estimation sample implies an aggregate increase in developer revenue of approximately $117 million per month, or $1.4 billion annually. Assuming a 30% commission rate, this translates into approximately $421 million in additional annual



(a) Evolution of Revenue per User.



(b) Evolution of Active Users.



(c) Evolution of Revenue.

Figure 2: Aggregate Trends in App Performance Before and After ATT.

Notes: This figure provides visual evidence on the potential impact of the ATT policy by plotting aggregate trends in revenue per user, active users and revenue for iOS (black line) and Android (gray line) apps. The vertical red line represents the implementation of the ATT policy (April 2021).

commission revenue for Apple.,[8] Given that the number of active users remains stable while total revenue increases, revenue per user increases significantly, as shown in Column (3). Using the logarithmic specification,[9] Column (4) implies that revenue per user increases by 3.56% following the ATT policy.[10] Taken together, these results suggest that ATT improves the financial performance of gaming apps, mainly through higher revenue rather than user growth.

[8]Extrapolating the estimated effect for games to the entire App Store, which was estimated at approximately $18 billion in 2020, our estimates imply an (upper bound) additional $1.98 billion ($18 billion $\times$ 0.11) in annual App Store commission revenue following ATT.

[9]The outcome variable *LogRevpUser* is measured as *Log*(*RevpUser+1*).

[10]Since revenue per user is in logarithmic form, coefficients can be interpreted as percentage changes, calculated as $100 \times (\exp(\hat{\beta}) - 1)$.

Table 2: Impact of the ATT Policy on App Performance

Dependent Variable	(1) Users	(2) Revenue	(3) RevpUser	(4) LogRevpUser
iOS × Post	-8,606.955	46,801.897***	0.642***	0.035***
	(8,649.524)	(11,670.415)	(0.125)	(0.005)
Time FE	Yes	Yes	Yes	Yes
App-Platform FE	Yes	Yes	Yes	Yes
Observations	148,202	148,202	148,202	148,202
Clusters	2,499	2,499	2,499	2,499

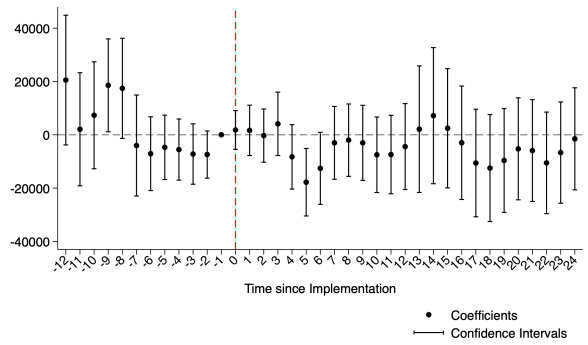
Notes: This table presents estimates from Equation (1). The dependent variables in Columns (1)–(4) are the number of active users, revenue, revenue per user, and the logarithm of revenue per user, respectively. The outcome variable *LogRevpUser* is measured as *Log*(*RevpUser+1*). Sixteen apps (32 observations) with only a single month of data are excluded from the regression. Standard errors clustered at the app level are reported in parentheses below coefficients. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

7.2 Dynamic Effects of ATT on App Performance

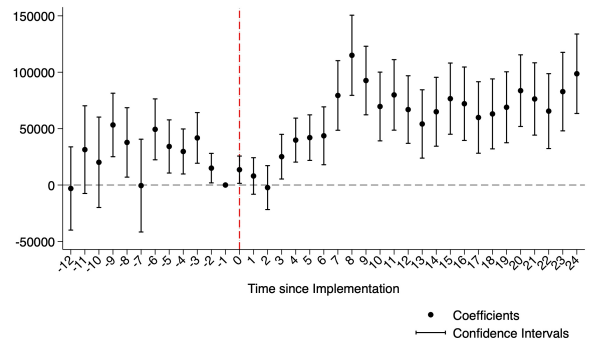
To assess the validity of the parallel trends assumption and to examine the evolution of treatment effects over time, we estimate the event-study specification in Equation (2) and plot the estimated coefficients in Fig. 3.[11]

The pre-treatment estimates support the parallel trends assumption, as the confidence intervals for the pre-treatment periods include zero across all panels. Panel (a) shows the dynamic effect on active users. The estimates are statistically insignificant throughout the post-treatment period, suggesting that ATT policy does not affect overall user base. Panel (b) presents the dynamic impact on revenue. The results show a clear increase in revenue following ATT implementation, with effects that persist over time. Finally, Panel (c) and (d) show the effects on revenue per user and log revenue per user, respectively. The patterns closely mirror those of total revenue, with a gradual increase in magnitude over time. This suggests a long-run improvement in monetisation efficiency for iOS apps.

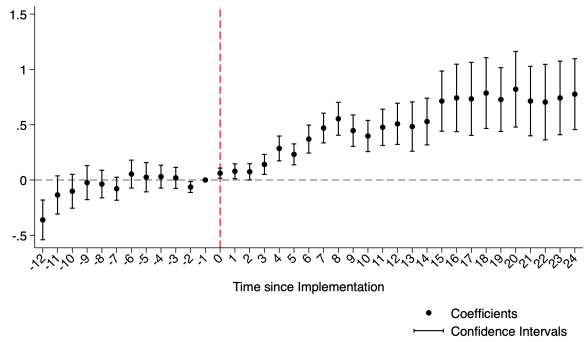
[11] Table B1 reports the corresponding estimated coefficients.



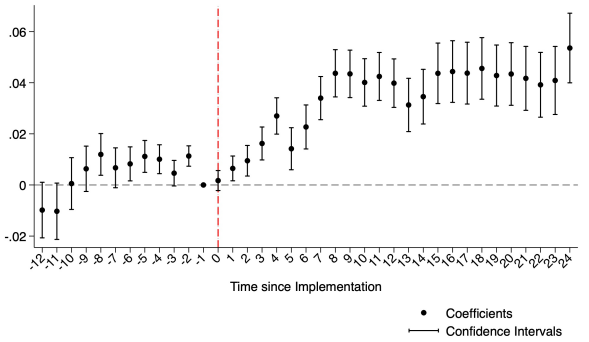
(a) Dynamic Effect on Active Users.



(b) Dynamic Effect on Revenue.



(c) Dynamic Effect on Revenue per User.



(d) Dynamic Effect on Revenue per User (Logarithm).

Figure 3: Dynamic Effect of the ATT Policy.

Notes: This figure plots estimated coefficients with 95% confidence intervals from estimating Equation (2). Panels (a)–(d) correspond to the number of active users, revenue, revenue per user, and the logarithm of revenue per user plus one, respectively. Periods more than 12 months before ATT implementation are grouped into $k = -12$, and periods more than 24 months after implementation are binned into $k = 24$. The month immediately before implementation ($k = -1$) is omitted as the reference period.

7.3 Policy Heterogeneity and Robustness Checks

We next explore how the effects of ATT vary by genre. While most multi-homing apps list multiple genres on the App Store, Android apps typically report only a single genre. We therefore rely on App Store information and define each app's genre using its primary App Store classification.[12] There are 18 genres, including Action, Adventure, Arcade, Board, Card, Casino, Casual, Education, Family, Music, Puzzle, Racing, Role Playing, Simulation, Sports, Strategy, Trivia, and Word. Fig. C1 shows the distribution of apps across these genres. Casual games are the most common, accounting for approximately 20.6% of apps, followed by Action (13.5%) and Simulation (13%). Card and Casino games together comprise around 5% of apps. More niche genres, such as Education (0.1%), Music (0.9%), and Trivia (1.4%), are relatively rare.

To examine heterogeneous effects, we interact the ATT treatment with genre dummies and plot the results in Fig. 4 (with the estimated coefficients reported in Table B2, Column (1)). We find that the positive effects on revenue per user are particularly pronounced in genres such as casino, card, and strategy, which traditionally rely heavily on in-app purchases and deep engagement. In contrast, more casual genres show smaller or more heterogeneous effects. For some genres, we observe modest declines in revenue per user, suggesting that not all game types can easily adapt to the new environment. Overall, however, the dominant pattern is one of positive but heterogeneous gains.

Robustness checks. Our main results are robust across a variety of alternative sample selections and regression specifications.

Alternative Clustering. To account for potential correlation within app publishers, we collect publisher-level information and re-estimate Equation (1), clustering standard errors at the publisher level. Results shown in Table B3 remain robust.

[12]Results remain robust when defining game genre using the single genre listed on the Android store, as shown in Fig. C2 and reported in Table B2, Column (2).

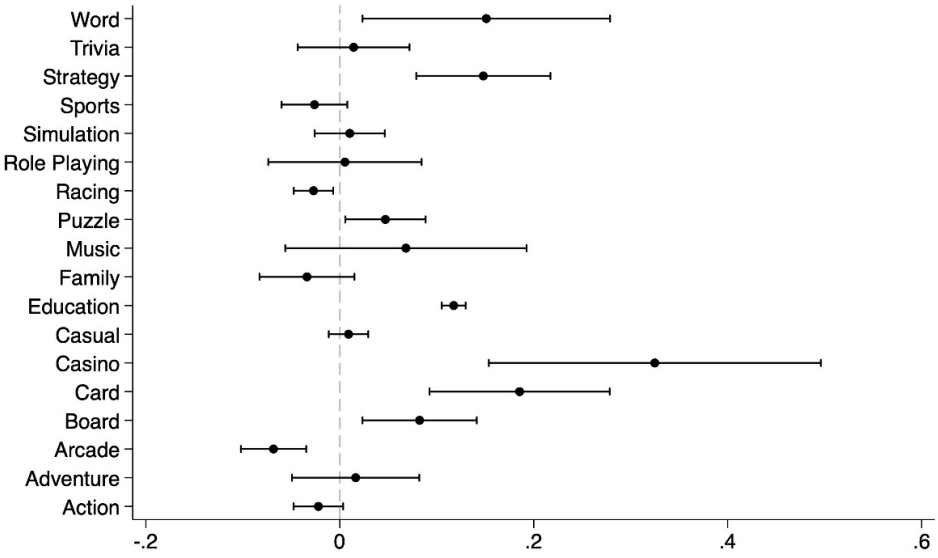


Figure 4: Heterogeneous Effects by Game Genre

Notes: This figure shows heterogeneous effects by game genre, obtained by interacting the ATT treatment with each genre. The outcome variable is *LogRevpUser*. Estimated coefficients are reported in Table B2, Column (1). This figure displays the estimated coefficients along with their 95% confidence intervals.

Alternative Sample Choices. First, we consider a balanced panel of multi-homing apps that are present throughout the entire sample period, excluding entrants and exit. Results remain consistent (Table B4). Second, we expand the analysis to include the full sample of the top 5,000 apps and find similar results (Table B5). Finally, we extend the pre-treatment period to include 2019, and the findings again remain robust (Table B6).

7.4 Mechanisms: From Lost Ads to Higher In-App Monetization

We now investigate the mechanisms that generated the observed increase in total revenue and revenue per user, in the absence of a change in the size of the user base. The introduction of ATT appears to have initiated a gradual re-optimization of business models, rather than a one-off adjustment, with the resulting monetization gains accruing over time. This raises the question of why an essentially unchanged user base becomes willing to spend more. Specifically, we ask whether the increase in revenue is primarily driven by changes in game app

Table 3: Impact of the ATT Policy on APP Prices

Dependent Variable	(1) Price	(2) Paidapp	(3) IfChangeP
iOS × Post	0.001	-0.000	-0.000
	(0.002)	(0.000)	(0.000)
Time FE	Yes	Yes	Yes
App-platform FE	Yes	Yes	Yes
Observations	145,752	145,752	145,752
Clusters	2,485	2,485	2,485

Notes: This table presents estimates from Equation (1), using different measures of app prices as dependent variables. Column (1) uses app prices, Column (2) uses an indicator equal to one if the app is a paid app, and Column (3) uses an indicator equal to one if an app experienced a price change in a given month. These regressions use fewer observations due to missing values in the pricing variables. Standard errors clustered at the app level are reported in parentheses below coefficients. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

pricing policies, or whether it is instead attributable to quality-enhancing investments and more nuanced modifications in in-app purchase (IAP) design. We examine these mechanisms next.

Free vs paid apps. We start with the obvious: did ATT push the apps to turn from free to paid? Table 3 presents difference-in-differences estimates using app prices as the outcome variables. Column (1) shows that app prices do not change following ATT implementation. Column (2) indicates that the paid-app indicator, PaidApp_{jpt} show no significant effect of ATT, with the coefficient on $iOS_p \times Post_t$ essentially zero. Thus, there is no evidence that apps are more likely to switch from free to paid on iOS than on Android after ATT. Finally, Column (3) shows that the policy does not significantly affect the likelihood of any price adjustment. Together, these results rule out a simple story in which developers respond to ATT by erecting paywalls at the download stage.

Posted IAP prices. Could the increased revenue stem from the increase in the list prices for in-app purchases? Unfortunately, detailed information on in-app purchases (IAPs) is available only for iOS applications. Consequently, our analysis is restricted to examining

Table 4: Changes in Posted IAP Prices Following the ATT Policy

Dependent Variable Sample	(1) IAPprice All iOS Apps	(2) IAPprice All iOS Apps	(3) IAPprice Common iOS Apps	(4) IAPprice Common iOS Apps
Post	-0.013*** (0.004)	-0.010*** (0.003)	-0.021*** (0.005)	-0.013*** (0.004)
App FE	Yes	Yes	Yes	Yes
Month and year FE	Yes	No	Yes	No
Linear Time Trend	No	Yes	No	Yes
Observations	138,359	138,359	72,624	72,624
Clusters	4,529	4,529	2,459	2,459

Notes: This table presents estimates from a simple before-and-after comparison regression. *Post* equals one for the post-implementation period. These regressions use only the iOS app sample, as IAP data are only available for iOS apps and no control group is available. Columns (1) and (2) use all top 5,000 iOS apps. The sample comprises 4,529 apps, fewer than 5,000 due to missing values for some apps. Columns (3) and (4) use the subset of iOS apps that are also available on Android. This sample comprises 2,459 iOS apps, fewer than the 2,499 apps used in the main table (Table 2) due to missing IAP information for some apps. Standard errors clustered at the app level are reported in parentheses below coefficients. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

changes in the behaviour of these apps before and after the implementation of the ATT policy. We examine indicators for IAP price changes in Table 4. Specifically, we perform the analysis for both the subsample of common iOS apps and the full sample of the top 5,000 iOS apps. Across a range of specifications, we find no systematic increase in posted IAP prices on iOS apps after ATT.[13] If anything, estimates suggest a slight decline in the frequency of positive price changes. These findings further support the view that the observed increase in revenue per user is not primarily attributable to straightforward changes in pricing policy, such as increases in the posted IAP prices.

IAP menu and ranking. In contrast, ATT has a clear effect on the structure of IAP menus. Fig. 5 plot the share of iOS apps with increasing pseudo-revenue for IAP packages over time. This substantial increase is driven by firms introducing new options and packages, to which consumers respond by purchasing these offerings more frequently, thereby improving their ranking. The figure shows that before June 2020, very few apps experience increases

[13]Results remain robust when using the alternative measure of posted IAP prices (Table B7).

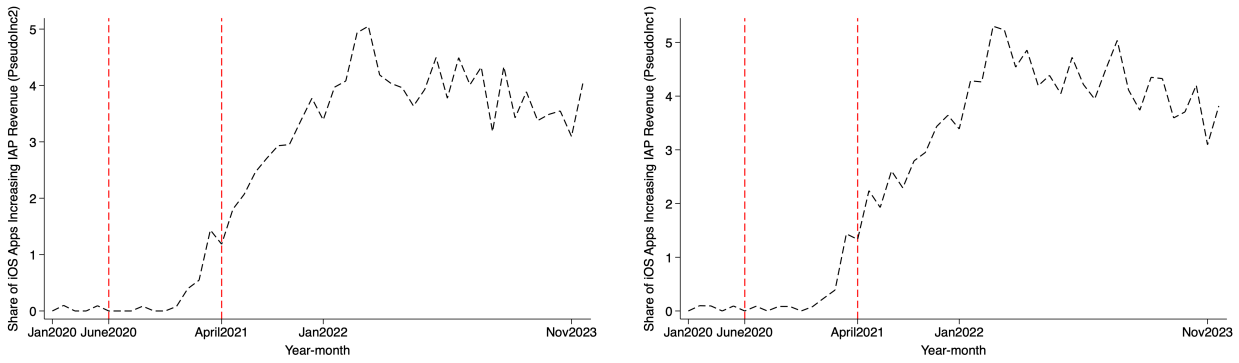
in pseudo-revenue. After the ATT policy announcement, however, the share of apps increasing pseudo-revenue rises sharply and stabilises only about a year after implementation, a pattern consistent across both alternative measures. As the figure shows an increasing trend in IAP pseudo-revenue prior to the actual implementation of ATT, we examine both the announcement and implementation periods in the following regression analysis. We perform the analysis for both the subsample of common iOS apps and the full sample of the top 5,000 iOS apps.

Table 5 shows that, following ATT implementation, the share of iOS games that update their IAP menus in ways that increase pseudo-revenue rises significantly, regardless of the sample used.[14] The coefficient for the implementation is positive and significant across specifications, while the coefficient on announcement is also positive in columns (1), (2), and (4). The patterns are consistent with developers experimenting with menu design and bundling of IAP packages to encourage higher spending per user, rather than simply raising prices. Taken together, these results provide strong evidence that ATT prompted developers to re-optimise their IAP menus, and that consumers responded positively to these changes, thereby contributing to higher revenue per user.

But why consumers increase their demand and spend more? The last piece in this puzzle is the role of quality investment, proxied by major updates.

Link between quality investment and monetization. We interact the ATT treatment with measures of app updates. Panel (a) in Table 6 examines whether having a major update is associated with increases in pseudo-revenue for the IAP menu around the ATT policy, while Panel (b) considers the number of updates. The interaction term is positive and statistically significant across all specifications in both panels. Panel (a) shows that following the ATT policy, apps with a major update are more likely to experience a rise in pseudo-revenue. Moreover, Panel (b) indicates that months with more major updates are associated with

[14]We also use an alternative measure of the pseudo-revenue index. *PseudoIncAlt* focuses on the last update of the month and equals one if the pseudo-revenue index of the final update is higher than that of the previous update. Results remain robust when using this alternative measure(Table B8).



(a) PseudoInc. (b) PseudoIncAlt.

Figure 5: Share of iOS Apps Increasing IAP Pseudo-Revenue.

Notes: This figure plots the share of iOS Apps with increasing pseudo-revenue in IAP packages over time. We use two alternative measures of IAP pseudo-revenue index. Panel (a) uses $PseudoInc$ and Panel (b) uses an alternative measure $PseudoIncAlt$. The plot includes only the iOS app sample, as IAP data are available exclusively for iOS apps. The two vertical red lines represents the timing of ATT announcement (June 2020) and implementation (April 2021) respectively.

Table 5: Changes in IAP Menu Pseudo-Revenue Following the ATT Policy

	(1)	(2)	(3)	(4)
Dependent Variable	PseudoInc	PseudoInc	PseudoInc	PseudoInc
Sample	All iOS Apps	All iOS Apps	Common iOS Apps	Common iOS Apps
Announce	0.003***	0.004***	0.005	0.008***
	(0.001)	(0.001)	(0.003)	(0.002)
Implement	0.006**	0.009***	0.003**	0.004***
	(0.002)	(0.002)	(0.001)	(0.001)
App FE	Yes	Yes	Yes	Yes
Month and year FE	Yes	No	Yes	No
Linear Time Trend	No	Yes	No	Yes
Observations	138,359	138,359	72,624	72,624
Clusters	4,529	4,529	2,459	2,459

Notes: This table presents estimates from a simple before-and-after comparison regression. *Annouce* equals one for the period between the ATT announcement and implementation, and *Implement* equals one for the post-implementation period. These regressions use only the iOS app sample, as IAP data are only available for iOS apps and no control group is available. Columns (1) and (2) use all top 5,000 iOS apps. The sample comprises 4,529 apps, fewer than 5,000 due to missing values for some apps. Columns (3) and (4) use the subset of iOS apps that are also available on Android. This sample comprises 2,459 iOS apps, fewer than the 2,499 apps used in the main table (Table 2) due to missing IAP information for some apps. Standard errors clustered at the app level are reported in parentheses below coefficients. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

a higher probability of pseudo-revenue increases after ATT.[15] These findings support the hypothesis that ATT raises the incentive to invest in game quality and that major updates are followed by noticeable spikes in monetization.

7.5 ATT's Effect on Entry and Concentration

Finally, we examine how ATT affects market structure at the platform level.

Concentration. We calculate the HHI across all games and concentration ratios for the top 1,000 and top 2,000 apps, with rankings based on the average number of active users between January 2020 and December 2023. Fig. 6 presents the time-series evolution of market concentration on iOS and Android platforms. The plots show that app market concentration has increased over time following ATT implementation, with a sharper rise on iOS, and that this pattern holds across different concentration measures.

Platform–month regressions, shown in Table 7, indicate that concentration increases significantly on iOS relative to Android after ATT. The estimated effect sizes imply noticeable rises in HHI and in the share of revenue captured by the largest titles. These findings are consistent with Sutton-style mechanisms in which higher returns to quality and monetization investments favor larger incumbents.

Entry. Entry decisions, which often require long-term planning, may have responded to the ATT announcement prior to its rollout in April 2021. Accordingly, we examine both the announcement and implementation periods in the DiD regression. Using the number (or log number) of entrants as the dependent variable, we find that the number of new games entering the top 5,000 ranking declines on iOS relative to Android following both the ATT announcement and implementation (Table 8). These results are consistent with the mechanism whereby ATT increases the importance of quality and monetization sophistication,

[15] Results remain robust when using the alternative measure of the pseudo-revenue index (Table B9.

Table 6: IAP Pseudo-Revenue and APP Major Updates After ATT

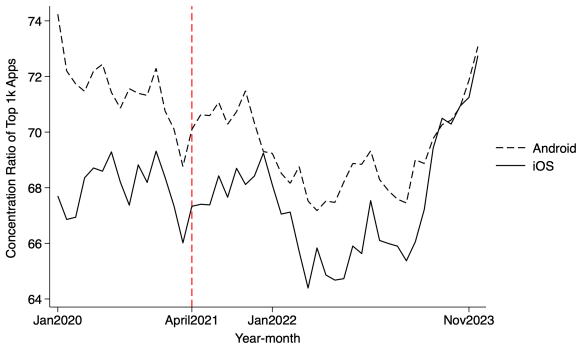
Panel (a)

	(1)	(2)	(3)	(4)
Dependent Variable	PseudoInc	PseudoInc	PseudoInc	PseudoInc
Sample	All iOS Apps	All iOS Apps	Common iOS Apps	Common iOS Apps
Announce × IfMajorUpdate	0.012***	0.012***	0.009***	0.009***
	(0.003)	(0.003)	(0.003)	(0.003)
Implement × IfMajorUpdate	0.015***	0.015***	0.016***	0.016***
	(0.003)	(0.003)	(0.003)	(0.003)
IfMajorUpdate	0.003***	0.003***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Announce	0.002**	0.003***	0.002	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Implement	0.004*	0.008***	0.003	0.006**
	(0.002)	(0.002)	(0.003)	(0.002)
App FE	Yes	Yes	Yes	Yes
Month and year FE	Yes	No	Yes	No
Linear Time Trend	No	Yes	No	Yes
Observations	138,359	138,359	72,624	72,624
Clusters	4,529	4,529	2,459	2,459

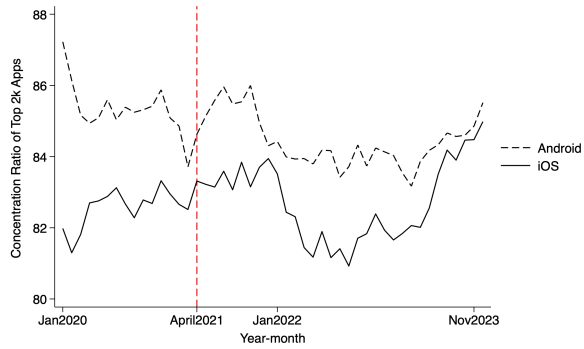
Panel (b)

	(1)	(2)	(3)	(4)
Dependent Variable	PseudoInc	PseudoInc	PseudoInc	PseudoInc
Sample	All iOS Apps	All iOS Apps	Common iOS Apps	Common iOS Apps
Announce × MajorUpdates	0.009***	0.009***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
Implement × MajorUpdates	0.011***	0.011***	0.014***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)
MajorUpdates	0.002***	0.002***	0.003***	0.003***
	(0.000)	(0.000)	(0.001)	(0.001)
Announce	0.002	0.002***	0.002	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Implement	0.004	0.008***	0.002	0.005**
	(0.002)	(0.002)	(0.003)	(0.002)
App FE	Yes	Yes	Yes	Yes
Month and year FE	Yes	No	Yes	No
Linear Time Trend	No	Yes	No	Yes
Observations	138,359	138,359	72,624	72,624
Clusters	4,529	4,529	2,459	2,459

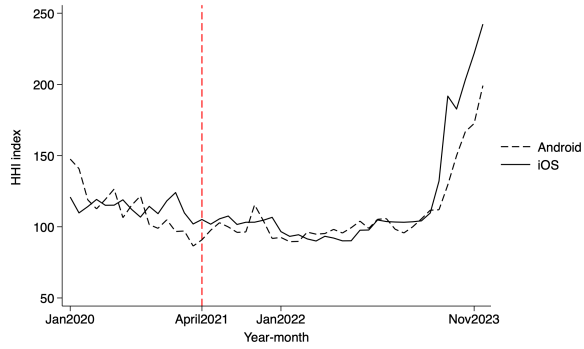
Notes: This table presents estimates from a simple before-and-after comparison regression. *Annouce* equals one for the period between the ATT announcement and implementation, and *Implement* equals one for the post-implementation period. These regressions use only the iOS app sample, as IAP data are only available for iOS apps and no control group is available. $IfMajorUpdate$ equals one if the app experiences a major update. $MajorUpdates$ denotes the number of major updates. Columns (1) and (2) use all top 5,000 iOS apps. The sample comprises 4,529 apps, fewer than 5,000 due to missing values for some apps. Columns (3) and (4) use the subset of iOS apps that are also available on Android. This sample comprises 2,459 iOS apps, fewer than the 2,499 apps used in the main table (Table 2) due to missing IAP information for some apps. Standard errors clustered at the app level are reported in parentheses below coefficients. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$



(a) Concentration Ratio of the Top 1,000 Apps.



(b) Concentration Ratio of the Top 2,000 Apps.



(c) Herfindahl-Hirschman Index (HHI).

Figure 6: Evolution of App Market Concentration on iOS and Android.

Notes: This figure presents the time-series evolution of market concentration on iOS (black line) and Android (dashed line) platforms. Panel (a) and (b) use the concentration ratio for the top 1,000 and top 2,000 apps, respectively, ranked by the average number of active users over the period from January 2018 to December 2023. Panel (c) uses the Herfindahl-Hirschman Index. The vertical red line represents the implementation of the ATT policy (April 2021).

Table 7: Impact of the ATT Policy on Market Structure

Dependent Variable	(1) CR1k	(2) CR2k	(3) HHI
iOS × Post	1.587***	1.077***	7.189***
	(0.000)	(0.000)	(0.000)
Time FE	Yes	Yes	Yes
Platform FE	Yes	Yes	Yes
Observations	96	96	96

Notes: This table presents estimates from Equation (1), using different measures of market concentration as dependent variables. Columns (1) and (2) use the concentration ratio, defined as the sum of the market shares of the top 1,000 and top 2,000 apps for each platform in each month, respectively. Column (3) uses the Herfindahl-Hirschman Index. Standard errors clustered at the platform level are reported in parentheses below coefficients. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

thereby raising the effective sunk costs of competing in the iOS gaming market and, in turn, discouraging entry.

Across a wide range of specifications and outcomes, our results paint a coherent picture. ATT substantially increases total revenue and revenue per user for iOS games relative to Android, with little effect on the number of active users. The revenue gains are not driven by apps becoming paid or by higher posted prices of IAPs. Instead, developers respond by re-optimising IAP menus and investing more in major quality updates, which in turn raise monetization per user. The benefits of ATT are larger for genres that rely heavily on in-app purchases, suggesting that the policy amplifies existing monetization capabilities. ATT is associated with higher concentration and lower entry on iOS relative to Android, consistent with a shift towards a higher fixed-cost, quality-intensive competitive regime.

Taken together, these findings provide strong empirical support for the waterbed story outlined in our conceptual framework: stricter privacy rules that weaken targeted advertising can, in a two-sided platform environment, lead to higher consumer monetization, increased quality investment, and a more concentrated market structure. In this sense, privacy regulation in the form of ATT is not a losing game for the industry as a whole, but its benefits and costs are unevenly distributed across market participants.

Table 8: Impact of the ATT Policy on Entry

Dependent Variable	(1) Entry	(2) Log(Entry+1)
iOS × Implement	-2.739***	-0.044***
	(0.000)	(0.000)
iOS × Announce	-4.100***	-0.074***
	(0.000)	(0.000)
Time FE	Yes	Yes
Platform FE	Yes	Yes
Observations	96	96

Notes: This table presents estimates from Equation (1), using the number of entrants (Column (1)) and its logarithm form (Column (2)) as the dependent variable. The number of new games is defined with respect to the top 5,000 ranking. Standard errors clustered at the platform level are reported in parentheses below coefficients. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

8 Discussion and Policy Implications

8.1 Reconciling ATT with prior evidence on privacy regulation

A central finding of our analysis is that Apple's ATT policy, which sharply restricts cross-app tracking on iOS, is associated with higher revenue and revenue per user for mobile games, despite only modest effects on user numbers. This result contrasts with much of the existing empirical literature on privacy regulation, particularly studies of GDPR and related laws, which typically document negative effects on firm performance. Our findings can be reconciled with this earlier evidence by recognising several important differences between platform-imposed privacy policies such as ATT and government-imposed regulations such as GDPR.

First, ATT is implemented within a single platform ecosystem. Apple controls both the operating system and the app distribution channel, and it can redesign privacy rules in a way that simultaneously advances its strategic objectives. In particular, ATT reduces the profitability of third-party advertising while leaving in-app purchases, on which Apple charges a commission, unaffected or relatively more attractive. This creates strong incentives

for developers to shift monetization from advertising to in-app purchases, a margin that is readily available in the freemium gaming model.

Secondly, the mobile gaming industry is characterized by high flexibility in business models. Developers can adjust the mix between advertising and consumer payments without fundamentally changing the product, by altering IAP menus, introducing new content, or modifying progression mechanics. In contrast, many of the industries affected by GDPR have less scope for such rapid re-optimization of monetization strategies, making it harder to offset compliance costs.

Thirdly, ATT is implemented in an environment where users may already have high willingness-to-pay for digital entertainment. Our results show that consumers respond to quality improvements and menu re-optimization by spending more per active user, even in the presence of stricter privacy protections. This suggests that, in some digital markets, privacy regulation can coexist with, or even reinforce, strong monetization when firms adapt appropriately.

Taken together, these observations highlight that the impact of privacy interventions is highly context-dependent. Platform-level policies that interact with flexible business models and strong consumer demand may generate very different outcomes from broad, cross-sector regulations.

8.2 Implications for platform governance and competition

Our results have several implications for how we think about platform governance and competition in digital markets.

First, ATT illustrates how a platform can use privacy policy as a strategic instrument. By limiting access to device identifiers, Apple not only enhances user privacy but also reshapes the distribution of surplus within the ecosystem. Third-party ad networks and advertisers face reduced targeting capabilities, while developers are nudged towards in-app monetization channels that are more tightly controlled and monetized by the platform. In this sense,

privacy policy becomes part of the platform's competitive toolkit, alongside commission rates, ranking algorithms, and API access.

Secondly, the observed increase in market concentration and reduction in entry on iOS suggest that ATT may have non-trivial consequences for competition. While top games benefit from higher revenue per user and can invest more heavily in quality, smaller developers and potential entrants face higher effective sunk costs. They must compete in a market where successful monetization requires sophisticated IAP design and frequent major updates, rather than simply relying on ad-supported models and low-cost user acquisition.

This pattern is reminiscent of Sutton's (1991, 1998) endogenous sunk cost framework: a shock that increases the returns to quality investment can lead to a more concentrated equilibrium with higher barriers to entry. Our findings suggest that privacy policies that operate through platform governance can have similar structural effects, even when they are not explicitly designed as competition tools.

Thirdly, the heterogeneous impact of ATT across genres raises questions about distributional effects within the developer community. From a policy perspective, this underscores the need to consider not only the average impact of privacy interventions, but also their implications for diversity and innovation in app ecosystems.

8.3 Consumer welfare and the quality–privacy–competition trade-off

From a consumer-welfare perspective, ATT generates a complex mix of effects. On the positive side, users benefit from enhanced privacy: cross-app tracking is disabled for the majority of iOS users, and data collection is subject to explicit consent. At the same time, our evidence indicates that developers respond by investing more in quality, as proxied by major updates, and by refining IAP menus. The combination of higher privacy and improved product quality suggests that consumers may be better off in terms of both data protection and the gaming experience.

However, higher monetization per user implies that consumers spend more within games. Whether this is welfare-enhancing depends on how we interpret such spending. If additional purchases reflect higher enjoyment and willingness-to-pay for new content, welfare may increase. If, instead, they are driven by exploitative design or behavioural biases, the welfare implications are less clear.[16] Our data do not allow us to distinguish these channels directly, but the strong association between major content updates and increased spending suggests that at least part of the effect is linked to genuine quality improvements.

On the negative side, the increase in concentration and reduction in entry may reduce variety and innovation in the long run. A more concentrated market dominated by a small number of high-quality, heavily monetized games may offer fewer opportunities for niche titles or experimental concepts. The net effect on consumer welfare thus involves a trade-off between higher quality and privacy for existing titles, and potentially lower diversity and dynamism in the ecosystem. Overall, our results point to a quality–privacy–competition trade-off rather than a simple privacy–profit trade-off. ATT appears to deliver more privacy and higher quality, but at the cost of a more concentrated market structure.

8.4 Lessons for regulators and policy design

Our analysis yields several lessons for regulators and policymakers concerned with digital privacy and competition.

First, platform-imposed privacy interventions such as ATT can have profound and asymmetric effects on different sides of the market. While they may enhance user privacy and even increase total industry revenue, they can also reallocate surplus from some actors (e.g. third-party ad networks) to others (e.g. the platform, large incumbents). Evaluations of

[16] In EU, the Digital Services Act (DSA) and Digital Fairness Act (DFA) recently establish a broad regulatory framework aimed at curbing psychological and economic exploitation in digital environments. The DSA prohibits manipulative user interfaces ("dark patterns") that undermine autonomous decision-making, for example by obstructing account deletion or opt-out choices. The DFA complements this by targeting predatory monetisation practices inside apps, including drip pricing, subscription traps, and gamified mechanisms such as loot boxes and artificial urgency that are designed to induce impulsive spending. Together, these instruments seek to reorient app design towards transparency and genuine consumer choice rather than behavioural manipulation.

such policies should therefore consider the full set of affected parties, not just end users.

Secondly, the interaction between privacy policy and business models is crucial. In environments where firms can flexibly shift monetisation from advertising to direct consumer payments, privacy regulation need not be a losing game for industry performance. However, this shift may entrench the role of platforms that control payment channels and app distribution. Regulators may wish to monitor whether privacy changes are accompanied by other platform policies (e.g. commission rates, self-preferencing in app stores) that could raise competitive concerns.

Thirdly, our findings suggest that competition and privacy policy cannot be designed in isolation. Privacy rules that rely heavily on platform governance may inadvertently strengthen the competitive position of dominant platforms, even as they protect users. This raises the question of whether complementary measures, such as data-portability requirements, interoperability mandates, or constraints on self-preferencing, are needed to preserve competition while advancing privacy goals.

Finally, our results highlight the importance of granular, high-frequency data for evaluating digital policies. The ability to track app-level outcomes and platform-level market structure over time is essential for understanding how firms and consumers adjust to new rules. Policymakers may wish to encourage greater data transparency from platforms, or to support independent measurement infrastructures, to facilitate such evaluations.

8.5 Limitations and directions for future research

Our study has several limitations that suggest avenues for further work.

First, we focus on the mobile gaming sector in the United States. While this sector is economically important and particularly responsive to advertising and in-app monetisation, other app categories (e.g. productivity, social networking, utilities) may respond differently to ATT. Extending the analysis to non-gaming apps and to other countries would provide a more comprehensive picture of ATT's overall impact.

Secondly, we do not observe advertising revenue directly. Our interpretation of the waterbed effect relies on the combination of higher total revenue, higher revenue per user, and the absence of price-based explanations, together with industry knowledge about the decline in ad effectiveness. Access to data that separately identify ad and in-app revenue would allow for a more precise decomposition of the channels at work.

Thirdly, our welfare analysis is necessarily indirect. We infer quality improvements from major updates and monetisation patterns, but we do not observe individual-level engagement, satisfaction, or time use. Future research could combine app-level data with user-level panels or experiments to quantify consumer surplus and to distinguish between welfare-enhancing and potentially exploitative monetisation strategies.

Fourthly, while we document increases in concentration and decreases in entry, we do not fully characterise the long-run innovation effects of ATT. It remains an open question whether the new equilibrium will feature fewer but higher-quality games, or whether reduced entry will dampen innovation and variety over time. Structural models of entry and innovation, calibrated to our empirical estimates, could shed light on these long-run consequences.

Despite these limitations, our results demonstrate that platform-level privacy interventions can significantly reshape monetisation, quality investment, and market structure in digital industries. Understanding these interactions is essential for designing policies that protect privacy without unduly compromising competition and innovation.

9 Conclusions

This paper has examined the impact of Apple's App Tracking Transparency (ATT) policy on the mobile gaming industry. Using rich app–platform–month data from SensorTower for the US market over 2020–2023, and exploiting the fact that ATT applies to iOS but not to Android, we have implemented a difference-in-differences design that compares the evolution of the same games across platforms before and after ATT.

Our analysis yields four main conclusions. First, ATT substantially increases total revenue and revenue per active user for iOS games relative to their Android counterparts, while having little effect on the number of active users. Event-study evidence shows that these monetization gains emerge after implementation and grow over time, with no sign of reversal by the end of our sample. This pattern stands in contrast to much of the existing evidence on privacy regulation, which typically finds negative effects on firm performance.

Secondly, we show that these revenue gains are not driven by simple price-based adjustments. We find no evidence that games are more likely to switch from free to paid on iOS after ATT, nor that posted prices of in-app purchases systematically increase relative to Android. Instead, developers respond by re-optimising their in-app purchase menus and investing more in major quality updates. Our pseudo-revenue measures indicate that iOS games are more likely to restructure IAP menus in ways that increase potential revenue, and our update data show that major content releases become more frequent and are associated with higher revenue per user, especially in the post-ATT period. These findings support a "waterbed" mechanism in which reduced advertising profitability is offset by deeper consumer monetisation, supported by higher quality and more sophisticated menu design.

Thirdly, the impact of ATT is heterogeneous across genres. Genres that traditionally rely heavily on in-app purchases and deep engagement (such as casino, card, and strategy) benefit more than casual genres. This suggests that ATT amplifies existing monetisation capabilities.

Fourthly, ATT has important implications for market structure. We document significant increases in revenue concentration and declines in entry on iOS relative to Android after ATT. These patterns are consistent with a shift towards a competitive regime in which success requires substantial sunk investments in quality and monetization infrastructure, in line with Sutton's (1991, 1998) endogenous sunk cost framework. While users may enjoy higher privacy and higher-quality games, the industry becomes more concentrated and less open to new entrants.

Taken together, these results show that privacy interventions implemented through platform governance can have non-trivial and sometimes counter-intuitive effects. In the case of ATT, stricter privacy does not appear to be a losing game for the mobile gaming industry in aggregate: revenue and quality rise, and the platform itself benefits from increased in-app monetization. However, the distribution of gains and losses is uneven. Large incumbents and the platform gain, whereas smaller developers and third-party ad networks may be disadvantaged, and market concentration increases.

From a broader perspective, our findings highlight that privacy, quality, and competition are jointly determined in digital platform markets. Policies that enhance privacy can simultaneously reshape business models and market structure, in ways that depend critically on platform incentives and the flexibility of firms' monetization strategies. For regulators and policymakers, this underscores the importance of evaluating privacy interventions not only in terms of user protection, but also in terms of their competitive and innovation effects, and of considering complementary measures when necessary.

Future work extending our analysis to non-gaming apps, other countries, and alternative platform policies will be important to assess the generality of these conclusions. Nonetheless, the evidence presented here demonstrates that Apple's ATT policy has fundamentally altered the economics of mobile gaming, providing a salient example of how platform-level privacy rules can transform a major digital industry.

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NOT FOR PUBLICATION, ONLINE APPENDIX ONLY

A Appendix: Constructing IAP Pseudo-Revenue Index

Table A1 illustrates the construction of the IAP pseudo-revenue index for an iOS app with two menu updates within the same month. Column (1) shows the rank of each IAP package in the menu, where 1 is the top-ranked and 10 is the lowest. Note that the data are available only for the top 10 packages, so the lowest rank refers to the lowest among these top 10 packages. Column (2) shows the weight assigned to each package, calculated as the inverse of its rank: $w_r = \frac{1}{r_{pack}}$. This weighting ensures that higher-ranked packages contribute more to the pseudo-revenue index. Column (3) lists the price of each package at the start of the month, and Column (4) shows the weighted contribution of each package, computed as: Weighted Contribution$_{pack} = P_{pack} \times w_r = P_{pack} \times \frac{1}{r_{pack}}$. For example, a package ranked 2nd with a price of \$3.99 has a weight of 1/2, giving a weighted contribution of $3.99 \times 1/2 \approx 2.00$ (rounded to two decimal places). Summing all weighted contributions yields the initial pseudo-revenue index of approximately 18.65 (rounded to two decimal places).

At the first update (Column (5)), a package priced at \$3.99 moved to the first position, while a package priced at \$2.99 moved to the second position (highlighted in bold). Recalculating the weighted contributions (Column (6)) gives a new pseudo-revenue index of 19.15. At the second update (Column (7)), the top four packages change (in bold). Recalculating the weighted contributions and summing them gives a pseudo-revenue index of 19.07. Overall, in this example, the pseudo-revenue index increases from 18.65 to 19.15 in the first update, before slightly decreasing to 19.07 in the second update.

Since our main outcome variables are measured at the monthly level, we aggregate the pseudo-revenue index across updates. *PseudoInc* captures the cumulative change across all updates within the month. Here, as the cumulative change is positive: $(19.15 - 18.65) + (19.07 - 19.15) = 0.42$, we set $PseudoInc = 1$. For robustness, we also use an alternative definition considering only the final update of the month. *PseudoIncAlt* equals one if the pseudo-revenue index of the final update is higher than that of the previous update. In this example, since the index decreases in the second update ($19.07 < 19.15$), $PseudoIncAlt = 0$.

Table A1: Example Calculation of the IAP Pseudo-Revenue Index

		Beginning-of-month		**First Update**		**Second Update**	
(1) Rank	(2) Weight ($1/r$)	(3) Package Price	(4) Weighted Contribution	(5) Package Price	(6) Weighted Contribution	(7) Package Price	(8) Weighted Contribution
1	1	2.99	2.99	**3.99**	3.99	**2.99**	2.99
2	1/2	3.99	2.00	**2.99**	1.50	**3.99**	2.00
3	1/3	4.99	1.66	4.99	1.66	**9.99**	3.33
4	1/4	9.99	2.50	9.99	2.50	**4.99**	1.25
5	1/5	24.99	5.00	24.99	5.00	24.99	5.00
6	1/6	6.99	1.17	6.99	1.17	6.99	1.17
7	1/7	7.99	1.14	7.99	1.14	7.99	1.14
8	1/8	5.99	0.75	5.99	0.75	5.99	0.75
9	1/9	4.99	0.55	4.99	0.55	4.99	0.55
10	1/10	8.99	0.90	8.99	0.90	8.99	0.90
Pseudo-revenue index			18.65		19.15		19.07

Note: Numbers for weighted contributions and the pseudo-revenue index are rounded to two decimal places.

B Appendix: Additional Tables

Table B1: Dynamic Effect of the ATT Policy on App Performance

Dependent Variable	(1) Users	(2) Revenue	(3) RevpUser	(4) LogRevpUser
iOS × Day (k=-12)	20,514.603*	-3,063.218	-0.361***	-0.010*
	(12,414.567)	(18,822.383)	(0.092)	(0.006)
iOS × Day (k=-11)	2,067.742	31,376.616	-0.135	-0.010*
	(10,824.645)	(19,833.341)	(0.088)	(0.006)
iOS × Day (k=-10)	7,307.174	20,158.147	-0.102	0.001
	(10,233.541)	(20,444.734)	(0.078)	(0.005)
iOS × Day (k=-9)	18,547.663**	53,247.685***	-0.024	0.006
	(8,886.116)	(14,363.381)	(0.079)	(0.005)
iOS × Day (k=-8)	17,415.835*	37,776.233**	-0.037	0.012***
	(9,572.199)	(15,706.307)	(0.064)	(0.004)
iOS × Day (k=-7)	-4,037.633	-506.569	-0.079	0.007*
	(9,665.853)	(20,986.512)	(0.053)	(0.004)
iOS × Day (k=-6)	-7,095.771	49,363.544***	0.053	0.008**
	(7,054.897)	(13,772.363)	(0.064)	(0.003)
iOS × Day (k=-5)	-4,718.305	34,189.754***	0.025	0.011***
	(6,156.677)	(12,023.560)	(0.068)	(0.003)
iOS × Day (k=-4)	-5,552.791	29,741.210***	0.030	0.010***
	(5,852.306)	(10,181.697)	(0.053)	(0.003)
iOS × Day (k=-3)	-7,224.723	41,764.311***	0.019	0.005*
	(5,777.972)	(11,453.906)	(0.049)	(0.003)
iOS × Day (k=-2)	-7,408.170	14,984.048**	-0.063**	0.011***
	(4,519.680)	(6,677.189)	(0.025)	(0.002)
iOS × Day (k=0)	1,806.436	13,578.629**	0.062***	0.002
	(3,702.525)	(6,169.905)	(0.023)	(0.002)
iOS × Day (k=1)	1,648.963	8,016.112	0.079**	0.006***
	(4,814.904)	(8,264.080)	(0.034)	(0.002)

Continued on next page

Table B1 continued

Dependent Variable	(1) Users	(2) Revenue	(3) RevPuser	(4) LogRevPuser
iOS × Day (k=2)	-314.669	-2,286.881	0.074**	0.009***
	(5,096.062)	(9,933.941)	(0.037)	(0.003)
iOS × Day (k=3)	4,108.157	25,130.051**	0.141***	0.016***
	(6,059.414)	(10,103.546)	(0.046)	(0.003)
iOS × Day (k=4)	-8,273.377	39,821.954***	0.285***	0.027***
	(6,165.664)	(9,952.283)	(0.057)	(0.004)
iOS × Day (k=5)	-17,795.564***	42,014.885***	0.232***	0.014***
	(6,457.620)	(10,297.413)	(0.048)	(0.004)
iOS × Day (k=6)	-12,584.563*	43,647.989***	0.370***	0.023***
	(6,893.223)	(13,091.130)	(0.065)	(0.004)
iOS × Day (k=7)	-3,021.751	79,403.199***	0.470***	0.034***
	(6,973.045)	(15,742.202)	(0.069)	(0.004)
iOS × Day (k=8)	-2,016.748	115,024.126***	0.554***	0.044***
	(6,921.134)	(18,127.638)	(0.076)	(0.005)
iOS × Day (k=9)	-3,020.834	92,641.388***	0.446***	0.043***
	(7,179.323)	(15,511.779)	(0.072)	(0.005)
iOS × Day (k=10)	-7,494.159	69,622.766***	0.398***	0.040***
	(7,225.692)	(15,549.970)	(0.072)	(0.005)
iOS × Day (k=11)	-7,408.266	79,898.778***	0.477***	0.042***
	(7,504.865)	(15,952.929)	(0.084)	(0.005)
iOS × Day (k=12)	-4,425.857	66,921.324***	0.508***	0.040***
	(8,223.658)	(15,285.189)	(0.095)	(0.005)
iOS × Day (k=13)	2,103.762	54,141.312***	0.483***	0.031***
	(12,111.785)	(15,459.887)	(0.114)	(0.005)
iOS × Day (k=14)	7,163.915	64,956.353***	0.529***	0.035***
	(13,021.335)	(15,584.698)	(0.108)	(0.005)
iOS × Day (k=15)	2,457.670	76,577.911***	0.713***	0.044***
	(11,416.487)	(16,101.821)	(0.139)	(0.006)
iOS × Day (k=16)	-2,997.688	72,083.443***	0.742***	0.044***
	(10,848.795)	(16,606.828)	(0.156)	(0.006)
iOS × Day (k=17)	-10,587.582	59,881.003***	0.734***	0.044***
	(10,292.687)	(16,170.811)	(0.168)	(0.006)
iOS × Day (k=18)	-12,485.841	63,059.673***	0.786***	0.046***
	(10,239.247)	(15,818.878)	(0.163)	(0.006)
iOS × Day (k=19)	-9,641.364	68,930.285***	0.727***	0.043***
	(9,931.987)	(16,044.201)	(0.147)	(0.006)
iOS × Day (k=20)	-5,276.679	83,665.616***	0.821***	0.043***
	(9,753.504)	(16,203.891)	(0.175)	(0.006)
iOS × Day (k=21)	-5,921.925	76,293.571***	0.714***	0.042***
	(9,737.683)	(16,357.742)	(0.160)	(0.006)
iOS × Day (k=22)	-10,544.228	65,522.414***	0.705***	0.039***
	(9,722.688)	(16,938.936)	(0.174)	(0.006)
iOS × Day (k=23)	-6,676.656	82,821.148***	0.742***	0.041***
	(9,690.756)	(17,755.785)	(0.170)	(0.007)
iOS × Day (k=24)	-1,517.079	98,656.077***	0.776***	0.054***
	(9,769.293)	(17,973.079)	(0.164)	(0.007)
Time FE	Yes	Yes	Yes	Yes
App-Platform FE	Yes	Yes	Yes	Yes
Observations	148,202	148,202	148,202	148,202
Clusters	2,499	2,499	2,499	2,499

Notes: This table presents estimates from Equation (2). The dependent variables in Columns (1)–(4) are the number of active users, revenue, revenue per user, and the logarithm of revenue per user, respectively. The outcome variable *LogRevpUser* is measured as *Log*(*RevpUser+1*). Sixteen apps (32 observations) with only a single month of data are excluded from the regression. Standard errors clustered at the app level are reported in parentheses below coefficients. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B2: Heterogeneous Effects by Game Genre

Dependent Variable	(1) LogRevpUser	(2) LogRevpUser
iOS × Post × Action	-0.022*	-0.014
	(0.013)	(0.013)
iOS × Post × Adventure	0.016	0.011
	(0.033)	(0.035)
iOS × Post × Arcade	-0.068***	-0.020*
	(0.017)	(0.011)
iOS × Post × Board	0.082***	0.121**
	(0.030)	(0.049)
iOS × Post × Card	0.185***	0.148***
	(0.047)	(0.039)
iOS × Post × Casino	0.325***	0.361***
	(0.087)	(0.075)
iOS × Post × Casual	0.009	0.014
	(0.010)	(0.015)
iOS × Post × Education	0.118***	0.024
	(0.006)	(0.046)
iOS × Post × Music	0.068	0.043
	(0.064)	(0.032)
iOS × Post × Puzzle	0.047**	0.035*
	(0.021)	(0.019)
iOS × Post × Racing	-0.027***	-0.049***
	(0.010)	(0.013)
iOS × Post × Role Playing	0.005	0.025
	(0.040)	(0.042)
iOS × Post × Simulation	0.010	-0.000
	(0.018)	(0.013)
iOS × Post × Sports	-0.026	-0.030
	(0.017)	(0.021)
iOS × Post × Strategy	0.148***	0.170***
	(0.035)	(0.057)
iOS × Post × Trivia	0.014	-0.022
	(0.029)	(0.017)
iOS × Post × Word	0.151**	0.150***
	(0.065)	(0.049)
iOS × Post × Family	-0.034	
	(0.025)	
Time FE	Yes	Yes
App-Platform FE	Yes	Yes
Observations	148,202	148,202
Clusters	2499	2499

Notes: Column (1) (plotted in Fig. 4) defines game genre using the primary classification listed on the Apple App Store, while Column (2) (plotted in Fig. C2) uses the single genre listed on the Android platform. Specifically, the "Family" genre is not included in Column (2), as Google Play categorizes games differently from the Apple App Store. Unlike Apple, which separates "Family" as a distinct genre, Google Play subsumes family-oriented content under broader categories such as "Casual" or "Education." The outcome variable *LogRevpUser* is measured as $Log(RevpUser+1)$. Standard errors clustered at the app level are reported in parentheses below coefficients. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table B3: Robustness Check: Alternative Clustering at App Publisher Level

Dependent Variable	(1) Users	(2) Revenue	(3) RevpUser	(4) LogRevpUser
iOS × Post	-8,606.955	46,801.897***	0.642***	0.035***
	(11,642.909)	(13,478.427)	(0.161)	(0.006)
Time FE	Yes	Yes	Yes	Yes
App-Platform FE	Yes	Yes	Yes	Yes
Observations	148,202	148,202	148,202	148,202
Clusters	767	767	767	767

Notes: This table presents estimates from Equation (1). The dependent variables in Columns (1)–(4) are the number of active users, revenue, revenue per user, and the logarithm of revenue per user, respectively. The outcome variable *LogRevpUser* is measured as *Log(RevpUser+1)*. Sixteen apps (32 observations) with only a single month of data are excluded from the regression. Standard errors clustered at the app publisher level are reported in parentheses below coefficients. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B4: Robustness Check: Using a Balanced Panel of Multi-homing Apps

Dependent Variable	(1) Users	(2) Revenue	(3) RevpUser	(4) LogRevpUser
iOS × Post	4,853.862	63,380.278***	0.768***	0.037***
	(11,926.085)	(16,149.008)	(0.166)	(0.007)
Time FE	Yes	Yes	Yes	Yes
App-Platform FE	Yes	Yes	Yes	Yes
Observations	74,222	74,222	74,222	74,222
Clusters	887	887	887	887

Notes: This table presents estimates from Equation (1), using a balanced panel of multi-homing apps that are present throughout the entire sample period. The dependent variables in Columns (1)–(4) are the number of active users, revenue, revenue per user, and the logarithm of revenue per user, respectively. The outcome variable *LogRevpUser* is measured as *Log(RevpUser+1)*. Standard errors clustered at the app level are reported in parentheses below coefficients. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B5: Robustness Check: Using the Full Sample of the Top 5,000 Apps

Dependent Variable	(1) Users	(2) Revenue	(3) RevpUser	(4) LogRevpUser
iOS × Post	7,684.181	34,090.642***	0.505**	0.019***
	(7,436.997)	(7,233.403)	(0.201)	(0.004)
Time FE	Yes	Yes	Yes	Yes
App-Platform FE	Yes	Yes	Yes	Yes
Observations	260,501	260,501	260,501	260,501
Clusters	6484	6484	6484	6484

Notes: This table presents estimates from Equation (1), using the full sample of the top 5,000 apps. The dependent variables in Columns (1)–(4) are the number of active users, revenue, revenue per user, and the logarithm of revenue per user, respectively. The outcome variable *LogRevpUser* is measured as *Log(RevpUser+1)*. Standard errors clustered at the app level are reported in parentheses below coefficients. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B6: Robustness Check: Extending the Pre-treatment Period

Dependent Variable	(1) Users	(2) Revenue	(3) RevpUser	(4) LogRevpUser
iOS × Post	-7,701.359	80,093.357***	0.895***	0.046***
	(13,003.621)	(14,765.474)	(0.159)	(0.005)
Time FE	Yes	Yes	Yes	Yes
App-Platform FE	Yes	Yes	Yes	Yes
Observations	169,248	169,248	169,248	169,248
Clusters	2580	2580	2580	2580

Notes: This table presents estimates from Equation (1), extending the pre-treatment period to 2019. The dependent variables in Columns (1)–(4) are the number of active users, revenue, revenue per user, and the logarithm of revenue per user, respectively. The outcome variable *LogRevpUser* is measured as *Log(RevpUser+1)*. Standard errors clustered at the app level are reported in parentheses below coefficients. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B7: Robustness Check: Using Alternative Measure of Posted IAP Prices

Dependent Variable	(1) IAPpriceAlt	(2) IAPpriceAlt	(3) IAPpriceAlt	(4) IAPpriceAlt
Sample	All iOS Apps	All iOS Apps	Common iOS Apps	Common iOS Apps
Post	-0.011**	-0.008**	-0.013*	-0.007
	(0.004)	(0.004)	(0.007)	(0.006)
App FE	Yes	Yes	Yes	Yes
Month and year FE	Yes	No	Yes	No
Linear Time Trend	No	Yes	No	Yes
Observations	138,359	138,359	72,624	72,624
Clusters	4,529	4,529	2,459	2,459

Notes: This table presents estimates from a simple before-and-after comparison regression. *Post* equals one for the post-implementation period. These regressions use only the iOS app sample, as IAP data are only available for iOS apps and no control group is available. *IAPpriceAlt* is an alternative measure of posted IAP prices and equals one if the net price change of listed IAPs is positive for the last update in a given month. Columns (1) and (2) use all top 5,000 iOS apps. The sample comprises 4,529 apps, fewer than 5,000 due to missing values for some apps. Columns (3) and (4) use the subset of iOS apps that are also available on Android. This sample comprises 2,459 iOS apps, fewer than the 2,499 apps used in the main table (Table 2) due to missing IAP information for some apps. Standard errors clustered at the app level are reported in parentheses below coefficients. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B8: Robustness Check: Using Alternative Measure of Pseudo-Revenue Index

	(1)	(2)	(3)	(4)
Dependent Variable	PseudoIncAlt	PseudoIncAlt	PseudoIncAlt	PseudoIncAlt
Sample	All iOS Apps	All iOS Apps	Common iOS Apps	Common iOS Apps
Announce	0.001	0.003***	0.002	0.005**
	(0.001)	(0.001)	(0.004)	(0.002)
Implement	0.001	0.005***	0.002	0.002***
	(0.003)	(0.002)	(0.002)	(0.001)
App FE	Yes	Yes	Yes	Yes
Month and year FE	Yes	No	Yes	No
Linear Time Trend	No	Yes	No	Yes
Observations	138,359	138,359	72,624	72,624
Clusters	4,529	4,529	2,459	2,459

Notes: This table presents estimates from a simple before-and-after comparison regression. *Annouce* equals one for the period between the ATT announcement and implementation, and *Implement* equals one for the post-implementation period. These regressions use only the iOS app sample, as IAP data are only available for iOS apps and no control group is available. $PseudoIncAlt$ focuses on the final update of the month and equals one if the pseudo-revenue index increases between the last update in a given month and the previous update. Columns (1) and (2) use all top 5,000 iOS apps. The sample comprises 4,529 apps, fewer than 5,000 due to missing values for some apps. Columns (3) and (4) use the subset of iOS apps that are also available on Android. This sample comprises 2,459 iOS apps, fewer than the 2,499 apps used in the main table (Table 2) due to missing IAP information for some apps. Standard errors clustered at the app level are reported in parentheses below coefficients. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B9: Robustness Check: Using Alternative Measure of Pseudo-Revenue Index

Panel (a)

	(1)	(2)	(3)	(4)
Dependent Variable	PseudoIncAlt	PseudoIncAlt	PseudoIncAlt	PseudoIncAlt
Sample	All iOS Apps	All iOS Apps	Common iOS Apps	Common iOS Apps
Announce × IfMajorUpdate	0.009***	0.009***	0.007**	0.007**
	(0.003)	(0.003)	(0.003)	(0.003)
Implement × IfMajorUpdate	0.010***	0.010***	0.014***	0.014***
	(0.003)	(0.003)	(0.004)	(0.004)
IfMajorUpdate	0.002***	0.002***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Announce	0.000	0.002***	0.002	0.002**
	(0.001)	(0.001)	(0.002)	(0.001)
Implement	0.000	0.004**	0.001	0.004
	(0.003)	(0.002)	(0.004)	(0.002)
App FE	Yes	Yes	Yes	Yes
Month and year FE	Yes	No	Yes	No
Linear Time Trend	No	Yes	No	Yes
Observations	138,359	138,359	72,624	72,624
Clusters	4,529	4,529	2,459	2,459

Panel (b)

	(1)	(2)	(3)	(4)
Dependent Variable	PseudoIncAlt	PseudoIncAlt	PseudoIncAlt	PseudoIncAlt
Sample	All iOS Apps	All iOS Apps	Common iOS Apps	Common iOS Apps
Announce × MajorUpdates	0.008***	0.008***	0.005**	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Implement × MajorUpdates	0.008***	0.008***	0.011***	0.011***
	(0.002)	(0.002)	(0.003)	(0.003)
MajorUpdates	0.001***	0.001***	0.002***	0.002***
	(0.000)	(0.000)	(0.001)	(0.001)
Announce	-0.000	0.001**	0.001	0.001*
	(0.001)	(0.001)	(0.002)	(0.001)
Implement	-0.000	0.004**	-0.000	0.003
	(0.003)	(0.002)	(0.004)	(0.002)
App FE	Yes	Yes	Yes	Yes
Month and year FE	Yes	No	Yes	No
Linear Time Trend	No	Yes	No	Yes
Observations	138,359	138,359	72,624	72,624
Clusters	4,529	4,529	2,459	2,459

Notes: This table presents estimates from a simple before-and-after comparison regression. *Annouce* equals one for the period between the ATT announcement and implementation, and *Implement* equals one for the post-implementation period. These regressions use only the iOS app sample, as IAP data are only available for iOS apps and no control group is available. *PseudoIncAlt* focuses on the final update of the month and equals one if the pseudo-revenue index increases between the last update in a given month and the previous update. Columns (1) and (2) use all top 5,000 iOS apps. The sample comprises 4,529 apps, fewer than 5,000 due to missing values for some apps. Columns (3) and (4) use the subset of iOS apps that are also available on Android. This sample comprises 2,459 iOS apps, fewer than the 2,499 apps used in the main table (Table 2) due to missing IAP information for some apps. $IfMajorUpdate$ equals one if the app experiences a major update. $MajorUpdates$ denotes the number of major updates. Standard errors clustered at the app level are reported in parentheses below coefficients. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

C Appendix: Additional Figures

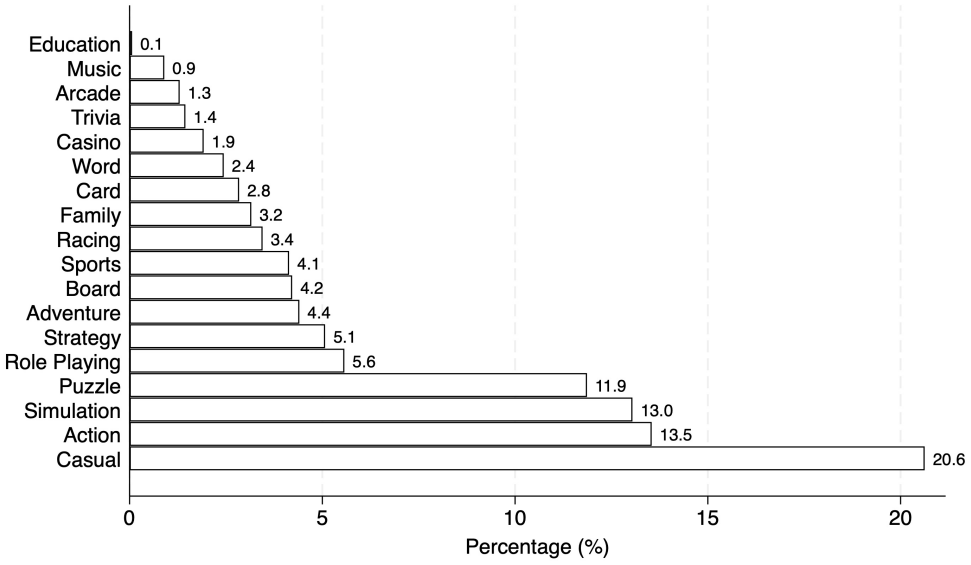

Figure C1: Distribution of Apps by Game Genre (in %)

Notes: This figure shows the distribution of gaming apps across 18 genres in the sample, expressed as percentages. Genre is defined using the primary classification listed on the Apple App Store. Values are labeled directly on each bar for clarity.

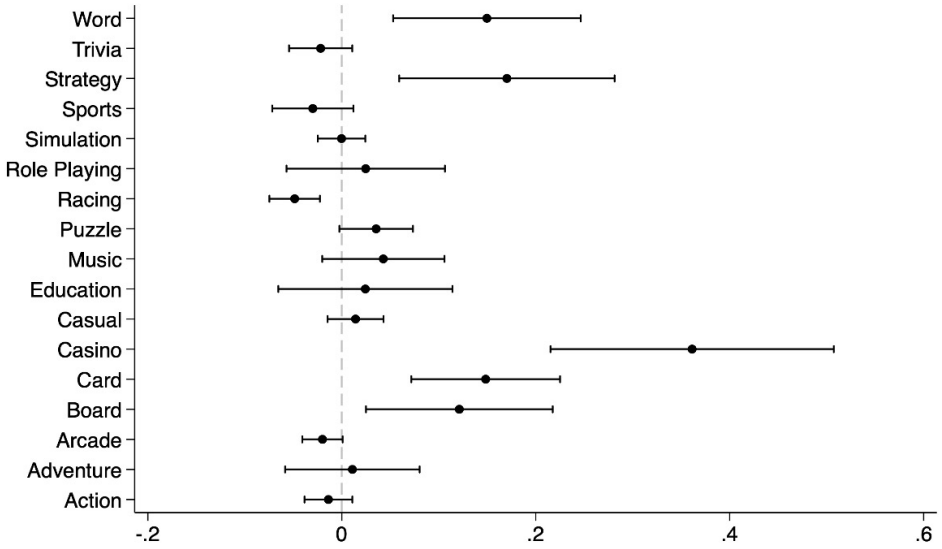

Figure C2: Robustness Check: Heterogeneous Effects by Game Genre

Notes: This figure shows heterogeneous effects by game genre, obtained by interacting the ATT treatment with each genre. Game genre is defined using the single genre listed on the Android platform, which covers 17 genres in total. Specifically, the "Family" genre is not included, as Google Play categorizes games differently from the Apple App Store. Unlike Apple, which separates "Family" as a distinct genre, Google Play subsumes family-oriented content under broader categories such as "Casual" or "Education." The outcome variable is *LogRevpUser*. Estimated coefficients are reported in Table B2, Column (2). This figure displays the estimated coefficients along with their 95% confidence intervals.