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Abstract

We examine how app developers on the Android mobile platform adjust their innovation efforts (rate and direction) and value capture strategies in response to Google's entry threat and actual entry into their markets. We find that, after Google's entry threat increases, affected developers reduce innovation and raise the prices for the affected apps. Once Google enters, the developers reduce innovation and increase prices further. However, app developer's incentives to innovate are not completely suppressed; rather, they shift innovation to unaffected and new apps. Given many apps already offering similar features, Google's entry may reduce such social inefficiency.

Keywords: platform-owner entry, entry threat, innovation, complementors, mobile app industry

1. Introduction

As platforms become increasingly important in our economy, concerns are growing about the platform owners' misuse of their market power with respect to other firms in their ecosystems. Recently, for example, the European Union imposed a record-high fine on Google for using its market power in the search engine market to favor its own comparison-shopping service.[1] In a similar vein, with every major update of Apple's iOS operating system, Apple uses its own offerings to compete with many third-party app developers. When Amazon sources its successful products directly from suppliers, many third-party sellers complain that Amazon is competing against them. Because a large platform owner can favor its own offerings through bundling or prominent displays, its direct entry into a product space could significantly affect complementors' incentives to innovate and their ability to capture value (e.g., Bakos and Brynjolfsson 2000; Farrell and Katz 2000; Gawer and Cusumano 2002; Gawer and Henderson 2007; Pierce 2009; Zhu and Liu 2016; Parker and Van Alstyne forthcoming; Li and Agarwal forthcoming). While such practices have become hotbeds for policy debate, there is scant empirical evidence on how the threat or the actual platform-owner entry affects the innovation incentives of complementors.

In this paper, we study the mobile app market, in which third-party developers typically develop apps for Google's Android system and/or Apple's iOS system. We examine how, in response to Google's entry threat and actual entry into Android app markets, Android app developers (a) adjust the rate and direction of their innovation efforts and (b) adjust their value capture strategies through pricing.

As direct competitors in the mobile platform space, Google and Apple often follow each other's moves. Thus, to capture Google's entry threats to various mobile app markets, we look at instances in which Apple released its own apps on its iOS system, because Apple's direct entry into an iOS app market substantially changes Android app developers' perceptions of the likelihood of Google's entry into the corresponding Android app market. We use this empirical design to identify Google's *threat* of entry separately from its *actual* entry.

We compile a list of apps and important iOS features that Apple released from 2007 to 2015 and identify 31 entry events in which Apple directly competed with app developers on iOS. We then map these events with the entry events in which Google released its apps on Android. We find that 81 percent of the time, Google entered the same app spaces. In 80 percent of those instances, Apple entered before Google.

Given the data availability, our empirical analysis focuses on Apple's entry into three app spaces: Flashlight, Guided Access, and Podcasts. For each, we use a combination of manual reading of app descriptions and automatic search in the Google Play store to identify apps likely to be affected by these

[1] See, for example, http://money.cnn.com/2017/06/27/technology/business/google-eu-antitrust-fine/index.html, accessed August 2017.

entry events. Taking a difference-in-differences approach, we find that, relative to unaffected developers' apps in the same category, app developers vulnerable to Google's entry threat reduce their innovation efforts on the affected apps and increase these apps' prices. After Google's actual entry, they further reduce innovation efforts on the affected apps and further increase the prices. They do not, however, abandon the platform; rather, they shift their innovation efforts, manifested in an increase in updates of their unaffected apps during the entry-threat and actual-entry periods.

We extend our analyses in two ways. First, we investigate whether Google's entry threats and actual entry influence new app introduction, which can be considered as an alternative proxy for developers' innovation direction. Our results suggest that there are significantly fewer new apps released in the affected markets after Google becomes a credible threat; meanwhile, Google's entry threats and actual entry encourage affected developers to introduce more apps in unrelated markets. Second, we provide suggestive evidence on why app developers reduce innovation and increase prices even before Google's actual entry. One plausible explanation is that many app developers, being resource-constrained, must reallocate their limited resources from affected areas to unaffected areas even before the actual entry. We show that developers with fewer resource constraints, such as those with many app offerings or those with very successful apps, react differently from other developers.

Overall, although policymakers are concerned that platform-owner entry may discourage innovation, we find that in Android's case, app developers' innovation is not completely stifled but reallocated. Given the large number of apps already offering similar features in these markets, Google's entry threat and actual entry may have reduced wasteful effort of developing duplicate apps.

Our paper is related to several streams of literature. First, it adds to the empirical literature on how firms react to the threat of entry (e.g., Goolsbee and Syverson 2008; Pan et al. forthcoming; Seamans 2012; Wilson et al. 2017). This literature is small largely because it is hard to empirically identify the threat of entry separately from actual entry. Goolsbee and Syverson (2008) and Prince and Simon (2015) find that incumbent airlines reduce prices and service quality in response to the threat of entry by Southwest Airlines. Seamans (2012) finds that incumbent cable television firms use upgrades to deter municipal entrants. Dafny (2005) and Ellison and Ellison (2011) find non-monotonic relationships between incumbents' incentives to deter entry and market potential in the hospital procedure and pharmaceutical markets, respectively. Wilson et al. (2017) find that potential broadband providers delay their entry into a local market when facing entry threats from competing firms in neighboring markets. Unlike these studies, which focus on how firms respond to threats from comparable or smaller entrants, we study how small firms react to threats from large firms which it would be nearly impossible to deter. In addition to pricing, we examine how entry threats affect the innovation efforts of small firms.

Our study is also related to the literature on the incentives and consequences of platform owners' entry into complementary markets. The theoretical literature often finds that this entry strategy allows a platform owner to strengthen its market power and extract more value (e.g., Whinston 1990; Economides 1998; Klein 2001; Carlton and Waldman 2002), but it may discourage complementors from investing and innovating (e.g., Farrell and Katz 2000; Becchetti and Paganetto 2001; Choi and Stefanadis 2001; Heeb 2003; Miller 2008; Parker and Van Alstyne forthcoming). Only a few papers empirically study this phenomenon. In an in-depth study of Intel, Gawer and Cusumano (2002) and Gawer and Henderson (2007) find that Intel avoids competing directly with complementors, and it enters certain markets because it is not satisfied with complementors' products and wants to motivate them to improve. Edelman and Lai (2016) show that Google's prominent placement of its Flight Search service increases the clicks on paid advertising listings while decreasing the clicks on organic search listings by about the same quantity. Zhu and Liu (2016), examining the pattern of Amazon's entry into third-party sellers' product spaces, find that Amazon is likely to target popular product spaces and that after its entry, the affected third-party sellers are discouraged from growing their businesses on Amazon. Li and Agarwal (forthcoming) show that Facebook's integration of Instagram has a positive effect on complementors competing with Instagram by expanding the market demand for such apps.

This paper builds on this literature to examine strategic moves of complementors under both entry threat and actual entry. In many platform markets, the complementors' side is characterized by free entry. It is well known that free entry can lead to social inefficiency (e.g., Spence 1976a, 1976b; Dixit and Stiglitz 1977; Mankiw and Whinston 1986; Berry and Waldfogel 1999; Hsieh and Moretti 2003). When there are enough varieties in the market and consumers derive no additional benefits from more entrants, the additional resources used by entrants in developing these products are wasted. Platform owners' entry threats and actual entry may help reduce this social inefficiency.

More broadly, our work adds to the large literature on the relationship between competition and innovation (e.g., Schumpeter 1942; Arrow 1962; Greenstein and Ramey 1998; Cabral 2016). The evidence from both theoretical and empirical studies is mixed. While some find that competition favors innovation (e.g., Schmalensee 1974; Bertschek 1995; Nickell 1996), others show that competition reduces innovation incentives (e.g., Loury 1979; Gal-Or 1983; Vives 2008), has different effects on established or new players (Nagaraj and Piezunka 2017) or has no clear impact on them (e.g., Levin and Reiss 1984; Scott 1984; Levin et al. 1985; Scherer and Huh 1992). Boone (2000) and Lee (2009) find that the relationship depends on the firm's efficiency level or competence relative to rivals. In a similar vein, we find that in response to potential competition, both the top app developers (whose apps attract many downloads) and those with few resource constraints behave differently from the rest. More recent work also finds an inverted U-shaped relationship between the two (e.g., Aghion et al. 2005). Our study not only shows that competition affects the rate of innovation, but also provides the first large-scale empirical study on how competition shifts firms' innovation directions (e.g., Lerner and Stern 2012).

2. Empirical Design

2.1. Empirical Setting

We investigate how Android app developers react to the threat of Google's entry into a range of Android app markets. Several features of the Android platform make it an appealing empirical setting. First, Google has been developing Android as its operating system for touchscreen mobile devices. Meanwhile, according to our data collection, Google has also introduced approximately 200 mobile apps on Android between 2008 and 2015. Here, then, is a setting in which complementors keep facing entry threats from the platform owner.

Second, to identify which mobile app market is threatened by the platform owner's entry, we can use the entry patterns of a competing platform owner into its own complementary markets. A key assumption of this approach is that the competing platform owner's entry is highly correlated with the focal platform owner's entry. Within the mobile space, as we show later, not only do the two dominant platform providers, Apple and Google, enter into a range of app markets on their own platforms, but Google also follows Apple's moves closely. Thus, we are able to identify increases in Google's entry threat by looking at which iOS app markets Apple decides to enter.

Third, as mobile devices and their associated apps have become a central part of our everyday life, the mobile market is interesting and important to examine in itself. It has undoubtedly become a fertile ground that sprouts many innovations. It is also characterized by free entry and fierce competition. Our study attempts to shed light on how a mobile platform owner's actions could shape the competition and innovation landscape in the mobile ecosystem.

2.2. Identifying Shifts in Google's Entry Threats

Since the launch of its first-generation iPhone along with iOS in 2007, Apple has introduced a variety of standalone apps and new features for its iOS. With each one, Apple became a direct competitor to developers offering apps with similar functionalities on the iOS platform. For example, when Apple added a flashlight feature to its iOS Control Center in 2013, industry observers thought this might kill many previously essential third-party flashlight apps on iOS. Similarly, when iTunes Radio was introduced, observers suggested that music-streaming apps such as Spotify and Pandora could be rendered much less popular on iOS.[2]

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[2] For more discussion, see http://www.cultofmac.com/231121/seven-apps-apple-killed/, accessed August 2017.

We use the following three steps to compile the list of apps introduced by Apple for its iOS. First, we manually search in its app store for all apps that indicate the seller was Apple, such as iTunes U, GarageBand, and Keynote.[3] We take the first version release date as the entry date.

Second, we search in the SDC Merger and Acquisitions Database to identify mobile app companies Apple acquired: If Apple had not entered into an app market in which the acquired company was operating, we considered it to have done so with the acquisition. However, except in the case of acquiring Siri, Inc., we notice that Apple generally made acquisitions to enhance its existing apps, such as its acquisition of Locationary Inc. and Embark for its Maps app, its acquisition of Prss for its Newsstand app, and its acquisition of Beats Music for its iTunes Radio. Because Apple had already operated in the related app markets before these acquisitions, we do not include these instances in our list.

Third, we manually examine all Apple press releases[4] to identify the new features introduced in each iOS release that could directly compete with a third-party app developer, such as the Flashlight feature mentioned above, the AirDrop feature that could compete with file-sharing apps, and the Guided Access feature that could compete with parental control apps. We use the announcement dates of these new features to define their entry dates.

Using the same procedure, we obtain a list of apps introduced by Google on Android. Then, we manually match Apple's and Google's apps. This mapping allows us to verify whether Google follows Apple's moves closely when determining what apps to introduce on its own platform and, if so, allows us to use the app markets which Apple enters before Google as a proxy for the markets in which Google could pose greater entry threats.

Table 1 presents the full list of apps introduced by Apple and the matched Google apps. It reveals some interesting entry patterns. First, the period that sees the most intensive entry by Apple into its iOS markets is between 2009 and 2012, during which it entered 23 app markets. Most of Google's entries into the same markets, on the other hand, took place between 2011 and 2014.[5] Second, there is considerable overlap between the apps introduced by Apple and Google. Specifically, both introduced almost the same set of default apps in the first version of their mobile platform (as shown in the last row of Table 1); of the other 31 markets Apple entered, Google had entered 25 (81 percent) by the end of our sample period. As indicated by the entry date, among the 25 overlapped app markets, Apple entered into 20 of those 25 (80 percent) earlier than Google. Thus, the evidence supports our use of Apple's entry to predict Google's future entry.

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[3] We exclude apps that are extensions of Apple's desktop apps or are clearly used to support Apple's hardware products, such as Logic Remote and AirPort Utility.
[4] All iOS release news articles can be accessed through http://www.apple.com/pr/library/, accessed August 2017.
[5] Note that we only consider entry; that is, the first release of an app. Based on our manual reading of the news releases, both Apple and Google have made frequent improvements to the apps they introduced.

Because our sample period is from 2012 to 2015, in our difference-in-differences estimation, we can only examine the Apple entry events that occur after 2012—the first three events listed in Table 1.

2.3. Empirical Framework

For each of Google's entry threats (as triggered by an Apple entry), we compare Android apps by developers that are likely to be affected by the threat (the treatment group) with Android apps by developers unaffected by the threat but in the same app category (the control group). Because our primary interest is to understand how entry threats shift both the rate and the direction of developers' innovation efforts, we decompose our treatment group into (a) affected developers' affected apps (denoted as *ADAA*) and (b) affected developers' unaffected apps (denoted as *ADUA*). Our control group consists of apps by developers that are unaffected by shifts in Google's entry threats. We use apps in the same app category to construct the control group, because we expect these apps will show similar patterns in innovation and pricing before the entry threat.

Our baseline regression model is the following specification at the app-month level:

$$(1)\quad Outcome_{it} = \beta_0 * Under\ Entry\ Threat_{it} + \gamma_0 * Under\ Actual\ Entry_{it} + \beta_1 * Under\ Entry\ Threat_{it} * ADAA_i + \gamma_1 * Under\ Actual\ Entry_{it} * ADAA_i + \beta_2 * Under\ Entry\ Threat_{it} * ADUA_i + \gamma_2 * Under\ Actual\ Entry_{it} * ADUA_i + Control_{it} + v_i + \eta_t + \varepsilon_{it}$$

The dependent variable ($Outcome_{it}$) is either the level of innovation a developer conducts on app *i* in month t or the app's price in month *t*. The dummy variable, $Under\ Entry\ Threat_{it}$, equals 1 in the period during which app *i* faces an increased entry threat to its app category from Google but does not face Google's actual entry; the dummy variable, $Under\ Actual\ Entry_{it}$, equals 1 after Google actually enters. $ADAA_i$ indicates whether app *i* is affected by Google's entry threat; $ADUA_i$ equals 1 if app *i* is not affected by Google's entry threat but is published by a developer whose other app(s) is(are) affected.

In the next section, we describe how we measure $ADAA_i$ and $ADUA_i$ and how we construct $Control_{it}$. We use v_i to control for any app-level fixed effects, which absorb the direct effects of $ADAA_i$ and $ADUA_i$. We also use the full set of month dummies in all analyses, as indicated by η_t. Because the innovation and pricing decisions across multiple apps developed by the same developer may be correlated, we cluster standard errors at the developer level for all of the regression analyses.

3. Sample and Variables

3.1. Sample

Our dataset from a mobile app analytics firm includes approximately 200,000 active Android apps listed in the Google Play store. For each app, we have its description, category, release date, publisher, and the following history from January 2012 through August 2015: (a) new version release events, (b) price change events, (c) user ratings, and (d), for an app that was ranked in the top 500 in its category or among all apps, its exact ranking.

Given our difference-in-differences research design and the data availability, we could only use the first three events listed in Table 1, which have observations for both the before- and after-threat periods. In our baseline analysis, we only use apps released before their matched entry threat events so that we can compare their behavior before and after.

The apps Apple released in these three events—Guided Access, Podcasts, and Flashlight—belong to the Tools, Entertainment, and Tools or Productivity categories, respectively.[6] Our analysis sample therefore consists of all Android apps in our dataset in these categories. One frequently downloaded type of app is "corporate apps"—such as a banking app, airline app, or hotel app—developed to support offline businesses (Bresnahan, Orsini, and Yin 2015). The innovation activities for such corporate apps are likely to be different from those for other mobile apps and may not be affected by platform-owner entry, so we manually eliminated them from our sample. In the end, we have 3,986 apps in the regression sample, with 162,473 observations at the app-month level.

3.2. Variables

For our first dependent variable, we measure the innovation efforts a developer devotes to an app by the frequency of updates, such as adding new features, redesigning the interface, and fixing bugs. As a developer may update the same app multiple times in a month, we use the number of new versions released in month t by app i ($Updates_{it}$) to capture the innovation efforts.[7] Our second dependent variable is the price of app i in month t.

Among the apps matched to each of Google's entry threats (as proxied by an Apple entry), we use a combination of manual reading and automatic search to identify those for which Google's potential entry would create direct competition. We first have several research assistants manually read the descriptions of a subset of apps in our sample and identify about 100 apps that are similar in functionality to the three introduced by Apple.[8] We then use Google's "similar apps" feature in the Google Play store to identify apps similar to these 100 apps. Although we do not know the exact algorithm used by Google to determine similar apps, those that are in same category and that have similar keywords and the same target

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[6] Flashlight is classified into both the Productivity category and the Tools category.
[7] Because some of these new version releases could be major and others relatively minor, we later test the robustness of our results by examining only major updates.
[8] Given the large number of apps in our dataset, it is difficult to rely entirely on manual reading to identify apps affected by each entry threat.

country/language would be more likely to be listed as similar apps.[9] This algorithm is consistent with our definition of *ADAA* apps: if Google were to enter, it would compete directly against apps with these features. In this way, we identify 378 apps (out of 3,986 in our sample) that will be directly affected by entry. Consequently, the dummy variable $ADAA_i$ equals 1 if app i is one these 378 apps and 0 otherwise. If a developer has any app(s) affected by the entry threats, we define this developer as an affected developer; $ADUA_i$ equals 1 if app i is not affected by the matched entry threat event but has been developed by an affected developer.

Table 2 presents the number of apps affected and unaffected by each of the three entry events. There are more affected apps in the Flashlight market than the other two markets, possibly because a flashlight app is the easiest of the three types to develop.

The existing market competition could influence both Google's entry decision and the other developers' innovation and pricing strategies. Thus, in the $Control_{it}$ vector in Specification (1), we use a variable, $Competitors_{it}$, to control for the competition app i faces in month t. Because we do not have data on all available apps in each category during our sample period, we cannot compute the total number of competitors that app i faces. Instead, we measure that as the percentage of our sample's apps in the same category that are similar to the focal app i. We again use Google's "similar apps" feature in the Google Play store to find apps similar to app i.[10]

We also control for the age of an app i in month t, measured in months and denoted as Age_{it}, which could be correlated with the frequency of version releases and could also reflect the market's technological maturity or opportunities, which could in turn be correlated with both Apple and Google's decisions on what markets to enter.

3.3. Summary Statistics

In Table 3, we report summary statistics of the variables. On average, an app is updated every three months. Although half of the apps are less than $1, some are over $200.[11] The level of competition for an app varies widely. On average, about 0.8 percent of apps in the same category directly compete with a focal app, but that can go as high as 7 percent. Because the variables $Updates_{it}$ and $Price_{it}$ are highly skewed, we use their log transformations in the regression analyses.

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[9] For more information, see https://www.quora.com/How-does-the-Google-Play-Store-determine-similar-apps, accessed August 2017.

[10] Our approach to measuring competition on the basis of Google's "similar apps" recommendation is consistent with other studies on mobile apps; e.g., Kesler, Kummer, and Shulte (2017).

[11] To mitigate the concern that the observed high prices drive our results, we conduct a robustness check after dropping apps that were ever priced above $30 the 90[th] percentile of *Price*) and the results are qualitatively the same.

We first provide some descriptive evidence on how Android developers react to an increase in Google's entry threat. Based on the raw data, we plot the monthly average updates and price for affected apps and unaffected apps over a period of 11 months before and after the three entry threats. As shown in Figure 1a, affected and unaffected apps exhibit similar updating patterns for the five months *before* and the month *during which* the threat begins; but for the five months *after*, affected apps receive fewer updates than unaffected apps. Similarly, as suggested by Figure 1b, prices for affected and unaffected apps are similar before Google's entry threats, but prices of affected apps increase sharply after the threats in comparison to those of unaffected apps. These two figures show preliminary evidence that, on average, affected developers reduce innovation and increase price for affected apps when they expect Google to enter their markets.

4. Results

4.1. Baseline Results

In Table 4, we present our baseline results, based on the full sample and using a fixed-effects OLS (ordinary least squares) model.[12] The coefficients of Column (1) suggest that, under Google's entry threat, an affected developer reduces his updates on an affected app by 5 percent relative to an unaffected developer's app, whereas after Google actually enters, the affected developer reduces updates on the affected app by 8 percent. The statistically significant difference between the two coefficients suggests that Google's actual entry has a greater negative effect on an affected app's innovation than does the threat. Interestingly, we find that when Google threatens to enter the app market, the affected developer increases updates on its unaffected apps by 4 percent and maintains that level after Google's actual entry.

To better control for market growth and other time-varying unobserved factors at the app-category level that may affect both Google's entry decision and app developers' innovation strategies, we augment our regressions by adding a set of linear time trends specific to each entry event. The results, reported in Column (2) of Table 4, are consistent with the baseline results.

We are also concerned about apps by multi-homing developers—those that publish apps on both iOS and Android. These developers could be affected both by Apple's actual entry on the iOS platform and by Google's entry threat on the Android platform. Their innovation decisions might differ from those of developers that publish only on Android. The results of eliminating all multi-homing developer apps from the sample, reported in Column (3) of Table 4, are, qualitatively similar to the baseline results.

[12] Although our measure of innovation is a count variable, we use a linear model for several reasons. First, as implied by Table 3, there are many months in which a given app in our sample has no updates, so nonlinear models may lead to loss of many observations. Second, a linear model allows for easier interpretation of the implied marginal effects from the interaction terms.

Overall, the results in Columns (1) – (3) of Table 4 provide evidence that complementors on a platform do respond both to a platform owner's entry threat and to its actual entry. Once there is an entry threat, a complementor is discouraged from innovating in the affected market. After the actual entry, it becomes optimal for the complementor to reduce innovation efforts even further, because there is little chance for the complementor to win the competition against the platform owner. Nevertheless, the complementor does not withdraw from the platform completely. Rather, it shifts innovation effort to an unaffected market.

To investigate developers' pricing decisions, we repeat our analyses and report the results in Columns (4) – (6). In summary, affected developers increase the prices of affected apps by 1.8 percent when entry threat increases and by 3.6 percent after Google actually enters, relative to the prices of unaffected developers' apps. It seems that once a developer is aware that Google might enter its market, it focuses on short-term profits. Longer-term strategies such as using low prices to generate good word of mouth and then capturing value from future customers no longer make sense. A high price allows the developer to exploit price-insensitive users who value its apps the most.[13] Affected developers do not, however, increase the price of unaffected apps, though they increase their innovation efforts for those apps.

4.2. Falsification Exercises

Certain unobservables may be correlated with both Apple's entry into iOS markets and Android app developers' behavior in the equivalent Android markets. For example, relatively mature markets may be particularly attractive places for platform owners (including both Apple and Google) to enter; meanwhile, we might see a decline in innovation by app developers in those markets given their technological maturity. We would then observe a negative relationship between Google's entry threat and innovation in the affected markets. To mitigate the concern that the observed effects may be driven by such unobservables, we conduct two sets of falsification exercises, examining whether the effect shows the right timing and whether it appears in the right markets.

4.2.1. Timing Falsification Exercises

If our estimates reflect a causal relationship, the appearance of Google's entry threats (or Apple's actual entry into its iOS markets) should have no effect on affected app developers' innovation and pricing

[13] For example, a developer's app may be different from Google's corresponding app. This differentiation would enable a developer to increase his app price to exploit consumers who value the differences. A developer could also exploit consumers who do not use the latest Android releases and thus do not use Google's corresponding app. Retail pharmacies have used similar responses, increasing prices for branded drugs after the entry of generics (e.g., Frank and Salkever 1997).

decisions prior to the entry threat. We therefore create three dummies: *0 Month Pre-entry Threat* equals 1 if the observation is from the month in which the threat occurs; *1-3 Month Pre-entry Threat* equals 1 if the observation is from the first to the third month before the threat; and *4-6 Month Pre-entry Threat* equals 1 if the observation is from the fourth to sixth month before the threat. We add these three dummies and their interactions with *ADAA* and with *ADUA* to the baseline specification. We also decompose the time dummy *Under Entry Threat* into four time dummies that equal 1 in different months under the entry threat and we decompose *Under Actual Entry* into three time dummies that equal 1 in different months under the actual entry. This new specification affords a deeper look at how the effects of Google's entry threat and actual entry vary across different periods.

Columns (1) and (4) of Table 5 report the results of including only the post-threat monthly dummies and their interactions with *ADAA* and *ADUA* for update regressions and price regressions, respectively. Although the magnitudes of these coefficients differ slightly at different times, they are qualitatively similar to the results in Columns (1) and (4) of Table 4.

We next add the dummies *0 Month Pre-entry Threat* and *1-3 Month Pre-entry Threat* and their interaction terms to the specification. In Columns (2) and (5) of Table 5, the estimated coefficients for the interactions with *1-3 Month Pre-entry Threat* suggest that the affected developers do not take actions on updates and prices in the months leading up to Google's entry threat. We note that for the updates regression, the interaction of *0 Month Pre-Entry Threat* with *ADAA* is statistically significant and its magnitude is similar to that of the post-threat interaction coefficients, whereas its interaction with *ADUA* is close to zero. This result is expected, as it is easier for developers to reduce update efforts than to increase them. In Columns (3) and (6), we add the dummy *4-6 Month Pre-entry Threat* and its interaction terms. The results again indicate no preexisting trend before Google's entry threat. Although the magnitudes of the pre-threat, entry-threat, and actual-entry interaction coefficients vary slightly across different specifications because we use different months as the comparison periods,[14] they are qualitatively consistent with those observed in the baseline of Table 4. Overall, this set of results boost our confidence that shifts in app developers' behavior are caused by entry threats.

4.2.2. Falsification Exercises Using Markets that Google Entered Before Apple

Table 1 shows three markets that Google entered before Apple: maps, mobile wallet (e.g., Apple's Passbook, used for storing various credit cards, boarding passes, and tickets), and file-sharing (e.g., Apple's AirDrop). In these markets, Android app developers should not respond to Apple's entry because Google

[14] That is, in Columns (1) and (4), the comparison period is the period up to the month in which the threat occurs; in Columns (2) and (5), it is the period up to the fourth month before the threat; and in Columns (3) and (6), it is the period up to the seventh month before the threat.

was already there. If, however, Apple's entry has effects on Android app developers' behavior similar to those found in our baseline results, then it is possible that our baseline results may have picked up some unobserved effects correlated both to Apple's entry and to the Android developers' decisions.

We conduct this analysis using the following specification:

$$(2)\quad Outcome_{it} = \beta_0 * Under\ Entry\ Threat_{it} + \beta_1 * Under\ Entry\ Threat_{it} * ADAA_i + \beta_2 * Under\ Entry\ Threat_{it} * ADUA_i + Control_{it} + \nu_i + \eta_t + \varepsilon_{it}$$

Because Google entered these markets before Apple, we do not include the direct effect of *Under Actual Entry*$_{it}$ and its interactions with $ADAA_i$ and $ADUA_i$. We use the same time dummies and control variables used in Specification (1). To construct the analysis sample and measure the variables $ADAA_i$ and $ADUA_i$, we use the same procedure used in our baseline analyses, yielding a sample of 3,272 apps with 137,893 observations.

Column (1) of Table 6 reports the regression results, with *log(Updates)* as the dependent variable. Column (2) adds entry-specific time trends, Column (3) drops apps by multi-homing developers, and Columns (4) – (6) use the same set of specifications but with *log(Price)* as the dependent variable. Overall, we do not find significant reactions by affected developers to Apple's entry. The results suggest that Google's entry threat (as triggered by Apple's entry into its iOS markets) is a key driver of the actions of Android app developers.

4.3. Use of Different Control Groups

Another concern is the comparability of apps in the treatment and control groups in terms of how the price and rate of innovation may change over time. The graphic analysis in Figure 1 seems to allay this concern, as the treatment and control groups display almost indistinguishable patterns during the pre-threat period. Nevertheless, we implement a "coarsened exact matching" (CEM) procedure (e.g., Blackwell et al. 2010; Iacus, King, and Porro 2012) that identifies a control app for each treatment app on the basis of a set of covariates. We use the following covariates for the matching: (a) average number of monthly updates during the pre-threat period; (b) average monthly price during the pre-threat period; (c) minimal within-category ranking (to proxy for demand[15]) during the pre-threat period; and (d) age up to the month in which the threat occurs. We expect that after matching these criteria, the expected future price and rate of updates should be largely similar for each treatment app and its corresponding control app. On the basis of the

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[15] The rankings in Google Play are based on an eight-day history of downloads (Bresnahan, Orsini, and Yin 2015).

covariates and the corresponding buckets,[16] we are able to match 529 of the 689 treatment apps (including apps in the *ADAA* and *ADUA* categories). This gives us 1,058 (529 x 2) apps and 43,256 app-month observations. Upon replicating all the specifications used in Table 4 with the CEM sample,[17] the results are qualitatively similar to those based on the baseline sample.

The consistency of the CEM procedure depends on the "selection-on-observables" assumption (Singh and Agrawal 2011). However, the likelihood of *treatment*—that is, an app facing an entry threat—could be determined by some unobserved factors. We take advantage of the multiple entry events in our setting to implement an alternative matching strategy. For a treated market that Apple entered, we use as the control sample another market that Apple was equally likely to enter but did not. We expect both the treatment sample and the control sample to face a similar likelihood of "treatment" except for the small difference in entry timings.

From Table 1, the difference in Apple's entry timing between the Guided Access market and the Flashlight market allows us to implement such matching. For the period from January 2012 through May 2013, during which Apple introduced Guided Access but did not introduce Flashlight, we use the Guided Access market as the treatment sample and the Flashlight market as the control sample.[18] One limitation of this matching strategy is that we can only test the effect of Apple's entry (as a proxy for Google's entry threat) but not the effect of Google's actual entry. That is, because Apple introduced Flashlight in June 2013 and Google introduced Guided Access in November 2014, the period after June 2013 cannot be used as the control sample. Nevertheless, given the advantage of this matching strategy (which directly matches on the likelihood of being treated) over CEM (which matches on a small set of observables), we conduct the analysis. The signs of the interaction terms *Under Entry Threat X ADAA* and *Under Entry Threat X ADUA* are as expected, but with larger magnitudes than the baseline results, possibly due to a different comparison group.

4.4. Other Robustness Checks

First, we explore whether the observed negative relationship between updates on affected apps and Google's entry threat (proxied by Apple's actual entry) reflects a demand effect. Apple's actual entry into certain iOS markets could make Android users aware of these apps and interested in downloading them from the Android platform. Developers of these Android apps may therefore no longer need frequent updates to attract customers and may also increase their prices in light of increased demand. To address this

[16] We use 14 buckets for updates, 14 for price, 6 for ranking, and 3 for age. Due to limited space, we do not include the details on how to define these buckets, but it is available upon request.
[17] Results from our robustness checks in this section are included in the appendix.
[18] We do not use the Podcasts market as the treatment sample and the Flashlight market as the control sample because apps in these two markets belong to two completely different categories and may not be comparable.

concern, we construct a dummy, *Ranked Top* 100_{it}, indicating whether app *i* in month *t* is ranked in the top 100 apps across all categories, and investigate how entry threat affects the likelihood of an affected app being in the top 100.

A positive relationship would suggest that the entry threat has a demand expansion effect. The results, with *Ranked Top* 100_{it} as the dependent variable, are presented in Table 7, where we use the linear probability model to estimate the same baseline specification and robustness checks as in Table 4.[19] The negative coefficients for both *Under Entry Threat X ADAA* and *Under Actual Entry X ADAA* do not support this alternative hypothesis. Moreover, the positive and significant coefficients for *Under Entry Threat X ADUA* and *Under Actual Entry X ADUA* suggest that more frequent updating on unaffected apps by the affected developers seems to increase demand for those apps.

Second, we check the robustness of our main results by examining each entry event separately. The results[20] are qualitatively similar to those in Table 4. Examining updates reveals some difference in the magnitudes of the coefficients between the Guided Access and Flashlight markets. This might be due to the difference in these markets' technical features: Guided Access could be more complex and therefore require more effort and more frequent updating than Flashlight.[21] Developers of Guided Access apps may therefore be more sensitive to factors that change the return to their investment.

Third, in our baseline measure for $Updates_{it}$, we consider all types of version release. One concern is that some of these releases could be major updates, such as adding new functions and revamping the user interface, while others are relatively minor, such as adding patches and fixing bugs. Major updates reflect more fundamental changes to an existing app and require greater development efforts. We use the version number to identify major versus minor updates. As defined by Android,[22] the release version number should follow the format <major>.<minor>.<point>. Therefore, we use the <major> field to count the major releases of app *i* in month *t* (denoted as $MajorUpdates_{it}$) and use that as the dependent variable. The results are qualitatively similar to the baseline results.[23]

Fourth, it is possible that some app developers want to offer free apps due to their intrinsic or non-monetary extrinsic motives such as desire to help others and learning (e.g., von Hippel 2016); some may offer free apps but generate revenue by other means such as advertising. There would then not be any price

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[19] We use the linear probability model to ease the interpretation of interaction variables. In our analysis, more than 90 percent of the predicted probabilities lie between 0 and 1. As shown in Horrace and Oaxaca (2006) and Angrist and Pischke (2008), linear probability models with robustness standard errors could, in this case, yield unbiased and consistent estimates.

[20] Results from this and the following robustness checks in this section are included in the appendix.

[21] Based on our sample prior to the entry threat, Guided Access apps release a new version every month, on average, whereas Flashlight apps release a new version every two months.

[22] For more details, see https://developer.android.com/studio/publish/versioning.html, accessed August 2017.

[23] These results should be interpreted cautiously because app developers determine version numbers themselves and differ considerably in what they consider a major or minor release.

action for them to take when facing the entry threat and actual entry. We therefore re-run the analysis, excluding apps that are free for the entire sample period. We find that developers increase the price of affected apps by 6.3 percent after facing the entry threat (as compared to 1.8 percent in the baseline result in Table 4); after Google's actual entry, the price of affected apps becomes 9.2 percent higher than in the pre-threat period (as compared to 3.6 percent in Table 4). This suggests that app developers' motives do influence their responses.

Finally, we estimate the baseline Specification (1) using a sample that excludes apps for which there were no updates during the sample period. We also use a specification that does not include any control variables. We obtain similar results from these robustness checks.

4.5. The Impact of Entry Threat and Actual Entry on New App Introduction

Thus far we have focused on how developers change their innovation effort and pricing for *existing* apps. An important question is whether the decision to introduce *new apps* is affected as well, which would be an alternative measure for developers' innovation direction. We expect that Google's entry threat and actual entry may (a) reduce developers' incentives to introduce new apps similar to those Google is about to release (denoted as *similar apps*) and (b) motivate affected developers to introduce more new apps unrelated to the entry threats (denoted as *unrelated apps*).

To examine the effect of entry threats and actual entry on the introduction of *similar apps*, we again use Google's "similar apps" search to identify apps likely to be affected by the three entry events. We obtain their release dates to compute the number of similar apps introduced at a given time. The average number of similar apps introduced in a month during the before-threat, entry-threat, and actual-entry periods is shown in Figure 2. Taking Figure 2a as an example, the average number of new Flashlight-related apps released per month was 38 during the before-threat period, but only 10 during the entry-threat period and only 7 after the entry. The t-tests show that the mean differences between the before-threat and entry-threat periods and between the before-threat and actual-entry periods are statistically significant. Figures 2b and 2c demonstrate similar trends in the Guided Access and Podcasts markets. Overall, these figures suggest that after Google becomes a credible threat in certain markets, developers become less interested in offering new products in those markets. This finding is consistent with our earlier ones on developers' incentives to release updates of existing affected apps.

We next investigate how entry threats and actual entry influence the introduction of new *unrelated apps*. Our unit of analysis is at the developer-month level; we compare the number of new unrelated apps in a month introduced by developers that are affected (the treatment group) to that are not affected (the control group). While, in our baseline analysis, we could match each app to only one entry event to look at the effects of the three entry events together, in this analysis we must examine the effect of each entry event separately, as a developer could face multiple entry events. Thus, for a given entry event, we use the following specification:

(3) $log(Number\ of\ New\ Unrelated\ Apps_{jt}) = \beta_0{*}Under\ Entry\ Threat_t + \gamma_0{*}Under\ Actual\ Entry_t + \beta{*}Under\ Entry\ Threat_t{*}Affected\ Developer_j + \gamma{*}Under\ Actual\ Entry_t{*}Affected\ Developer_j + Control_{jt} + v_j + \eta_t + \varepsilon_{jt}$

The dependent variable *Number of New Unrelated Apps*$_{jt}$ is the number of new apps introduced by developer *j* in month *t* that are unrelated to any of the three entry events. Because it is highly skewed, we take the log transformation. *Affected Developer*$_j$ is equal to 1 if developer *j* has any app that is affected by the focal entry event.[24] We again use a fixed-effects model (as indicated by v_j) and the full set of month dummies (as indicated by η_t). We use developer *j*'s age in month *t* in *Control*$_{jt}$. Standard errors are clustered at the developer level.

In Columns (1), (2), and (3) of Table 8, we report the results for each of the three entry events. Taking Column (1) for illustration, the estimated coefficients suggest that relative to an unaffected developer, a developer affected by Google's entry threat in the Flashlight market increases the introduction of new unrelated apps by 3.1 percent. Once Google enters the Flashlight market, the affected developer keeps up a similar rate of introducing new unrelated apps. The results for the Guided Access and Podcasts markets[25] are similar. As in our baseline analysis above, we test the robustness of the results by excluding multi-homing developers. The results, shown in Columns (4) – (6), are largely consistent with the results in Columns (1) – (3).

4.6. Exploring the Mechanism

Our finding that there is no entry deterrence behavior, such as price reduction and additional innovation, before the actual entry is consistent with the fact that, because of the platform owner's power, its entry is unlikely to be deterred. Developers' post-entry behavior is consistent with entry accommodation, in which affected developers seek to exploit users of different segments—either those willing to pay for unique features from a given developer or those who do not update their operating systems and so do not have access to the new offering from the platform owner. An interesting discovery is that under entry threat, developers already start reallocating their innovation effort and increasing the affected app's price. This

[24] *Affected Developer*$_j$ is equal to 0 if developer *j* is not affected by any of the three focal entry events. Hence, for a given entry event, we exclude from the control group developers affected by any of the other two entry events.
[25] Because Google had not actually entered into the Podcasts market by the end of our sample period, we cannot estimate the coefficient of *Under Actual Entry X Affected Developer* for this event.

strategy seems to contradict the view that developers should delay reducing updates and raising the price until the actual entry, because taking these steps too early could lose customers and hinder the developers' business if the entry turns out not to occur (Goolsbee and Syverson 2008). While the difficulties of identifying underlying mechanisms behind strategic moves are well known, we seek some understanding of the observed responses. One plausible explanation is that Google's entry threat may motivate developers to start devoting more resources to unaffected markets to establish competitive positions in unaffected areas as early as possible. However, most developers may lack resources to maintain the same level of innovation in affected markets while investing more resources in unaffected markets. Under resource constraints, they would have to reallocate their limited resources away from affected markets to other unaffected area even before entry takes place. This resource constraint could also motivate them to raise prices in order to have more financial resources to devote to new areas. If this is the underlying mechanism, we would expect more resource-constrained developers to react more strongly.

We use the variety of apps offered by a developer prior to an entry threat to proxy for its resource constraints. We expect developers offering only a few apps prior to a threat to have more resource constraints and thus to respond to Google's entry threat and actual entry more strongly in the affected markets than developers offering many apps do. We collect data on the number of apps offered by each developer prior to entry threats and split the sample by the median, which is four. We use Specification (1) for these two subsamples and report the results in Table 9. As anticipated, developers with more resource constraints (those that offered fewer than four apps prior to entry threats) reduce updates on affected apps by 8 percent after the entry threat and by 13 percent after the actual entry, twice the effect observed on developers with fewer resource constraints. Moreover, as shown in Column (2), it is the more-resource-constrained developers that are aggressive in exploiting customers in the affected markets, which might enable them to overcome their resource constraints to some extent. For more-resource-constrained developers, we do not find a significant increase in innovation in unaffected markets during the entry-threat and actual-entry periods, probably because this analysis is based on the sample of existing apps, of which these developers do not have many. If we look at their introduction of new unrelated apps, as shown in Table 10, both types of developers introduce more new apps in unaffected markets during the entry-threat and actual-entry periods.

As an alternative test, we examine very successful developers. We take them to be more technically competent and thus more likely to have resources, not only from their previous success but also because that success will attract more external investment. Due to above-average technical capability, they may have incentives to accelerate innovation to draw in as many users as possible before Google enters. This strategy also positions them as strong competitors should Google chooses not to enter or as attractive acquisition targets for Google if it does.

We identify top app developers on the basis of their ranking history prior to Google's entry threats. The subsample of top apps includes any app that had ever been ranked in the top 500 across all categories prior to Google's entry threat,[26] giving us 342. The baseline result is presented in Column (1) of Table 11. Unlike the average developer, an affected developer *increases* its affected top app's updates by 7.4 percent under entry threat, relative to an unaffected top app by an unaffected developer. After Google actually enters, the developer reduces its updates significantly when compared with the entry-threat period. As implied by the estimated coefficients, an affected top app developer also increases innovation on unaffected apps under entry threat and maintains that level after Google actually enters. The magnitude of this increase is also worth noting: 17 percent to 19 percent for both the entry-threat and actual-entry periods, which is significantly greater than the 4 percent observed for an average developer.

Column (4) of Table 11 further investigates pricing strategies. Unlike an average developer, an affected top developer does not raise the affected app's price when entry threat increases. After the actual entry, however, the price goes up by 5.5 percent, compared to 3.6 percent for an average developer. We extend this analysis by using the same set of robustness checks as in our baseline sample analysis and report the results in the other columns of Table 11. They are all largely consistent with the baseline results in Columns (1) and (4).

In summary, this set of results provides evidence suggesting that resource constraints could be the reason for developers to withdraw early from the affected areas and focus on developing new apps in other areas.

5. Conclusion

Digitalization has led to the emergence of platforms in a wide range of industries, including Airbnb in the accommodation industry, Uber in the transportation industry, Alibaba and eBay in the retail market, and General Electronic in industrial equipment. A large body of literature in the Information Systems field has looked at both economic and social implications of digital platforms for consumers and complementors (e.g., Bapna et al. 2016; Greenwood and Agarwal 2016; Jing et al. 2017; Nagaraj 2017; Wei and Xiao 2017; Kumar et al. forthcoming; Lee et al. forthcoming; Li and Wu forthcoming), as well as strategic choices by platform owners (e.g., Sun et al. 2016; Chellappa and Mukherjee 2017; Huang et al. 2017; Chen et al. forthcoming; Wei and Lin forthcoming). By providing efficient matching or development kits, such platforms have also significantly lowered the barriers for many small firms or individuals to innovate and to market their products and services. However, potential conflicts could exist between platforms and the

[26] Although one could define a top app sample more exclusively, that would leave us with too small a sample. For example, using only apps that had ever been ranked in the top 100, we would have a sample of only 54 apps.

firms in their ecosystems. The impact of those conflicts on firms' incentives to innovate have captured regulators' attention and have resulted in a number of policy interventions (e.g., Chiou and Tucker 2015; Athey et al. 2017).

Our empirical evidence examines one prevalent source of conflict: platform owners' entry into complementary product spaces. Unlike most prior studies, we empirically investigate whether complementors react to entry threats—that is, before the actual entry. Our findings show that they do adjust their value creation strategies through product innovation and value capture strategies. When they are threatened by the platform owner, they do not stop investing and innovating; rather, they shift innovation effort from affected markets to unaffected markets. In addition, Google's entry threats and actual entry discourage further investment in developing duplicative features and encourage app developers to introduce more new apps in other markets. Hence, platform owners could use direct entry to shape the innovation directions of complementors, reduce social inefficiency, and encourage more variety. Policymakers may need to take these positive effects on innovation into account when evaluating the impact of platform owners' actions.

Our study also points to many opportunities for future research. Our empirical design hinges on the predictability of Google's entry based on Apple's entry but is agnostic to the motivations behind Apple's entry and Google's imitation of Apple's moves.[27] Future research could seek to identify such motivations (e.g., Gawer and Cusumano 2002; Yoffie and Kwak 2006; Gawer and Henderson 2007; Bennett and Pierce 2016). Also, our empirical setting is the mobile app market, where only two platform owners dominate. In some other platform-based markets, complementors may switch to platforms that have a better reputation for treating complementors well. In some cases, platform owners' own offerings might be significantly better than a third-party's offerings. If these superior offerings could attract more consumers to the platform, that could benefit complementors and encourage more entrepreneurs to join the platform and innovate in new areas. Therefore, the long-term impact of a platform owner's entry on the growth and innovativeness of its ecosystem remains an open question.

[27] For example, the timing of Google's introduction of its flashlight app might be influenced by users' privacy concerns about some flashlight apps. In December 2013, Goldenshores Technologies, which developed a popular "Brightest Flashlight Free" app for Android phones, agreed to settle the FTC's charges that the app supplied location information to marketers. The event led to close scrutiny of flashlight apps on mobile phones. See, https://www.ftc.gov/news-events/press-releases/2013/12/android-flashlight-app-developer-settles-ftc-charges-it-deceived, accessed September 2017, for details. All of our results continue to hold when we exclude flashlight apps.

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Table 1: Apple's entries into app markets

		Apple app	Apple entry date	Matched Google app	Google entry date
Used in the main difference-in-differences analysis	1	Guided Access	June 2012	Android restricted user activity	November 2014
	2	Podcasts	June 2012		
	3	Flashlight	June 2013	Flashlight	November 2014
Dropped (Apple's entry date is earlier than 2012)	4	Notes	June 2007	Google Keep (notes and lists)	March 2013
	5	Stocks	June 2007		
	6	Weather	June 2007		
	7	Remote	July 2008	Android TV Remote Control	June 2014
	8	VoiceOver	June 2009	Google Talkback	December 2011
	9	Zoom	June 2009	Android Magnification gestures	November 2012
	10	Compass	June 2009		
	11	Find My iPhone	June 2009	Android Device Manager	August 2013
	12	Spotlight Search	June 2009	Google Quick Search Box (QSB)	October 2009
	13	Voice Memos	June 2009	Google Keep (notes and lists)	March 2013
	14	Keynote	April 2010	Google Slides	June 2014
	15	Numbers	April 2010	Google Sheets	April 2014
	16	Pages	April 2010	Google Docs	April 2014
	17	iBooks	April 2010	Google Play Books	November 2010
	18	Game Center	April 2010	Google Play Games	May 2013
	19	FaceTime	June 2010	Google Hangouts	May 2013
	20	iMovie	June 2010		
	21	GarageBand	March 2011		
	22	iCloud	June 2011	Google Drive	November 2011
	23	Newsstand	June 2011	Google Play Newsstand	June 2012
	24	Reminders	June 2011	Tasks	January 2014
	25	Find My Friends	October 2011	Google+	February 2013
	26	Siri	October 2011	Voice Actions (Google Now)	July 2012
Dropped (Google entered first or entered at the same time as Apple)	27	Maps	June 2012	Maps	September 2008
	28	Passbook	June 2012	Google Wallet	September 2011
	29	AirDrop	June 2013	Android Beam	October 2011
	30	iTunes Radio	June 2013	Google Play Music	May 2013
	31	Health	June 2014	Google Fit	June 2014
Dropped (default apps in the first version of iOS/Android	32	Calculator, Calendar, Camera, Clock, Contacts, Mail, Messages, Music, Phone, Photos, Safari, Settings, Videos	June 2007	Calculator, Calendar, Camera, Alarm Clock, People / Contacts, Gmail, Message/Google Talk, Music, Dialer, Pictures, Browser, Settings, Media Player	September 2008

Notes: This table does not provide the complete list of apps introduced by Google on Android. Although it is interesting to look at all of Google's apps, our focus is to understand the effects of Google's entry threats based on Apple's entry patterns. Therefore, our analysis is restricted to the markets which Apple entered and which Google either entered subsequently or had not yet entered by August 2015 (the end of our sample).

Table 2: Number of affected apps versus unaffected apps

	Google entry threat (proxied by Apple's actual entry)			Total
	Flashlight	Guided Access	Podcasts	
# of affected apps by affected developers (ADAA)	251	48	79	378
# of unaffected apps by affected developers (ADUA)	191	53	67	311
# of unaffected apps by unaffected developers (UDUA)	2054	432	811	3297

Table 3: Summary statistics

Variable	Obs.	Mean	Std. dev.	Min	Max	Median
Updates	162,473	0.321	1	0	20	0
Price	162,473	2.473	9	0	239	1
Affected developers' affected apps (ADAA)	162,473	0.093	0	0	1	0
Affected developers' unaffected apps (ADUA)	162,473	0.078	0	0	1	0
Under Entry Threat	162,473	0.580	0	0	1	1
Under Actual Entry	162,473	0.168	0	0	1	0
Competitors	162,473	0.008	0	0	0.070	0.006
Age	162,473	23.184	13	0	76	23

Table 4: Baseline results and robustness check

	log(Updates)			log(Price)		
	Baseline	Add entry-specific time trends	Drop apps by multi-homing developers	Baseline	Add entry-specific time trends	Drop apps by multi-homing developers
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Under Entry Threat X ADAA	-0.052***	-0.051***	-0.051***	0.018***	0.018***	0.014***
	(0.016)	(0.016)	(0.018)	(0.005)	(0.005)	(0.005)
Under Actual Entry X ADAA	-0.082***	-0.081***	-0.075***	0.036***	0.036***	0.032***
	(0.021)	(0.021)	(0.022)	(0.008)	(0.008)	(0.008)
Under Entry Threat X ADUA	0.042***	0.044***	0.032**	-0.001	-0.001	-0.003
	(0.013)	(0.012)	(0.014)	(0.009)	(0.009)	(0.010)
Under Actual Entry X ADUA	0.046***	0.048***	0.043**	0.011	0.011	0.008
	(0.016)	(0.016)	(0.017)	(0.013)	(0.014)	(0.015)
Under Entry Threat	-0.037***	-0.014**	-0.038***	0.005	0.004	0.005
	(0.008)	(0.007)	(0.009)	(0.005)	(0.004)	(0.005)
Under Actual Entry	-0.089***	0.003	-0.093***	0.006	0.001	0.007
	(0.011)	(0.012)	(0.012)	(0.009)	(0.007)	(0.009)
Competitors	-8.470***	-8.242***	-9.694***	-2.110	-2.106	-2.149
	(2.252)	(2.238)	(2.495)	(1.684)	(1.684)	(1.491)
Age	-0.001	-0.003***	-0.001	-0.001***	-0.001	-0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Monthly dummies	Yes	Yes	Yes	Yes	Yes	Yes
App fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of apps	3,986	3,986	3,425	3,986	3,986	3,425
Observations	162,473	162,473	139,484	162,473	162,473	139,484
Adjusted R-squared	0.049	0.050	0.053	0.005	0.005	0.005

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Columns (1) – (3) use *log(Updates)* as the DV and Columns (4) – (6) use *log(Price)* as the DV. *ADAA* is a dummy that equals 1 for affected developers' affected apps and *ADUA* is a dummy that equals 1 for affected developers' unaffected apps. Robust standard errors clustered at the developer level.

Table 5: Timing falsification exercises

	log(Updates)			log(Price)		
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
4-6 Month Pre-entry Threat X ADAA			-0.010			0.001
			(0.026)			(0.005)
1-3 Month Pre-entry Threat X ADAA		-0.029	-0.032		0.007	0.007
		(0.024)	(0.027)		(0.006)	(0.007)
0 Month Pre-entry Threat X ADAA		-0.050*	-0.053		-0.003	-0.003
		(0.030)	(0.033)		(0.008)	(0.009)
1-3 Month Entry Threat X ADAA	-0.052***	-0.066***	-0.069***	0.009*	0.011*	0.011
	(0.017)	(0.022)	(0.026)	(0.005)	(0.006)	(0.007)
4-6 Month Entry Threat X ADAA	-0.044**	-0.058**	-0.062**	0.016**	0.018**	0.018**
	(0.020)	(0.025)	(0.028)	(0.007)	(0.008)	(0.008)
7-9 Month Entry Threat X ADAA	-0.037**	-0.051**	-0.054**	0.011	0.013	0.013
	(0.019)	(0.022)	(0.025)	(0.007)	(0.008)	(0.009)
After 10 Month Entry Threat X ADAA	-0.058***	-0.072***	-0.075***	0.022***	0.024***	0.024***
	(0.019)	(0.022)	(0.025)	(0.006)	(0.007)	(0.007)
1-3 Month Actual Entry X ADAA	-0.068***	-0.081***	-0.085***	0.029***	0.031***	0.031***
	(0.022)	(0.025)	(0.028)	(0.008)	(0.009)	(0.009)
4-6 Month Actual Entry X ADAA	-0.086***	-0.099***	-0.103***	0.037***	0.039***	0.039***
	(0.023)	(0.026)	(0.029)	(0.009)	(0.009)	(0.010)
7-9 Month Actual Entry X ADAA	-0.090***	-0.103***	-0.106***	0.040***	0.042***	0.042***
	(0.022)	(0.026)	(0.028)	(0.009)	(0.010)	(0.010)
4-6 Month Pre-entry Threat X ADUA			0.006			-0.011
			(0.021)			(0.011)
1-3 Month Pre-entry Threat X ADUA		0.020	0.022		-0.015	-0.019
		(0.019)	(0.022)		(0.011)	(0.014)
0 Month Pre-entry Threat X ADUA		0.003	0.005		-0.021	-0.024
		(0.029)	(0.030)		(0.013)	(0.016)
1-3 Month Entry Threat X ADUA	0.042**	0.048**	0.051**	-0.001	-0.007	-0.011
	(0.018)	(0.021)	(0.022)	(0.008)	(0.012)	(0.015)
4-6 Month Entry Threat X ADUA	0.064***	0.070***	0.073***	0.003	-0.003	-0.007
	(0.016)	(0.019)	(0.021)	(0.009)	(0.012)	(0.015)
7-9 Month Entry Threat X ADUA	0.046***	0.052**	0.054**	-0.016*	-0.023*	-0.027*
	(0.017)	(0.020)	(0.022)	(0.010)	(0.012)	(0.015)
After 10 Month Entry Threat X ADUA	0.035**	0.042**	0.044**	0.002	-0.005	-0.009
	(0.014)	(0.017)	(0.019)	(0.011)	(0.013)	(0.016)
1-3 Month Actual Entry X ADUA	0.032*	0.037*	0.040*	0.009	0.002	-0.001
	(0.017)	(0.019)	(0.021)	(0.012)	(0.015)	(0.017)
4-6 Month Actual Entry X ADUA	0.053***	0.058***	0.060***	0.013	0.006	0.003
	(0.018)	(0.020)	(0.022)	(0.014)	(0.016)	(0.019)
7-9 Month Actual Entry X ADUA	0.055***	0.060***	0.062***	0.012	0.006	0.002
	(0.019)	(0.021)	(0.023)	(0.015)	(0.017)	(0.019)
Competitors	-8.517***	-8.391***	-8.177***	-2.082	-2.108	-2.134
	(2.253)	(2.251)	(2.236)	(1.686)	(1.686)	(1.687)
Age	-0.001	0.001	0.001	-0.001***	-0.001***	-0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Monthly dummies	Yes	Yes	Yes	Yes	Yes	Yes
App fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of apps	3,986	3,986	3,986	3,986	3,986	3,986
Observations	162,473	162,473	162,473	162,473	162,473	162,473
Adjusted R-squared	0.049	0.049	0.050	0.005	0.005	0.005

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Columns (1) – (3) use *log(Updates)* as the DV and Columns (4) – (6) use *log(Price)* as the DV. *ADAA* is a dummy that equals 1 for affected developers' affected apps and *ADUA* is a dummy that equals 1 for affected developers' unaffected apps. Due to the limited space, the direct effect of monthly dummies (*1-3 Month Entry Threat*, *4-6 Month Entry Threat*, etc.) are not shown. Robust standard errors clustered at the developer level. We do not include the interaction of *ADAA*/*ADUA* with *After 10 Month Actual Entry*, as no observation in our sample falls into this period.

Table 6: Falsification exercises using markets which Google entered before Apple

	log(Updates)			log(Price)		
	Baseline	Add entry-specific time trends	Drop apps by multi-homing developers	Baseline	Add entry-specific time trends	Drop apps by multi-homing developers
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Under Entry Threat X ADAA	0.018	0.017	-0.007	-0.007	-0.003	-0.003
	(0.014)	(0.014)	(0.019)	(0.012)	(0.012)	(0.010)
Under Entry Threat X ADUA	0.017	0.013	0.002	0.006	0.01	-0.007
	(0.018)	(0.017)	(0.030)	(0.018)	(0.016)	(0.027)
Under Entry Threat	-0.034***	0.009	-0.031**	0.01	0.004	0.018*
	(0.012)	(0.012)	(0.013)	(0.009)	(0.007)	(0.010)
log (Competitors)	0.030***	0.01	0.029***	0.003	0.009	0.002
	(0.010)	(0.009)	(0.011)	(0.007)	(0.006)	(0.008)
log (Age)	-0.121***	-0.115***	-0.136***	0.011	0.01	0.012
	(0.010)	(0.010)	(0.011)	(0.008)	(0.009)	(0.009)
Monthly dummies	Yes	Yes	Yes	Yes	Yes	Yes
Entry-specific time trends	No	Yes	No	No	Yes	No
App fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of apps	3,272	3,272	2,552	3,272	3,272	2,552
Observations	137,893	137,893	106,969	137,893	137,893	106,969
Adjusted R-squared	0.026	0.028	0.038	0.004	0.005	0.005

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *ADAA* is a dummy that equals 1 for affected developers' affected apps and *ADUA* is a dummy that equals 1 for affected developers' unaffected apps. Robust standard errors clustered at the developer level.

Table 7: Effect of Google's entry threat and actual entry on app ranking

	Ranked top 100		
	Baseline	Add entry-specific time trends	Drop apps by multi-homing developers
Dependent variable	(1)	(2)	(3)
Under Entry Threat X ADAA	-0.014*	-0.014*	-0.012*
	(0.007)	(0.007)	(0.007)
Under Actual Entry X ADAA	-0.029***	-0.029***	-0.027***
	(0.011)	(0.011)	(0.011)
Under Entry Threat X ADUA	0.005**	0.005**	0.005**
	(0.002)	(0.002)	(0.002)
Under Actual Entry X ADUA	0.007***	0.007***	0.006***
	(0.002)	(0.002)	(0.002)
Under Entry Threat	-0.001	-0.001	-0.001
	(0.002)	(0.001)	(0.001)
Under Actual Entry	-0.004	-0.001	-0.004**
	(0.002)	(0.003)	(0.002)
Competitors	0.071	0.059	0.743
	(0.691)	(0.685)	(0.676)
Age	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Monthly dummies	Yes	Yes	Yes
App fixed effects	Yes	Yes	Yes
Number of apps	3,986	3,986	3,425
Observations	162,473	162,473	139,484
Adjusted R-squared	0.006	0.006	0.006

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The dependent variable *Ranked Top 100* is equal to 1 if an app is ranked in the top 100 across all categories. *ADAA* is a dummy that equals 1 for affected developers' affected apps and *ADUA* is a dummy that equals 1 for affected developers' unaffected apps. Robust standard errors clustered at the developer level.

Table 8: Effect of Google's entry threat and actual entry on introduction of new unrelated apps

	log(Number of New Unrelated Apps)					
	Baseline sample			Drop apps by multi-homing developers		
	Flashlight	Guided Access	Podcasts	Flashlight	Guided Access	Podcasts
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Under Entry Threat X Affected Developer	0.031***	0.096***	0.079***	0.026***	0.098***	0.051**
	(0.009)	(0.022)	(0.023)	(0.009)	(0.025)	(0.024)
Under Actual Entry X Affected Developer	0.027**	0.082***		0.013	0.073***	
	(0.012)	(0.025)		(0.012)	(0.028)	
Age	-0.135***	-0.136***	-0.134***	-0.136***	-0.136***	-0.135***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Monthly dummies	Yes	Yes	Yes	Yes	Yes	Yes
Developer fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of developer	2,377	1,930	1,975	2,091	1,706	1,710
Observations	100,234	81,484	83,558	88,104	72,009	72,266
Adjusted R-squared	0.063	0.071	0.066	0.068	0.075	0.073

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *Affected Developer* is a dummy that equals 1 if a developer has any app that is affected by the focal entry event. Because Google had not actually entered into the Podcasts market by the end of our sample period, we cannot estimate the coefficient of *Under Actual Entry X Affected Developer* for this event. Robust standard errors clustered at the developer level.

Table 9: Compare developers with different resource constraints for their actions on existing apps

	Subsample of developers with more resource constraints		Subsample of developers with fewer resource constraints	
	log(Updates)	log(Price)	log(Updates)	log(Price)
Dependent variable	(1)	(2)	(3)	(4)
Under Entry Threat X ADAA	-0.079**	0.034***	-0.039**	0.008
	(0.033)	(0.009)	(0.017)	(0.006)
Under Actual Entry X ADAA	-0.131***	0.069***	-0.063***	0.013
	(0.043)	(0.016)	(0.023)	(0.009)
Under Entry Threat X ADUA	0.015	-0.009	0.047***	-0.009
	(0.055)	(0.023)	(0.014)	(0.009)
Under Actual Entry X ADUA	0.014	0.007	0.046***	-0.007
	(0.049)	(0.031)	(0.018)	(0.014)
Under Entry Threat	-0.023**	-0.005	-0.046***	0.010**
	(0.012)	(0.010)	(0.010)	(0.005)
Under Actual Entry	-0.070***	-0.023	-0.100***	0.024***
	(0.016)	(0.017)	(0.014)	(0.008)
Competitors	-1.799	2.436	-11.298***	-3.581*
	(3.950)	(3.334)	(2.720)	(1.834)
Age	-0.001	-0.001***	-0.001	-0.001***
	(0.001)	(0.001)	(0.001)	(0.001)
Monthly dummies	Yes	Yes	Yes	Yes
App fixed effects	Yes	Yes	Yes	Yes
Number of apps	1,529	1,529	2,457	2,457
Observations	61,272	61,272	101,201	101,201
Adjusted R-squared	0.045	0.009	0.052	0.006

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Developers that offered fewer than four apps are classified as having more resource constraints; others are classified as having fewer resource constraints. *ADAA* is a dummy that equals 1 for affected developers' affected apps and *ADUA* is a dummy that equals 1 for affected developers' unaffected apps. Robust standard errors clustered at the developer level.

Table 10: Compare developers with different resource constraints for their introduction of new apps

	log(Number of New Unrelated Apps)					
	Subsample of developers with more resource constraints			Subsample of developers with fewer resource constraints		
	Flashlight	Guided Access	Podcasts	Flashlight	Guided Access	Podcasts
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Under Entry Threat X Affected Developer	0.035***	0.071***	0.071***	0.047***	0.117***	0.084**
	(0.008)	(0.021)	(0.015)	(0.014)	(0.038)	(0.042)
Under Actual Entry X Affected Developer	0.045***	0.059***		0.038**	0.093**	
	(0.009)	(0.015)		(0.018)	(0.047)	
Age	-0.078***	-0.083***	-0.082***	-0.181***	-0.183***	-0.180***
	(0.004)	(0.005)	(0.004)	(0.007)	(0.008)	(0.008)
Monthly dummies	Yes	Yes	Yes	Yes	Yes	Yes
Developer fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of developer	1,184	1,028	1,050	1,180	888	909
Observations	48,690	42,432	43,484	50,986	38,450	39,386
Adjusted R-squared	0.044	0.054	0.049	0.083	0.093	0.087

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *Affected Developer* is a dummy that equals 1 if a developer has any app that is affected by the focal entry event. This table is based on Specification (3). Developers that offered fewer than four apps are classified as having more resource constraints; others are classified as having fewer resource constraints. Robust standard errors clustered at the developer level.

Table 11: Responses from top app developers

	log(Updates)			log(Price)		
	Baseline	Add entry-specific time trends	Drop apps by multi-homing developers	Baseline	Add entry-specific time trends	Drop apps by multi-homing developers
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Under Entry Threat X ADAA	0.074**	0.069*	0.083*	0.012	0.012	0.003
	(0.037)	(0.037)	(0.043)	(0.015)	(0.014)	(0.012)
Under Actual Entry X ADAA	0.003	0.001	0.009	0.055*	0.055**	0.027
	(0.052)	(0.052)	(0.060)	(0.028)	(0.028)	(0.020)
Under Entry Threat X ADUA	0.169***	0.168***	0.142***	-0.020	-0.020	-0.033
	(0.035)	(0.034)	(0.034)	(0.023)	(0.023)	(0.026)
Under Actual Entry X ADUA	0.188***	0.188***	0.171***	0.006	0.005	-0.028
	(0.049)	(0.049)	(0.051)	(0.036)	(0.035)	(0.034)
Under Entry Threat	-0.105***	-0.075**	-0.090**	0.003	0.007	0.017
	(0.031)	(0.031)	(0.035)	(0.015)	(0.011)	(0.012)
Under Actual Entry	-0.162***	-0.045	-0.122*	-0.025	-0.028	0.003
	(0.045)	(0.052)	(0.062)	(0.030)	(0.023)	(0.023)
Competitors	-3.673	-3.212	-9.833	-3.563	-3.251	-10.906*
	(7.716)	(7.894)	(9.368)	(5.983)	(6.000)	(6.469)
Age	-0.004**	-0.006***	-0.005**	0.001	0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Monthly dummies	Yes	Yes	Yes	Yes	Yes	Yes
App fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of apps	342	342	245	342	342	245
Observations	14,452	14,452	10,340	14,452	14,452	10,340
Adjusted R-squared	0.096	0.098	0.111	0.006	0.006	0.011

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The top app sample includes any app that had ever been ranked in the top 500 across all categories prior to Google's entry threat. *ADAA* is a dummy that equals 1 for affected developers' affected apps and *ADUA* is a dummy that equals 1 for affected developers' unaffected apps. Robust standard errors clustered at the developer level.

Figure 1

Figure 1a: Monthly average updates for affected and unaffected apps

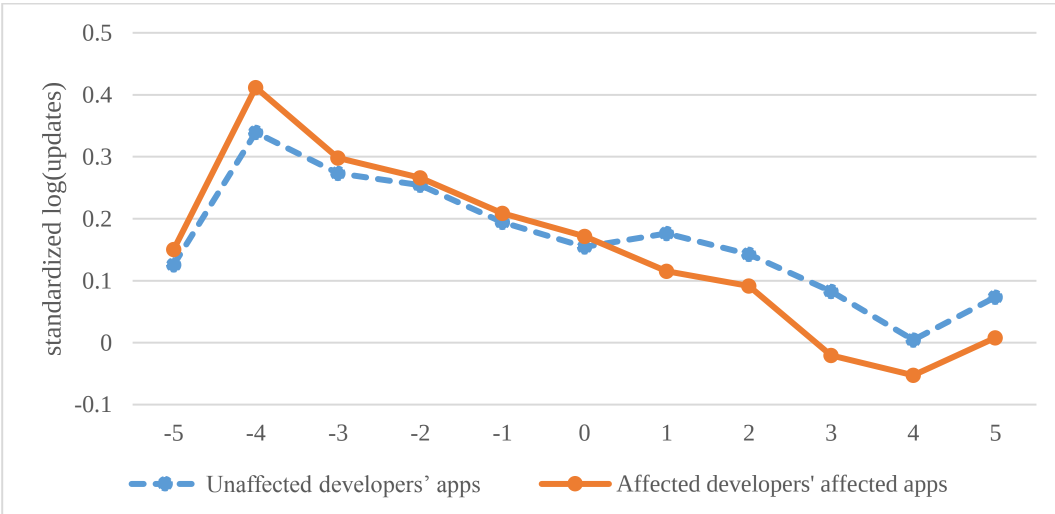
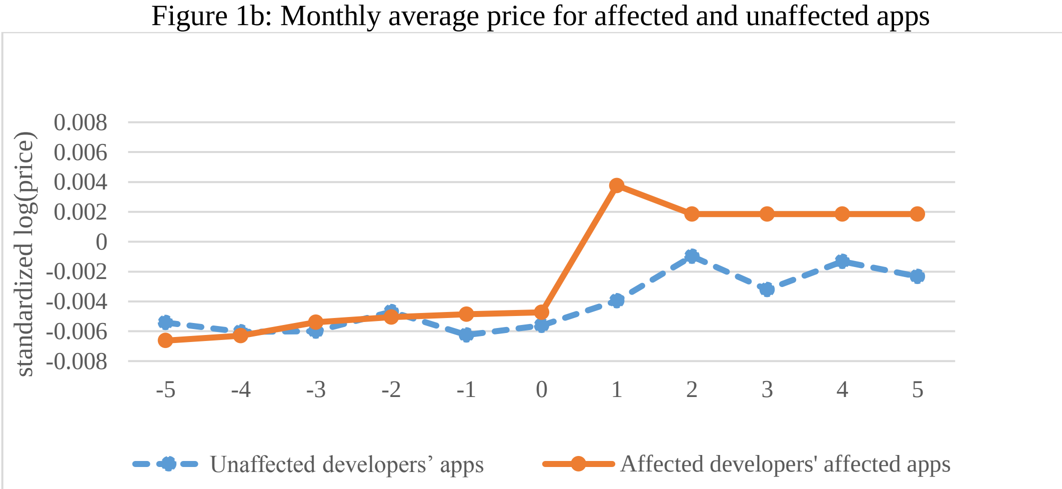


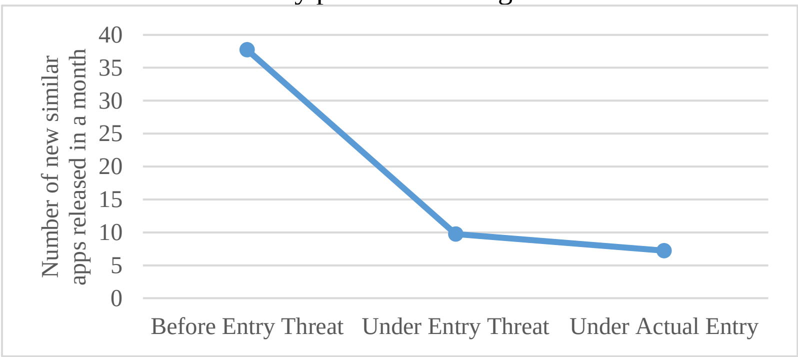
Figure 1b: Monthly average price for affected and unaffected apps



Notes: These two graphs plot the monthly average logged updates and price for affected and unaffected apps over a period of 11 months before and after the entry threat. The X-axis represents time, where 0 indicates the month in which the threat occurs, -1 means the first month before the threat, 1 means the first month after the threat, and so on. Because we consider the three entry threat events together, we first standardize updates and price to reduce the heterogeneity of the apps across different categories and then compute the average value for each month.

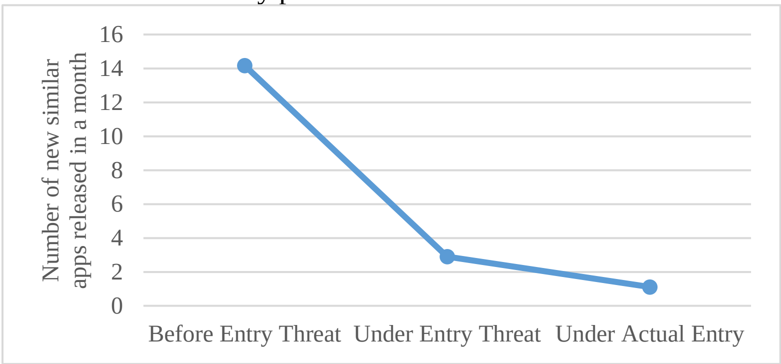
Figure 2

Figure 2a: Average number of new similar apps during the before-threat, entry-threat, and actual-entry periods: Flashlight



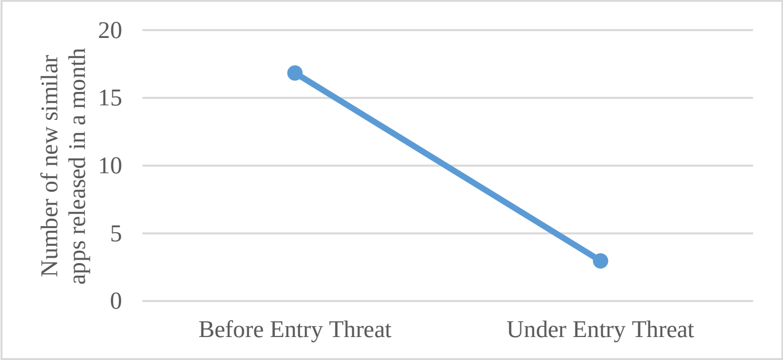
Notes: The t-test statistic for the mean difference in number of new similar apps between the before-threat and the entry-threat period (actual-entry period) is 2.272 (1.791).

Figure 2b: Average number of new similar apps during the before-threat, entry-threat, and actual-entry periods: Guided Access



Notes: The t-test statistic for the mean difference in number of new similar apps between the before-threat and the entry-threat period (actual-entry period) is 3.447 (2.198) with p-value 0.001 (0.02).

Figure 2c: Average number of new similar apps during the before-threat, entry-threat, and actual-entry periods: Podcasts



Notes: Because we do not observe Google's actual entry, we have only two data points. The t-test statistic for the mean difference in number of new similar apps between the before-threat and the entry-threat period is 4.922 with p-value 0.001.