

Effects of Platform Vertical Integration on Direct Competitors: Evidence from the Mobile Application Market

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Abstract

The rapid expansion of digital ecosystems has intensified regulatory scrutiny regarding the "dual role" of digital platforms, with ongoing debates over whether platform owners' entry into their own platforms suppresses third-party competitors. Using a stacked Difference-in-Differences approach and a comprehensive panel dataset, we evaluate the impact of Apple and Google's first-party app launches on their most direct functional rivals. On Apple's iOS, first-party app entry immediately and significantly reduces direct rivals' downloads, revenues, and update frequencies, followed by a delayed decline in prices. Conversely, on the Google Play Store, platform entry yields no significant disruption to rivals' demand, pricing, or long-term innovation strategies. These findings highlight that the consequences of platform vertical integration are highly nuanced and ecosystem-specific, cautioning against broad, one-size-fits-all ex-ante regulations in favor of targeted, platform-level analyses.

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1. Introduction

Over the last two decades, the digital economy and the mobile app market have experienced dramatic, transformative growth. The number of internet users worldwide expanded from 1 billion in 2005 to 6 billion in 2025, and global app downloads between 2014 and 2024 exceeded one trillion (ITU, 2025; Sensor Tower, 2025). As these digital ecosystems have expanded, public discourse and regulatory scrutiny regarding their governance have intensified. Recent legislative frameworks, such as the proposed American Innovation and Choice Online Act in the United States and the implemented Digital Markets Act in the European Union, reflect a growing interest among government officials in ex-ante regulation of digital markets.

At the center of this regulatory debate is the “dual role” of digital platforms—specifically, whether a platform owner (such as Apple or Google) should be permitted to directly participate in its own marketplace as a competitor to third-party developers, or at least have that participation be subject to government oversight. Critics of the vertically integrated platforms frequently argue that they possess both the incentive and the means to engage in anticompetitive behavior, notably “self-preferencing”, wherein a platform gives its own products favorable treatment through behaviors like manipulated search rankings or exclusive access to APIs. Proponents of regulation argue that such conduct suppresses rival products, raises prices, and ultimately stifles innovation.

However, whether alleged discriminatory conduct actually reduces overall economic welfare remains an open empirical question. This paper thus investigates the effects of mobile platforms’ presence in their own app stores, for both Apple iOS and Google Play Store, on the market outcomes of their most direct rivals. While our data do not allow us to directly isolate algorithmic self-preferencing, we evaluate the observed effects of first-party app launches on third-party downloads, pricing, revenue, and app updates. Specifically, we rely on a stacked difference-in-differences approach to assess how the entry of first-party apps impacts those third-party apps that are in direct competition with the entering first-party app. We find that the effects of platform owner entry are highly nuanced and heterogeneous across platforms: While Apple’s introduction of its first-party apps on its platform generally led to reduced downloads, revenue, and app updates for direct rivals, these rivals’ prices didn’t decline until one to two years after Apple’s own app introduction. As for Google, there are negative but nonsignificant changes in downloads, prices, update frequency, and only a somewhat significant temporary decline in revenue for these rivals. We provide brief policy conclusions based on these findings.

2. Literature Review and Theoretical Hypotheses

This research contributes to the growing literature on the dual roles of digital platforms. Previous empirical work on the mobile application market has largely focused on how first-party entry affects third-party innovation, often yielding contradictory results. For example, Foerderer et al. (2018) found that the launch of Google Photos on the Android platform increased the innovation activity of similar apps due to “attention spillovers”—whereby the platform’s entry raises consumer interest in the entire app category. Conversely, Wen & Zhu (2019) examined Google’s

entry into other app categories and found that it led to a reduction in third-party innovation. We expand upon these studies by moving beyond a few selected app releases to utilize a comprehensive dataset covering both Apple and Google platforms over a near-decade.

As for empirical research on self-preferencing, the literature is relatively new but growing rapidly. In the context of mobile app markets, Teng (2025) is the only study on self-preferencing that we are aware of. Using a change in Apple’s search algorithm in July 2019, the author finds that higher ranks for Apple apps are partly due to self-preferencing (beyond consumer preferences). Simulations find that this self-preferencing results in a loss of consumer surplus, though the magnitude of that loss is rather small at -3%.

Most other empirical studies on self-preferencing examine Amazon’s seller activity on its own marketplace. Zhu & Liu (2018) find that Amazon is more likely to compete with third-party sellers in product spaces that are more successful in terms of sales and ratings. Lee & Musolff (2025) find that Amazon tweaks its algorithms so that its products are displayed more prominently than third-party products, which they also find aligns with consumers’ preferences, as consumers would often prefer Amazon’s products anyway. Using data from actual consumer searches, Farronato et al. (2023) arrive at a similar conclusion: Given a consumer search, Amazon products rank higher on average than third-party counterparts, and this difference cannot be explained away by any observed factors. Finally, Dube (2024) points out similarities between Amazon’s brand strategy and traditional retailers’ private-label brands.

Following the literature, we structure our current empirical inquiry around three core hypotheses regarding the mechanisms of platform entry:

- **The Spillover Hypothesis:** Platform entry creates “attention spillovers” that expand the overall market, increasing demand (downloads) for rival apps, and therefore, their revenue.
- **The Competition Hypothesis:** As a first-party app enters and competes with direct rivals, with or without discriminatory actions, demand for those rivals declines, and their prices decline as well.
- **The Quality Hypothesis:** Platform entry forces third-party developers to update their apps to remain competitive.

3. Data and Descriptive Statistics

To test these hypotheses, we employ a rich monthly panel dataset sourced from Sensor Tower, a leading mobile analytics firm. The dataset spans from January 2012 to May 2021 for the Apple App Store and from January 2014 to May 2021 for the Google Play Store. To ensure robustness, the sample includes all apps that have achieved at least 100,000 all-time global downloads or \$100,000 in all-time global revenue. This inclusion criterion captures approximately 406,900 unique apps, representing 96% of all global downloads and 99% of global revenue during the sample period. Figure 1 provides an overview of growth in the app space across both platforms.

For each app-month observation, we track several critical market variables: global and U.S. downloads, the number of updates, the app’s price at the end of the month, and estimated app revenue (from app sales and in-app purchases only). Summary statistics reveal that the app market is heavily skewed, with a massive volume of relatively small apps and a handful of “superstar” apps. Notably, the global user demand for Android apps is nearly four times that of Apple’s, with Google reaching approximately 9 billion monthly global downloads compared to Apple’s 2.5 billion in early 2020.

A major challenge in estimating competitive effects is accurately defining the relevant market. Relying solely on broad platform-defined primary categories (e.g., classifying both Netflix and Ticketmaster under “Entertainment”) lumps together too many apps that possess negligible substitutability. To identify direct competitors, we augment the Sensor Tower data with crowdsourced information from *AlternativeTo.net*. This website allows its users to identify specific, functional alternatives to software applications. By matching platform apps (30 from Apple, 114 from Google in Sensor Tower) with their user-identified alternatives, we define a granular “Neighborhood” of direct functional substitutes. Currently, our analysis of these neighborhood apps focuses on U.S. downloads, U.S. revenues, prices, and the number of updates.

Therefore, central to our analysis is how we define the functional “neighborhood” of apps to these first-party apps. One feature of the *AlternativeTo.net* website is that they allow users to input or select “features” of a particular app. We thus collected these features for all Apple and Android apps on the website, and defined an app to be in the neighborhood of the platform owners’ app if it is 1) in the same platform-defined primary category as the first-party app, and 2) shares at least one feature with the first-party app. We then merge this neighborhood dataset with the Sensor Tower dataset. Given the availability of app data on *AlternativeTo.net*, we were able to match 23 Google-released apps and 6 Apple-released apps. Tables 1.1 and 1.2 summarize the statistics for the variables of the combined dataset in the Apple App Store and Google Play Store, respectively. The matched platform owners’ first-party apps, along with the number of identified immediate neighbors, are listed in Table 4.

4. Exogeneity of Platform Owner’s Entry

Before we delve into the empirical analysis, a central challenge in evaluating the competitive effects of vertical integration is the potential endogeneity of the platform owner’s decision to enter a specific complementary market. As noted by Zhu and Liu (2018), platform owners like Amazon may strategically target and enter highly successful, lucrative product niches, suggesting that the “treatment” of platform entry is correlated with the unobserved potential of those markets. However, within our stacked Difference-in-Differences (DiD) framework, we argue that the treatment variable—specifically, the exact timing of the first-party app launch and the motivation behind it—is plausibly exogenous to the immediate neighborhood of competitors, resting on two primary arguments.

First, the protracted and complex nature of software development dictates that the exact launch timing of a first-party app acts as an exogenous shock to third-party developers. Developing a flagship app for the Apple iOS or Google Android ecosystem requires extensive internal R&D, beta testing, and alignment with corporate strategy. Consequently, the precise month of a platform’s entry ($t = 0$) is determined by internal engineering schedules and major corporate events (e.g., Apple’s Worldwide Developers Conference) rather than by unobserved short-term demand fluctuations within a specific app neighborhood. This is consistent with Foerderer et al. (2018), who use the release of Google Photos as an exogenous shock to complementors, and with Koval et al. (2025), who note that platform-initiated software releases follow independent, relatively predictable corporate trajectories that serve as exogenous technological shocks to third-party multi-product portfolios.

Second, the strategic motivation for platform entry fundamentally differs from that of a standard competitor, mitigating concerns of micro-level endogeneity. According to the theory of “platform envelopment” (Eisenmann et al., 2011), platform owners frequently enter adjacent or complementary markets to bundle functionalities, leveraging shared user relationships to protect or expand their core network effects. Similarly, Gawer and Henderson (2007) argue that platform owners often enter complementary markets to signal commitment to a category or to drive ecosystem-wide hardware sales, rather than to expropriate marginal rents from a specific, tiny software niche. Because Apple and Google’s entry decisions are driven largely by macro-level, ecosystem-wide strategic goals, their entry is conditionally exogenous to the localized, short-term market conditions of the specific “neighbor” apps evaluated in our model.

5. Empirical Analysis of Immediate Neighbors

To assess the impact of a first-party app launch on its app “neighbors”, we utilize a stacked Difference-in-Differences (DiD) framework. This methodology allows us to compare the outcomes of a platform’s new app within its immediate neighborhood with those of non-competitive apps, thereby smoothing out broader temporal trends.

The regression equation is specified as:

$$Y_{itc} = \alpha + \beta Treat_{ic} \cdot Post_{tc} + f_{ic} + m_{tc} + \varepsilon_{itc}$$

Where Y_{itc} represents the outcome variable (log of U.S. downloads, log of price, log of revenue, and number of updates) for app i at time t on either platform¹. Subscript c denotes a “stack” within this stacked DiD framework. $Treat_{ic}$ indicates if the app is a direct neighbor, $Post_{tc}$ is the treatment indicator equal to 1 for the intervals 0 to 2 months (where month 0 is the calendar month during which a platform app is released), 3 to 5 months, 6 to 8 months, 9 to 11 months, and finally 12 to 24 months following the platform’s app release, with pre-release period always set to the

¹ Because our variables assume nonnegative values including zero, whenever we take a log, we scale the variable up by one, so that the variable of interest is $\log(x+1)$.

period of 12 months prior. We chose these intervals to capture both the short-term and long-term impacts of the platform owners’ release of their own apps. f_{ic} controls for app-by-stack fixed effects², and m_{tc} captures the month-by-stack fixed effects. Following standard practice for stacked Difference-in-Differences estimators (Cengiz et al., 2019; Wing et al., 2024), we cluster our standard errors at the primary category by stack level. This level of clustering not only accounts for the mechanical duplication of control units inherent in the stacked dataset but also absorbs unobserved, correlated demand shocks among apps in the same broad market space.

The coefficient of interest is β , which captures the differential impact of the platform owners’ entry into their own platform on direct neighbors. For the log of U.S. downloads, for example, a negative, statistically significant value would indicate that, after the platform owner’s entry, there predictably decreases the number of downloads within the direct “neighborhood” of rivals previously defined, above and beyond the trend experienced by all other apps.

6. Results

We observe significant negative impacts on U.S. downloads, revenue, and the number of updates for neighbor apps immediately following an Apple first-party app release (Table 2.1, 2.3-2.4). At their heights, direct rivals’ downloads and revenue declined by 53.7% and 58.6% 12 to 24 months after Apple’s entry into its platform³, and the number of monthly updates declined by 0.965 zero to two months after Apple’s own app entry (all coefficients are significant at the 1% level). However, we do not find a significant reduction in the sticker price of neighboring apps immediately following Apple’s entry (Table 2.2). The prices of neighborhood apps eventually declined by 5.6% one to two years after Apple’s first-party app entry, significant at the 1% level.

When Google introduces a new first-party app, we observe no significant impact on rivals’ fundamental business outcomes, pricing, or innovation strategy, although the impact is in the same direction as observed on Apple’s platform. Specifically, we find negative, but mostly not statistically significant changes in the downloads, prices, revenues, or update frequencies of neighbor apps on the Android platform (Tables 3.1 – 3.4). Note that, for revenues, since the Sensor Tower dataset only includes app sales and in-app purchases, we do not have information on whether these Android app developers experimented with their advertising strategies after Google’s first-party app entry into their space. Overall, the only notable coefficient is on revenue

² With the stacked dataset, combined with having app-by-stack fixed effects, we run into a dimensionality-related computational problem. At the current stage, in order to mitigate the problem and properly estimate the DiD estimators, we randomly select a sub-group of “control” apps by stack, to end up with around 20,000 observations for most of our stacked regressions (keeping around 80% of all apps on the Apple iOS and about 8% of all apps on the Google Play Store).

³ To find the percentage change from coefficient on the log transformed value, we use $\exp(-0.77) - 1 = -0.537$ and $\exp(-0.881) - 1 = -0.586$. Subsequent coefficient estimates are also converted to percentages in the same manner.

9 to 11 months after Google’s first-party app introduction, with a decline of 12.5% and significant at the 5% level.

Finally, the validity of our stacked Difference-in-Differences estimates rests on the parallel trends assumption—the premise that, in the absence of the platform owner’s entry, the treatment group (immediate-neighbor apps) and the control group (non-neighbor apps) would have followed similar trajectories in demand and innovation. While perfectly randomized treatment is impossible in observational platform data, our econometric specification is designed to robustly defend this assumption. By incorporating app-by-stack fixed effects (f_{ic}) and month-by-stack fixed effects (m_{tc}), our model systematically absorbs app-specific unobserved heterogeneity and broader macroeconomic shocks—such as the massive surge in digital demand during the COVID-19 pandemic—that affect the entire platform over time. For endogeneity to bias our coefficient of interest (β), the platform owner would have to precisely time its multi-year app development cycle to coincide with an unobserved shock that uniquely affects only the granular, crowdsourced neighborhood of functional substitutes, but not the entire platform, or even the broader primary category in which these apps reside. Given the scale of Apple and Google’s operations, we consider micro-targeted timing highly improbable, which reinforces the causal interpretation of our DiD estimates.

7. Discussion and Conclusions

This research provides an empirical evaluation of the consequences of digital platforms participating as direct suppliers in their own marketplaces. Focusing on the most granular definition of direct competitors (neighbors in terms of app features), our findings present a complex picture of the impact of first-party entry into their own platform. For Google, vertical integration seemingly generated no significant disruption to its direct rivals’ downloads, revenue, pricing, or innovation strategies, although the coefficients generally point in the negative direction for downloads and revenue, and slightly positive for innovation efforts. For Apple, its first-party app entry led to significant declines in downloads, revenue, and software updates for direct rivals, with these rivals’ sticker prices eventually falling one to two years after Apple’s own app entry.

In terms of our three core hypotheses, the broad picture is quite nuanced. We find no support for the spillover hypothesis regarding downloads for Google and Apple. We also find some evidence towards the competition hypothesis. In the case of Apple, rivals’ app downloads declined immediately and significantly, while the sticker price of apps didn’t change until much later after Apple’s first-party app entry. In the case of Google, first-party entry had no significant impact on the number of downloads or on the pricing strategy. We do not find evidence for the quality hypothesis on either platform and note that, in fact, for Apple’s rivals, the number of updates decreased after Apple’s own app entered the iOS platform.

From a policy perspective, these findings caution against broad, categorical prohibitions on platform self-participation. The evidence indicates that platform owners’ entry into their own platforms yields nuanced outcomes and, in the case of Apple and Google, a markedly different

overall picture across platforms. Our results suggest that any regulatory interventions should be highly targeted and rely on platform-level analyses rather than blanket bans.

In conclusion, while we are unable to directly test for anticompetitive conduct in this study, at least in the case of Apple, we are unable to rule it out. Additionally, we find different outcomes for direct rival apps between Apple's and Google's first-party app entry on their respective platforms. In the case of Apple, rivals' downloads, revenues, and app updates declined immediately after first-party app entry, while price remained the same for one to two years. In the case of Google, there is no significant impact on direct rivals from first-party app entry, except for a temporary revenue decline within a year of Google's own app entry on its platform. Future research should examine both the strategic aspects of these rivals' post platform owner entry, particularly the question of why prices didn't change immediately after platform owners' first-party app entry, especially for Apple's direct rival apps, and address the question of self-preferencing directly.

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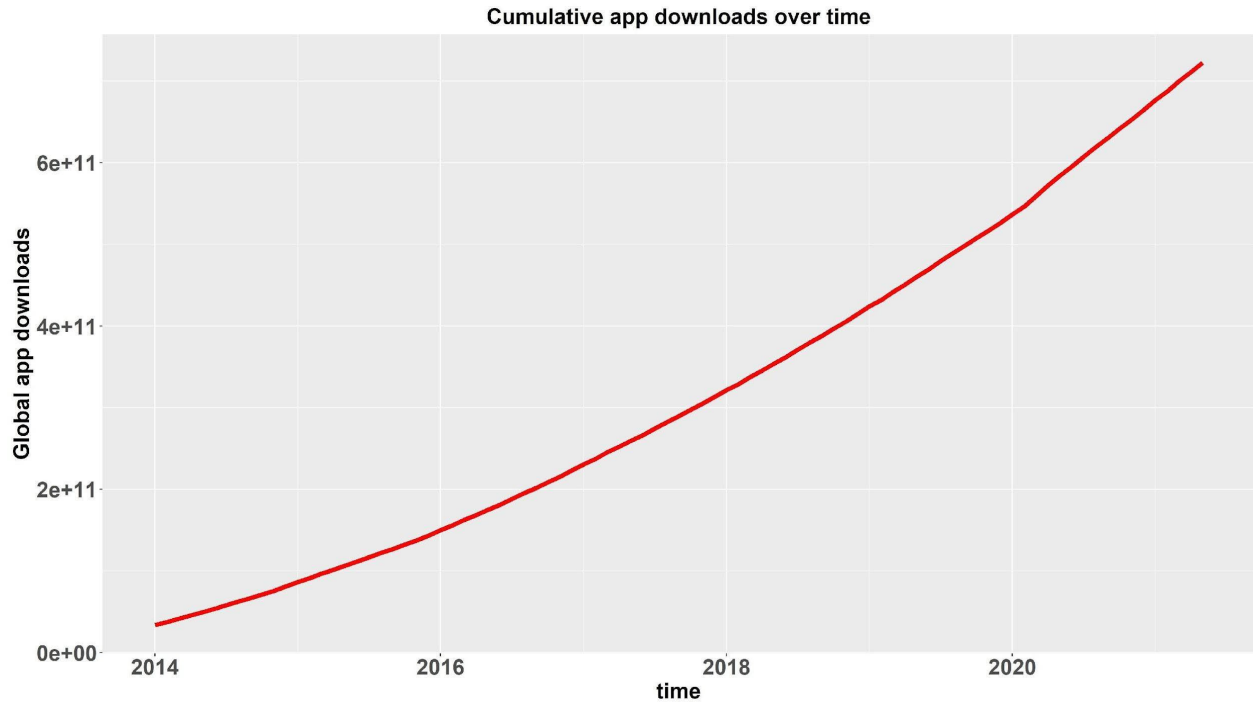
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Figures and Tables

Figure 1. Cumulative number of app downloads since 2014



Data Source: Sensor Tower. Note that the cumulative number of downloads is assumed to be zero prior to 2014, as our data becomes available in 2014. Note also that the cumulative number of downloads shown above is a floor (lower bound) estimate. It shows downloads only for those apps included in our dataset.

Table 1.1 Combined Dataset Summary statistics – Apple iOS

Statistic	Mean	Median	St. Dev.	Min	Max	N
Non-neighbor Apps						
US Downloads	50,742.18	887	231,536.1	0	6,720,951	93,676
US Revenue	72,890.4	42.16	813,471.7	0	37,574,952	93,676
Price (End of Month)	1.950	0.000	23.749	0	999.99	93,676
log(US downloads + 1)	6.550	6.789	3.695	0	15.721	93,676
log(US Revenue + 1)	3.793	3.756	3.994	0	17.442	93,676
log(US Price + 1)	0.401	0.000	0.732	0	6.909	93,676
# updates per month	0.561	0.000	0.984	0	10	93,676
Neighbor Apps						
US Downloads	220,690.1	3,938	580,981.9	0	5,832,479	2,958
US Revenue	389,392.6	51.71	2,820,649	0	37,574,952	2,958
Price (End of Month)	1.602	0.000	2.904	0	13.99	2,958
log(US downloads + 1)	7.682	8.279	4.368	0	15.579	2,958
log(US Revenue + 1)	4.176	3.965	4.557	0	17.442	2,958
log(US price + 1)	0.526	0.000	0.836	0	2.707	2,958
# updates per month	0.690	0.000	1.191	0	8	2,958

Each observation is an app-month. Neighbor apps are any apps that are in the immediate neighborhood of any Apple first-party app released. Non-neighbor apps are all other apps that are not neighbor apps. Data spanning January 2012 to May 2021.

Table 1.2 Combined Dataset Summary Statistics – Google Play Store

Statistic	Mean	Median	St. Dev.	Min	Max	N
Non-neighbor Apps						
US Downloads	34,398.52	305	195,620	0	7,792,012	86,645
US Revenue	46,322.36	0.000	575,064	0	25,822,472	86,645
Price (End of Month)	0.577	0.000	5.352	0	580.47	86,645
log(US downloads + 1)	5.030	5.724	4.550	0	15.869	86,645
log(US Revenue + 1)	2.379	0.000	3.659	0	17.067	86,645
log(US price + 1)	0.179	0.000	0.525	0	6.366	86,645
# updates per month	0.622	0.000	1.195	0	13	86,645
Neighbor Apps						
US Downloads	29,324.75	63	132,203	0	2,152,875	6,138
US Revenue	160.11	0.000	771.89	0	16,551.95	6,138
Price (End of Month)	0.323	0.000	1.573	0	37.82	6,138
log(US downloads + 1)	4.516	4.159	4.656	0	14.582	6,138
log(US Revenue + 1)	0.886	0.000	2.197	0	9.714	6,138
log(US price + 1)	0.118	0.000	0.417	0	3.659	6,138
# updates per month	0.595	0.000	1.127	0	12	6,138

Each observation is an app-month. Neighbor apps are any apps that are in the immediate neighborhood of any Google first-party app released. Non-neighbor apps are all other apps that are not neighbor apps. Data spanning January 2014 to May 2021.

Table 2.1. Apple log(U.S. Downloads + 1)

VARIABLES	0 to 2m	3 to 5m	6 to 8m	9 to 11m	12 to 24m
Treat · Post	-0.465*** (0.042)	-0.662*** (0.0714)	-0.545*** (0.0737)	-0.620*** (0.0805)	-0.770*** (0.152)
Observations	20,374	20,994	21,268	21,326	48,966
R-squared	0.950	0.942	0.893	0.892	0.866

Stacked DiD results. Errors clustered at the primary-category-by-stack level in parentheses. See text for detailed explanation. *** p<0.01, ** p<0.05, * p<0.1

Table 2.2. Apple log(Price + 1)

VARIABLES	0 to 2m	3 to 5m	6 to 8m	9 to 11m	12 to 24m
Treat · Post	0.000 (0.000)	-0.00180 (0.00178)	-0.00697* (0.00376)	-0.00273 (0.00827)	-0.0581*** (0.0199)
Observations	20,374	20,994	21,268	21,326	48,966
R-squared	0.985	0.987	0.983	0.984	0.952

Stacked DiD results. Errors clustered at the primary-category-by-stack level in parentheses. See text for detailed explanation. *** p<0.01, ** p<0.05, * p<0.1

Table 2.3. Apple log(U.S. Revenue + 1)

VARIABLES	0 to 2m	3 to 5m	6 to 8m	9 to 11m	12 to 24m
Treat · Post	-0.458*** (0.0490)	-0.611*** (0.0425)	-0.598*** (0.0440)	-0.569*** (0.0542)	-0.881*** (0.177)
Observations	20,374	20,994	21,268	21,326	48,966
R-squared	0.907	0.942	0.938	0.937	0.915

Stacked DiD results. Errors clustered at the primary-category-by-stack level in parentheses. See text for detailed explanation. *** p<0.01, ** p<0.05, * p<0.1

Table 2.4. Apple # of Updates

VARIABLES	0 to 2m	3 to 5m	6 to 8m	9 to 11m	12 to 24m
Treat · Post	-0.965*** (0.0312)	-0.693*** (0.0502)	-0.825*** (0.0528)	-0.773*** (0.0494)	-0.745*** (0.0579)
Observations	20,374	20,994	21,268	21,326	48,966
R-squared	0.430	0.394	0.416	0.389	0.381

Stacked DiD results. Errors clustered at the primary-category-by-stack level in parentheses. See text for detailed explanation. *** p<0.01, ** p<0.05, * p<0.1

Table 3.1. Google log(U.S. Downloads + 1)

VARIABLES	0 to 2m	3 to 5m	6 to 8m	9 to 11m	12 to 24m
Treat · Post	-0.643 (0.609)	-0.335 (0.513)	-0.463 (0.393)	-0.128 (0.452)	0.304 (0.549)
Observations	20,928	21,318	20,565	20,814	53,523
R-squared	0.759	0.707	0.735	0.724	0.721

Stacked DiD results. Errors clustered at the primary-category-by-stack level in parentheses. See text for detailed explanation. *** p<0.01, ** p<0.05, * p<0.1

Table 3.2. Google log(Price + 1)

VARIABLES	0 to 2m	3 to 5m	6 to 8m	9 to 11m	12 to 24m
Treat · Post	-0.0140 (0.0336)	0.034 (0.0505)	0.008 (0.0302)	-0.0124 (0.0314)	-0.0037 (0.0282)
Observations	20,928	21,318	20,565	20,814	53,523
R-squared	0.931	0.882	0.901	0.889	0.902

Stacked DiD results. Errors clustered at the primary-category-by-stack level in parentheses. See text for detailed explanation. *** p<0.01, ** p<0.05, * p<0.1

Table 3.3. Google log(U.S. Revenue + 1)

VARIABLES	0 to 2m	3 to 5m	6 to 8m	9 to 11m	12 to 24m
Treat · Post	-0.082* (0.0481)	-0.073 (0.130)	-0.101 (0.092)	-0.133** (0.0577)	0.118 (0.193)
Observations	20,928	21,318	20,565	20,814	53,523
R-squared	0.901	0.899	0.899	0.898	0.887

Stacked DiD results. Errors clustered at the primary-category-by-stack level in parentheses. See text for detailed explanation. *** p<0.01, ** p<0.05, * p<0.1

Table 3.4. Google # of Updates

VARIABLES	0 to 2m	3 to 5m	6 to 8m	9 to 11m	12 to 24m
Treat · Post	0.134 (0.175)	0.0043 (0.102)	0.0234 (0.103)	0.115 (0.116)	0.192 (0.170)
Observations	20,928	21,318	20,565	20,814	53,523
R-squared	0.481	0.386	0.433	0.437	0.382

Stacked DiD results. Errors clustered at the primary-category-by-stack level in parentheses. See text for detailed explanation. *** p<0.01, ** p<0.05, * p<0.1

Table 4. Platform Owners' App Neighbors

Platform Owner Apps	Platform Owner's App Name	Neighborhood Apps
Apple	Apple Podcasts	3
	Music Memos	1
	Pages	8
	iMovie	3
	iTunes Remote	1
	iTunes U	8
	Average for Apple	4
Google	Cardboard Camera	5
	Files by Google	3
	Google Arts & Culture	6
	Google Classroom	5
	Google Docs	4
	Google Drive	7
	Google Home	1
	Google Lens	4
	Google Maps	7
	Google Maps Go	2
	Google Meet	2
	Google One	3
	Google Play Music	2
	Google Street View	4
	Google Translate	2
	Google Voice	3
	Hangouts	8
	Snapseed	10
	YouTube	1
	YouTube Go	5
	YouTube Music	2
	YouTube Studio	1
	YouTube VR	1
	Average for Google	3.826

Neighborhood Apps are defined as 1) in the same primary category as the platform owners' app, and 2) share at least one user-supplied feature as recorded on the website *AlternativeTo.net*