Sherlocking: The Effects of Platform-Owner Entry on the Competitive Behavior of Third-Party Firms*

Benjamin T. Leyden†

January 16, 2026

Working paper. The latest draft is available here.

I study how third-party firms respond when a platform owner enters its own marketplace by analyzing 23 instances of Apple entering App Store submarkets between 2016 and 2021. Using text embeddings to define markets from product descriptions and a staggered difference-in-differences design, I document striking heterogeneity in competitive responses. Monetization and quality responses vary across markets, with many markets showing no meaningful responses. Within markets, impacts vary spatially: apps similar to Apple's offering often experience substantially different effects than more differentiated apps. Responses also depend on how Apple entered: integrated OS features generate different responses compared to standalone apps. This heterogeneity—across markets, spatially within markets, and between entry types—suggests a more nuanced approach to regulating platform-owner entry may be warranted relative to categorical, platform-wide restrictions.

*I am grateful to Qihong Liu, Chiara Farronato, Devesh Raval, and participants at the 20^{th} Annual International Industrial Organization Conference, the NYU Economics of Strategy Workshop, the NUS Economics of Platforms Workshop, ASSA 2023, the US DOJ Economic Analysis Group, the Cornell Strategy and Economics of Digital Markets Conference, HKUST workshop, the 2025 CESifo Economics of Digitization Conference, the University of Sydney, and APIOC 2025 for helpful comments. I thank Yujie Feng for excellent research assistance, and I acknowledge the Cornell Center for Social Sciences for financial support.

†Cornell University; CESifo; leyden@cornell.edu

1 Introduction

Platform-owner entry into digital marketplaces has become a central issue in antitrust policy and the regulation of digital markets (De Chant, 2022). The practice—where marketplace operators compete with third-party sellers in their own platforms—has prompted significant regulatory debate worldwide. The European Union's Digital Markets Act, enacted in 2022, explicitly restricts "gatekeepers" from engaging in "any form of differentiated or preferential treatment... in favour of products or services it offers itself" (EUR-Lex, 2022). In the United States, the previously proposed American Innovation and Choice Online Act would have similarly banned platforms from using "nonpublic data... to offer... products or services... that compete... with products or services offered by business users" (Congress.gov, 2022). Indeed, in some cases, politicians have called for an outright ban on the practice (Warren, 2019). These blanket restrictions reflect growing concerns that platform owners exploit their unique position to discriminate against competitors, leveraging privileged information and control over marketplace infrastructure to advantage their own offerings (Crémer, de Montjoye, and Schweitzer, 2019; Scott Morton et al., 2019).

Yet the economic effects of platform-owner entry remain theoretically ambiguous (Anderson and Bedre Defolie, 2024; Hagiu, Teh, and Wright, 2022). While entry introduces a typically well-resourced competitor that may engage in self-preferencing or restrict access to essential features, it can also generate positive spillovers through technology diffusion, market expansion, and complementary infrastructure investments. The debate over appropriate regulatory responses—ranging from outright bans to conduct remedies to laissez-faire approaches—hinges critically on understanding the magnitude, heterogeneity, and mechanisms underlying these effects.

To help inform this debate, I study how Apple's release of competing apps and software functionality affects third-party developers. This "Sherlocking" phenomenon—named after Apple's incorporation of the third-party search app *Watson*'s functionality into its own *Sherlock* product—is a first-order concern for developers, who routinely track Apple's entry into App Store submarkets (see Figure 1). Developers face substantial uncertainty about whether and when Apple might enter their product space, complicating long-term investment decisions. For those whose products are targeted, the stakes are high: Apple's entry has the potential to render years of development effort obsolete overnight.

Figure 1: Developer Reactions to "Sherlocking"

Note: Tweets from developers reacting to Apple's WWDC 2022 announcements of new iOS features that compete with existing third-party apps.

In the context of mobile software platforms, platform-owner entry takes two distinct forms that have received insufficient attention in both academic literature and policy discussions. Apple's entry into submarkets within its App Store marketplace occurs through either *standalone entry*—developing and releasing a new separately installable application—or *integrated entry*—incorporating competing functionality directly into the operating system. Standalone entry involves Apple creating a new app that users can discover and choose to download from the App Store, competing alongside third-party offerings. Examples include Measure (an augmented reality measurement tool), Translate (language translation), and Magnifier (visual assistance). These apps appear in search results, have product pages with descriptions and ratings, and can be uninstalled by users—though some may come pre-installed by default. The competitive dynamic is relatively transparent: consumers actively choose whether to adopt Apple's offering over alternatives.

Integrated entry involves Apple integrating functionality directly into iOS that automatically becomes available to all users. Examples include health tracking features integrated into the Health app, weather widget improvements, enhanced Maps functionality, and camera feature additions. This functionality cannot be separately uninstalled and often comes bundled with new APIs that third-party developers can leverage, representing a more fundamental alteration of the platform's capabilities. Users receive these features automatically, without making an active adoption decision.

This distinction matters for competitive dynamics. Integrated entry creates unavoidable competition—third-party apps must compete with functionality that every user already possesses. It also has the potential to generate stronger technology spillovers, as OS-level integration often introduces new hardware capabilities or software frameworks that benefit the broader developer ecosystem.

This paper provides comprehensive evidence on platform-owner entry effects by studying 23 instances of Apple entering submarkets in its App Store between March 2016 and September 2021. The analysis encompasses 14 standalone app releases and 9 integrated OS integrations, enabling systematic comparison across entry types and market characteristics.[1]

I make three key contributions to the literature on platform competition and regulation. First, the scale of analysis—examining 23 entry events over multiple years compared to the handful studied in prior work—enables systematic investigation of heterogeneous treatment effects across markets. This reveals substantial variation in competitive responses that single-market studies cannot detect. Second, I develop a novel empirical approach using continuous distance measures derived from text embeddings to capture within-market heterogeneity based on competitive proximity. This methodology recognizes that not all apps in an affected market are equally "treated" by platform entry. Third, this analysis documents multi-dimensional heterogeneity in first-party entry effects—both across markets and within markets by competitive distance—that fundamentally challenges one-size-fits-all regulatory approaches.

My empirical strategy leverages a staggered difference-in-differences design, using comparable Android apps and not-yet-treated iOS apps as a control group for iOS apps affected by Apple's entry. Market definitions rely on semantic similarity of app descriptions, with apps exceeding a similarity threshold considered part of the competitive market around each entrant.

The analysis reveals striking heterogeneity that challenges both pro-platform entry and anti-platform entry narratives. Perhaps most surprisingly, a substantial proportion of markets experience no statistically significant effects from Apple's entry in many of the outcomes considered in this analysis. This prevalence of null effects, particularly pronounced for quality metrics, contradicts claims of either universal harm or universal benefit from platform competition.

When effects do occur, they vary across markets and space. Apps close to Apple's offering in semantic space experience substantial, often negative impacts, while more distant competitors

[1] Work is ongoing to integrate additional markets of both types into this analysis.

remain largely unaffected. This creates a limited "competitive radius" around each entrant which can vary in size by market and outcome.

Entry type proves crucial: integrated OS features generate systematically larger effects than standalone app releases. Price increases are 8-fold larger for integrated entry ($1.17) versus standalone ($0.15), while the proportion of free apps declines by 16.5 percentage points for integrated versus only 1.6 percentage points for standalone.

These patterns of heterogeneity—across markets, within markets by distance, and between entry types—suggest that platform-owner entry effects depend critically on contextual factors that current regulatory proposals largely ignore. The evidence strongly supports targeted, context-specific oversight rather than the blanket restrictions embodied in recent legislation.

This paper contributes to several strands of literature on platform competition and digital markets. Most directly, it extends empirical work on platform-owner entry effects. Wen and Zhu (2019) study Google's entry into Android submarkets, finding evidence of reduced innovation and increased prices among affected developers. Zhu and Liu (2018) document that Amazon targets successful product categories and that its entry increases demand but discourages third-party investment. Foerderer et al. (2018) find that Google's entry into photo management increased both demand and third-party innovation. My analysis expands this literature by examining a larger set of entry events, enabling systematic analysis of heterogeneous effects. While I focus on competitive effects, complementary work by Halckenhaeusser et al. (2025) examines what drives platform-owner entry decisions. They find that Apple's iOS entries target platform categories characterized by low user satisfaction, limited innovation, and high market concentration.

A related literature examines specific mechanisms of platform advantage. Studies of self-preferencing document that platforms favor their own products in search and recommendations, with mixed welfare implications (Teng, 2023; Lee and Musolff, 2025; Lam, 2023; Raval, 2023). Work on "insider imitation" explores how platforms leverage proprietary data to select entry markets (Madsen and Vellodi, 2025; Hagiu, Teh, and Wright, 2022). While I do not isolate specific mechanisms, my reduced-form estimates capture the net effect of all channels through which platform entry affects competition.

The paper also relates to the "platforms as regulators" literature, which recognizes that platform owners shape competitive dynamics through rules, design choices, and technical standards

(Boudreau and Hagiu, 2011). Recent work shows how platform policies on privacy (Kesler, 2022; Li and Tsai, 2022; Johnson et al., 2025; Cheyre et al., 2025), ratings systems (Jabr et al., 2020; Leyden, 2025), and product categorization (Ershov, 2024) affect within-platform competition. My findings suggest that entry decisions represent another regulatory lever, with effects varying by how entry is implemented.

Methodologically, the paper advances techniques for defining and measuring competition in digital markets. Building on Leyden (2023), I use transformer-based language models to construct product spaces from text descriptions, enabling more nuanced market definitions than traditional classification systems. The continuous distance measure allows for gradient effects within markets, recognizing that competitive pressure varies with product differentiation.

The remainder of the paper proceeds as follows. Section 2 describes the data sources, market definition methodology, and sample construction. Section 3 presents the empirical analysis, beginning with identification strategy, then examining market dynamics (Section 3.1) and incumbent app responses (Section 3.2). Section 4 explores mechanisms, focusing on how entry type (standalone versus integrated) shapes competitive responses. Section 5 discusses policy implications and directions for future research.

2 Data

2.1 Data Sources

I use a monthly panel dataset of all apps available in the US App Store and Google Play Store provided by the data analytics company AppMonsta. The full sample runs from January 2015 to June 2022 and consists of 14.4 million unique apps across both platforms. For each app-month, I observe product characteristics including name, price, average rating, rating count, and whether the app was updated that month. The data also includes developer-written text descriptions that serve as apps' primary marketing content and provide a reliable indication of product functionality and purpose. Additionally, I use daily ranking lists for product sales and revenue to construct sample restrictions focused on actively competing apps. Key variables for the analysis include monetization outcomes: Price, Free (indicator for price = \$0), In-App Purchases (IAP) availability, and Price-Paid (price conditional on price > \$0); quality outcomes: Average Rating (1-5 stars),

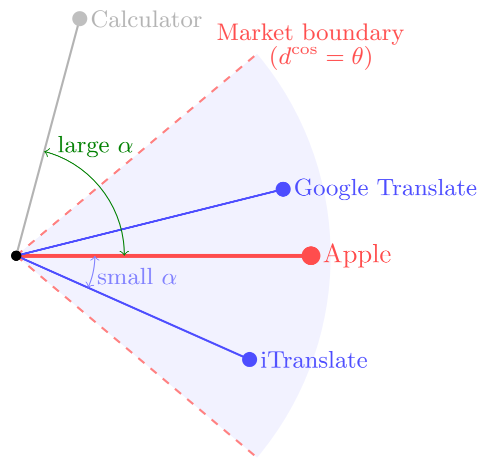
Figure 2: Semantic Similarity in Vector Space: An Illustration

Apple Translate:
"Translate lets you quickly and easily translate your voice and text..."

Google Translate:
"Translate between up to 249 languages...."

iTranslate:
"Seamlessly translate text, websites, objects, or start voice-to-voice conversations in..."

Calculator App:
"Easily type out math with the basic and scientific calculators for quick solutions..."



Note: Left panel: Excerpts from product descriptions used as input to the SBERT model. Right panel: SBERT maps descriptions to vectors in a high-dimensional space where semantic similarity corresponds to geometric proximity (small angles between vectors). Translation apps cluster together despite using different terminology, while the calculator app is distant. The dashed lines represent market boundaries at threshold θ.

Update indicator, and rating count growth (log-differenced: $\Delta \ln(\text{rating\_count} + 1)$, a proxy for consumer demand); and entry/exit outcomes: market-level counts of new app entries and exits, transformed using $\ln(x + 1)$ for regression analysis.

2.2 Market Definition

Given the millions of products observed over the sample period, identifying which third-party apps are potentially affected by platform-owner entry requires precise market definitions. Platform-provided categories (e.g., Games, Productivity) are too broad—the Productivity category alone encompasses password managers, shift scheduling apps, document editors, and many other distinct product types.

I define markets using semantic similarity of product descriptions, leveraging recent advances in natural language processing. Specifically, I apply Sentence-BERT (SBERT), a transformer-based neural network model, to embed text descriptions into a 384-dimensional vector space in which semantically similar products are located closer together (Reimers and Gurevych, 2019). These embeddings are trained so that functionally similar apps—regardless of the specific terminology used by the developers—cluster in the embedding space.

I measure the similarity between any pair of apps i and j, characterized by description vectors

$desc_i$, $desc_j$, using cosine similarity

$$d^{\cos}(desc_i, desc_j) = \frac{desc_i^\top desc_j}{\|desc_i\|_2 \, \|desc_j\|_2} \in [-1, 1], \tag{1}$$

where $\|\cdot\|_2$ denotes the Euclidean norm. Geometrically, cosine similarity is the cosine of the angle α between the two vectors, so vectors pointing in similar directions (small α) have similarity close to 1. Figure 2 illustrates this approach using language translation apps as an example: SBERT maps textually distinct but functionally similar descriptions to nearby vectors, while unrelated apps like calculators are placed far away.

Given a first-party entrant a with description vector $desc_a$, I define the market J_a^θ as all apps j satisfying:

$$J_a^\theta = \{j \in J^{\text{iOS}} \cup J^{\text{Android}} : d^{\cos}(\text{desc}_a, \text{desc}_j) \geq \theta\} \tag{2}$$

The parameter θ governs market size: higher values impose stricter similarity requirements, yielding smaller, more tightly defined markets, while lower values produce larger markets that include more distant competitors. In practice, I set $\theta = 0.6$, which defines relatively tight, more focused competitive sets than lower alternative thresholds. This ensures the treated sample consists of apps that are meaningfully similar to the entrant, reducing concerns about including tangentially related products that might bias estimates toward zero. The threshold choice balances two considerations: setting θ too high yields markets that are too narrow and may miss relevant competitors, while setting it too low includes apps that are not meaningful substitutes.

Each app i in market a thus has a continuous distance measure $d_i \in [\theta, 1]$ from the entrant, enabling analysis of how treatment effects vary with competitive proximity. This continuous treatment approach, developed in Section 3, represents a methodological advance over binary in/out market definitions.

2.3 Apple's Entrants

I study 23 instances of Apple entering submarkets within its App Store ecosystem between March 2016 and September 2021. Apple implements entry through two distinct strategies. In *standalone entry*, Apple releases a new separately installable application that users can discover and download from the App Store; my sample includes 14 such events. These apps compete directly alongside third-party offerings with their own product pages, ratings, and the ability to be uninstalled, though some may come pre-installed on devices by default. Examples include Schoolwork (classroom management), Breathe (meditation), and Translate (language translation). In the second case, *integrated entry*, Apple integrates competing functionality directly into iOS through operating system updates; my sample includes 9 such events. This functionality is automatically available to all users, cannot be separately uninstalled, and often introduces new APIs that third-party developers can leverage. Examples include Health app enhancements, Apple Music features, camera improvements, and Maps functionality updates.

For standalone entries, the description vector $desc_a$ used in Equation (2) is simply the app's App Store product page description. For integrated entries, which lack natural product pages, I construct comparable descriptions using Apple's official iOS release notes as the source text. These release notes document each feature's functionality at the time of the iOS version release. Because release note entries can be terse, I augment brief descriptions with additional context from Apple's developer documentation. I then generate App Store-style descriptions using OpenAI's GPT-5.1 with few-shot learning, providing actual Apple app descriptions as style examples to ensure the generated text matches the tone, structure, and vocabulary typical of the App Store.[2] This approach produces description vectors that are semantically comparable to standalone entries and third-party apps, enabling consistent market definition across both entry types.

Table 1 provides the complete list of all 23 entry events with their dates and types. This comprehensive set of entry events, spanning diverse product categories and entry modes, enables systematic analysis of heterogeneous platform-owner entry effects.

2.4 Analysis Samples

Following the text-based market definition approach outlined above, I limit analysis to apps that ranked 200th or better for at least 10% of days they were available. This excludes hobby projects, abandoned apps, and experimental products that are not actively competing during the sample

[2]The generation process samples 20 Apple app descriptions as style examples for each integrated entry feature. The prompt instructs the model to produce 200–400 word descriptions that focus on user benefits and match the style of the examples. I use Apple's own app descriptions (e.g., Pages, Keynote, GarageBand) as style references because they represent the canonical App Store voice and are semantically neutral with respect to the markets being defined.

Table 1: Complete List of Apple Entry Events

Market	Entry Date	Type	iOS Apps	Android Apps
Schoolwork	2016-03	Standalone	97	30
Breathe	2016-09	Standalone	18	11
Clock 10.0	2016-09	Integrated	180	113
Health 10.0	2016-09	Integrated	19	9
Homekit 10.0	2016-09	Integrated	83	63
Camera 11.0	2017-09	Integrated	123	70
Development 11.0	2017-09	Integrated	202	11
Notes 11.0	2017-09	Integrated	238	94
Animoji	2017-11	Standalone	71	23
Health 11.3	2018-03	Integrated	116	67
Ibooks 11.4	2018-05	Integrated	50	8
Measure	2018-09	Standalone	61	19
Walkie Talkie	2018-09	Standalone	47	28
Apple Music 13.0.2	2019-09	Integrated	78	41
Ecg	2019-09	Standalone	39	16
Radio	2019-09	Standalone	3	4
Reality Composer	2019-09	Standalone	67	16
Apple Research	2019-11	Standalone	22	8
Sleep	2020-09	Standalone	114	60
Translate	2020-09	Standalone	327	152
Blood Oxygen	2020-10	Standalone	9	4
Find Items	2021-04	Standalone	29	19
Magnifier	2021-09	Standalone	41	18

Notes: App counts based on $\theta = 0.6$ threshold, apps ranked 200+ for 10%+ days.

period. For each Apple entrant, I construct an 18 month balanced panel centered around the first-party entry date. The resulting dataset contains 52,524 app-months of observations across 23 markets.

Market sizes vary substantially based on product space density. Figure 3 illustrates this heterogeneity for four representative markets. Each panel shows how many apps would be included in a market as the similarity threshold θ varies from 0.5 to 1.0 (prior to the rank restrictions discussed above). At the baseline threshold of $\theta = 0.6$, prior to imposing the ranking threshold described above, market sizes range from approximately 200 apps in specialized markets (Measure, ECG) to over 1,000 apps in broader product categories (Translate, Schoolwork). The sharp increases visible at $\theta < 0.6$ demonstrate that loosening the threshold would dramatically expand markets to include many tangentially-related apps, motivating the choice of a conservative threshold that focuses on close competitors.

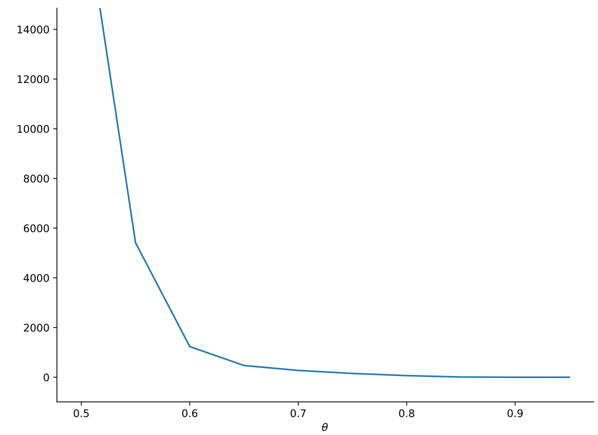
I use similar apps on the Google Play Store as a control group for App Store apps affected by Apple's entry.[3] Android represents the other major mobile platform with a comparable developer ecosystem and user base. Markets are defined using the same SBERT process across platforms, ensuring that treated iOS apps and control Android apps operate in the same product spaces. The use of Android as a control is particularly compelling because Google does not systematically enter the same markets at the same times as Apple, and both platforms experienced similar technological and demand shocks during the sample period.

2.5 Summary Statistics

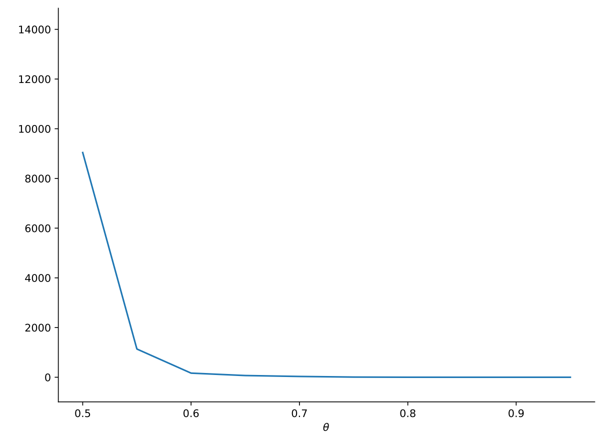
Table 2 presents summary statistics for the three datasets used in the analysis, comparing pre-treatment (9 months before Apple's entry) and post-treatment (9 months after) periods. Market-level summary statistics are provided in Appendix C. Panel A reports app-month level statistics for incumbent apps—those present in the market before Apple's entry. The pre-treatment average price of \$0.81 reflects that 79.9% of apps are free; among paid apps, prices average \$4.01. The post-treatment period shows substantial changes: average prices increase to \$1.55, driven by a 15.9 percentage point decline in the share of free apps. In-app purchase adoption increases slightly (from

[3] Android IAP data is only available starting September 2016. As a result, 5 markets (Schoolwork, Breathe, Health 10.0, Homekit 10.0, and Clock 10.0) are excluded from all IAP analyses because they entered before sufficient pre-period data was available.

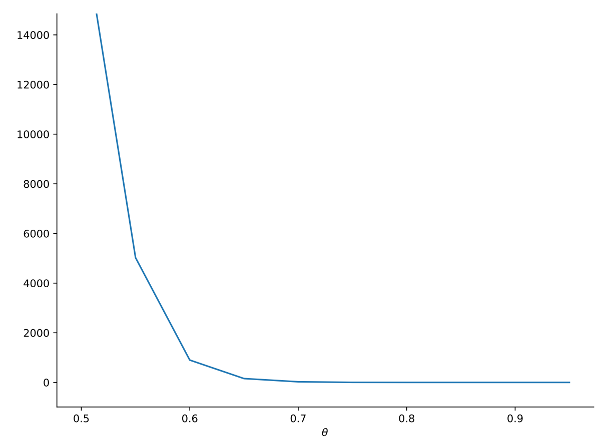
Figure 3: Market Size Heterogeneity: Cumulative App Counts by Similarity Threshold



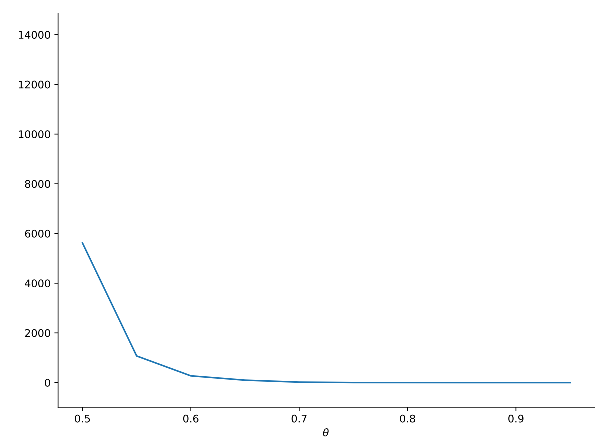
(a) Translate



(b) Measure



(c) Schoolwork



(d) ECG

Note: Each panel plots the cumulative number of apps with cosine similarity to the first-party entrant at or above threshold θ. The first-party entrant is located at $\theta = 1.0$. As θ increases moving rightward, fewer apps meet the threshold, yielding smaller, more focused markets.

Table 2: Summary Statistics

	Pre-Treatment	Post-Treatment	Change
Panel A: Incumbent Apps			
Price	0.807	1.548	+0.741
Price (Paid Apps)	4.014	4.296	+0.282
Free	0.799	0.640	-0.159
In-App Purchases	0.350	0.369	+0.019
Avg. Rating	3.978	3.979	+0.001
Update	0.252	0.238	-0.013
Δ Log # Ratings	0.047	0.030	-0.017
N	26,262	26,262	
Panel B: Market-Level Entry and Exit			
Log Entry	0.543	0.518	-0.024
Log Exit	0.397	0.428	+0.031
N	414	414	
Panel C: Entering Cohorts			
Price	0.492	0.668	+0.176
Price (Paid Apps)	3.103	3.581	+0.478
Free	0.842	0.814	-0.028
In-App Purchases	0.186	0.259	+0.073
Avg. Rating	4.200	4.071	-0.129
Log # Ratings	1.518	1.816	+0.298
Similarity	0.660	0.659	-0.001
N	448	413	

Notes: Panel A reports app-month level statistics for incumbent apps observed in an 18-month balanced panel around each entry event. Panel B reports market-month level entry and exit counts. Panel C reports statistics for apps observed once upon entry (repeated cross-section). Pre-Treatment refers to the 9 months before Apple's entry; Post-Treatment refers to the 9 months after.

35.0% to 36.9%), while update frequency declines modestly (from 25.2% to 23.8%). Rating count growth (log-differenced) is positive in both periods, suggesting ongoing user engagement over time.

Panel B reports market-month level log entry and log exit counts. Entry rates are nearly unchanged between periods, while exit rates increase slightly. Panel C reports statistics for the entering cohort analysis, a repeated cross-section where each app is observed once upon entry. Entrants in both periods are predominantly free (84% pre-treatment, 81% post-treatment) with substantially lower prices than incumbents, consistent with new entrants using free pricing strategies to compete against established apps. Similarity to the Apple entrant is nearly identical across periods (0.66).

3 Empirical Analysis

I estimate the effects of platform-owner entry on third-party developers using a staggered difference-in-differences design that exploits variation in the timing of Apple's entry across 23 submarkets, comparing iOS apps to similar apps on Android's Google Play Store as controls. The analysis examines two dimensions of competitive response: market dynamics (entry, exit, and the composition of entering cohorts) and incumbent responses (monetization and quality outcomes).

The fundamental identification challenge is that we cannot observe counterfactual outcomes—what would have happened to affected apps absent Apple's entry. The identifying assumption is that absent Apple's entry, iOS and Android apps in the same product market would have followed similar outcome trajectories. The credibility of this design relies on two key institutional features: (1) Google does not systematically enter the same markets at the same times as Apple, avoiding contamination of the control group, and (2) both platforms experience similar technological and demand shocks during the sample period. Requirement (1) holds for all first-party entrants considered here, and requirement (2) is supported by the fact that both Apple and Google's platforms are frontier mobile operating systems, which closely mirror each other in the technological hardware these platforms operate on, and which both compete for largely the same consumers in the mobile phone market. To support this assumption, I present evidence regarding pre-trends through event study specifications throughout my analysis.

A potential threat to identification is spillover effects among multi-homing apps—products available on both platforms. If an iOS app adjusts its strategy in response to Apple's entry, the Android version might also change, contaminating the control group. However, platform-specific development teams, different technology stacks, and distinct user bases often lead to independent strategies across platforms. This specification includes all apps regardless of multi-homing status, maximizing sample size while acknowledging this potential limitation.

3.1 Market Dynamics

I begin by examining how Apple's entry affects market structure—specifically, whether third-party entry and exit patterns change and how the characteristics of new entrants shift.

3.1.1 Entry and Exit

I first examine how Apple's entry affects market structure through changes in the number of third-party apps entering and exiting markets. To understand the effect of first-party entry on third-party entry and exit, I estimate a two-way fixed effects (TWFE) model:

$$y_{apt} = \alpha \cdot D_{apt} + \delta_{ap} + \eta_t + \varepsilon_{apt}. \tag{3}$$

y_{apt} is the outcome (log entry or exit count) for market a on platform p at month t. The treatment indicator $D_{apt} = \mathbf{1}[p = \text{iOS}, t \geq T_a]$ equals one for iOS observations in periods at or after market a's entry date T_a, and zero otherwise; Android observations have $D_{apt} = 0$ throughout, serving as a never-treated control group. δ_{ap} are market-platform fixed effects, η_t are year-month fixed effects, and α is the coefficient of interest. The outcome variables are market-level counts of new app entries and app exits, transformed using $\ln(x + 1)$ to handle zeros. Standard errors are clustered at the market-platform level. Results are similar across alternative estimators (Wooldridge, 2021; Sun and Abraham, 2021); see Appendix A and the event study plots below for comparison.

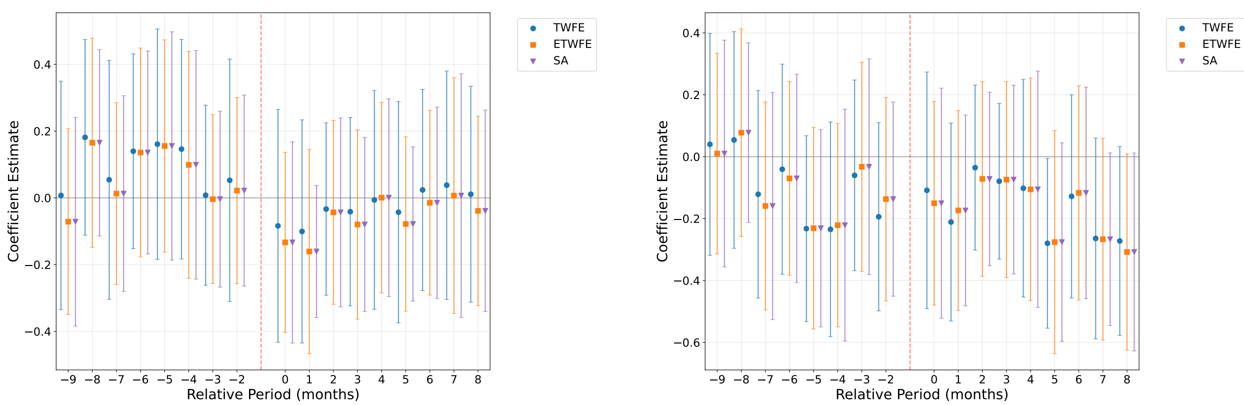
Table 3 presents the estimates and Figure 4 presents event study estimates for entry and exit. Notably, I find no statistically significant effect on third-party entry. The estimate shows an imprecisely estimated 2.6% decrease. The exit regression shows evidence of a decline following Apple's entry with the estimate indicating a 15% decline in exit, but this is also imprecisely estimated. This evidence that exit is unaffected, or potentially falls, suggests that incumbent apps may be "locked

Table 3: Entry and Exit

	(1) Log Entry Count	(2) Log Exit Count
ATT	-0.0262	-0.1646
	(0.1350)	(0.1272)
Baseline Mean	0.5427	0.3968
N	828	828

Notes: Two-way fixed effects (TWFE) DiD estimates at the platform-market-month level. Standard errors clustered at the platform-market level are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Figure 4: Entry and Exit Dynamics



(a) Log Entry Count

(b) Log Exit Count

Note: Event study estimates showing dynamic treatment effects relative to one month before entry. TWFE is the primary estimator; ETWFE (Wooldridge (2021)) and SA (Sun and Abraham (2021)) shown for comparison. Analysis is at the platform-market-month level. Standard errors are clustered at the platform-market level. Error bars represent 95% confidence intervals.

in" once Apple enters, potentially due to sunk development costs or strategic value of maintaining presence despite increased competition. It may also reflect a long-run strategy to retain users as those users become accustomed to the product category and seek alternative or more fully featured applications. Additionally, it is inexpensive for most developers to keep their products in the store even while abandoning active development. In Section 3.2.2, I consider an alternative measure of developers' participation and effort on the platform, the rate of product updating.

3.1.2 Composition of Entering Cohorts

In addition to affecting entry and exit counts, platform-owner entry may alter the composition of new entrants. I examine how entering cohorts differ before versus after Apple's entry using a cross-sectional difference-in-differences design. Each entering app is observed once, at entry. I estimate the model

$$y_i = \tau \cdot D_i + \delta_{pa} + \eta_t + \varepsilon_i \tag{4}$$

using OLS. y_i represents entry characteristics for app i. The treatment indicator $D_i = \mathbf{1}[i \in \text{iOS}, t_i \geq T_{a(i)}]$ equals one for iOS apps that entered at or after their market's treatment date, and zero otherwise, where t_i is app i's entry date and $a(i)$ denotes its market. Android apps have $D_i = 0$ throughout. δ_{pa} are platform-market fixed effects and η_t are month fixed effects. The coefficient τ captures the differential change in entry characteristics for iOS apps relative to Android apps following Apple's entry. Standard errors are clustered at the market-platform level. Because each app is observed only once—in its first month on the platform—this analysis constitutes a repeated cross-section rather than a panel.[4]

Table 4 presents the results from estimating the cohort entry characteristics model Equation (4).[5] The results reveal systematic changes in the composition of entering apps following Apple's entry. Among paid apps, price levels show no statistically significant change, suggesting that conditional on charging, new entrants do not adjust their prices in response to Apple's presence. However, the probability of offering a free app *decreases* by 9.3 percentage points (significant at the 10% level), indicating a compositional shift toward paid apps among new iOS entrants relative to Android. This shift on the free/paid margin—arguably the primary monetization decision for app developers—suggests that developers entering after Apple may pursue differentiation strategies that can command a price despite Apple's free alternatives. In-app purchase adoption shows no significant change.

Quality metrics at entry show notable patterns. Ratings for new iOS entrants are approximately

[4]Estimators like Sun and Abraham (2021) that rely on within-unit variation over time are not applicable to this data structure. While ETWFE can in principle accommodate repeated cross-sections (Wooldridge, 2021), the methodology estimates separate treatment effect parameters for each cohort-time cell. The cross-sectional nature of the entry data yields sparse cohort-time cells with many containing only a handful of observations, insufficient for reliable cell-specific identification. TWFE's pooling across cohorts is better suited to this data structure.

[5]I present event study estimates in Appendix B.

0.26 stars higher than for Android entrants following Apple's entry (6.1% relative to the baseline mean of 4.2 stars), though this effect is not statistically significant. New iOS entrants receive significantly more user engagement as measured by log rating counts, possibly reflecting increased category visibility that Apple's entry brings to the market or a selection effect whereby only higher-quality or more highly-differentiated apps choose to enter.

Table 4: Cohort ATT Estimates

	(1) Price	(2) Price (Paid Apps)	(3) Free App	(4) In-App Purchases	(5) Rating	(6) Log Rating Count
ATT	0.3386	0.1050	-0.0928*	-0.0297	0.2564	0.4224*
	(0.2596)	(0.5384)	(0.0482)	(0.0504)	(0.1969)	(0.2458)
Baseline Mean	0.4917	3.103	0.8415	0.2056	4.199	1.518
N	861	148	861	644	442	861

Notes: Cross-sectional DiD estimates for entering cohorts. Each app observed once at entry. Standard errors clustered at market-platform level shown in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

3.2 Incumbent Responses

I next examine how incumbent apps respond to Apple's entry across monetization and quality dimensions. All analyses in this subsection use a balanced monthly panel of apps operating on the platforms for the 9 months before and after Apple's entry. In my primary analysis, I estimate a two-way fixed effects (TWFE) model:

$$y_{it} = \alpha \cdot D_{it} + \gamma_i + \eta_t + \varepsilon_{it}. \tag{5}$$

y_{it} is the outcome for app i in month t. The treatment indicator $D_{it} = \mathbf{1}[i \in \text{iOS}, t \geq T_{a(i)}]$ equals one for iOS apps in periods at or after their market's entry date, and zero otherwise, where $a(i)$ denotes the market containing app i. Android apps have $D_{it} = 0$ throughout, serving as a never-treated control group. γ_i are app fixed effects and η_t are year-month fixed effects. The coefficient α represents the average treatment effect on the treated (ATT). Standard errors are clustered at the app level. For robustness, I also report results from alternative DiD estimators in Appendix A: the extended two-way fixed effects (ETWFE) estimator of Wooldridge (2021) and the interaction-weighted estimator of Sun and Abraham (2021). Results are similar across methods.

Notably, not all apps in an affected market are equally "treated" by platform entry. An app providing nearly identical functionality to Apple's entrant faces different competitive pressure than a tangentially related app at the market periphery. I exploit the continuous similarity measure from the SBERT embeddings to estimate how treatment effects vary with competitive proximity. I use B-splines to flexibly estimate this relationship within the difference-in-differences framework.

For each app i in market a with cosine similarity $d_i \in [\theta, 1]$ to the entrant, I estimate distance heterogeneity by interacting K B-spline basis functions with the treatment indicator,

$$y_{it} = \sum_{k=1}^{K} \phi_k \cdot D_{it} \cdot B_k(d_i) + \gamma_i + \eta_t + \varepsilon_{it}. \tag{6}$$

D_{it} is defined as above, $B_k(\cdot)$ are B-spline basis functions, K is the number of basis functions (degrees of freedom), γ_i are app fixed effects, and η_t are year-month fixed effects. This approach allows me to flexibly estimate how the treatment effect varies in an apps' similarity to Apple's first-party product without imposing a specific functional form.

I select K via 10-fold cross-validation at the app level, testing values from 3 to 8 and choosing the specification that minimizes normalized root mean squared error. This data-driven approach balances model flexibility against overfitting. In the analysis below, I plot the treatment effect at each similarity level,

$$\tau(d) = \sum_{k=1}^{K} \phi_k \, B_k(d). \tag{7}$$

This captures the treatment effect for apps at similarity d, showing how competitive pressure varies with distance from the entrant.

I interpret $\tau(d)$ as the treatment effect at a given similarity level to the entrant. For presentation, I evaluate and plot $\tau(d)$ on a grid $d \in [\theta, 1]$ together with pointwise 95% confidence intervals (standard errors are clustered at the app level). This profile shows how competitive pressure varies with similarity.

3.2.1 Monetization Responses

Apple's entry can affect incumbent apps' monetization strategies through three main channels: app prices (measured in dollars for all apps including those charging $0), the proportion of apps offered for free, and in-app purchase adoption (whether an app offers additional paid content within the app).[6]

Table 5: Incumbent App Monetization Outcomes

	(1) Price	(2) Price (Paid Apps)	(3) Free App	(4) In-App Purchases
ATT	0.7019***	0.0462	-0.0971***	-0.0093***
	(0.0507)	(0.0330)	(0.0084)	(0.0033)
Baseline Mean	0.8069	4.014	0.7990	0.3626
N	52,524	14,741	52,524	41,310

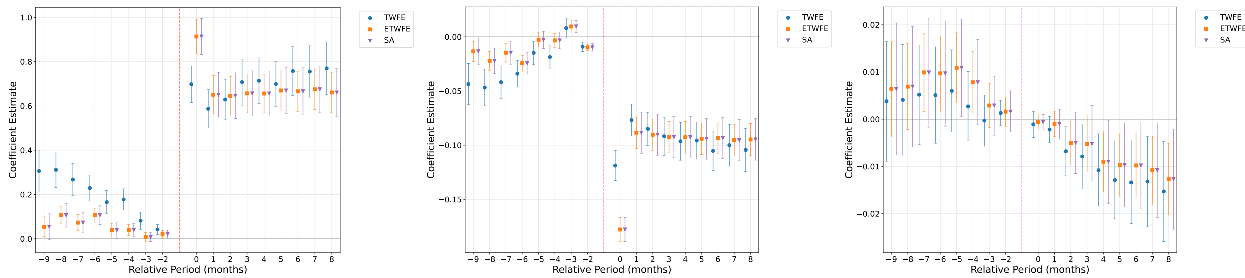
Notes: Two-way fixed effects (TWFE) DiD estimates at the app-month level. For the IAP outcome, 5 markets are excluded due to insufficient Android in-app purchase data in the pre-period. Standard errors clustered at the app level are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 5 presents estimates for the monetization outcomes. I find that price increases by $0.70 following entry, representing a remarkable 87% increase relative to the pre-treatment mean of $0.81. This aggregate price increase masks important compositional changes. Apps become nearly 10 percentage points less likely to be free—representing approximately a 12% decrease in free offerings. However, conditional on charging a positive price, the price effect is modest ($0.05) and not statistically significant, suggesting the overall price increase is driven primarily by apps switching from free to paid rather than existing paid apps raising prices. In-app purchase (IAP) adoption falls by 0.9 percentage points, a 2.6% decline. One interpretation is that developers simplify monetization strategies under competitive pressure, moving from complex freemium models to straightforward paid downloads, or that they move monetization from on-platform IAPs to off-platform subscriptions, which are not subject to Apple's typical commission.

Figure 5 presents event studies for all monetization outcomes. TWFE is the primary estimator, but I present estimates from the ETWFE and SA estimators for comparison. Estimates are generally aligned across estimators. The one notable exception is for the price outcome, where the TWFE pre-trend estimates diverge from the ETWFE and SA estimates. Nonetheless, the point estimate presented in Table 5 is aligned with the other estimators—see Appendix A. The price increase and the decline in the proportion of free apps show a large initial response, which then settle out at a less extreme, but still substantial shift. This suggests developers may engage in some experimentation immediately following Apple's entry into their market. IAP adoption begins to

[6] I am unable to observe whether and to what extent apps rely on advertising or the sale of data as a source of revenue.

Figure 5: Monetization Dynamics



(a) Price (All Apps) (b) Free (c) In-App Purchases

Note: Event study estimates showing dynamic treatment effects relative to one month before entry. TWFE is the primary estimator; ETWFE (Wooldridge (2021)) and SA (Sun and Abraham (2021)) are shown for comparison. Analysis is at the app-month level. For the IAP outcome, 5 markets are excluded due to insufficient Android in-app purchase data in the pre-period. Standard errors are clustered at the app level. Error bars represent 95% confidence intervals.

decline at entry and shows signs of stabilizing around the fifth post-treatment month.

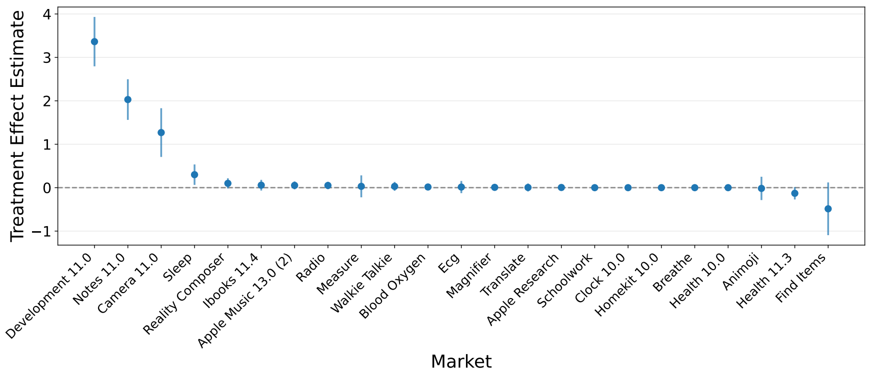
To examine heterogeneity across markets, I estimate separate treatment effects for each market by interacting the treatment indicator with market dummies. Figure 6 reveals heterogeneity in monetization responses across markets. Price effects vary substantially in magnitude, with many markets showing limited or no response. Free proportions decline in a number of markets, though, again, many markets show limited or no response.

Finally, Figure 7 presents $\tau(d)$ for the monetization outcomes, showing how monetization responses vary with competitive distance from the first-party entrant, which is located at cosine similarity, $d = 1$. While the price effect is positive throughout most of the study domain, the effect is the largest in the middle region—among apps that are not most nor least exposed to Apple's entrant. Panels (b) and (c) suggest this is driven by a relatively spatially homogenous effect on the likelihood of being Free and a shallow, inverted-U effect on prices conditional on being Paid. The effect of entry on IAP adoption varies substantially with distance. Apps farthest from Apple's entrant appear less affected, with IAP adoption consistently falling at a much faster rate closer to Apple's entrant.

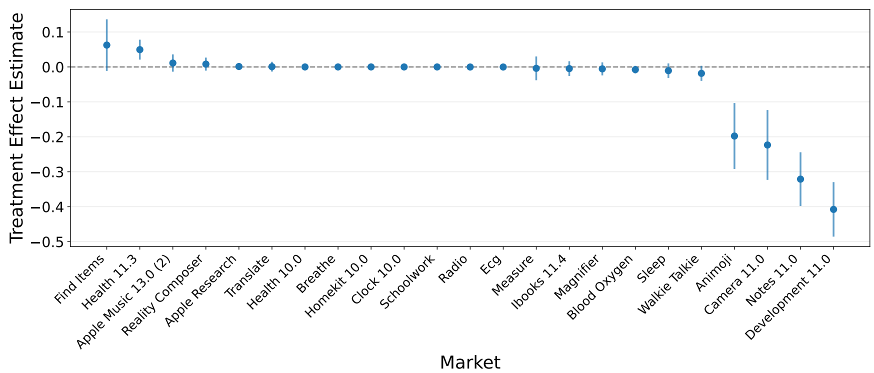
3.2.2 Quality Responses

Apple's entry can affect incumbent app quality through three dimensions: app ratings (average user star ratings on a 1-5 scale), update frequency (as a measure of development intensity and quality

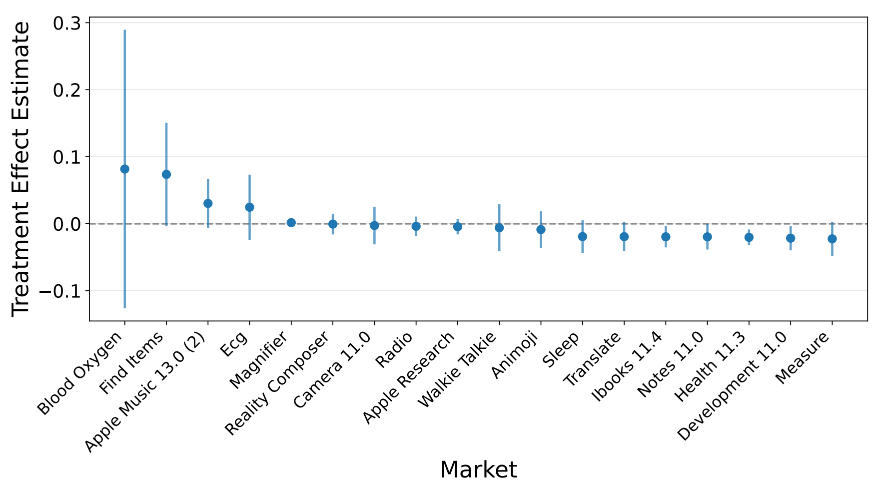
Figure 6: Market Heterogeneity in Monetization



(a) Price (All Apps)



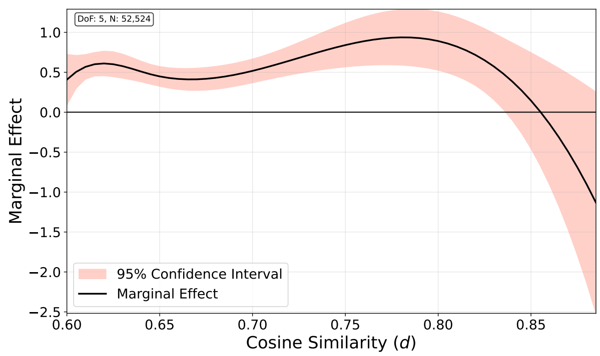
(b) Free



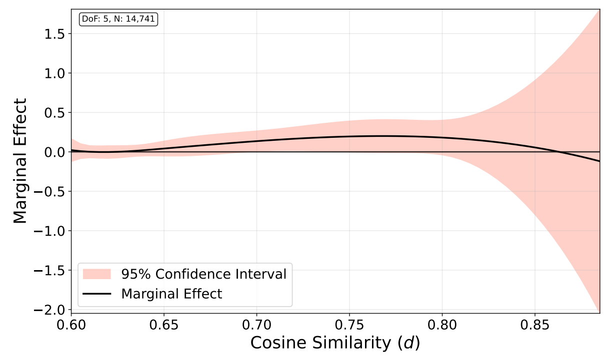
(c) In-App Purchases

Note: Market-specific treatment effects from TWFE model (Equation (5)). Analysis is at the app-month level. For the IAP outcome, 5 markets are excluded due to insufficient Android in-app purchase data in the pre-period. Standard errors are clustered at the app level. Points show estimates with 95% confidence intervals for each of 23 markets.

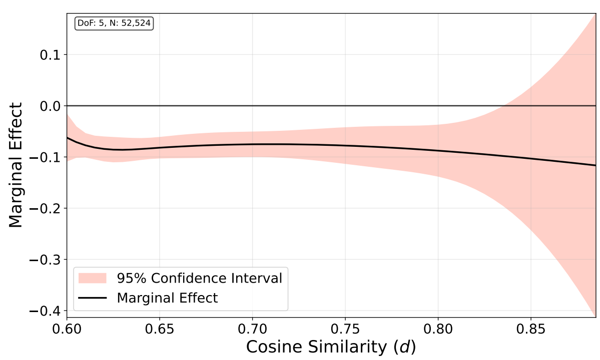
Figure 7: Monetization Effects by Distance from Entrant



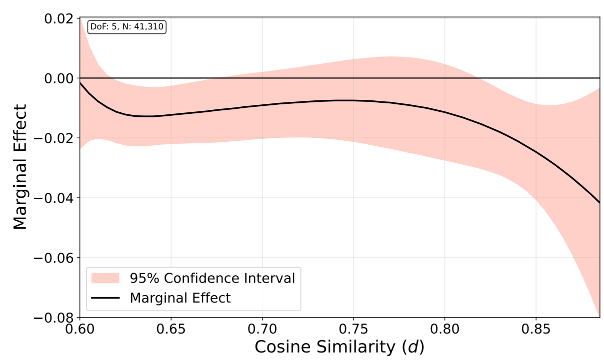
(a) Price (All Apps)



(b) Price (Paid Apps Only)



(c) Free



(d) In-App Purchases

Note: Treatment effects across competitive distances from distance regression (Equation (6)). Degrees of freedom selected via cross-validation. Analysis is at the app-month level. For the IAP outcome, 5 markets are excluded due to insufficient Android in-app purchase data in the pre-period. Standard errors are clustered at the app level. Shaded areas represent 95% confidence intervals. $\tilde{d} = 1$ represents entrant location.

investment), and rating count growth. For rating count, I use the log-difference transformation: $\Delta \ln(\text{rating\_count} + 1)$, which captures the growth rate of cumulative ratings. Since new ratings arrive as users engage with apps, rating count growth serves as a proxy for consumer demand and ongoing engagement with the product.

Table 6: Incumbent App Quality Outcomes

	(1) Rating	(2) Update	(3) Δ Log Rating Count
ATT	0.0126**	-0.0006	0.0122***
	(0.0051)	(0.0112)	(0.0035)
Baseline Mean	3.978	0.2515	0.0468
N	50,099	52,524	52,524

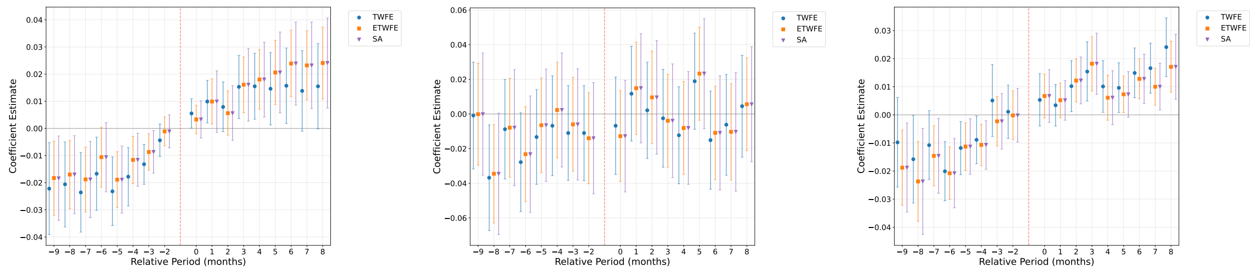
Notes: Two-way fixed effects (TWFE) DiD estimates at the app-month level. Standard errors clustered at the app level are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 6 presents estimates for quality outcomes and Figure 8 presents event studies for all quality outcomes. Figure 9 presents market-level differences in the quality outcomes. Average ratings rise by 0.013 stars relative to a base of approximately 4.0 stars, approximately 0.3% increase. Update frequency shows essentially no response. This suggests that, on average, developers may increase effort by producing higher quality updates, even though the frequency of updates does not change. However, this average masks heterogeneous responses across apps as displayed in Figure 9 panel (b).

Rating count growth (log-differenced), a proxy for demand and user engagement, shows a positive and highly significant effect: treated apps experience 1.2 percentage points higher monthly growth in rating counts, representing a 26% faster growth rate relative to the baseline of 4.7%. Combined with stable or slightly improved ratings, this suggests that Apple's entry may expand overall category visibility or demand, benefiting incumbents alongside the platform owner. This finding is consistent with the positive effect observed for entering cohorts, indicating that Apple's entry generates positive spillovers for both incumbents and new entrants in terms of user engagement.

Figure 10 presents distance gradients for quality outcomes. Apps closest to the entrant exhibit sharp declines in ratings, with the negative effect diminishing with a developer's distance from Apple. Eventually, the sign flips, as more peripheral products see ratings improvements. This

Figure 8: Quality Dynamics



(a) Rating (b) Update Frequency (c) Rating Count Growth

Note: Event study estimates showing dynamic treatment effects relative to one month before entry. TWFE is the primary estimator; ETWFE (Wooldridge (2021)) and SA (Sun and Abraham (2021)) shown for comparison. Analysis is at the app-month level. Standard errors are clustered at the app level. Error bars represent 95% confidence intervals.

demonstrates that quality competition varies substantially with distance, possibly reflecting the fact that the quality (or perceived quality) of the closest competitors is harmed by first-party entry, while more distant apps may benefit from complementaries with the entrant or related improvements in the overall software and hardware platform. Update frequency follows a similar but more muted pattern.

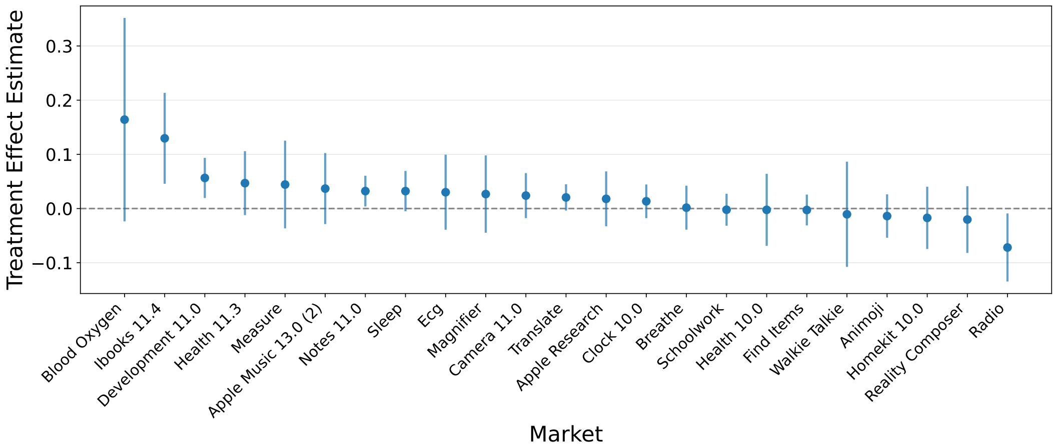
3.2.3 Two Key Dimensions of Heterogeneity

The incumbent analysis documents substantial heterogeneity along two independent dimensions. First, effects vary *across markets*: some markets show positive responses (expansion, quality improvements) while others show negative responses (contraction, defensive pricing). Notably, many show no response.

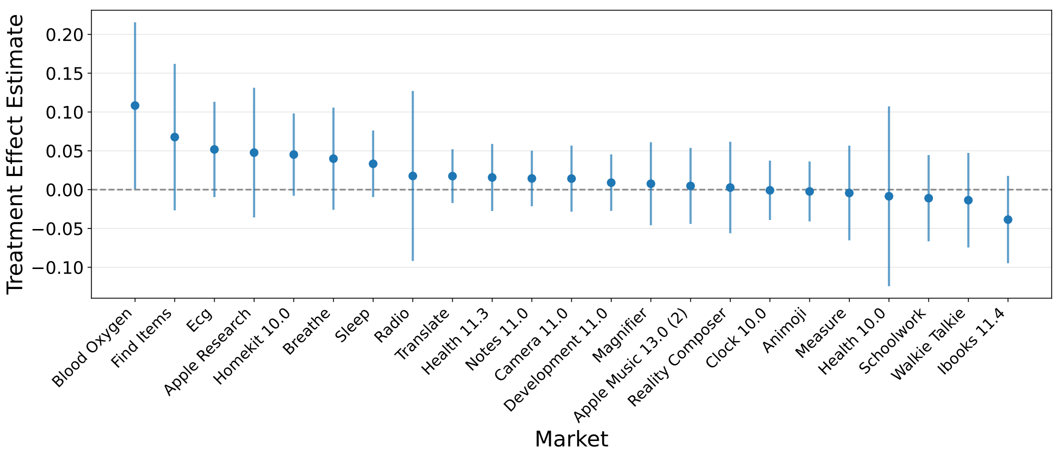
Table 7 quantifies this heterogeneity, showing that across all outcomes, 68% of market-outcomes experience no statistically significant effects from Apple's entry, indicating that many markets are largely unharmed by first-party entry. For price, 74% of markets show no significant effect, while 22% show increases. For free app proportions, 52% show no significant effect, while 35% show declines. Similarly, quality outcomes are largely unaffected, with 70% of markets showing no significant change in ratings and 87% showing no change in update frequency.

Of course, these statistics average across the spatial heterogeneity demonstrated in Figures 7 and 10. Effects vary *within markets* by competitive proximity. Apps closer to the entrant in

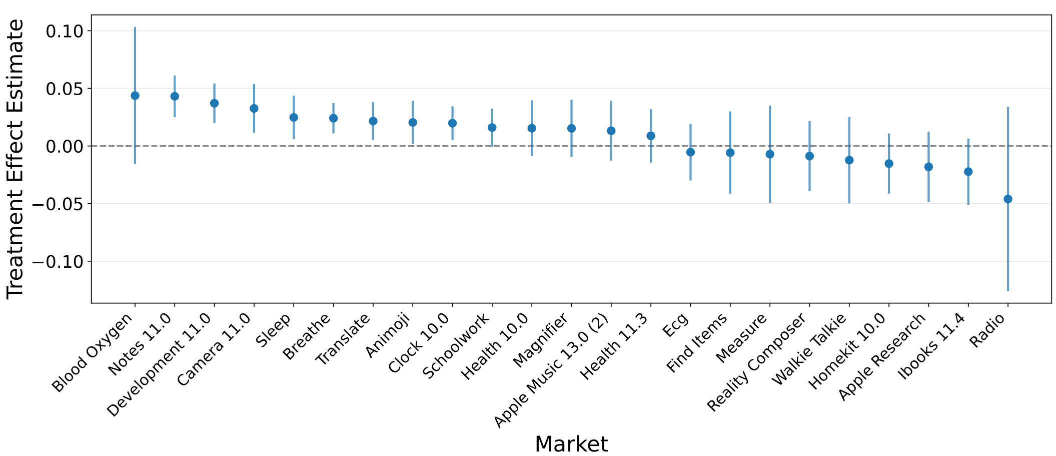
Figure 9: Market Heterogeneity in Quality



(a) Rating



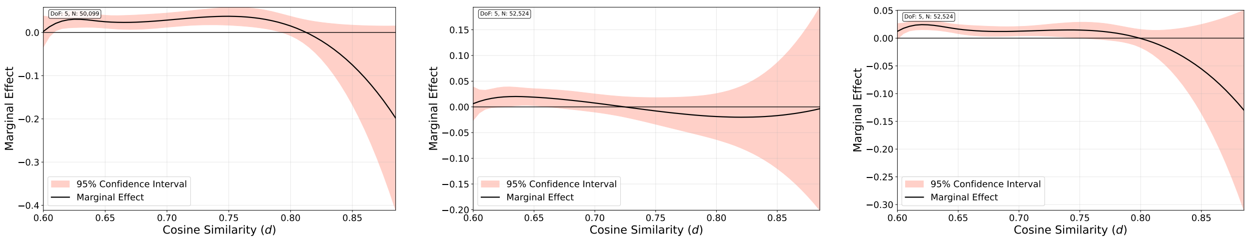
(b) Update Frequency



(c) Rating Count Growth

Note: Market-specific treatment effects from TWFE model (Equation (5)). Analysis is at the app-month level. Standard errors are clustered at the app level. Points show estimates with 95% confidence intervals for each of 23 markets.

Figure 10: Quality Effects by Distance from Entrant



(a) Rating (b) Update Frequency (c) Rating Count Growth

Note: Treatment effects across competitive distances from distance regression (Equation (6)). Degrees of freedom selected via cross-validation. Analysis is at the app-month level. Standard errors are clustered at the app level. Shaded areas represent 95% confidence intervals. $\tilde{d} = 1$ represents entrant location.

Table 7: Distribution of Market-Level Treatment Effects

	Percentage of Markets			
Outcome	Positive	Negative	Null	Dominant Pattern
Monetization				
Price	22%	4%	74%	No effect
Free	13%	35%	52%	No effect
In-App Purchases	13%	30%	57%	No effect
Price (Paid Apps)	13%	9%	78%	No effect
Quality				
Rating	26%	4%	70%	No effect
Update Frequency	13%	0%	87%	No effect
Δ Log Rating Count	39%	0%	61%	No effect
Average	**20%**	**12%**	**68%**	–

Notes: Based on market-level TWFE estimates for 23 markets. Effects are classified as positive or negative if statistically significant at the 10% level. "Null" indicates no statistically significant effect. Dominant pattern shows the most common effect type for each outcome.

product space experience larger treatment effects than distant apps. This creates a "competitive radius" around each entrant, beyond which effects dissipate. Importantly, distance gradients themselves vary across markets—some show steep decay (proximity matters greatly) while others show relatively flat gradients (proximity matters less).

Figure 11 reveals the full extent of heterogeneity by showing distance gradients for all 23 markets. Because markets differ in their distribution of competitive distances, each market's curve is displayed only within its observed similarity range, avoiding extrapolation beyond the data support. Some outcomes, such as Price and Free (which, recall, are closely aligned) present remarkable variation among affected markets: some markets exhibit substantial increases in price, while others shift sign as cosine similarity increases. Others, such as Rating Count Growth show a tight distribution of curves.

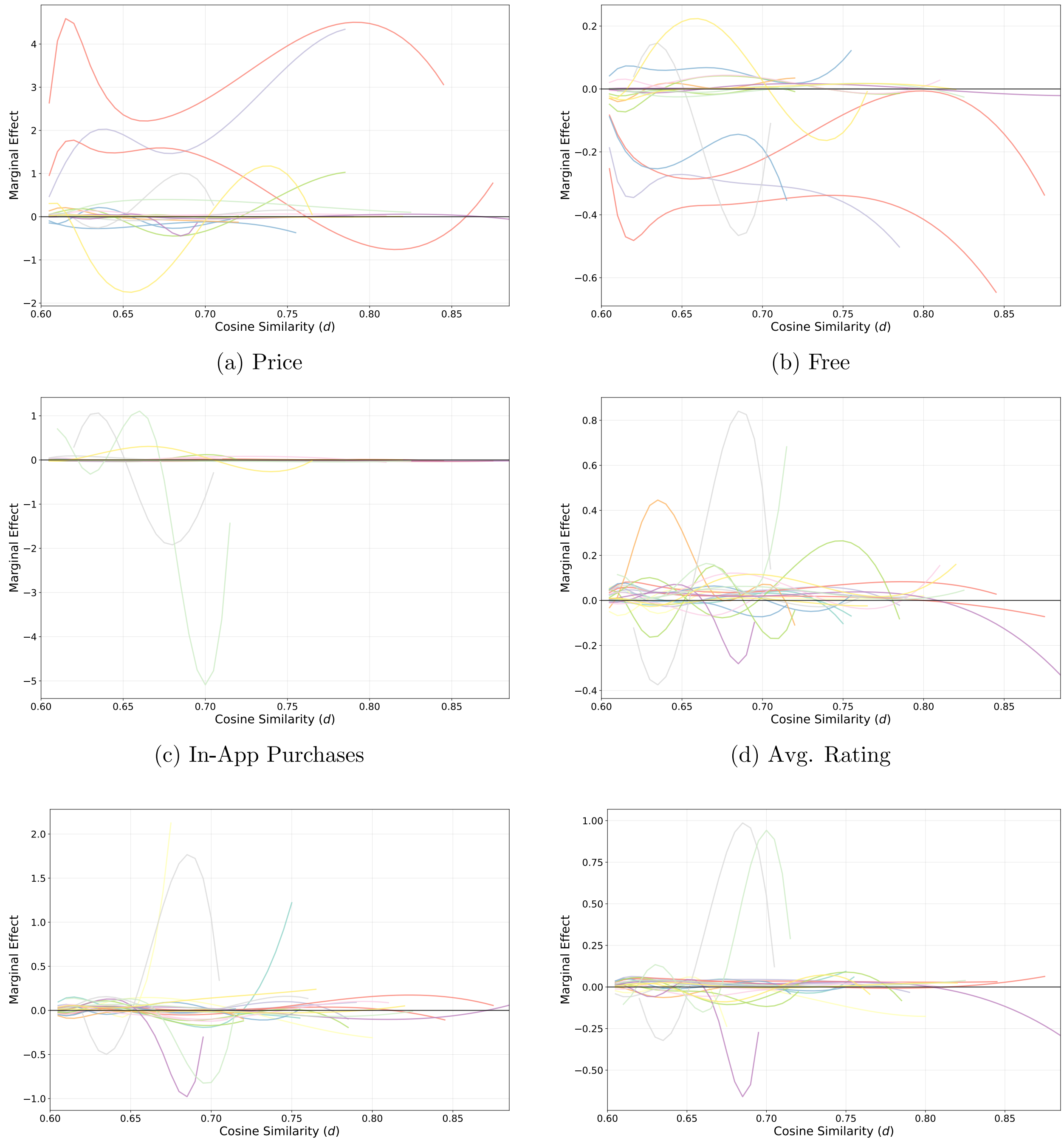
The IAP and rating count panels reveal contrasting patterns. IAP adoption declines are relatively consistent across distances within markets that show effects, though the magnitude varies across markets. Rating count effects are more dispersed, with some markets showing increased engagement for close competitors while others show uniform declines across all distances. In both cases, markets also vary in the sign of the estimated effect. This variation in competitive patterns across outcomes suggests that platform entry affects different aspects of app strategy through distinct mechanisms.

Three striking patterns emerge from this comprehensive view of heterogeneity. First, as documented in Table 7, a substantial proportion of markets show essentially no response to Apple's entry. This suggests that platform entry often has limited competitive impact, contrary to concerns about systematic foreclosure. Second, market responses are often non-linear, and in varying ways across markets. Third, the "competitive radius" varies dramatically across affected markets: some show effects only for particularly close apps, while others affect a much broader set of apps.

4 Mechanisms and Interpretation

I have documented substantial heterogeneity across markets and within markets by distance. What explains the cross-market variation in average effects? In this section, I investigate if entry type—whether Apple enters via a new app (standalone entry) or OS integration (integrated entry)—can

Figure 11: Distance Gradients Across All Markets



(a) Price

(b) Free

(c) In-App Purchases

(d) Avg. Rating

(e) Update

(f) Rating Count Growth

Note: Market-specific treatment effects across competitive distances from distance regression (Equation (6)). Degrees of freedom selected via cross-validation. Analysis is at the app-month level. For the IAP outcome, 5 markets are excluded due to insufficient Android in-app purchase data in the pre-period. Standard errors are clustered at the app level. Each line represents one market's treatment effects across distance, with $d = 1$ representing entrant location. Curves are restricted to each market's observed similarity range to avoid extrapolation beyond the data.

explain the variation in observed responses. Note that distance analysis (Section 3.2.3) already explains within-market variation; here I focus on cross-market differences.

To directly test whether entry type affects competitive outcomes, I estimate a TWFE model with entry type interactions. Rather than running separate regressions for standalone (explicit) and integrated (implicit) markets, I pool all markets and estimate:

$$y_{it} = \alpha_{\text{SA}} \cdot D_{it} + \alpha_{\text{Diff}} \cdot D_{it} \times \text{Integrated}_i + \gamma_i + \eta_t + \varepsilon_{it} \tag{8}$$

where D_{it} is defined as in Equation (5) and Integrated_i indicates whether app i is in a market where Apple entered via OS integration rather than a standalone app. The coefficient α_{SA} captures the treatment effect for standalone entry (the baseline group), α_{Diff} captures the additional effect for integrated entry, and their sum $\alpha_{\text{SA}} + \alpha_{\text{Diff}}$ yields the total effect for integrated entry. This specification directly tests the hypothesis that entry type matters: a significant α_{Diff} indicates systematically different responses. I present the results in Table 8.

Table 8: Entry Type Heterogeneity: Standalone vs Integrated

Outcome	All	Standalone	Integrated	Difference
Price	0.702***	0.146***	1.17***	1.02***
	(0.0507)	(0.0221)	(0.0829)	(0.0769)
Price (Paid Apps)	0.046	0.035	0.074	0.038
	(0.0330)	(0.0345)	(0.0475)	(0.0435)
Free	-0.097***	-0.016***	-0.165***	-0.148***
	(0.0084)	(0.0034)	(0.0137)	(0.0126)
In-App Purchases	-0.0093***	-0.013***	-0.0062*	0.0065
	(0.0033)	(0.0042)	(0.0037)	(0.0044)
Update	-0.0006	-0.0065	0.0041	0.011
	(0.0112)	(0.0147)	(0.0152)	(0.0197)
Rating	0.013**	0.0058	0.019***	0.013
	(0.0051)	(0.0060)	(0.0070)	(0.0083)
Δ Log Rating Count	0.012***	0.013***	0.012**	-0.0004
	(0.0035)	(0.0042)	(0.0049)	(0.0060)

Notes: TWFE estimates with standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. All: 23 markets (14 standalone + 9 integrated). Difference: Integrated − Standalone.

Two key patterns emerge from Table 8. First, integrated entry generates dramatically larger monetization effects. Price increases are 8.0-fold larger for integrated ($1.17) than standalone ($0.15) entry. The proportion of free apps declines by 16.5 percentage points for integrated versus 1.6 percentage points for standalone—a 10.3-fold difference. These dramatic differences suggest fundamentally different competitive dynamics: integrated entry forces aggressive monetization responses, while standalone entry generates modest adjustments. Second, the entry types exhibit similar demand responses, as proxied by the growth rate of rating counts. This suggests that any attention-grabbing demand expansion associated with Apple's entry into a submarket does not necessarily depend on how Apple implements entry.

One possible explanation for these differences is the unavoidability of integrated releases. OS-integrated features cannot be separately uninstalled or avoided by users, creating fundamentally different competitive pressure than marketplace apps. When Apple releases a standalone app like Translate, users must actively discover it in the App Store, evaluate it against alternatives, and choose to download it. Market forces operate normally—if third-party alternatives are superior, users may never adopt Apple's offering.

Integrated entry eliminates this choice architecture. When Apple integrates translation capabilities directly into iOS, every user automatically possesses this functionality upon updating their device. Third-party translation apps must now compete against a feature that users already have, cannot remove, and may discover through system prompts or Siri suggestions. This unavoidability likely explains the larger monetization responses to integrated entry: facing an unremovable competitor, third-party apps must differentiate more aggressively through pricing and business model changes.

5 Concluding Discussion

This paper provides systematic evidence on how platform-owner entry affects third-party developers across multiple markets. Studying 23 instances of Apple entering submarkets in its App Store—14 through standalone app releases and 9 through integrated OS features—I uncover striking heterogeneity that challenges both pro-platform and anti-platform narratives. The evidence reveals that platform entry is neither uniformly beneficial nor uniformly harmful, but rather generates widely varying effects that depend systematically on market context, competitive proximity, and entry implementation. The heterogeneity I document operates along three key dimensions. First, effects vary meaningfully across markets. Second, within markets, effects vary with the similarity to Apple's entrant. Third, entry type matters fundamentally: integrated OS features generate pricing and monetization effects that are roughly an order of magnitude larger than standalone apps.

Perhaps most surprisingly, I find that many markets experience no statistically significant effects on average. Across all outcomes, 68% of market-level estimates are statistically indistinguishable from zero, with quality metrics particularly unaffected—87% of markets show no significant changes in update frequency on average. This prevalence of null effects contradicts popular claims of either universal harm from foreclosure or overwhelming benefits from technology spillovers. When effects do occur, they largely concentrate in monetization strategies, suggesting that platform entry primarily triggers business model adjustments rather than changes to product development.

Several important limitations qualify these findings and their policy implications. Most fundamentally, the reduced-form approach employed here estimates net competitive effects but cannot directly assess consumer welfare. Additionally, the combination and variation of effects documented here have ambiguous welfare implications. For example, apps changing from free to paid pricing may also reduce reliance on or otherwise change advertising intensity, data collection practices, or on- or off-platform subscription models that affect consumer welfare in ways this analysis cannot capture.

Despite these limitations, these findings open important avenues for future research. The stark heterogeneity I document—both across markets and within markets by competitive distance—calls for deeper investigation into what determines these differential effects. Understanding why only 32% of market-outcome pairs show positive or negative changes while others exhibit null effects could help predict which markets are most vulnerable to platform competition and inform more targeted regulatory approaches. The systematic differences between standalone and integrated entry also warrant further study, particularly as platforms increasingly blur the lines between operating system features and marketplace applications.

The longer-run dynamics of platform competition remain largely unexplored. The nine-month post-entry window considered here may miss important evolutionary patterns where initial defensive responses give way to accommodation, innovation, or exit. Technology spillovers from platform entry might take years to fully materialize, particularly when new APIs and frameworks require developers to learn new skills and rebuild applications. Understanding these dynamic patterns could reveal whether the immediate competitive harm from platform entry is offset by longer-run innovation benefits, or whether initial advantages compound over time into durable market dominance.

These findings provide crucial empirical evidence for the ongoing global debate over platform regulation and antitrust enforcement. The evidence reveals that calls for blanket restrictions (see, for example, Warren (2019)) fundamentally misunderstand the nature of platform competition. The prevalence of null effects demonstrates that categorical bans would prevent substantial platform entry that causes limited to no competitive harm whatsoever. More troublingly, the concentration of effects among close competitors means that broad statutory language could restrict entry that affects only a narrow segment of apps while leaving the vast majority unaffected.

The differences between standalone and integrated entry provide actionable guidance for antitrust enforcement and regulatory design. Integrated OS features present fundamentally different competitive concerns than standalone apps that users can choose to ignore. This distinction maps directly onto antitrust theory: integrated features resemble tying-like arrangements or technological bundling that can increase foreclosure risk, while standalone apps are more likely to compete on merit in the marketplace.[7] Antitrust authorities should therefore apply different levels of scrutiny based on entry mode, with integrated features triggering heightened review similar to merger analysis in adjacent markets. The unavoidability of integrated features creates the kind of foreclosure concerns that antitrust law is designed to address, while standalone apps' market-based adoption provides the competitive constraints that normally obviate regulatory intervention. Furthermore, the competitive radii documented in this paper have implications for regulatory and antitrust market definitions. The methods employed here provide an empirically grounded approach to defining relevant markets in platform cases—an often difficult challenge.

The heterogeneity across markets further challenges the premise underlying many current regulatory proposals—that platform entry is categorically harmful to innovation and competition. Rather than categorical entry prohibitions, policy should focus on conduct remedies that address specific mechanisms of harm: prohibiting self-preferencing in search rankings, mandating equal API access, requiring transparency in data usage, and ensuring user choice for default applications.

[7] Although, pre-installed standalone apps may warrant greater scrutiny.

Ultimately, as policymakers worldwide grapple with platform power, evidence-based approaches that recognize the fundamental heterogeneity in platform competition effects will be essential for crafting interventions that preserve innovation incentives while preventing competitive harm. The complex, multi-dimensional nature of platform competition revealed in this study underscores that simple narratives—whether platforms are inherently good or bad for competition—fail to capture the nuanced reality of digital markets.

References

Anderson, Simon and Özlem Bedre Defolie. 2024. "Hybrid platform model: monopolistic competition and a dominant firm." *The RAND Journal of Economics* 55 (4):684–718. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/1756-2171.12478. 2

Boudreau, Kevin J. and Andrei Hagiu. 2011. "Platform Rules: Multi-Sided Platforms as Regulators." In *Platforms, Markets, and Innovation*, edited by Annabelle Gawer. Edward Elgar Publishing, Inc. 6

Cheyre, Cristobal, Benjamin T. Leyden, Sagar Baviskar, and Alessandro Acquisti. 2025. "Did Apple's App Tracking Transparency Framework Harm the App Ecosystem?" *Working Paper* . 6

Congress.gov. 2022. "Text – S. 2992 – 117th Congress (2021–2022): American Innovation and Choice Online Act." https://www.congress.gov/bill/117th-congress/senate-bill/2992/text. Accessed 23 June 2025. 2

Crémer, Jacques, Yves-Alexandre de Montjoye, and Heike Schweitzer. 2019. "Competition policy for the digital era." URL https://data.europa.eu/doi/10.2763/407537. 2

De Chant, Tim. 2022. "Antitrust bill that bars Big Tech self-preferencing advances in Senate." *Ars Technica* URL https://arstechnica.com/tech-policy/2022/01/antitrust-bill-that-bars-big-tech-self-preferencing-advances-in-senate/. 2

Ershov, Daniel. 2024. "Variety-Based Congestion in Online Markets: Evidence from Mobile Apps."

American Economic Journal: Microeconomics 16 (2):180–203. URL https://www.aeaweb.org/articles?id=10.1257/mic.20200347. 6

EUR-Lex. 2022. "Regulation (EU) 2022/1925 of the European Parliament and of the Council of 14 September 2022 on contestable and fair markets in the digital sector and amending Directives (EU) 2019/1937 and (EU) 2020/1828 (Digital Markets Act)." http://data.europa.eu/eli/reg/2022/1925/oj. Official Journal L 265/1, 12 October 2022. Accessed 23 June 2025. 2

Foerderer, Jens, Thomas Kude, Sunil Mithas, and Armin Heinzl. 2018. "Does Platform Owner's Entry Crowd Out Innovation? Evidence from Google Photos." *Information Systems Research* 29 (2):444–460. 5

Hagiu, Andrei, Tat-How Teh, and Julian Wright. 2022. "Should platforms be allowed to sell on their own marketplaces?" *The RAND Journal of Economics* 53 (2):297–327. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/1756-2171.12408. 2, 5

Halckenhaeusser, André, Jens Forderer, Armin Heinzl, and Ola Henfridsson. 2025. "Strategic Drivers of Core Expansion on Software Platforms: Evidence from Apple iOS." *Information Systems Research* URL https://doi.org/10.1287/isre.2023.0347. Articles in Advance. 5

Jabr, Wael, Dominik Gutt, Jurgen Neumann, and Dennis Kundisch. 2020. "The Fate of the App: Economic Implications of Updating under Reputation Resetting." *Working Paper* . 6

Johnson, Garrett, Tesary Lin, James C. Cooper, and Liang Zhong. 2025. "COPPAcalypse? The YouTube Settlement's Impact on Kids Content." Working paper, SSRN. Available at SSRN: https://ssrn.com/abstract=4430334 or http://dx.doi.org/10.2139/ssrn.4430334. 6

Kesler, Reinhold. 2022. "The Impact of Apple's App Tracking Transparency on App Monetization." *Working Paper* . 6

Lam, H. Tai. 2023. "Platform Search Design and Market Power." Working Paper. 5

Lee, Kwok-Hao and Leon Musolff. 2025. "Two-Sided Markets Shaped By Platform-Guided Search." Working Paper. 5

Leyden, Benjamin T. 2023. "There's an App for That: Understanding Product Updating Under Digitization." *Working Paper* . 6

———. 2025. "Platform design and innovation incentives: Evidence from the product rating system on Apple's App Store." *International Journal of Industrial Organization* 99:103133. URL https://www.sciencedirect.com/science/article/pii/S0167718724000882. 6

Li, Ding and Hsin-Tien Tsai. 2022. "Mobile Apps and Targeted Advertising: Competitive Effects of Data Exchange." *Working Paper* . 6

Madsen, Erik and Nikhil Vellodi. 2025. "Insider Imitation." *Journal of Political Economy* 133 (2):652–709. URL https://doi.org/10.1086/732888. 5

Raval, Devesh. 2023. "Steering in One Click: Platform Self-Preferencing in the Amazon Buy Box." Working Paper. 5

Reimers, Nils and Iryna Gurevych. 2019. "Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks." In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics. URL https://arxiv.org/abs/1908.10084. 7

Scott Morton, Fiona, Pascal Bouvier, Ariel Ezrachi, Bruno Jullien, Roberta Katz, Gene Kimmelman, A Douglas Melamed, and Jamie Morgenstern. 2019. "Market Structure and Antitrust Subcommittee Report." In *Stigler Committee on Digital Platforms: Final Report*, edited by Luigi Zingales, Guy Rolnik, and Filippo Maria Lancieri. George J. Stigler Center for the Study of the Economy and the State, The University of Chicago Booth School of Business, 23–138. URL https://research.chicagobooth.edu/-/media/research/stigler/pdfs/digital-platforms---committee-report---stigler-center.pdf. 2

Sun, Liyang and Sarah Abraham. 2021. "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects." *Journal of Econometrics* 225 (2):175–199. URL https://www.sciencedirect.com/science/article/pii/S030440762030378X. Themed Issue: Treatment Effect 1. 15, 16, 17, 18, 21, 25, 38, 39

Teng, Xuan. 2023. "Self-preferencing, Quality Provision, and Welfare in Mobile Application Markets." Working Paper. URL https://ssrn.com/abstract=4259639. 5

Warren, Elizabeth. 2019. "Here's how we can break up Big Tech." *Medium* URL https://medium.com/@teamwarren/heres-how-we-can-break-up-big-tech-9ad9e0da324c. 2, 33

Wen, Wen and Feng Zhu. 2019. "Threat of platform-owner entry and complementor responses: Evidence from the mobile app market." *Strategic Management Journal* 40 (9):1336–1367. 5

Wooldridge, Jeffrey M. 2021. "Two-Way Fixed Effects, the Two-Way Mundlak Regression, and Difference-in-Differences Estimators." Tech. rep. URL https://ssrn.com/abstract=3906345. SSRN working paper, version August 16, 2021. 15, 16, 17, 18, 21, 25, 38, 39

Zhu, Feng and Qihong Liu. 2018. "Competing with complementors: An empirical look at Amazon.com." *Strategic Management Journal* 39 (10):2618–2642. 5

Appendices

A Comparison Across DiD Estimators

This appendix compares results across multiple difference-in-differences estimators to assess robustness. The main text uses two-way fixed effects (TWFE) as the primary specification. This appendix presents the extended two-way fixed effects (ETWFE) estimator following Wooldridge (2021) and the Sun and Abraham (2021) interaction-weighted estimator (SA) as alternatives for comparison.

Extended Two-Way Fixed Effects (ETWFE). The ETWFE estimator from Wooldridge (2021) saturates the model with cohort-time treatment indicators, providing consistent estimates under heterogeneous treatment effects. By avoiding the use of already-treated units as controls, ETWFE circumvents the negative weighting problems that can afflict standard TWFE with staggered treatment adoption.

Sun & Abraham (SA). The SA estimator from Sun and Abraham (2021) uses never-treated and not-yet-treated units as controls, explicitly avoiding the use of already-treated units that can introduce bias through negative weights. Like ETWFE, SA provides heterogeneity-robust estimates by allowing for cohort-specific treatment effects.

Incumbent Analysis Robustness. Table 9 presents estimates across all three estimators for incumbent app outcomes. Results are similar across methods, supporting the robustness of our main TWFE findings.

Entry/Exit Analysis Robustness. Table 10 presents market-level entry and exit results across estimators. Entry effects are imprecisely estimated across all methods, consistent with our finding of no robust effect on third-party entry. Exit effects are consistently negative across all estimators, confirming the TWFE results reported in the main text.

Table 9: DiD Point Estimates

Outcome	(1) TWFE	(2) ETWFE	(3) SA
Δ Log Rating Count	0.0122***	0.0106***	0.0106***
	(0.0035)	(0.0028)	(0.0035)
Free App	-0.0971***	-0.1022***	-0.1022***
	(0.0084)	(0.0070)	(0.0089)
In-App Purchases	-0.0093***	-0.0071***	-0.0071**
	(0.0033)	(0.0025)	(0.0034)
Price	0.7019***	0.6882***	0.6882***
	(0.0507)	(0.0437)	(0.0500)
Rating	0.0126**	0.0161***	0.0161***
	(0.0051)	(0.0045)	(0.0058)
Update	-0.0006	0.0008	0.0008
	(0.0112)	(0.0104)	(0.0129)

Notes: Analysis is at the app-month level. Columns show treatment effect estimates from TWFE (two-way fixed effects), ETWFE (extended two-way fixed effects; Wooldridge (2021)), and SA (interaction-weighted estimator; Sun and Abraham (2021)). For the IAP outcome, 5 markets are excluded due to insufficient Android in-app purchase data in the pre-period. Standard errors clustered at the app level are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table 10: DiD Point Estimates

Outcome	(1) TWFE	(2) ETWFE	(3) SA
Log Entry Count	-0.0262	-0.0601	-0.0601
	(0.1350)	(0.3985)	(0.1136)
Log Exit Count	-0.1646	-0.1715	-0.1715
	(0.1272)	(0.4520)	(0.1393)

Notes: Analysis is at the platform-market-month level. Columns show treatment effect estimates from TWFE (two-way fixed effects), ETWFE (extended two-way fixed effects; Wooldridge (2021)), and SA (interaction-weighted estimator; Sun and Abraham (2021)). Standard errors clustered at the platform-market level are in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

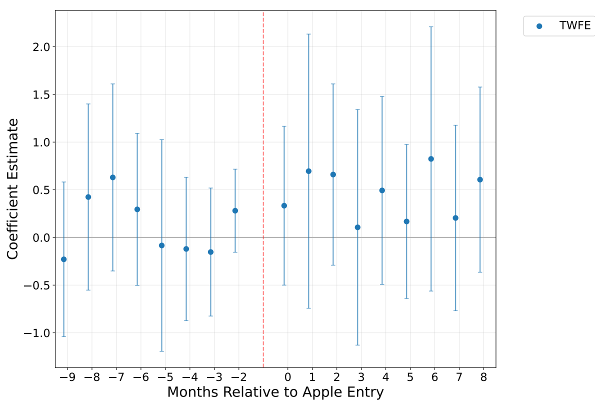
B Cohort Analysis Event Studies

This appendix presents event study estimates for the cohort composition analysis described in Section 3.1.2. I estimate:

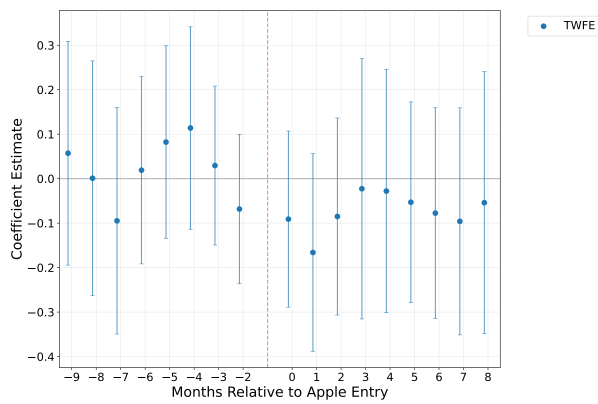
$$y_i = \sum_{k=-9}^{8} \beta_k \cdot \mathbf{1}[t_i - t_a^* = k] \times \mathrm{iOS}_i + \mathbf{X}_i' \boldsymbol{\beta} + \delta_a + \eta_t + \varepsilon_i \tag{9}$$

where t_i is the month app i enters, t_a^* is Apple's entry month in market a, and $\mathbf{X}_i$ includes market-specific quadratic time trends with platform differentials. Coefficients β_k show how the iOS-Android gap in entry characteristics evolves relative to Apple's entry timing.

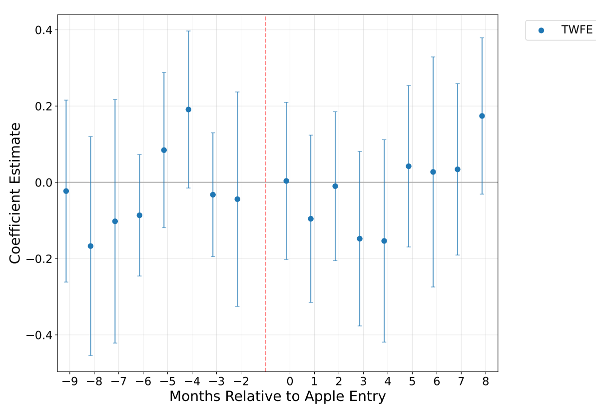
Figure 12: Cohort Event Studies: Monetization Outcomes



(a) Price (All Apps)



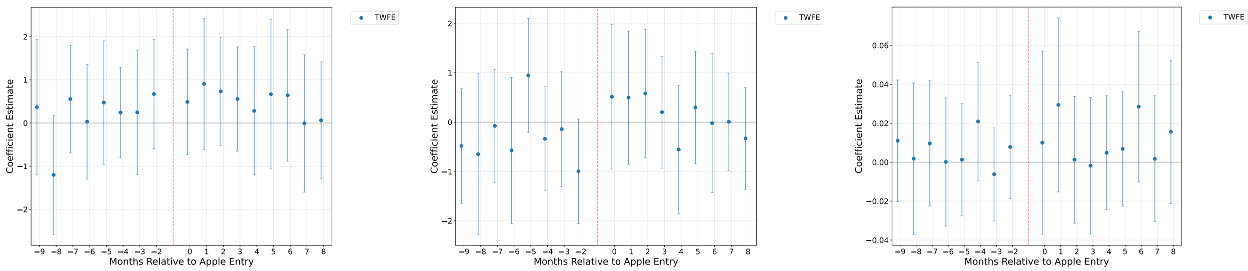
(b) Free



(c) In-App Purchases

Note: Event study estimates from cross-sectional DiD model showing how the iOS-Android gap in monetization characteristics evolves relative to Apple's entry timing. Each app is observed once at entry. Standard errors are clustered at the market-platform level. Error bars represent 95% confidence intervals.

Figure 13: Cohort Event Studies: Quality and Location Outcomes



(a) Rating (b) Log Rating Count (c) Similarity

Note: Event study estimates from cross-sectional DiD model showing how the iOS-Android gap in quality and location characteristics evolves relative to Apple's entry timing. Each app is observed once at entry. Standard errors are clustered at the market-platform level. Error bars represent 95% confidence intervals.

Figures 12 and 13 present event study estimates for entering cohort characteristics.

C Data Appendix

This appendix presents detailed market-level summary statistics for the three datasets used in the main analysis. Table 2 in the main text reports aggregate pre-treatment and post-treatment means; the tables below decompose these by market to illustrate the heterogeneity in market characteristics.

C.1 Incumbent App Summary Statistics

Tables 11 and 12 present app-month level summary statistics for incumbent apps, broken down by market for the pre-treatment and post-treatment periods respectively. These statistics correspond to Panel A of Table 2.

C.2 Entry and Exit Summary Statistics

Tables 13 and 14 present market-month level entry and exit statistics, broken down by market for the pre-treatment and post-treatment periods respectively. These statistics correspond to Panel B of Table 2.

	Price	Price-Paid	Free	IAP	Avg. Rating	New Avg. Rating	Update	Δ Log Ratings	N
Animoji	0.17	1.59	0.89	0.34	3.70	3.70	0.13	0.04	846
Apple Music 13.0 (2)	1.10	2.99	0.63	0.34	4.00	4.10	0.27	0.04	1071
Apple Research	1.58	5.92	0.73	0.23	4.07	4.12	0.26	0.05	270
Blood Oxygen	0.84	2.19	0.62	0.31	3.37	3.73	0.23	0.08	117
Breathe	0.00		1.00	0.22	4.14	4.22	0.07	0.04	261
Camera 11.0	0.00		1.00	0.20	3.91	3.95	0.25	0.06	1737
Clock 10.0	0.00		1.00	0.26	4.17	4.06	0.18	0.04	2637
Development 11.0	0.00		1.00	0.32	3.78	3.84	0.24	0.03	1917
Ecg	2.98	4.20	0.29	0.28	3.76	3.93	0.10	0.04	495
Find Items	1.43	4.07	0.65	0.53	3.99	3.99	0.29	0.06	432
Health 10.0	0.00		1.00	0.21	3.87	3.83	0.19	0.03	252
Health 11.3	0.29	3.39	0.91	0.09	3.56	3.41	0.41	0.07	1647
Homekit 10.0	0.00		1.00	0.27	3.58	3.45	0.40	0.09	1314
Ibooks 11.4	1.19	3.92	0.70	0.26	3.64	3.56	0.30	0.06	522
Magnifier	1.32	2.87	0.54	0.32	4.12	3.76	0.12	0.02	531
Measure	3.11	3.92	0.21	0.24	3.92	3.92	0.18	0.05	720
Notes 11.0	0.00		1.00	0.32	4.04	4.04	0.24	0.04	2988
Radio	1.23	2.86	0.57	0.29	3.90	4.17	0.16	0.06	63
Reality Composer	2.67	4.85	0.45	0.37	3.95	3.85	0.24	0.05	747
Schoolwork	0.00		1.00	0.33	4.01	3.93	0.33	0.06	1143
Sleep	1.56	3.55	0.56	0.48	4.27	4.09	0.29	0.05	1566
Translate	1.77	4.70	0.62	0.59	4.25	4.16	0.24	0.04	4311
Walkie Talkie	1.54	3.44	0.55	0.33	3.70	3.53	0.26	0.05	675
All Markets	0.81	4.01	0.80	0.35	3.98	3.93	0.25	0.05	26262

Table 11: Incumbent App Summary Statistics by Market (Pre-Treatment)

	Price	Price-Paid	Free	IAP	Avg. Rating	New Avg. Rating	Update	Δ Log Ratings	N
Animoji	0.85	1.61	0.47	0.37	3.68	3.63	0.11	0.02	846
Apple Music 13.0 (2)	1.10	3.05	0.64	0.36	3.99	3.82	0.25	0.04	1071
Apple Research	1.56	5.87	0.73	0.23	4.10	4.17	0.31	0.02	270
Blood Oxygen	0.84	2.19	0.62	0.38	3.45	3.48	0.21	0.05	117
Breathe	0.00		1.00	0.22	4.09	4.15	0.08	0.02	261
Camera 11.0	1.84	4.12	0.55	0.23	3.92	3.91	0.24	0.04	1737
Clock 10.0	0.00		1.00	0.29	4.16	4.00	0.17	0.02	2637
Development 11.0	4.12	5.95	0.31	0.32	3.83	3.85	0.24	0.03	1917
Ecg	2.95	4.16	0.29	0.31	3.76	4.03	0.12	0.03	495
Find Items	1.13	3.62	0.69	0.58	3.99	3.92	0.24	0.02	432
Health 10.0	0.00		1.00	0.26	3.88	3.73	0.19	0.01	252
Health 11.3	0.49	3.58	0.86	0.09	3.57	3.51	0.39	0.06	1647
Homekit 10.0	0.00		1.00	0.30	3.52	3.37	0.41	0.04	1314
Ibooks 11.4	1.37	3.97	0.66	0.26	3.73	3.69	0.26	0.03	522
Magnifier	1.32	2.85	0.53	0.32	4.13	3.90	0.09	0.01	531
Measure	3.08	3.94	0.22	0.26	3.94	4.06	0.16	0.04	720
Notes 11.0	2.43	4.33	0.44	0.33	4.06	3.99	0.25	0.03	2988
Radio	1.26	2.93	0.57	0.29	4.40	4.13	0.16	-0.00	63
Reality Composer	2.66	4.89	0.46	0.37	3.89	3.94	0.23	0.03	747
Schoolwork	0.00		1.00	0.36	3.98	3.86	0.29	0.03	1143
Sleep	1.73	3.98	0.57	0.51	4.26	4.06	0.27	0.03	1566
Translate	1.78	4.78	0.63	0.61	4.24	4.17	0.21	0.02	4311
Walkie Talkie	1.53	3.37	0.55	0.36	3.70	3.45	0.28	0.03	675
All Markets	1.55	4.30	0.64	0.37	3.98	3.90	0.24	0.03	26262

Table 12: Incumbent App Summary Statistics by Market (Post-Treatment)

	Log Entry	Log Exit	N
Animoji	0.91	0.86	18
Apple Music 13.0 (2)	0.48	0.80	18
Apple Research	0.08	0.12	18
Blood Oxygen	0.15	0.12	18
Breathe	0.08	0.00	18
Camera 11.0	1.04	0.64	18
Clock 10.0	0.99	0.41	18
Development 11.0	0.57	0.47	18
Ecg	0.08	0.14	18
Find Items	0.15	0.12	18
Health 10.0	0.14	0.00	18
Health 11.3	0.69	0.41	18
Homekit 10.0	0.90	0.23	18
Ibooks 11.4	0.15	0.12	18
Magnifier	0.25	0.04	18
Measure	0.48	0.38	18
Notes 11.0	1.22	1.11	18
Radio	0.10	0.08	18
Reality Composer	0.46	0.25	18
Schoolwork	0.60	0.43	18
Sleep	0.53	0.46	18
Translate	1.20	0.89	18
Walkie Talkie	1.23	1.07	18
All Markets	0.54	0.40	414

Table 13: Market-Level Entry and Exit by Market (Pre-Treatment)

	Log Entry	Log Exit	N
Animoji	1.14	1.16	18
Apple Music 13.0 (2)	0.37	0.41	18
Apple Research	0.08	0.12	18
Blood Oxygen	0.27	0.06	18
Breathe	0.08	0.08	18
Camera 11.0	0.83	0.73	18
Clock 10.0	1.25	0.51	18
Development 11.0	0.45	0.37	18
Ecg	0.15	0.19	18
Find Items	0.28	0.25	18
Health 10.0	0.08	0.14	18
Health 11.3	0.55	0.48	18
Homekit 10.0	1.18	0.31	18
Ibooks 11.4	0.12	0.19	18
Magnifier	0.12	0.28	18
Measure	0.33	0.33	18
Notes 11.0	0.98	0.87	18
Radio	0.08	0.04	18
Reality Composer	0.40	0.14	18
Schoolwork	0.70	0.31	18
Sleep	0.60	0.54	18
Translate	1.20	1.20	18
Walkie Talkie	0.69	1.15	18
All Markets	0.52	0.43	414

Table 14: Market-Level Entry and Exit by Market (Post-Treatment)

C.3 Entering Cohort Summary Statistics

Tables 15 and 16 present summary statistics for the entering cohort analysis (repeated cross-section), broken down by market for the pre-treatment and post-treatment periods respectively. These statistics correspond to Panel C of Table 2.

	Price	Price-Paid	Free	IAP	Avg. Rating	Log # Ratings	Similarity	N
Animoji	0.32	2.74	0.88	0.03	4.00	1.24	0.65	34
Apple Music 13.0 (2)	0.25	1.99	0.88	0.00	4.82	3.60	0.64	16
Apple Research	0.00		1.00	0.00		0.00	0.61	2
Blood Oxygen	1.25	4.99	0.75	0.00	5.00	1.46	0.64	4
Breathe	0.00		1.00	0.00	4.00	1.47	0.67	2
Camera 11.0	0.00		1.00	0.26	4.04	1.23	0.68	39
Clock 10.0	0.00		1.00	0.00	4.37	1.94	0.66	35
Development 11.0	0.00		1.00	0.28	3.98	1.11	0.65	18
Ecg	2.00	3.99	0.50	0.50		0.00	0.63	2
Find Items	0.50	1.99	0.75	0.75	4.67	2.72	0.68	4
Health 10.0	0.00		1.00	0.00	4.80	1.37	0.62	4
Health 11.3	0.00		1.00	0.00	4.09	0.78	0.67	24
Homekit 10.0	0.00		1.00	0.11	4.11	1.50	0.63	32
Ibooks 11.4	2.50	9.99	0.75	0.00	4.80	1.25	0.62	4
Magnifier	1.42	1.99	0.29	0.14	4.55	1.52	0.65	7
Measure	1.19	2.24	0.47	0.20	3.32	1.32	0.67	15
Notes 11.0	0.00		1.00	0.12	4.35	1.28	0.65	52
Radio	0.33	0.99	0.67	0.00	4.83	4.32	0.65	3
Reality Composer	2.82	6.57	0.57	0.21	3.88	1.74	0.64	14
Schoolwork	0.00		1.00	0.08	4.45	1.22	0.65	20
Sleep	1.31	3.49	0.62	0.31	4.66	1.60	0.66	16
Translate	0.60	3.74	0.84	0.52	4.22	1.33	0.70	50
Walkie Talkie	1.28	2.42	0.47	0.18	3.78	1.91	0.66	51
All Markets	0.49	3.10	0.84	0.19	4.20	1.52	0.66	448

Table 15: Entering Cohort Summary Statistics by Market (Pre-Treatment)

	Price	Price-Paid	Free	IAP	Avg. Rating	Log # Ratings	Similarity	N
Animoji	0.51	2.43	0.79	0.14	3.76	2.71	0.69	43
Apple Music 13.0 (2)	0.60	2.99	0.80	0.20	4.65	1.81	0.66	10
Apple Research	0.00		1.00	0.00	1.50	1.98	0.67	2
Blood Oxygen	0.28	1.99	0.86	0.14	4.07	2.90	0.70	7
Breathe	0.00		1.00	0.00		0.00	0.61	2
Camera 11.0	0.55	1.71	0.68	0.14	3.86	1.39	0.67	28
Clock 10.0	0.00		1.00	0.19	4.42	1.48	0.64	52
Development 11.0	1.38	3.59	0.62	0.38	3.98	2.03	0.65	13
Ecg	3.00	5.99	0.50	0.25		0.00	0.67	4
Find Items	1.75	3.49	0.50	0.25	4.00	1.77	0.67	8
Health 10.0	0.00		1.00		4.75	3.06	0.64	2
Health 11.3	0.00		1.00	0.00	4.68	1.79	0.65	16
Homekit 10.0	0.00		1.00	0.14	4.13	1.54	0.63	44
Ibooks 11.4	0.00		1.00	0.33	4.05	2.90	0.62	3
Magnifier	0.00		1.00	0.00	2.75	4.15	0.62	3
Measure	1.77	5.32	0.67	0.11	4.50	1.79	0.69	9
Notes 11.0	2.28	4.67	0.51	0.13	4.35	1.11	0.67	39
Radio	2.25	4.49	0.50	0.00	2.80	1.61	0.63	2
Reality Composer	1.84	4.79	0.62	0.31	4.32	1.46	0.67	13
Schoolwork	0.00		1.00	0.06	4.30	1.35	0.65	24
Sleep	0.12	1.24	0.90	0.80	4.24	1.98	0.66	20
Translate	0.65	5.99	0.89	0.63	4.10	1.87	0.67	46
Walkie Talkie	0.91	2.09	0.57	0.26	3.24	3.11	0.66	23
All Markets	0.67	3.58	0.81	0.26	4.07	1.82	0.66	413

Table 16: Entering Cohort Summary Statistics by Market (Post-Treatment)