Privacy Spillovers across Competing Platforms

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Draft Date: May 30th, 2025
(Preliminary draft for WEIS 2025)
(Click Here for the Latest Version)*

This paper investigates privacy spillovers, a phenomenon where privacy-enhancing policies by one platform impact competing platforms. This phenomenon occurs when "multihoming" suppliers—who straddle multiple environments—make cross-platform adjustments to their data practices in response to a policy change by one platform. Smartphone platforms are a perfect setting to study privacy spillovers due to intensity of fine-grained sensitive data collection, major policy changes and high incidence of developer multihoming. Specifically, we investigate spillovers on Android in the context of iOS App Tracking Transparency (ATT) policy, which restricts cross-app data collection on iOS. ATT may Android in one of two ways. Developers might uniformly adopt stricter privacy measures across all platforms to streamline operations. Conversely, developers might compensate for iOS data-collection restrictions by adopting more privacy-intrusive practices on Android. By contrasting the strategies by apps that are available on both iOS and Android with apps that are only available on Android, we document a notably positive spillover effect: multihoming apps significantly enhance app utility, evidenced by an increased adoption of third-party services that enhance features or real-time contextual solutions, and non-intrusive permissions. Furthermore, we note a strategic shift away from collecting and analyzing *user* data using third-party services. Consequently, multihoming apps witness significant increases in user ratings on Android marketplace post-ATT. Finally, these data-collection and utility improvements further fortify multihoming apps' market positioning, inadvertently affecting Android's market structure. We discuss practical implications for competing platforms to mitigate adverse effects on exclusive apps.

Key words: Data Privacy, Privacy Spillover, Multihoming, Platform Policy Change

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* Both authors contributed equally and their names are listed in alphabetical order. R.Mayya is grateful to the CGEB at NYU Stern for financial support. Authors sincerely thank Weichen Liu for her valuable help.

1. Introduction

Over the past decade, public perception of data collection practices has significantly evolved, shifting from viewing it as an enabler of the data economy (Bonchek and Choudary 2013) toward increasingly insisting on greater control over personal information. The shift in perception is especially evident regarding third-party data collection that occurs in the background: 86% of internet users reported actively implementing measures to avoid such "surveillance" (Madden and Rainie 2015).

In response, both public regulators and private platforms are acting to empower consumers (see Miller and Skiera (2024) for a list of all regulatory and platform-imposed tracking restrictions). Public regulatory approaches, such as the European Union's General Data Protection Regulation, adopt a top-down and jurisdiction-specific model. They focus on granting users the rights to control their private data and mandate that businesses disclose how they use consumer data. In parallel, private digital platforms are actively discouraging opaque third-party data practices and emphasizing transparent first-party data collection through visible interactions with users (Lin 2022, Mayya and Viswanathan 2024). For instance, smartphone apps are required to seek individual permissions for accessing location or microphone during active use, rather than securing blanket permissions at the time of app download.[1] This shift to *opt-out of data collection by default* marks a transformation in how platforms approach user data-sharing management. The change is particularly pronounced in smartphone platforms, where apps access highly sensitive personal data including precise location, private communications, and behavioral patterns. Consequently, burgeoning literature has examined consequences of privacy-enhancing policies on focal platform participants (Aridor et al. 2024, Bian et al. 2021, Kesler 2023, Kircher and Foerderer 2024, Leyden 2025, Mayya and Viswanathan 2024).

However, what is largely absent from the discourse is the potential "spillover" [2] of data collection restrictions by one smartphone platform onto competing smartphone platforms. The phenomenon of multi-market spillovers has been extensively studied, beginning with Bernheim and Whinston (1990)'s seminal work on multimarket contact facilitating marketwide price coordination. Subsequent research by Parker and Röller

[1] iOS Has App Permissions, Too: And They're Arguably Better Than Android's - HowToGeek

[2] Spillover, as defined by Jaffe (1986), refers to the indirect consequences of a policy in one domain (in this paper, iOS) on related domains (in this paper, Android). In this study, developers' adjustments are driven by iOS policy rather than Android considerations.

(1997) and Busse (2000) show that in the presence of firms with multimarket contact, even firms exclusive to one market sustain less competitive outcomes. Furthermore, when regulatory constraints are imposed in one market, studies have documented "compensatory effects." Firms often respond by raising prices in unregulated markets to recover lost revenue (e.g., Genakos and Valletti 2011).

Whereas multi-market spillovers resulting from price regulation have been well-established, spillovers resulting from data regulations in digital markets, especially in freemium digital markets, haven't been well-studied. Unlike price, which is purely extractive from the consumer's perspective, data in freemium markets serves as an input to the production function by enhancing personalization and user experience, meaning that data sharing can create positive utility for consumers (Lin 2022). Given the role of data in the freemium digital markets, which has no parallel in traditional markets, the market equilibrium favors extensive data collection to provide algorithmic personalization. Enhancing consumer satisfaction through personalization and generating revenue through targeted advertising are cost- and time-efficient strategies for apps (Allon et al. 2022) when compared to the effort of identifying and developing new features or real-time solutions to enhance consumer utility. Hence, apps across markets face little competitive pressure to limit tracking.

When any regulatory policy disrupts data-collection equilibrium on one platform, apps face a strategic choice absent in traditional markets. They can either adopt the traditional compensatory strategy, as outlined in the existing spillover literature, in which potential revenue losses caused by tightened privacy policies incentivize apps to "decouple" their strategies by maintaining separate codebases across platforms. This strategy enables them to adhere to stricter policies on the focal platform while maintaining or increasing data collection on the competing platform to offset revenue losses. Alternatively, they can adopt the unified strategy, a strategy unique to digital products because of the strong prevalence of cross-platform development tools like Google's Flutter and React Native. Under this unified scenario, apps concentrate their resources on enhancing real-time solutions and feature development on the focal platform, while simultaneously reducing behavioral tracking in response to data-collection restriction (Cheyre et al. 2023). These utility-enhancing changes are then pushed to the competing platform using cross-platform tools. Figure 1 illustrates the feasibility of the latter strategy: Sina Weibo added a development-specific integrated SDK spanning both platforms, and Sniper Strike removed an analytics-specific integrated SDK from both.

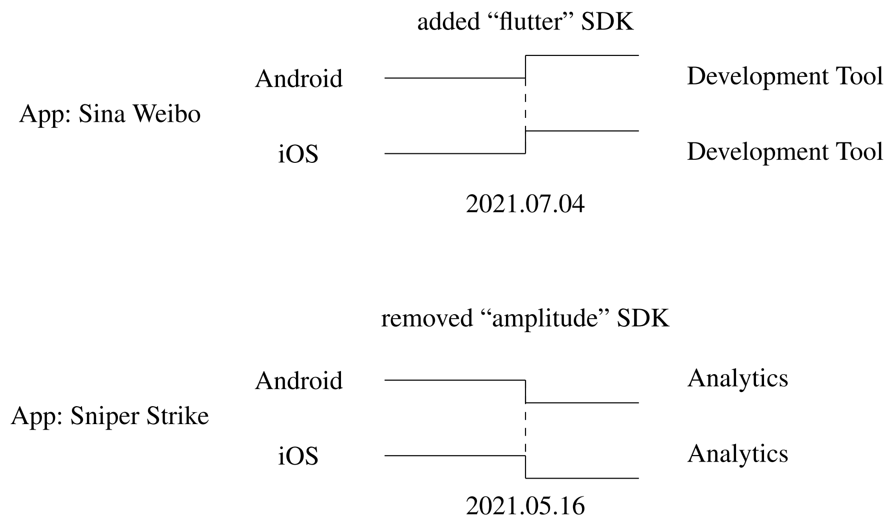


Figure 1 Illustration: How the common codebase pans out across two smartphone platforms

Determining which of these strategic responses dominates in practice presents a significant empirical challenge. Regardless of which path developers choose, spillover effects will occur, making it crucial to evaluate these effects for understanding market structure given the competition for resources between platforms, especially due to the prevalence of multihoming apps. However, two key factors complicate the evaluation of spillover effects: (a) the distinct sub-markets formed by each platform, and (b) the shared codebases across platforms. Consequently, there is no clear intuition on the size and direction of spillover.

We examine these spillover effects by focusing on Apple's App Tracking Transparency (ATT) policy enacted in April 2021, which changed cross-app tracking to *opt-out-by-default*, disrupting the advertisement economy dependent on cross-app tracking. This policy change created a natural experiment where multihoming apps faced the strategic choice outlined above, enabling us to investigate how multi-platform apps alter their Android strategies in response to iOS privacy restrictions relative to Android-exclusive apps.

First, to determine which strategic response—compensatory or unified—is observed in practice, we empirically measure how iOS ATT affects developers' data collection and feature development strategies on Android. Extant research has identified permission seeking and integrated third-party software development kits (SDKs) as two strategies that app developers implement in response to privacy-enhancing policies (e.g., Cheyre et al. 2023, Mayya and Viswanathan 2024). SDKs enable data analysis capabilities through specialized third-party services, whereas permissions achieve similar capabilities using first-party resources.

Investigating changes to data collection strategies is essential to comprehending which strategic path developers choose when data regulations on one platform disrupt the equilibrium for data collection. A shift toward enhanced core features or real-time contextual solutions would indicate that developers adopted the unified utility-enhancement strategy, whereas an increase in intrusive data collection and third-party tracking would suggest developers pursued the compensatory extraction strategy. This prompts our research question: *"How does a platform's privacy-enhancing policy affect developers' data collection strategies (e.g., permissions or integrated third-party services) on the competing platform?"*.

Next, we examine whether the strategic choices documented above translate into observable differences in app quality outcomes, as perceived by users. If multihoming apps adopt the unified strategy and implement utility-enhancing improvements on Android, we expect these apps to show higher quality improvements compared to Android-exclusive apps, which face no regulatory pressure to enhance features. Conversely, if apps adopt the compensatory strategy and increase data extraction on Android, this could negatively impact user experience and ratings. Given the uncertain net impact of these strategic adjustments, the direction and magnitude of the quality effects will reveal whether privacy spillovers ultimately benefit or harm consumers on the unregulated platform. This motivates our second research question: *"How does a platform's privacy-enhancing policy affect app quality outcomes (e.g., user ratings) on the competing platform?"*

Finally, we investigate the broader market structure implications of privacy spillover to a competing platform. Given that multihoming apps already hold two-thirds of the Android market share, understanding how their strategic choices because of iOS ATT affect competitive dynamics is crucial. If multihoming apps divert significant resources toward addressing iOS regulatory constraints, Android-exclusive apps may unexpectedly gain, as they focus only on Android users' needs without cross-platform compliance distraction. However, if multihoming apps successfully implement utility-enhancing features that spill over to Android, whereas Android-exclusive apps lack similar innovation pressures, this could further concentrate market power in favor of multihoming apps. This leads to our third research question, *"How does a platform's privacy-enhancing policy affect market structure of the competing platform?"*

To empirically examine ATT's spillover effects on Android, we employ a quasi-experimental design to compare apps available on both iOS and Android (those directly affected by ATT) with exclusive

Android apps (those not directly affected). Specifically, our dataset encompasses a comprehensive collection of 12,400 Android apps from a smartphone data-intelligence firm: 7,464 multihoming apps, and 4,936 Android-exclusive apps.[3] Using Coarsened and Exact Matching (Iacus et al. 2012) to perform one-to-one matching without replacement, we create a balanced dataset of 8,828 apps, with 4,414 apps each in the treated and control groups. For each app, we track weekly changes in permissions, integrated third-party software development kits (SDKs),[4] ratings value, and other relevant attributes. The main panel data spans 55 weeks, from September 2020 (after iOS 14 Release) to September 2021 (before iOS 15 Release), with 2 May 2021 (week 35) marking the policy implementation week. The primary analyses focus on 13 weeks before and after the policy to better isolate ATT's impact from other confounding factors, such as iOS and Android updates. We employ both Two-way Fixed Effects model and Synthetic Difference in Differences model. Following recent literature (e.g., Cheng et al. 2024, Yeverechyahu et al. 2024), we employed large language models to classify over 1300 integrated third-party SDKs into one of four functionally distinct categories: core feature development, analytics, ads and monetization, and data intelligence.

Our analysis reveals that multihoming apps on Android adopted the unified strategy, significantly increasing their feature enhancement efforts while reducing third-party user-level data collection. These apps show a significant increase in the number of permissions sought, specifically in *normal* permissions, which pertain to app usage data and features not linked to personally identifiable information. In contrast, we do not see a significant increase in seeking *runtime* permissions, which pertain to personally identifiable sensitive information. When examining Integrated SDKs, we observe a significant increase in the use of core feature development SDKs (e.g., those supporting backend infrastructure, commerce functionalities, communication, or social features), and data intelligence SDKs (those that use sensor data to offer contextual solutions to users) indicating an enhanced focus on improving app functionality. We also observe a significant decrease in the use of third-party analytics SDKs (e.g., attribution, marketing automation), suggesting a reduced focus on tracking. Notably, ads and monetization SDK usage remains unchanged, indicating a sustained reliance on advertising strategies. Overall, our findings suggest multihoming apps prioritize consumer utility enhancement over compensatory data extraction using analytics SDKs or sensitive permissions.

[3] In 2021, the top 12,400 apps accounted for over 85% of all activities (downloads/ratings) among 2.3 million apps on Play Store.

[4] Integrated Software Development Kits (SDKs) are pre-written functionalities developed by third parties, which apps can incorporate to assist with tasks such as e-commerce, advertising, analytics, etc.

Next, the analysis of user ratings suggests a significant positive spillover effect of the iOS ATT policy on multihoming apps' quality outcomes, consistent with the expectations from a unified utility enhancing strategy. Multihoming apps experience a 0.037 (from the TWFE DiD model) increase in their weekly average rating value on Android post-ATT. At a mean value of 859 new ratings per week, an increase of 0.037 translates to approximately 127 more users each month, giving these apps a rating that is one star higher, demonstrating that the utility-enhancing spillovers were recognized and valued by consumers.

Finally, why should competing platforms care if spillovers improve consumer utility? As a consequence of these quality and feature enhancements, we observe a substantial increase in market concentration on Android following the implementation of ATT, as measured by the Herfindahl-Hirschman Index (HHI), a measure of market concentration. This is driven by a significant increase in downloads for multihoming apps compared to Android-exclusive apps. Given that multihoming apps already held a dominant market share, the utility and quality enhancements spurred by ATT on iOS spillover to Android and further solidify their dominant position in the Android market, creating an unintended competitive disadvantage for platform-exclusive developers who lacked similar innovation pressures.

Our study makes contributions to platform policy and regulation literature in three ways. First,we demonstrate that privacy policy spillovers in freemium markets operate fundamentally differently than traditional cross-market spillovers documented in prior literature. Unlike compensatory price increases observed when firms face regulatory constraints in other markets (Genakos and Valletti 2011), we find that data collection restrictions can trigger utility-enhancing spillovers when data serves dual extractive and productive functions. Second, our analyses go beyond mere compliance with the ATT policy by exploring how apps strategically adapt their data practices in response. Multihoming apps maintain their advertising strategies while shifting towards app functionality enhancement and real-time contextual solutions. This strategic response represents a departure from the path-dependent equilibrium of data-driven personalization toward more resource-intensive but valuable feature development. Finally, by studying ATT's impact on Android, we shed light on the competitive dynamics of the mobile app market, demonstrating a critical unintended consequence of data regulation: Android-exclusive apps losing out since they lacked innovation pressures. Our findings emphasize the importance of considering the indirect policy effects and suggest platform owners to be vigilant about competitor policies, to avoid putting their exclusive apps at a disadvantage.

2. Literature Review

2.1. Multihoming and Regulatory Spillover in Freemium Markets

The phenomenon of cross-market spillovers has been extensively documented in the economics literature, with Bernheim and Whinston (1990) setting the theoretical foundation followed by others providing empirical validation (e.g., Parker and Röller 1997, Busse 2000). The main idea is that, in the presence of firms with multimarket contact, it is possible to sustain market-wide tacit coordination of prices. Interestingly, even single-market firms, not just the firms with multimarket contact, agree to set less competitive prices in equilibrium. Furthermore, when regulators constrain such coordination in one market, the extant framework predicts "compensatory effect" in unregulated markets (Genakos and Valletti 2011), i.e., any attempt to regulate one market results in firms increasing prices in unregulated segments to maintain overall profitability.

In digital marketplace contexts such as smartphone app stores, multimarket contact manifests as multihoming, where same apps are available across multiple platforms simultaneously. Research has investigated antecedents of multihoming decisions, with Tian et al. (2022) focusing on platform compatibility influences and Koh and Fichman (2014) investigating how selling/buying activities affect multihoming preferences in B2B exchanges. Studies have also examined the economic forces influencing these choices, where the primary focus has been the trade-offs between market reach and costs of decreased product differentiation or increased development effort. Li and Zhu (2021) document a link between information transparency and multihoming decisions.

The spillover effect of multihoming, where an app's presence on one platform influences its performance on another, is a specific form of economic force at play. Koryakina et al. (2016) documents an increase in sales from multihoming through enhanced user awareness and quality signaling. Geng et al. (2020) and Landsman and Stremersch (2011) note a trade-off between potential demand loss owing to compatibility and the benefits of expanded market reach. Barua and Mukherjee (2021), Dou and Wu (2021) and Bakos and Halaburda (2020) study the interplay between spillovers across different sides of the market, cross-side network effects, and price competition. Finally, the literature on indirect network effects also provides insights into supplier multihoming spillovers (Corts and Lederman 2009, Rysman 2004).

However, these studies focus primarily on demand spillovers, network effects, and strategic positioning in freemium markets. What remains unexplored is how privacy policies that restrict data collection on one platform affect multihoming developers' strategic responses across platforms.

2.2. Data Privacy Policies and Third-party vs. First Party Data

Unlike traditional competitive variables such as price, data in freemium markets serves a dual function: it generates revenue through targeted advertising while simultaneously enhancing user utility through personalization and improved app functionality (Lin 2022). This dual role creates fundamentally different strategic incentives for developers, as data collection can simultaneously extract value and create consumer benefits, distinguishing freemium platform competition from traditional market dynamics, where competitive variables are typically purely extractive (Bian et al. 2021, Kraft et al. 2023).

Given the hidden externalities of extensive data collection (Acquisti et al. 2016), alongside public regulations (e.g., Johnson et al. 2023, Ke and Sudhir 2023, Peukert et al. 2022), private digital platforms are proactively focusing on enhancing choices that consumers have regarding their personal data. For instance, all smartphone platforms now allow app users to decide during app usage whether or what type of sensitive data (e.g., location) apps can collect, a departure from a broad consent during download (Mayya and Viswanathan 2024). This shift towards greater user control has implications for the economic viability of online businesses reliant on targeted advertising (e.g., Kircher and Foerderer 2024, Miller and Skiera 2024).

One specific type of data protection policy that has gained prominence is the shift to *default opt-out* mechanisms, significantly impacting businesses reliant on targeted advertising (Miller and Skiera 2024). The 2021 iOS ATT framework exemplifies a default opt-out policy in mobile apps. Most ATT studies focus on developers' responses. Kesler (2023) and Cheyre et al. (2023) find that ATT led to a decrease in the use of third-party tracking tools along with an increase in the adoption of alternative monetization strategies, such as in-app purchases and subscriptions. Aridor et al. (2024) examine ATT's impact on conversion-optimized advertising effectiveness on Meta. Kollnig et al. (2022) note that while ATT has made individual user tracking more difficult, it has also led to a counter-movement in which developers explore alternative tracking methods, such as fingerprinting and cohort tracking. Li and Tsai (2022) document a decrease in new downloads, particularly for larger apps that relied heavily on third-party data for user acquisition.

Despite the prevalence of multihoming by apps, the spillover effect of a *default opt-out* privacy policy on competing platforms is not well studied. Consequently, whether apps homogenize or decouple their data practices across platforms in response to platform-specific regulations remains an open empirical question.

2.3. Literature Gaps and Research Questions

The convergence of three critical trends—widespread developer multihoming, the rise of privacy regulations, and the prevalence of cross-platform development tools—creates a fundamental gap in our understanding of digital platform competition. While existing spillover literature has established how regulatory constraints in traditional markets lead to compensatory price increases in unregulated segments (Genakos and Valletti 2011), no one has examined how privacy policies that restrict data collection—a dual-purpose resource in freemium markets—affect competitive dynamics across interconnected digital platforms.

This gap is particularly consequential because of a unique strategic choice in freemium digital markets absent in traditional markets. When privacy regulation disrupts the data-collection equilibrium on one platform, multihoming developers can either adopt compensatory strategies (increasing data extraction on unregulated platforms to offset losses) or unified strategies (implementing utility-enhancing improvements across all platforms using shared codebases). The prevalence of cross-platform development tools makes the latter strategy economically viable in ways that have no parallel in traditional multimarket competition.

The implications of this knowledge gap extend beyond academic theory to critical policy questions. If developers adopt compensatory strategies, privacy regulations could inadvertently harm consumers on unregulated platforms through increased data extraction. Conversely, if unified strategies prevail, privacy policies could create positive spillovers that enhance consumer utility across platforms while simultaneously affecting market concentration in unintended ways. Without empirical evidence, policymakers and platform owners cannot anticipate or manage these cross-platform effects.

Our research addresses this gap through three interconnected questions that collectively reveal how privacy spillovers reshape digital platform competition. First, *how does a platform's privacy-enhancing policy affect developers' data collection strategies on competing platforms?* This question determines whether compensatory or unified strategies dominate, providing fundamental insight into the mechanics of digital platform spillovers. Second, *how do these strategic responses affect app quality outcomes on competing platforms?* This reveals whether spillovers ultimately benefit or harm consumers on unregulated platforms. Third, *how do privacy policy spillovers affect market structure on competing platforms?* This uncovers the broader competitive implications, including potential unintended consequences for platform-exclusive developers and market concentration.

3. Context, Data, and Models

3.1. Business and Empirical Context

To test our theoretical framework of compensatory versus unified strategic responses to privacy spillovers, we require a setting where: (1) a privacy policy creates an exogenous shock to data collection practices on one platform, (2) a substantial number of apps multihome across platforms with shared development resources, and (3) the policy change is unrelated to competitive conditions on alternative platforms. Apple's App Tracking Transparency (ATT) policy provides an ideal natural experiment that satisfies all these conditions, creating clean treatment variation to isolate spillover effects from confounding factors. ATT policy was officially implemented on April 26, 2021, with iOS version 14.5. ATT mandated that all iOS apps must obtain explicit user permission before tracking their activities across other apps and websites. This policy aligned with Apple's privacy-focused branding, potentially helping Apple enhance user trust.

Prior to iOS version 14.5, apps could track users' activities across other apps and websites using a phone-generated unique identifier called IDentifier For Advertisers (IDFA), which functions similar to a third-party cookie in web browsing. Although users could limit tracking since 2012 through the "limit ad tracking" setting option, this wasn't widely publicized. However, ATT changed this approach by mandating apps to obtain explicit consent from iPhone users before accessing their IDFA. Figure 2 illustrates the notification that users receive in version 14.5 and beyond, the first time an app intends to access users' IDFA. In essence, iOS switched the tracking option from *opt-in-by-default* to *opt-out-by-default*. This change affected digital advertising as only about 20% of iOS users opted into allowing IDFA tracking.[5] Consequently, firms reliant on IDFA for targeted advertising reported substantial revenue losses (e.g., Aridor et al. 2024).[6]

[5] ATT Opt-In Rates: The Ugly Truth Behind Why The Numbers Vary So Widely - AdExchanger

[6] Facebook says Apple iOS privacy change will result in $10 billion revenue hit this year - CNBC

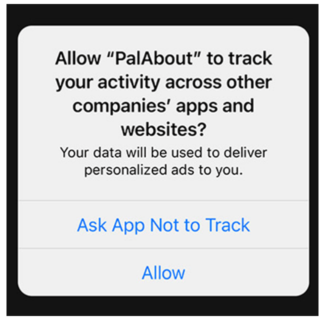


Figure 2 **App Tracking Transparency (Courtesy: (Apple Website))**

In examining ATT's spillover effects on Android, we exploit the policy change's quasi-experimental nature. Multihoming apps (operating on both iOS and Android) constitute our treatment group, as their mandatory ATT compliance may influence their Android data practices due to shared codebases and operational efficiencies. Android-exclusive apps serve as our control group, since they operate independently of the iOS and ATT requirements. Neither did iOS 14.5 introduce other major changes, nor did Android have any updates, which ensures that the exogenous shock has no confounders.

3.2. Data

Our dataset comprises top 12,400 Android apps, with 7,464 available on both iOS and Android platforms (treated *multihoming* apps), and 4,936 exclusively on Android (control *exclusive* apps). We work with a reputed smartphone data intelligence vendor to obtain the panel data that represents the global distribution of the app population (see Appendix Table A1 for category wise comparison and Appendix Figure A1 for rating distribution). For each app, we track their weekly ratings value, ratings count, permissions list, and integrated SDKs list. Our primary panel data spans 55 weeks from September 2020 to September 2021, with 34 weeks before and 21 weeks after ATT. This timeframe helps mitigate confounding factors from subsequent iOS 15 and Android 12 releases that could affect app development and user behavior. The main analyses are on 26 weeks, 13 weeks before and after the policy. Table 1 provides the variable description and summary statistics.

Permissions: To understand how developers alter their app development strategy, we utilize $Permissions_{it}$, which represents the number of permissions app i requests as of week t. We further disaggregate these permissions into *runtime* permissions and *normal* permissions, based on Android's official

Table 1 Variable Description and Summary Statistics after Matching

Table 1(a): Variable Description

Variable Name	Description
$RatingValue_{it}$	The cumulative user rating that the app i has received by the end of week t.
$Download_{it}$	The weekly download of the app i by the end of week t. calculated using the download estimates of the top 2,674 apps.
$Permissions_{it}$	A count variable indicating the count of permissions app i requests as of week t.
$Runtime-Permissions_{it}$	A count variable indicating the count of runtime permissions app i requests as of week t
SDK_Count_{it}	A count variable indicating the count of SDKs app i requests as of week t.
SDK_Count_{ijt}	A count variable indicating the count of SDKs app i requests of the type j ($j \in$ Core Feature Development, Analytics, Ads & Monetization, Data Intelligence) in week t.
$Multihoming_i$	A dummy variable that takes the value of 1 if app i is available on both iOS and Android platforms, and 0 if it is exclusively available on Android.
$ATTEnacted_t$	A dummy variable that takes the value of 1 for the weeks after the enactment of Apple's App Tracking Transparency (ATT) policy, and 0 for the weeks before.

Table 1(b): Summary Statistics post Matching

Variable	Obs	Mean	Std. Dev.	Min	Max
$RatingValue_{it}$	485,540	4.14	0.44	1	5
$Download_{it}$	96,264	636,567	3,186,526	0	177.82×10^6
$Permissions_{it}$	485,540	13.76	12.85	0	259
$RuntimePermissions_{it}$	485,540	2.73	2.86	0	31
SDK_Count_{it}	485,540	6.20	6.55	0	66
$MultiHoming_i$	485,540	0.23	0.5	0	1
$ATT\_Enacted_t$	485,540	0.60	0.5	0	1

classification. By definition, *runtime* permissions are needed to collect personally identifiable data whereas *normal* permissions are needed to collect usage-related data, such as network status, Wi-Fi, or vibration. [7]

Weekly measure of Rating Value: The dependent variable for the first research question captures the app quality: the weekly value of $RatingValue_{it}$ that app i receives in week t.[8]

Download Estimates: We obtain the weekly download estimates, $Download_{it}$, for the top 2,674 apps in our dataset from the data vendor.[9]

Integrated SDK Usage Measurement: Central to understanding developer strategies is identifying the types of third-party services that apps integrate through Software Development Kits (SDKs). These pre-packaged modules provide functionalities like in-app-ads, social media integration, user attribution, etc.

[7] More details can be found in Android's official website - Permissions on Android

[8] The value is calculated as $(RatingValue_{it} \times RatingCount_{it} - RatingValue_{it-1} \times RatingCount_{it-1})/(RatingCount_{it} - RatingCount_{it-1})$, where $RatingCount_{it}$ is the count of ratings that an app i has received by the end of the week t. We carry forward the weekly *RatingValue* from the previous week for apps that did not receive a rating that week.

[9] Downloads are extremely skewed towards popular apps, specifically the top 500 apps (Zhong and Michahelles 2013, Garg and Telang 2013). While Android has approximately 2.3 million apps (Prakash 2021), the top 2,500 apps account for about 65% of downloads using the lower bound of download bucket (e.g., treating '10000+' installs as exactly 10,000 installs) and 67% of the review counts, a potential proxy for downloads. Hence, we focus on the top 2,674 apps.

Understanding how apps start or stop certain SDKs provide insights into apps' monetization, data collection, and feature enhancement strategies. Hence, we obtain weekly panel data on integrated SDKs from the aforementioned business intelligence data provider, encompassing over 1,300 SDKs across 13 categories.[10]

Category Identification and Refinement: One challenge in analyzing modern SDKs is that they often bundle multiple complementary functionalities, aiming to differentiate themselves from other SDKs while offering apps a more streamlined development environment. For example, an analytics SDK may also offer marketing automation tools that leverage the analytics output. Such a bundling of complementary functionalities complicates SDK analysis. Adding to this complexity, our data vendor assigned category labels to each SDK without indicating those categorys' relative importance.

To address this complexity, we first analyze the SDK category co-occurrence patterns, recognizing that SDK categories that frequently occur together often serve related purposes. For instance, *Analytics* and *Marketing Automation* co-occurs frequently (19 times), suggesting a combined focus on tracking user behavior and automating marketing actions based on those insights. Similarly, *Development Tool* frequently co-occurs with *Backend* (27 times) and *Communication* (20 times), indicating their role in integrating core app functionalities. By identifying these co-occurrence patterns, we consolidate the original 13 SDK categories into four functionally distinct groups that represent the key pillars of the freemium app economy:

- **Core Feature Development** SDKs provide essential functionalities for user engagement, including backend services, commerce functionalities, communication features, and social integration.
- **Analytics** SDKs help data collection to understand user behavior and optimize performance through attribution, marketing automation, and user tracking.
- **Advertising and Monetization** SDKs enable monetization through display ads/targeted promotions.
- **Data Intelligence** SDKs automatically generate real-time insights from collected sensor data, such as location data, to provide contextual solutions directly benefiting users.

LLM-Based Annotation and Validation: Accurately categorizing 1,305 SDKs into these four categories based solely on co-occurrence patterns and vendor labels is a challenge given the absence of standardized categorization criteria for mobile SDKs. To address this challenge, we employed a Large Language Model (LLM) approach for efficient and accurate classification of SDK descriptions into our four categories.

[10] The thirteen categories as per our data vendor in 2021 are: Analytics, Ad Network, Attribution, Backend, Commerce, Communication, CRM, Data Intelligence, Development Tools, Game Engine, Marketing Automation, Social, and Survey.

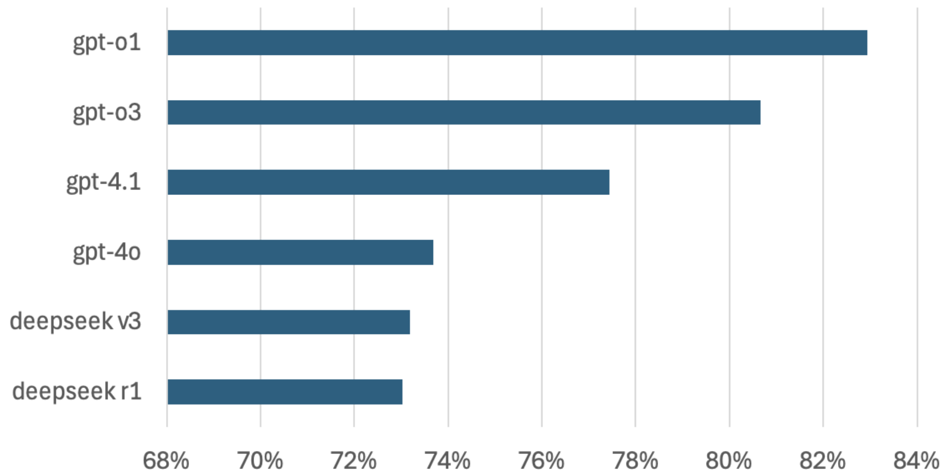
Based on recommendations by Cheng et al. (2024) for LLM-based annotation tasks, we developed detailed annotation guidelines that define each category with specific functionalities and examples. We recruited three human subjects and provided them the initial annotation guidelines. They were asked to tag a random sample of 25 SDKs and were instructed to meet on Zoom to discuss differences and then collaboratively improve the annotation guidelines to address differences in comprehension. Then another 25 SDKs were allocated and the process continued until taggers achieved over 66.66% mean Cohen's Kappa. Overall, three iterations were needed to cross the threshold agreement rate. As noted by Cheng et al. (2024), this process of discussing the differences addresses corner-cases and enhances the prescriptive nature of the guidelines and consequently enhance annotator agreements. This process also enhances taggers' subject knowledge, making them "annotation experts" to generate accurate human baselines. Appendix B presents the final annotation guidelines after three iterations, as well as the prompt structure used with the LLMs.

To choose the most suitable LLM for our task, we benchmarked the performance of six different models (GPT-4o, GPT-4.1, GPT-o3, GPT-o1, Deepseek R1, and Deepseek V3) against expert human annotations. We randomly selected 150 SDKs and their descriptions and had them tagged by the same three human annotators who iteratively improved the annotation guidelines in the prior step. We then compared the LLM outputs with human annotations and found that GPT-o1 outperformed other models with an 89.33% agreement rate and Cohen's Kappa of 0.83, indicating "almost perfect" agreement (Cohen 1960, McHugh 2012). Figure 3 visualizes the Cohen's Kappa value of different models against expert human annotations.

Using GPT-o1, we processed 1,305 unique SDKs, consuming about 1 million input tokens and generating 1.365 million output tokens for the complete annotation task. This process resulted in four weekly variables, each representing the number of SDKs an app has integrated from the respective group in a given week. Appendix Table A2 provides the list of integrated SDK categories, their respective category groups and a representative example in each category. The LLM-based approach ensures consistent and scalable categorization while maintaining high agreement with expert human judgment.

3.3. Empirical Strategy

In our empirical study, we examine iOS ATT's spillover effect on the Android marketplace. Given that this is a one-shot policy implementation without staggered adoption, we use the classical Two-Way Fixed



The x-axis is the Cohen's Kappa value against expert human baseline.

Figure 3 Model Outcomes for Annotation

Effect (TWFE) with Difference-in-Differences (DiD) model with app and time fixed-effects. The multihoming apps—affected by ATT because of their iOS presence—serve as our *treated* group, whereas Android-Exclusive apps are our *control* group.

3.3.1. Matching: Concerns about non-random treatment assignments can be addressed by pre-processing data through matching (Dehejia and Wahba 2002). We employ Coarsened and Exact Matching (CEM), a non-parametric matching technique (Iacus et al. 2012). CEM "coarsens" time-variant covariates (cumulative rating value, weekly rating value, rating count and permissions), and performs exact one-to-one match on these buckets and app category, yielding a balanced dataset of 4,414 treated and control apps each. Our empirical model is formally specified as:

$$Y_{it} = \alpha + \beta\, MultiHoming_i \times ATT\_Enacted_t + \mu_i + \upsilon_t + \varepsilon_{it} \tag{1}$$

where i and t index an app and week, respectively. α is the intercept, μ_i and υ_t represent the fixed effects for app i and absolute week t, respectively. The outcome variables of interest, Y_{it}, are the weekly values of Permissions and SDKs, Ratings, and Downloads, and β captures the DiD estimate.

3.3.2. Parallel Trends: We test the parallel trends assumption using the model from Autor (2003):

$$Y_{it} = \alpha + \sum_{\tau=-\kappa}^{-1} \alpha_j^p MultiHoming_i \times RelativeWeek_t + \mu_i + \upsilon_t + \varepsilon_{it} \tag{2}$$

where $RelativeWeek_t$ is a vector of dummies representing each week j before the treatment took place. The parallel trends assumption holds if the interaction terms (i.e., α_j^p) are insignificant prior to treatment. The results are presented in their respective sections: Permissions in Figure 4, SDKs in Figure 6, rating in Figure 10 and downloads in Figure 13. All trends are parallel before ATT.

3.4. Alternative Empirical Strategy using Synthetic Difference in Differences

Synthetic Difference-in-Differences (Synthetic DiD) approach (Arkhangelsky et al. 2021) is a nonparametric technique that constructs a "synthetic" control group (Abadie et al. 2010) to create a counterfactual scenario of what would have happened to the multihoming apps on Android had they not been subject to the iOS ATT policy changes. It is derived by identifying a weighted combination of control group apps that closely mirrors the treated group's outcomes in the pre-ATT period, while weighting time periods to emphasize weeks closer to ATT implementation. Comparing post-ATT outcomes of treated apps with their synthetic control isolates the causal impact of iOS ATT on the Android app ecosystem. Formally, the Synthetic DiD estimation procedure solves:

$$(\hat{\tau}, \hat{\mu}, \hat{\alpha}, \hat{\delta}) = \{\operatorname{argmin} \sum_{i=1}^{N} \sum_{T=1}^{t} (Y_{it} - \mu - \alpha_i - \delta_t - \text{ATT\_Enacted}_{it}\tau)^2 \hat{\omega}_i, \hat{\lambda}_t\} \tag{3}$$

Here, Y_{it}, represents outcomes (weekly rating value, permissions, or integrated SDKs) for app i in week t. The model includes app-fixed effects (α_i) and week-fixed effects (δ_t) to account for time-invariant app-specific factors and common time trends, respectively. $ATT\_Enacted_{it}$ denotes the treatment indicator. Parameter τ captures the average treatment effect on the treated (ATT), the causal effect of iOS ATT policy on outcomes for treated Android apps. $\hat{\omega}_i$ and $\hat{\lambda}_t$ represent app weights and time weights, respectively.

4. Results

4.1. How does iOS ATT impact developers' development strategies on Android?

Recent studies show that iOS developers responded to ATT by increasing paid features, switching to paid versions, and decreasing ads-dependent features (Kesler 2023, Cheyre et al. 2023), indicating a paradigm shift in which app users are increasingly required (and willing) to pay with real currency instead of personal data.[11] Given that Android did not introduce comparable restrictions on third-party tracking, we aim

[11] The Cisco 2024 Privacy Survey highlights this trend - Read here

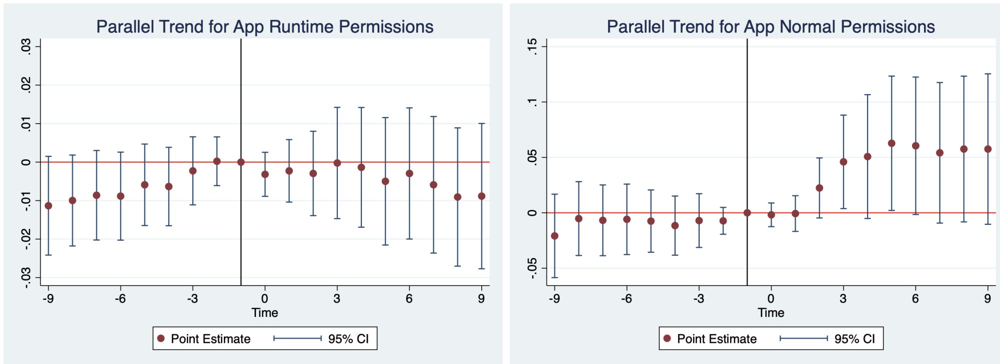
to understand if and how app developers alter their strategies on Android in response to the iOS policy change. Specifically, we analyze whether multihoming apps on Android adjust their (1) *permission seeking practices*, either regarding sensitive data or usage-related data, and (2) *integration of third-party services* for core feature development, analytics, or advertising.

4.1.1. How does iOS ATT impact Permission Seeking behavior on Android? Permissions are requests made by apps to access specific data or functionalities on a user's device. Android apps require two types of permissions: *normal* permissions and *runtime* permissions. Apps need *normal* permissions to collect usage-related data and can be obtained during app installation without explicit user consent (e.g., accessing Wi-Fi status, notification policies). Apps need *runtime* permissions to gather personally identifiable data and should be explicitly sought from users during app usage (e.g., location, contacts, microphone, SMS).[12] The key difference between the two types of permissions is that while *normal* permissions support basic app features, *runtime* permissions enable personalized experiences. Research shows that policy changes targeting personally identifiable permission-seeking strategies on Android induce strategic behavior among app developers (Mayya and Viswanathan 2024). We focus on whether changes in the iOS personal data collection policies influence how multihoming apps seek permissions on Android.

Using our matched dataset of 8,828 apps, as outlined in Section 3.3, and study the changes in permission requests before and after the ATT policy by estimating model 1 with permissions sought as the dependent variable. Panels (a) and (b) of Figure 4 visualize the lead-lag graph for *runtime* and *normal* permissions, respectively. The graphs suggest that the pre-treatment trends for multihoming apps and Android-exclusive apps are not significantly different. Table 2 presents our analysis results.

Multihoming apps significantly increase their overall permission requests compared to Android-exclusive apps (Column 1), driven primarily by *normal* permissions (Column 3) rather than *runtime* permissions (Column 2). Apps increase their collection of usage data, particularly related to user activity within the app. This could be indicative of new app features that rely on analyzing usage to optimize performance, provide relevant features, or enhance contextual awareness. For instance, apps might collect data on feature usage

[12] Permissions on Android - Android Portal



Joint significance test for pre-treatment is 1.14 ($p = 0.32$)

(a) Runtime (privacy sensitive) Permissions

Joint significance test for pre-treatment is 0.70 ($p = 0.75$)

(b) Normal (not privacy sensitive) Permissions

Figure 4 The impact of ATT on the number of Permissions on Android: Parallel Trends Graph

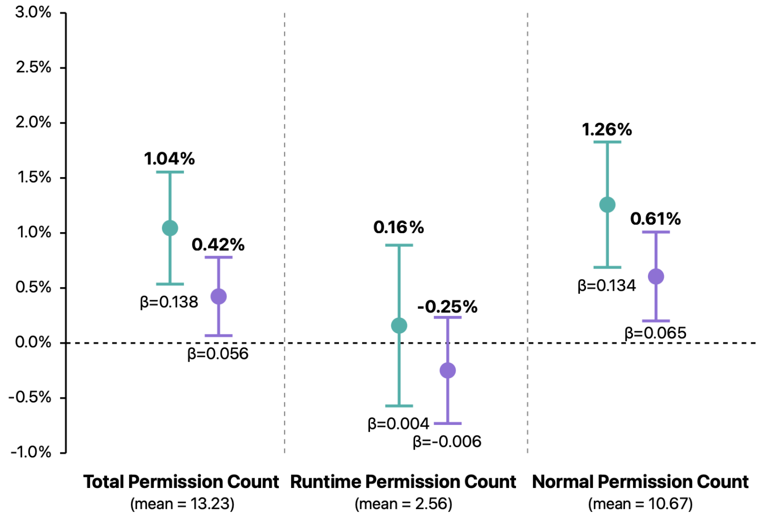
frequency or user navigation patterns. The focus on *normal* permissions over *runtime* permissions aligns with industry trends toward data-driven optimization and contextual advertising (Kraft et al. 2023). The results remain consistent using Synthetic DiD (Columns 4-6). Figure 5 presents the coefficient plot from extended analysis using 55 weeks (34 weeks before and 21 weeks after the policy).

Table 2 The impact of ATT on the number of Overall Permissions on Android

	Matching + TWFE DiD			Synthetic DiD		
	Overall Permissions (1)	Runtime Permissions (2)	Normal Permissions (3)	Overall Permissions (4)	Runtime Permissions (5)	Normal Permissions (6)
Multihoming × *ATT_Enacted*	0.070** (0.031)	0.002 (0.009)	0.068** (0.028)	0.052** (0.025)	−0.005 (0.006)	0.058** (0.023)
App FE	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y
Observations	229,528	229,528	229,528	322,400	322,400	322,400

*p<0.1; **p<0.05; ***p<0.01; Standard Errors clustered around apps in parentheses for TWFE DiD.
Bootstrapped Standard Errors with 100 replications in parentheses for Synthetic DiD.

4.1.2. How does iOS ATT affect Android apps' third-party services integration? Beyond permissions, third-party software development kits (SDKs) also offer insights into how developers adapt their data collection strategies in response to policies like ATT. SDKs are essential building blocks in app development, offering pre-packaged functionalities such as analytics, social media integration, and advertising. As an essential part of providing these functionalities, these SDKs access a trove of user information—some gather usage data for app features, while others collect personally identifiable information for targeting



Note: In each set, the left (green) coefficient is of TWFE DiD and the right (purple) one is of Synthetic DiD.

Figure 5 Coefficient Graph for Permissions - Longer Time Period (55 weeks)

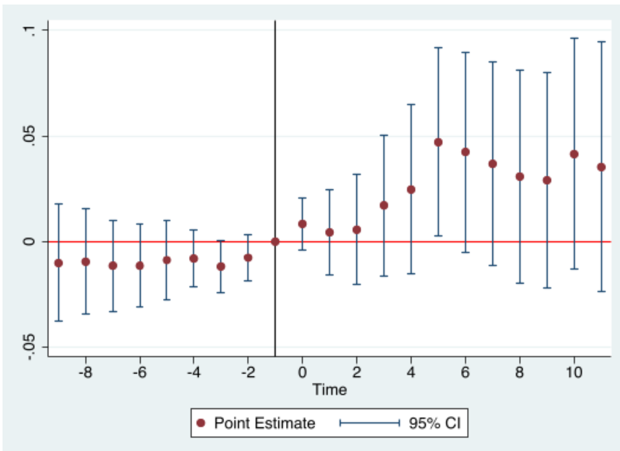
and personalization (Zhan et al. 2021). Examining changes to SDK integration patterns among Android apps, particularly those with iOS counterparts, we can understand how developers re-calibrate their data collection strategies following iOS ATT.

To examine how iOS ATT affects Android apps' third-party service integration, we leverage SDK usage dataset from the data vendor. We consolidate thirteen SDK categories into four broader categories as described in detail in Section 3.2: Core Feature Development, Analytics, and Ads and Monetization, and Data Intelligence. This consolidation reflects how SDKs often bundle complementary functionalities to differentiate their offerings and simplify integration for app developers.[13] These four consolidated categories represent the core aspects of value creation and capture within the free app economy. Core feature development SDKs (e.g., social integration, communications, backend services) are crucial for functionality; analytics SDKs provide insights into user behavior; and ads and monetization SDKs are essential for app monetization, and data intelligence SDKs provide real-time solutions using phone sensor data.

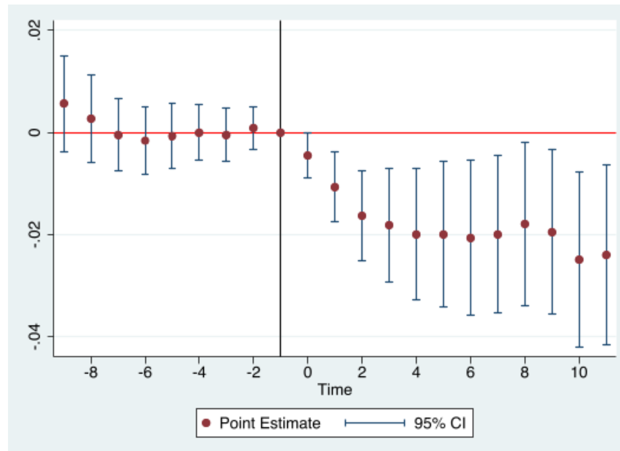
We estimate the model 1 on weekly panel of four categories of SDKs deployed by the matched 8,828 apps. We modify the model 1 to control for the total count of SDKs from other category groups, scaled to

[13] For example, both Medallia Digital or AppDynamics bundle marketing automation and analytics capabilities within their SDKs, enabling seamless user insights collection and and targeted campaigns based on those insights.

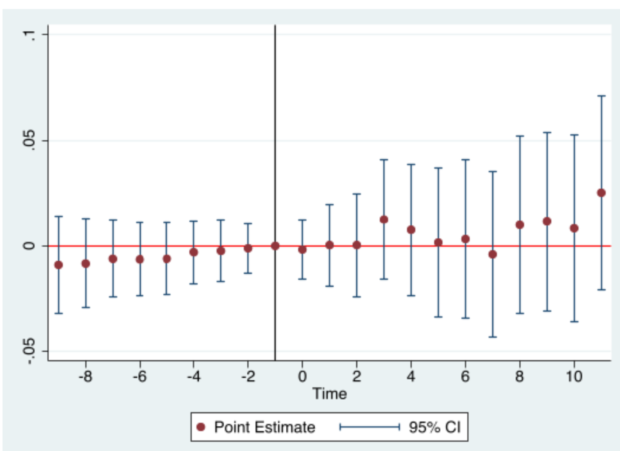
address the skewed nature of this count measure. Sub-figures (a) through (d) of Figure 6 visualize the lead-lag graphs for *Core Feature Development*, *Analytics*, *Advertising and Monetization*, and *Data Intelligence*, respectively. The graphs suggest no significant pre-treatment difference in trends.



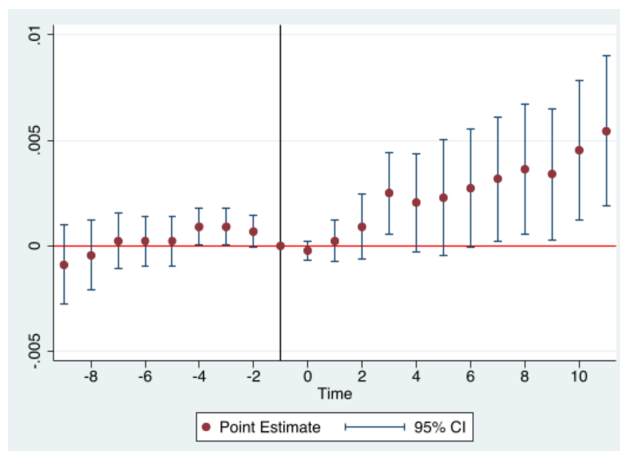
(a) Core Feature Improvement



(b) Analytics



(c) Ads and Monetization



(d) Data Intelligence

The x-axis represents time, and the y-axis represents the effect size (count of SDKs).

Figure 6 The impact of ATT on the Integrated SDKs on Android: Parallel Trends Graph

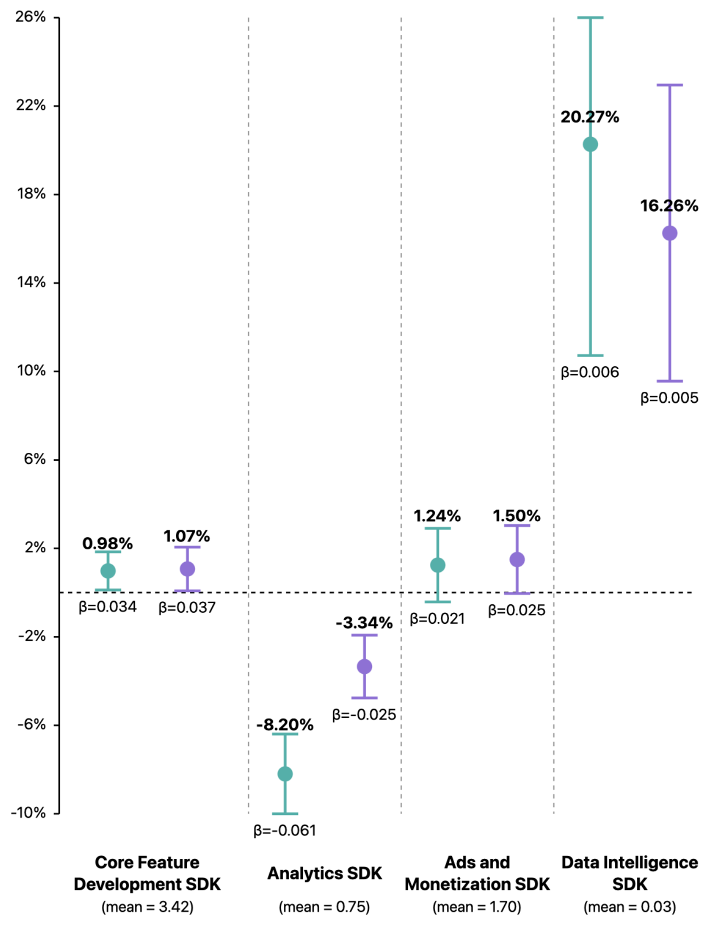
The results of the analysis are presented in Table 3. We observe a significant increase in the integration of core feature development SDKs (Column 1) and data intelligence SDKs (Column 4), and a decrease in the use of analytics SDKs (Column 2) following the treatment. Notably, the advertising and monetization SDKs usage remains unchanged (Column 3). The Synthetic DiD analysis (Columns 5-8) is consistent.

Table 3 The impact of ATT on Integrated SDK usage on Android

	Matching + TWFE DiD				Synthetic DiD			
	core feature improvement SDK	analytics SDK	ads and monetization SDK	data intelligence SDK	core feature improvement SDK	analytics SDK	ads and monetization SDK	data intelligence SDK
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Multihoming× *ATT_Enacted*	0.044** (0.022)	−0.024*** (0.007)	0.015 (0.017)	0.003** (0.001)	0.030** (0.015)	−0.020*** (0.005)	0.014 (0.013)	0.003*** (0.001)
App FE	Y	Y	Y	Y	Y	Y	Y	Y
Week FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	229,528	229,528	229,528	229,528	322,400	322,400	322,400	322,400

*p<0.1; **p<0.05; ***p<0.01; Standard Errors clustered around apps in parentheses for TWFE DiD.

Bootstrapped Standard Errors with 100 replications in parentheses for Synthetic DiD.



Note: In each set, the left (green) coefficient is of TWFE DiD and the right (purple) one is of Synthetic DiD.

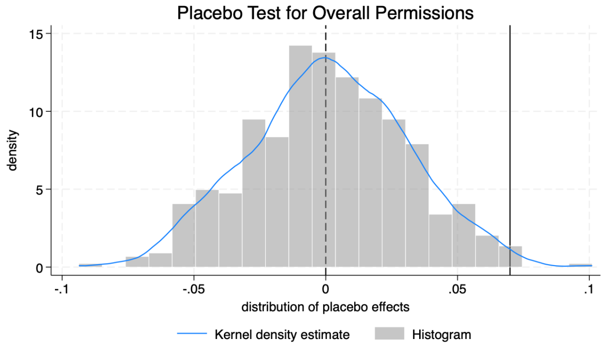
Figure 7 Coefficient Graph for SDKs - Longer Time Period (55 weeks)

Taking these findings together with the increase in the normal permissions sought in section 4.1.1, we observe two key changes among multihoming apps on Android following the implementation of iOS ATT. First, multihoming apps increase the development of new features on Android, arguably as a spillover effect from iOS. This is reflected in both the increased use of core feature development SDKs and the higher volume of *normal* permissions sought. Second, they reduce their reliance on third-party analytics tools on Android, also a spillover effect from iOS, where they naturally reduce gathering third-party data post ATT restrictions. Interestingly, this did not affect their ad strategies, suggesting that their ad strategy of displaying targeted advertisements can be effectively executed with first-party usage data instead of third-party analytics. In Sections 4.2 and 4.3, we further explore how these changes impact the app quality outcomes and market structure, respectively.

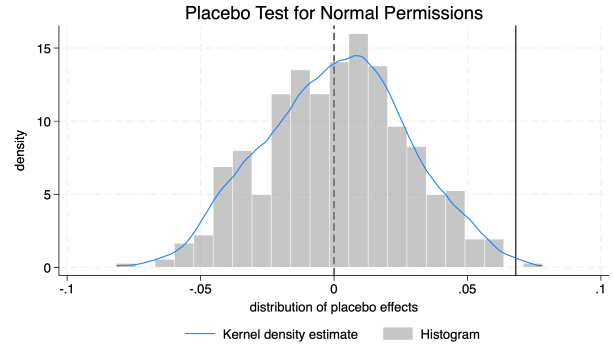
4.1.3. Robustness Checks The first robustness check involves employing a Poisson regression to account for the count nature of Permissions and SDK. Appendix Tables A3 and A5 present the results for *Permission* and *SDK* analyses, respectively. The findings align with our main findings.

Second, we address potential autocorrelation concerns in panel data by collapsing time-series data into two observations per app: one for pre-treatment and one for post-treatment period, following Bertrand et al. (2004). This approach mitigates the influence of time-dependent correlation within apps. We estimate the Model 1 on this collapsed dataset and present the results for permissions analysis in Appendix Table A4 and that for SDK analysis in Appendix Table A6. Both results remain consistent with our main findings.

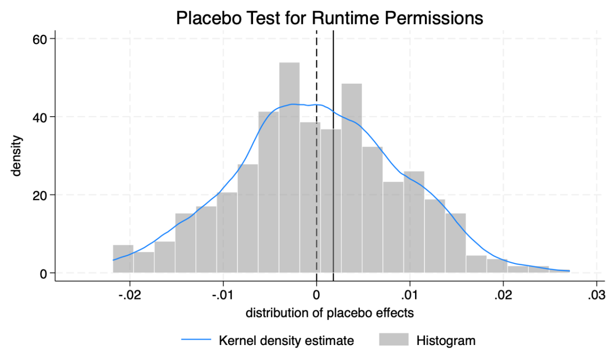
Finally, we bolster the robustness of our empirical strategy through the in-space placebo test, as demonstrated in the literature (Burtch et al. 2018, Mayya and Li 2024). In these tests, we randomly assign treatment status to Android-specific apps that were, in reality, never exposed to the treatment. By conducting simulations with these "fake" treatments and re-estimating our model, we can gauge the likelihood of observing effects of a similar magnitude to our actual treatment effect purely by chance. The results of these tests for the Permissions analysis for the three types of permissions (overall, normal, and runtime) are presented in Figure 8 and those for three integrated SDKs categories (core feature improvement, analytics, advertising and monetization, and data intelligence) in Figure 9. The distribution of the placebo effects, centered around zero, indicates that the observed impacts on permissions and SDKs are indeed attributable to iOS ATT exposure, rather than spurious correlations.



(a) Overall Permissions



(b) Normal Permissions



(c) Runtime Permissions

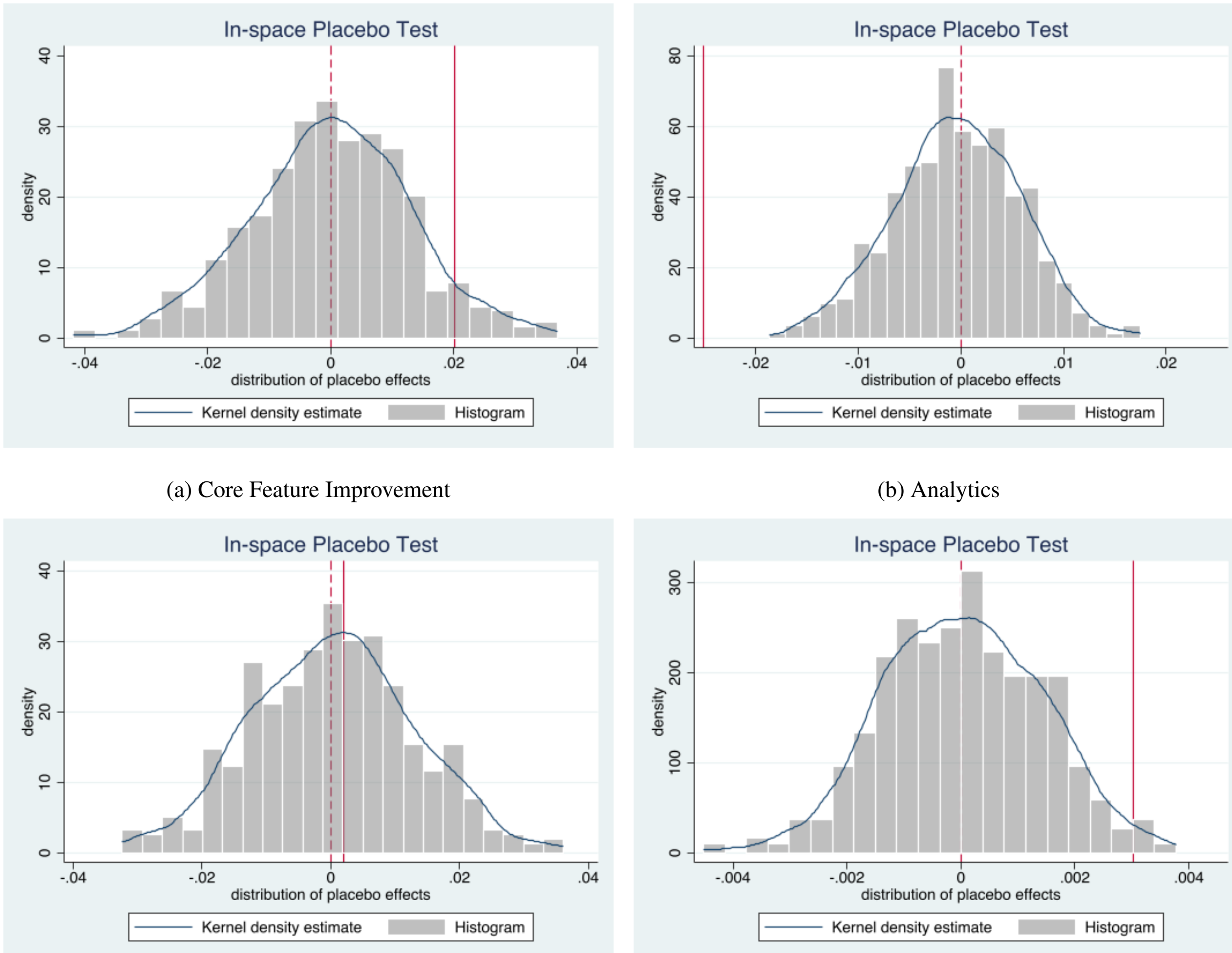
Note: The x-axis represents distribution of placebo effects and the y-axis represents the density.

Figure 8 The Placebo Test for the Permissions on Android

4.2. How does iOS ATT impact the Android App Quality Outcomes via Spillover?

Building on Section 4.1's finding that multihoming developers chose to adapt the utility-enhancing changes on iOS to their Android apps as well, we examine impacts on app quality outcomes. We estimate Equation 1 with the weekly value of $RatingValue_{it}$ as the dependent variable, which measures weekly aggregate of user satisfaction rating values. As detailed in Section 3.1, our analysis compares multihoming apps (treatment) with Android-exclusive apps (control). Figure 10 confirms parallel pre-treatment trends between groups, satisfying the quasi-experimental requirements.

The results are presented in Table 4. Multihoming apps experience a significant increase in their weekly average rating value on Android following the implementation of ATT, with coefficients of 0.037 (TWFE model) and 0.032 (Synthetic DiD model). To contextualize this observed effect, we perform a back-of-the-envelope calculation. Given our dataset's mean weekly rating count of 859, a 0.037 increase represents



(a) Core Feature Improvement

(b) Analytics

(c) Ads and Monetization

(d) Data Intelligence

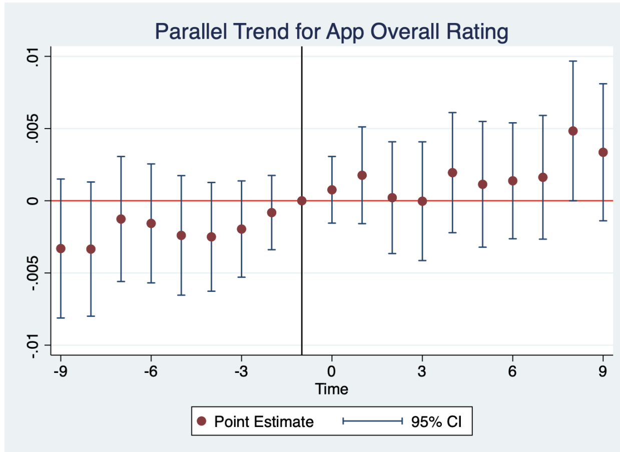
Note: The x-axis represents distribution of placebo effects and the y-axis represents the density.

Figure 9 The Placebo Test for the SDK Count on Android

approximately 127 users increasing their ratings by one additional star monthly (i.e., 859 ratings $\times$ 0.037 increase $\times$ 4 weeks). This effect is economically significant, especially considering rating stability in apps with large install bases (e.g., Ruiz et al. 2015). Next, we apply winsorization to the weekly ratings at the 10^{th} and 90^{th} percentiles to address rating boundary deviations.[14] Results remain consistent in columns (2) and (4) for TWFE DiD and Synthetic DiD, respectively.

4.2.1. Falsification Test: Rating impact on apps that increase "intrusiveness": We conduct a falsification test by examining the rating of multihoming apps that increased their intrusiveness on Android.

[14] Weekly *RatingValue* tend to deviate from the 1 and 5 boundary when Play Store removes flagged/fraudulent reviews.



Joint significance test for pre-treatment variables is 0.75 ($p = 0.70$)

Figure 10 Parallel Trend on App Rating

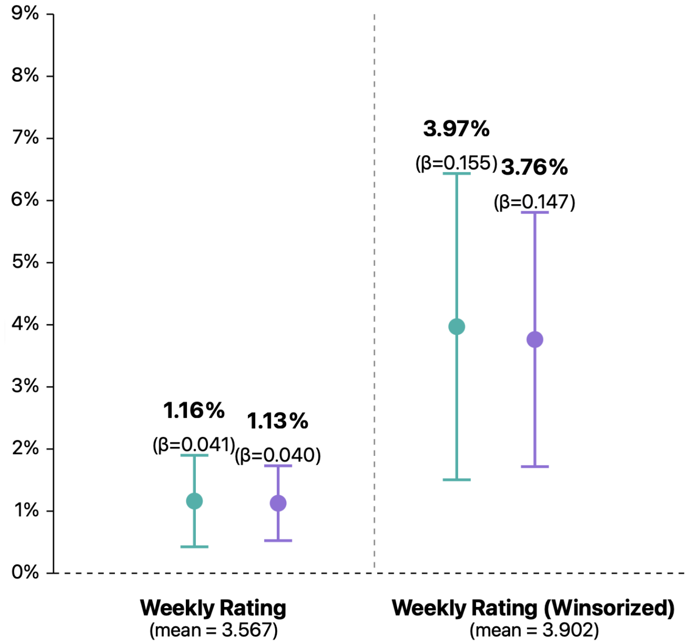
Table 4 Impact of iOS ATT on Weekly Rating on Android

	Matching + TWFE DiD		Synthetic DiD	
Dependent Variable	Weekly Rating (1)	Weekly Rating (winsorized) (2)	Weekly Rating (3)	Weekly Rating (winsorized) (4)
$Multihoming \times ATT\_Enacted$	0.037** (0.017)	0.152** (0.063)	0.032** (0.014)	0.125** (0.056)
App Fixed Effects	Y	Y	Y	Y
Week Fixed Effects	Y	Y	Y	Y
Observations	229,528	229,528	322,400	322,400

Note: *p<0.1; **p<0.05; ***p<0.01; Standard Errors clustered around apps in parentheses for TWFE. Bootstrapped Standard Errors with 100 replications in parentheses for Synthetic DiD.

We define “intrusiveness increase” as an increase in runtime permissions, Analytics SDKs, or Ad Network SDKs beyond the pre-ATT median value for each app. Out of the 4,414 apps, 924 apps that exhibited this behavior. So, we perform a triple difference analysis where we interact the DiD terms with the binary variable $Intrusive_i$ which carries the value of 1 for treated apps that increase the intrusiveness. We present the results in Appendix Table A7. Column (3) of Appendix Table A7 reveals a negative and significant impact on app ratings for apps that increased intrusiveness on Android faced negative consequences, as seen by the triple difference estimate. The sub-sample analyses on columns (1) and (2) provides similar insights.

4.2.2. Robustness Checks: As in section 4.1.3, we conduct multiple robustness checks. First, to ensure that our findings are not an artifact of the weekly rating measurement, we use the raw value of *RatingValue* as the dependent variable and re-estimate Equation 1. The results are presented in column (1) of Appendix



Note: In each set, the left (green) coefficient is of TWFE DiD and the right (purple) one is of Synthetic DiD.

Figure 11 Coefficient Graph for Weekly Ratings - Longer Time Period (55 weeks)

Table A8. Next, we perform a log transformation of cumulative rating and present the results in column (2) of Appendix Table A8. Both results are consistent with main findings. Next, we address potential auto-correlation concerns as noted by Bertrand et al. (2004) by collapsing the time-series data into two time-periods—before and after— and present the model estimation results in Appendix Table A9. The results remain consistent with our main findings.

Finally, we conduct in-space placebo tests, as outlined in Section 4.1.3, to further validate the robustness of our findings. The visual representations of these placebo tests for Weekly Ratings on Android and winsorized Weekly Ratings on Android, shown in Panels A and B of Appendix Figure A3 respectively, further validate our findings. Consistent with what we found in section 4.1.3, the distributions of the placebo effects are centered around zero. This strengthens our confidence that the observed effects are attributable to the actual treatment and not any spurious correlations.

4.3. How does iOS ATT impact the Market Structure on Android via Spillover?

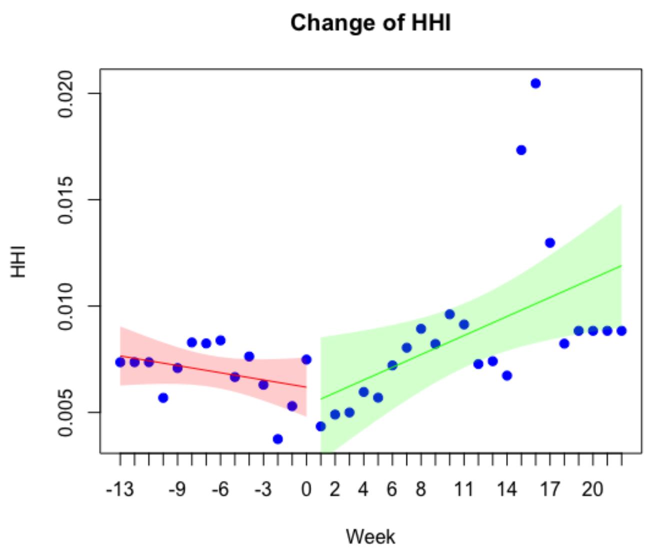
A pertinent question arises: why should competing platforms be concerned about such spillovers, especially if they seem beneficial? In fact, our empirical analysis so far suggests precisely that: the improvements in multihoming apps on Android are likely driven by iOS ATT, creating a positive externality that enhances the overall quality outcomes of the Android app ecosystem. Specifically, the introduction of iOS ATT, which restricted third-party tracking, incentivized multihoming apps to adapt and focus on enhancing app features (e.g., Kesler 2023) and investing in usage data collection to better understand user preferences and app bottlenecks. Such strategy adaptations on iOS and their eventual adaptations on Android are straightforward given the availability of a many tools like Google's Flutter, which help apps maintain a common codebase.

The central concern lies in the impact that policies on one platform may have on the market structure of the competing platform. Our analyses suggest that multihoming apps are "forced" to improve their utility on iOS, which spills over to Android, whereas the Android exclusive apps do not have such a jolt. Multihoming Android apps already held a substantial average market share of 64.79% among apps before ATT,[15] because of several factors, including visibility, reach and seamless user-experience when users move across mobile platforms. Given this substantial market share, understanding how iOS policy could influence the market structure on Android is crucial.

To examine the impact of iOS ATT on the market structure of Android, we analyze market concentration changes of the Android market using the Herfindahl-Hirschman Index (HHI). HHI, calculated as the sum of the squares of the market shares of all apps in the Android market in a week, measures the market concentration—higher values signify a more concentrated market, whereas a lower HHI indicates a more competitive market, with downloads more evenly distributed among apps. Using weekly download estimates of top 2,674 apps, we compute each app's market share as its downloads relative to total market downloads. We then measure the market concentration using the market shares, calculated as $\sum_i s_i^2$ where s_i is the market share of app i. As shown in Figure 12, we find that the average HHI, based on weekly download estimates of the top 2,674 apps, increases from a mean value of 0.00675 before ATT to 0.0090 after ATT, which represents a 33% increase.

To rigorously test our intuition regarding the market concentration, we set up a panel regression by pre-processing the 2,674 apps using matching techniques as outlined in Section 3.3 based on their pre-ATT

[15] We calculate this based on the average downloads for the 2,674 apps in our dataset.



The line represents the average HHI and the band represents 95% confidence interval.

Figure 12 Market Concentration in Android

rating, rating count, download estimate and permission count. This procedure results in a dataset of 2,334 apps included in the final analysis. Figure 13 confirms parallel pre-ATT trends.

We first examine if the market concentration changes reflect a "rich get richer" effect through an exploratory app-level analysis of market share based on download estimates. For each app, we calculate the average market share before-ATT ($PreATTShare_i$) and after-ATT ($PostATTShare_i$), and compute the market share increase percentage, $Marketshare\_Increase\_Pct_i$ as ($PostATTShare_i -$ $PreATTShare_i$)/($PreATTShare_i$). We then estimate the regression model:

$$Marketshare\_Increase\_Pct_i = \gamma \log(PreATTShare_i) + \mu_i AppCategory_i + \varepsilon_i \tag{4}$$

where, $AppCategory_i$ represents app category dummy. As noted above, this exploratory analysis has one observation per app. Panel (a) of Table 5 shows apps with higher pre-ATT market shares, as measured by $\log(PreATTShare_i)$, experienced larger percentage increases post-ATT.

Building on this exploratory analysis, we estimate a Fractional Logit model on the weekly market share for each of the 2,334 apps. Fractional Logit Models are useful if the dependent variable is a fractional value between 0 and 1 (Papke and Wooldridge 2008). Specifically, we utilize the mixed effect models, a class of statistical models that incorporate both fixed and random effects, allowing us to capture the unique characteristics of each app and to incorporate random intercepts for each app in the model. Panel (b) of Table 5 confirms an increasing market share for multihoming apps.

Table 5 Market Share Analysis

(a) Change in Market Share of Apps

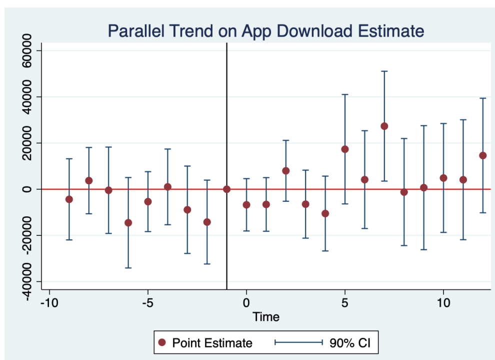
Dependent Variable	Marketshare Increase (Percentage)
log(PreATTShare)	0.023***
	(0.006)
Category Fixed Effects	Y
Observations	2,334

Note: *p<0.1; **p<0.05; ***p<0.01

(b) Impact of iOS ATT on Market Share

	Fractional Logit
Dependent Variable	Market share
Multihoming×	1.707***
ATT_Enacted	(0.345)
App Mixed Effects	Y
Week Fixed Effects	Y
Observations	84,024

Note: *p<0.1; **p<0.05; ***p<0.01



Joint significance test for pre-treatment variables is 0.91 $(p = 0.53)$

Note: The x-axis represents time and the y-axis represents the effect size.

Figure 13 The Parallel Trend on App Download Estimate

Finally, we estimate the model (1) using the log transformed downloads as the dependent variable for the matched 2,334 apps and present the results in Table 6. The result is positive and statistically significant: multihoming apps experience a 26.49% boost in downloads per TWFE model in Column (1) (calculated as $(e^{0.235} - 1) \times 100 = 26.49\%$) or a 15.95% boost in downloads per Synthetic DiD model in Column (2). Robustness checks using collapsed panel data (Appendix Table A10) and in-space placebo tests (Appendix Figure A4) confirm the robustness, with placebo distributions centered at zero.

Table 6 Impact of iOS ATT on Downloads

	Matching + TWFE DiD	Synthetic DiD
	log(Download) (1)	log(Download) (2)
$Multihoming \times ATT\_Enacted$	0.235*** (0.037)	0.148*** (0.028)
App FE	Y	Y
Week FE	Y	Y
Observations	84,024	96,264

Note: *p<0.1; **p<0.05; ***p<0.01; Standard Errors clustered around apps in parentheses for TWFE.
Bootstrapped Standard Errors with 100 replications in parentheses for Synthetic DiD.

Overall, our analysis of the Android market structure reveals a significant increase in market concentration following the implementation of iOS ATT, driven by a substantial download boost for multihoming apps compared to Android-exclusive apps. In other words, a privacy policy change on one platform can hinder innovation and reduce user choice over time on a competing platform.

Market Concentration and Rating: One potential interpretation is that the increased market concentration is not necessarily bad for consumers, as it is possible that the apps that lost market shares are the inferior ones. If this interpretation is true, the increased marketshare should be driven by apps which had higher rating prior to ATT. To test this possibility, we estimate the following model:

$$Marketshare\_Increase\_Pct_i = \gamma PreATTRating_i + \mu_i AppCategory_i + \varepsilon_i \tag{5}$$

where $PreATTRating_i$ is the mean rating of app i pre ATT. If γ is positive and significant, it asserts the aforementioned interpretation that high *quality* apps are more likely to gain market shares, i.e., the market being concentrated is a result of better apps becoming larger. Table 7 presents the results. The pre-ATT rating does not meaningfully explain a change in the app's marketshare, as seen by the insignificant γ. This provides evidence that there is no correlation between app quality and change in market shares, i.e., it is possible that apps with high pre-ATT rating also lose marketshare because of the lack of pressure from iOS ATT to innovate.

5. Discussion and Conclusion

The landscape of private platform data collection policies is undergoing a major transformation, driven by increasing consumer demand for greater control over their personal data (Madden and Rainie 2015). The

Table 7 Change in Market Share and Quality

Dependent Variable	Marketshare Increase (Percentage)
PreATTRating	0.013
	(0.043)
Category Fixed Effects	Y
Observations	2,334

Note: *p<0.1; **p<0.05; ***p<0.01

literature has extensively explored the impact of these privacy policies on the focal platforms themselves, with studies such as Aridor et al. (2024), Bian et al. (2021), Cheyre et al. (2023), Kesler (2023), Kircher and Foerderer (2024), Leyden (2025), Tripathi and Kyriakou (2021) and Mayya and Viswanathan (2024), providing valuable insights into the supply-side and demand-side effects of such policies. Concurrently, the phenomenon of developer multihoming is witnessing an increasing incidence due to the availability of modern cross-platform development tools, especially in the realm of mobile platforms. However, the intersection of these tree trends—the evolving privacy landscape, the prevalence of multihoming, and the explosion of popularity of cross-platform development tools—results in an complex interplay that has yet to be fully explored. The potential for privacy policies to spill over across platforms, particularly through shared codebases, raises interesting questions about their implications on platform ecosystems.

Whereas multimarket spillover due to regulations is not new—it is a classic topic that dates back to Bernheim and Whinston (1990) and Genakos and Valletti (2011)—most research has focused on spillovers of price-focused regulations. The extractive nature of price leads to an increase in price in the unaffected market as spillover (Genakos and Valletti 2011). Multimarket spillovers because of data regulations, on the other hand, is different and less studied. Its dual role—extractive, through targeted advertising, and productive, by enhancing personalization and user experience—fundamentally alters how developers strategically respond to privacy policies, and therefore could have outcomes significantly different from conventional economic models of compensatory price adjustments.

Ours is one of the first papers to study privacy spillovers in the context of competing smartphone platforms. If developers, in response to stricter privacy policies on one platform, choose to decouple their codebases and offset potential revenue losses by adopting more privacy-intrusive practices on competing platforms, it could significantly undermine user experiences and trust in competing platforms. Conversely, if developers opt to enhance both app quality and user experience across all platforms in response to privacy regulations on one of the platforms, it could benefit users on competing platforms through improved app functionality and data practices. Given that spillovers have far-reaching consequences for both consumers and platform owners, conducting a thorough empirical investigation of this phenomenon is imperative.

Our analysis of spillover effects reveals how developers adapt their Android strategies in response to iOS ATT. The permissions analysis shows that multihoming apps significantly enhanced their *normal* permissions usage. Normal permissions are used to obtain usage data, such as reading the network status (e.g., mobile data, no connection, etc.), phone status (e.g., carrier locked/unlocked), connectivity status (e.g., Bluetooth on/off, Wi-Fi Status, FM Radio, etc.) or app status (e.g., is an app operational). Normal permissions are also used to perform activities such as toggling networks, turning on the flashlight, phone vibration, or clearing the cache. All functionalities are used to enhance app utility without sensitive, personal data.

Similar to permission analysis, we analyze the use of integrated SDKs in apps. We observe a significant boost in the use of core feature development SDKs.[16] Core feature development SDKs assist apps with tasks such as backend processes, communication, CRM, social engine as well as core development tasks involving programming languages. Hence, an increase in such SDKs points towards enhancing app features. We also observe a notable increase in the use of data intelligence SDKs, which leverage first-party real-time sensor data to offer contextually relevant solutions directly benefiting users. The pattern is consistent with the change in core feature development SDKs. Interestingly, we observe a decrease in the use of third-party analytics SDKs on Android. The decrease indicates that developers move away from over-utilizing multiple different third-party data analytics, given the marked drop in behavioral insights without cross-app tracking in iOS. Given that these apps are forced to innovate on iOS, they find it efficient to push these improvements to Android and minimize relying on extensive behavioral tracking. In addition, while researchers have noted a decrease in ad network utilization on iOS following ATT implementation (e.g., Cheyre et al. 2023), we find that the use of advertising and monetization SDKs remains stable on Android. This implies that developers

[16] In an unreported test, we analyzed whether payment SDKs changed on Android, in line with Kesler (2023). We find no evidence that Android apps increased payment SDKs.

are not abandoning advertising and monetization strategies on Android because of iOS policy changes. Overall, this strategic shift towards first-party usage data and away from third-party user data aligns with the broader industry trend prioritizing user privacy and control over personal information. The two key takeaways from our mechanism analyses are that (a) multihoming apps do not compensate for their revenue loss on iOS by being intrusive on Android, and (b) apps do not fundamentally change their monetization strategy on Android to focus on paid features, unlike in iOS (Aridor et al. 2024, Kesler 2023, Cheyre et al. 2023). Instead, they continue to rely on ad revenue.

Next, we investigate whether the utility enhancing spillovers to Android are noticeable to the Android users. Indeed, multihoming apps experience significant increases in user ratings on Android after the implementation of iOS ATT policy. This supports our intuition that utility improvements made to multihoming apps on iOS, in response to ATT's stricter privacy regulations, reach Android versions due to the common codebase. Given that hiring additional developers to maintain separate codebases for each platform could be cost-prohibitive, this finding intuitively makes sense.

While the developers' actions have a positive spillover on Android, we document a surprising unintended consequence on Android's market structure. Our analysis reveals that the Herfindahl-Hirschman Index (HHI), a measure of market concentration, increases significantly for Android following the implementation of ATT on iOS. Specifically, the HHI rose significantly based on download estimates, indicating that the Android app market became more concentrated after the iOS privacy policy change. This increased concentration is driven by a substantial increase in downloads for multihoming apps, which rose by approximately 26.49% compared to Android-exclusive apps. While the short-term benefits for app users on Android because of the "extraterritorial" policy are imminent because of quality enhancement, the medium- to long-term impacts on users due to increased market concentration could be concerning to platform owners. This is due to uncompetitive market structures that this spillover may create.

5.1. Implications for Research

Our study contributes meaningfully to the literature on privacy regulation, multihoming, and platform competition, and addresses important gaps.

First, existing scholarship on regulatory spillovers predominantly emphasizes compensatory adjustments in pricing or product availability (Genakos and Valletti 2011). We extend this literature by uncovering and documenting a new form of spillover—privacy spillovers—driven by the dual role of data as both a productive and extractive resource. By demonstrating how privacy spillovers diverge fundamentally from price-based spillovers, our findings provide a new theoretical lens for understanding strategic interdependencies among digital platforms.

Second, previous studies examining developer responses to privacy regulation have focused primarily on single-platform adjustments, leaving unclear how such responses diffuse across platforms through shared development resources (Cheyre et al. 2023, Kesler 2023). We explicitly fill this gap by empirically showing how multihoming developers adopt unified strategies, transferring privacy-induced innovations from the regulated platform (iOS) to an unregulated competing platform (Android). This expands our theoretical understanding of multihoming behavior and highlights the centrality of shared codebases and cross-platform development tools in shaping regulatory spillover effects.

Third, although prior research extensively explores direct impacts of privacy policies on consumers and platform participants (e.g., Mayya and Viswanathan 2024), less attention has been paid to their indirect competitive consequences on market structures. Our findings fill this gap by illustrating how seemingly beneficial consumer-oriented privacy policies may unintentionally reinforce market dominance among multihoming developers. This enriches the discussion on digital market dynamics and structures.

5.2. Private Platform Policy and Practical Implications

For platform policymakers, our research underscores the need for a thorough understanding of the strategic implications of competitors' data collection policies. A key takeaway from our study is that a privacy-enhancing policy enacted on one platform can influence the market structure of competing platforms. Although the focus is often on enhancing privacy on the focal platform, we demonstrate that the spillover effects on competing platforms can be significant. Even if a competitor's policy change does not align with the focal platform's own revenue model, it is crucial to extensively evaluate and potentially implement similar policies to prevent unintended negative impacts on platform-specific apps. Therefore, platforms should proactively monitor competitors' policies to maintain a competitive edge while fostering a fair and thriving app ecosystem.

From a strategic perspective, our findings highlight a potential avenue for using privacy-enhancing policies to gain a competitive edge over competing platforms. The impact of privacy spillovers on competing platforms may depend on the underlying revenue model of that platform. We show that when platforms such as iOS, on which apps are relatively less reliant on ad revenues, enhance privacy, they trigger a series of events that lead to increased concentration within the competing platform's app ecosystem. Especially for competing platforms like Android, where ad revenue is the predominant revenue model, enhancing privacy may not be the most suitable approach. Nonetheless, our findings suggest that even platforms that are less suited for privacy enhancement should carefully evaluate and potentially adopt a variant of the privacy policy that aligns with their unique characteristics and revenue models. In a setting with only two dominant players, such a proactive policy enactment may shield competing platforms from the strategic deployment of privacy policies as a competitive weapon.

For app developers, especially those exclusively on one platform, a privacy-enhancing policy on an unrelated platform can also significantly affect their market standing. Staying informed about policy changes on competing platforms is crucial, as these changes can indirectly affect their market position, necessitating proactive strategies to enhance their offerings. This involves actively monitoring industry publications, engaging with developer communities, and participating in relevant conferences to keep themselves updated not just on policy changes but also on best practices. As noted by Mayya and Viswanathan (2024), even if implementing progressive policies may lead to a short-term revenue dip, it might be beneficial in the medium to long term. In the process, our paper extends burgeoning research that documents developers' strategies on focal platforms (Kesler 2023, Cheyre et al. 2023).

5.3. Future Research

Our research design focuses on the spillover effects of Apple's ATT, aimed at privacy enhancement on iOS, on the Android platform. Future research could extend this analysis to other contexts of supplier multihoming, such as ride-hailing (e.g., Uber, Lyft), hospitality (e.g., Airbnb), and online education (e.g., Coursera), to examine the generalizability of our findings. Different markets may experience varying degrees of competition, and the impact of privacy policy spillovers can become more or less pronounced depending on the specific market dynamics.

In our context, only one of the two competing platforms introduced a policy change. Future research could investigate contexts where both platforms introduce similar privacy-enhancing policies. This could help determine whether the impact on market concentration is mitigated if both platforms were to adopt comparable privacy measures. Such research could shed light on the competitive dynamics of privacy policy enactments and their implications for market structure.

Third, our study focuses on free apps, as these are more directly affected by privacy policies that target ad revenue models. However, investigating the spillover effects on paid apps may provide valuable insights into consumer behavior and developer strategies. Future research could examine whether consumers of paid apps are less sensitive to privacy changes and whether developers of paid apps adopt different strategies in response to privacy policies on competing platforms.

Finally, we restrict our market-structure analysis to the top 2,674 apps to ensure that data quality from any third-party vendor does not affect the analysis. Unlike ratings, permissions or the SDKs information, true download data is available only with Google and developers, and download *estimation* tracking errors increase with smaller apps. Furthermore, top 2600 apps cover over two-thirds of the downloads, so the insights are unlikely to change significantly by including smaller apps in the long-tail. Future researchers could collaborate with Android to run a large-scale study involving a broader pool of apps.

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Appendix

A. Appendix Figures and Tables

A.1. Appendix Figures

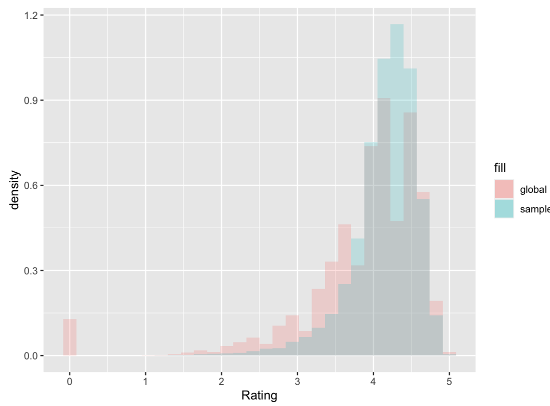
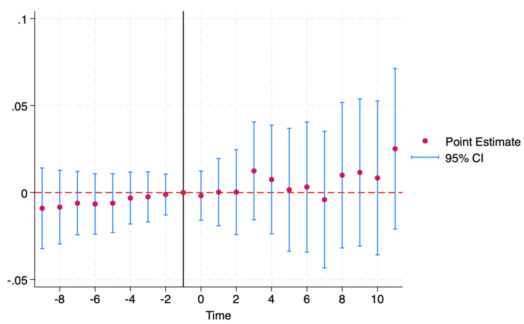


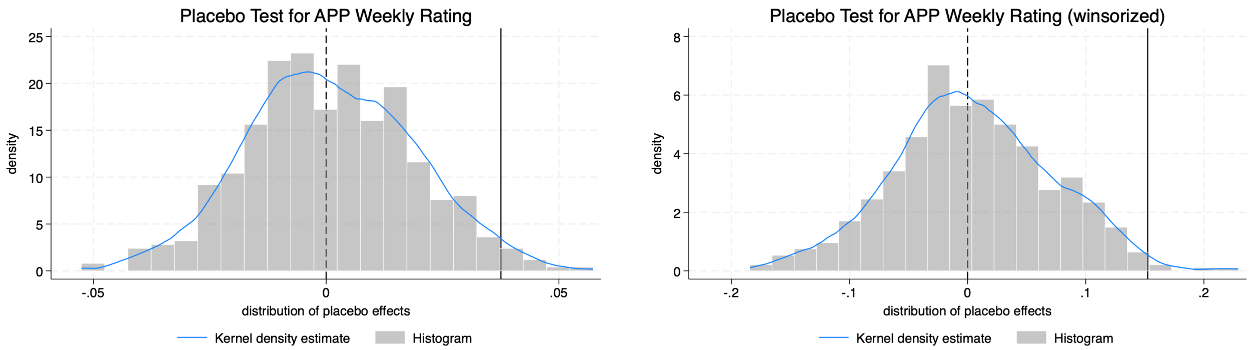
Figure A1 The distribution of rating value: our sample vs. global



Joint significance test for pre-treatment variables is 0.34 $(p = 0.98)$

Note: The x-axis represents time and the y-axis represents the count of ad network SDKs

Figure A2 The impact of ATT on the Ad Network SDKs on Android: Parallel Trends Graph



(a) Weekly Ratings on Android

(b) Weekly Ratings (Windsorized)

Note: The x-axis represents distribution of placebo effects and the y-axis represents the density

Figure A3 The Placebo Test for the Weekly Rating on Android

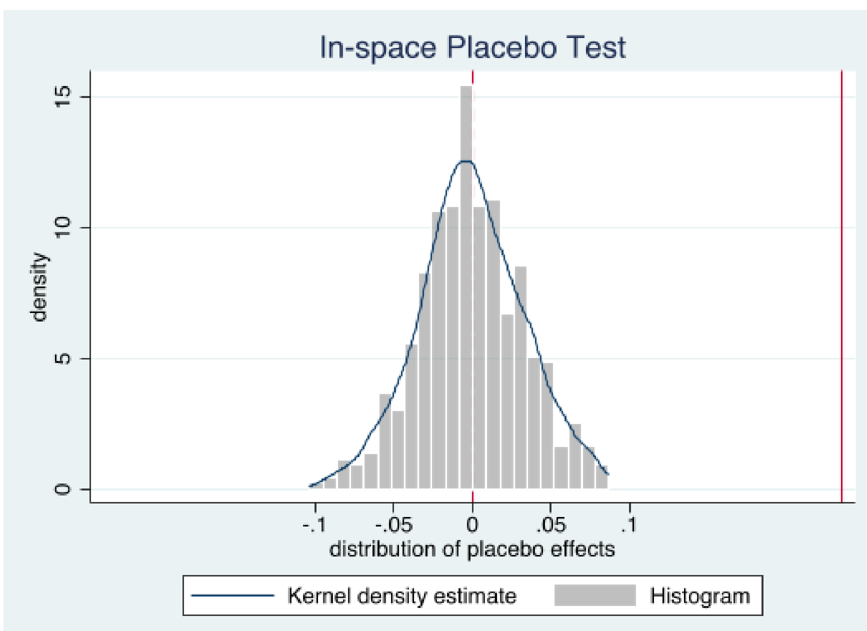


Figure A4 The Placebo Test for Download Estimate

A.2. Appendix Tables

Table A1 Comparison of Apps in our sample versus the global distribution

Category	Sample	Global
TOOLS	12.63%	11.09%
ENTERTAINMENT	8.72%	10.70%
EDUCATION	9.74%	9.97%
PERSONALIZATION	4.28%	7.32%
BOOKS & REFERENCE	3.73%	6.72%
MUSIC & AUDIO	5.70%	6.40%
LIFESTYLE	4.15%	5.86%
FINANCE	5.75%	4.55%
PHOTOGRAPHY	6.13%	4.33%
PRODUCTIVITY	4.74%	3.59%
HEALTH & FITNESS	3.04%	3.08%
COMMUNICATION	3.94%	2.70%
SHOPPING	4.85%	2.64%
SOCIAL	3.43%	2.56%
BUSINESS	2.40%	2.52%
TRAVEL & LOCAL	3.22%	2.49%
NEWS & MAGAZINES	1.92%	2.08%
VIDEO PLAYERS & EDITORS	2.92%	2.05%
MAPS & NAVIGATION	1.69%	1.57%
FOOD & DRINK	1.52%	1.28%
MEDICAL	0.85%	1.13%
WEATHER	1.24%	1.10%
ART & DESIGN	0.77%	0.96%
AUTO & VEHICLES	0.58%	0.82%
DATING	0.60%	0.57%
BEAUTY	0.26%	0.42%
HOUSE & HOME	0.43%	0.40%
COMICS	0.28%	0.40%
PARENTING	0.21%	0.32%
LIBRARIES & DEMO	0.18%	0.26%
EVENTS	0.13%	0.12%
Games		
SIMULATION	11.60%	11.47%
PUZZLE	10.54%	11.33%
CASUAL	13.49%	11.15%
SPORTS	5.62%	10.23%
ACTION	11.88%	8.15%
ARCADE	9.56%	7.85%
ADVENTURE	4.65%	6.76%
ROLE PLAYING	5.24%	5.42%
EDUCATIONAL	4.26%	5.10%
RACING	7.46%	4.00%
CARD	2.28%	3.49%
BOARD	2.65%	3.09%
STRATEGY	3.87%	2.85%
TRIVIA	1.32%	2.76%
WORD	2.61%	2.62%
CASINO	1.79%	2.51%
MUSIC	1.18%	1.22%

We exclude apps below 10000 downloads as most are experimental and one-time use apps (e.g., ICIS 2023 Mobile App).

Table A2 Integrated SDK Categories and their Functionally Relevant Groups

Functionally Relevant Groups	Explanation	SDK Categories	Example SDK
Core Feature Improvement	These integrated SDKs are used to provide a new feature or enhance the usability of the existing features.	Backend Commerce Communication CRM Development Tool Game Engine Social Survey	Amazon AWS Razorpay Telegram Passport Salesforce Mobile Apache Commons IO Unreal Engine 4 WeChat by Tencent Survey Monkey
Analytics	These integrated SDKs are used to understand user behavior and enhance marketing efficiency	Analytics Attribution Marketing Automation	Adobe Analytics Appsflyer SDK Mailchimp
Ads and Monetization	This SDK is used to connect advertisers and publishers	Ad Network	Airpush
Data Intelligence	This SDK is used to generate real-time insights from the collected sensor data for developers to offer contextual solutions	Data Intelligence	Guardsquare

Table A3 Poisson Regression: Impact of iOS ATT on Permissions on Android

	Matching + TWFE DiD		
	Overall Permissions (1)	Runtime Permissions (2)	Normal Permissions (3)
Multihoming× *ATT_Enacted*	0.008*** (0.002)	-0.004 (0.004)	0.012*** (0.002)
App FE	Y	Y	Y
Week FE	Y	Y	Y
Observations	229,528	229,528	229,528

*p<0.1; **p<0.05; ***p<0.01

Standard Errors clustered around apps in parenthesis.

Table A4 Impact of iOS ATT on Permissions on Android: Collapsing the Dataset

	Matching + TWFE DiD		
	Overall Permissions (1)	Runtime Permissions (2)	Normal Permissions (3)
Multihoming× *ATT_Enacted*	0.070** (0.031)	0.002 (0.009)	0.068** (0.028)
App FE	Y	Y	Y
Observations	17,656	17,656	17,656

*p<0.1; **p<0.05; ***p<0.01

Standard Errors clustered around apps in parenthesis.

Table A5 **Zero-Inflated Poisson Regression: Impact of iOS ATT on Integrated SDKs on Android**

	Matching + TWFE DiD			
	Core Feature Improvement SDK Count	Analytics SDK Count	Ads and Monetization SDK Count	Data Intelligence SDK Count
	(1)	(2)	(3)	(4)
$Multihoming \times$ $ATT\_Enacted$	0.013^{***} (0.005)	-0.029^{***} (0.011)	0.008 (0.007)	0.437^{***} (0.067)
Observations	229,528	229,528	229,528	229,528

*p<0.1; **p<0.05; ***p<0.01

Standard Errors for DiD in parenthesis.

Table A6 **Impact of iOS ATT on Integrated SDKs on Android: Collapsing the Dataset**

	Matching + TWFE DiD			
	Core Feature Improvement SDK Count	Analytics SDK Count	Ads and Monetization SDK Count	Data Intelligence SDK Count
	(1)	(2)	(3)	(4)
$Multihoming \times$ $ATT\_Enacted$	0.044^{**} (0.022)	-0.024^{***} (0.007)	0.014 (0.017)	0.003^{**} (0.001)
App FE	Y	Y	Y	Y
Observations	17,656	17,656	17,656	17,656

*p<0.1; **p<0.05; ***p<0.01

Standard Errors clustered around apps in parenthesis.

Table A7 **Impact of iOS ATT on Rating on Android: Intrusiveness* Analysis**

	Matching + TWFE DiD		
	Increased Intrusiveness	Did not increase Intrusiveness	All Apps
	Weekly Rating	Weekly Rating	Weekly Rating
	(1)	(2)	(3)
$Multihoming \times$ $ATT\_Enacted$	-0.039 (0.039)	0.058^{***} (0.019)	0.052^{***} (0.018)
$Multihoming \times$ $ATT\_Enacted \times Intrusive$			-0.068^{**} (0.031)
App FE	Y	Y	Y
Observations	48,048	181,480	229,528

*p<0.1; **p<0.05; ***p<0.01

Standard Errors clustered around apps in parenthesis.

* As noted in Section 4.2.1, increased intrusiveness is measured as an increase in runtime permissions, Analytics SDKs, or Ad Network SDKs beyond the pre-ATT median value for each app

Table A8 Impact of iOS ATT on Rating on Android: Cumulative Rating

	Matching + TWFE DiD	
Dependent Variable	Rating Value (1)	log(Rating Value) (2)
Multihoming× *ATT_Enacted*	0.004^{**} (0.002)	0.001^{*} (0.0005)
App Fixed Effects	Y	Y
Week Fixed Effects	Y	Y
Observations	229,528	229,528

Note: *p<0.1; **p<0.05; ***p<0.01

Standard Errors clustered around apps in parenthesis.

Table A9 Impact of iOS ATT on Weekly Rating on Android: Collapsing the Dataset

	Matching + TWFE DiD	
Dependent Variable	Weekly Rating (1)	Weekly Rating (winsorized) (2)
Multihoming× *ATT_Enacted*	0.038^{**} (0.017)	0.152^{**} (0.063)
App Fixed Effects	Y	Y
Observations	17,656	17,656

Note: *p<0.1; **p<0.05; ***p<0.01

Standard Errors clustered around apps in parenthesis.

Table A10 Impact of iOS ATT on Download: Collapsed Dataset

	Matching + TWFE
Dependent Variable	ln(Download)
Multihoming× *ATT_Enacted*	0.235^{***} (0.037)
App Fixed Effects	Y
Week Fixed Effects	Y
Observations	4,668

Note: *p<0.1; **p<0.05; ***p<0.01

Standard Errors clustered around apps in parenthesis.

B. Classifying Categories

The primary task is to determine the category of SDKs using their descriptions. The box below presents the annotation guidelines and the prompt that we used in employing LLMs for this classification task, developed using the guidelines by (Cheng et al. 2024). The prompt is as follows:

```
You are an experienced software engineer with extensive contributions to mobile app
development projects. You will receive the name of an integrated mobile SDK along with
its description. Your task is to meticulously analyze the description and classify the
SDK into one of the categories that apply from a list of four categories: Core Feature
Development, Analytics, Advertising and Monetization, and Data Intelligence, based on
its purpose or usage. Remember that an SDK might belong to more than one category, but
be sure to tag the most appropriate category based on its functionality and intended
use.
1. Core Feature Development: SDKs that provide essential functionalities for users'
utility. Core Feature Development SDKs can help improve the functionalities such as
simplifying the integration of backend services, audio and video editing features,
providing solutions for commerce, enabling in-app messaging, voice, and video calls
between users, managing customer relationships, improving code development workflows,
offering tools for game development, graphic rendering and immersive experiences,
integrating social media functionalities, including sharing, liking, and posting,
creating, distributing, and analyzing surveys within apps.
2. Analytics: SDKs that help data collection to understand user behavior and optimize
performance. Analytics SDKs can help improve the functionalities such as, attributing
user actions back to advertising campaigns or referral sources, automating marketing
tasks and workflows based on user behavior, and crash reporting and user flow tracking.
3. Advertising and Monetization: SDKs that enable monetization through displaying
advertisements. Advertising and Monetization SDKs can also help sampling apps or games
via displaying advertisements, targeted promotions, as well as providing tools for
marketing automation including geofencing.
```

```
4. Data Intelligence: SDKs that automatically generate real-time insights from the
collected sensor data, such as location or connectivity data, which can be used by
developers to offer contextual solutions.
Additionally, if you strongly feel that the SDK may also belong to a second category,
you can provide the potential second category and justify it in the reason.
Your response should be in a valid JSON format and strictly contain only the JSON,
with all string values enclosed in double quotes. The response must include the 'id'
(a string), 'category' (a string), 'potential_second_category' (a string), and
'reason' (a string). For example:
{
  \"id\": \"digiIntelligence SDK\",
  \"category\": \"Data Intelligence\",
  \"potential_second_category\": \"None\",
  \"reason\": \"This SDK offers real-time asset tracking solutions designed for every
  business.\"
}
Remember to consider the context and implications of each description while
categorizing the SDK. Do not include a double quote or commas inside the reason.
```

To choose the best model, we benchmarked some of their performances against human tagging. We first randomly selected 150 SDKs and their descriptions and got them tagged by three expert human annotators. We then compared the outcome from five different LLMs (GPT 4o, GPT 4.1, GPT o3, GPT o1, Deepseek R1 and Deepseek V3) with human tags and found that GPT o1 outperformed the other LLMs. Table B1 shows the outcomes of the model and the Cohen's Kappa for the agreement between expert human annotators and the LLM predictions. The Cohen's Kappa is above 0.6 for gpt o1 model, which puts the agreement at the "substantial" level, as noted in extant research (e.g., Cohen 1960, McHugh 2012). As a result, we employed gpt o1 for our annotation task. Table B2 presents the model details. The total input SDKs uploaded to the model for the entire process were around 1305 SDKs. The total output SDKs generated by the model were approximately 1305 SDKs.

Table B1 **The accuracy of LLMs compared to human annotated ground truth.**

Model	Agreement Rate	Cohen's Kappa
deepseek-reasoner (deepseek-r1)	83.33%	0.73
deepseek-chat (deepseek-v3)	83.33%	0.73
gpt-4o-2024-08-06	83.33%	0.74
gpt-4.1-2025-04-14	86.00%	0.77
gpt-o3 (o3-2025-04-16)	88.00%	0.81
gpt-o1 (o1-2024-12-17)	89.33%	0.83

Table B2 **The Model Parameters**

Model	Endpoint	Top-p	Frequency Penalty	Presence Penalty
o1-2024-12-17	chat completion	1.0	0.0	0.0