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**How Do Complementors Respond to the Threat of Platform Owner Entry?
Evidence from the Mobile App Market**

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How Do Complementors Respond to the Threat of Platform Owner Entry? Evidence from the Mobile App Market*

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Abstract

How do complementors respond to the *threat* of platform owner entry, and how do such responses differ from the responses to *actual* entry? Using the mobile platform Android as our research setting, we examine how app developers on Android adjust their *rate* and *direction* of innovation efforts and prices in response to Google's entry threat and actual entry into the app markets. Based on a difference-in-differences empirical framework, we find that app developers that are affected by Google's entry reduce their innovation efforts on affected apps after entry threats increase; after Google's actual entry, they reduce innovation efforts on affected apps further and also increase these apps' prices. However, we find that affected app developers do not withdraw from the platform completely—once the threat occurs, they shift innovation efforts from affected apps to other unaffected apps, as indicated by an increase in updates on unaffected apps during both the entry-threat and actual-entry period.

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

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1. Introduction

Platforms today, such as eBay, Etsy, Airbnb, Upwork and Android, have created digital infrastructures that enable millions of entrepreneurs, often referred to as complementors, to develop and sell complementary products and services to platform users. Collectively, these entrepreneurs create significant value and become important sources of innovation in our economy. For instance, more than 3.9 million apps had been developed for various mobile platforms by the end of 2015, such as Google's Android and Apple's iOS.

At the same time, platform owners have considerable influence over the livelihood of these entrepreneurs, and often become significant threats to them, particularly when they enter these entrepreneurs' product spaces with similar offerings (e.g., Farrell and Katz 2000; Gawer and Cusumano 2002; Gawer and Henderson 2007; Parker and Van Alstyne forthcoming; Zhu and Liu 2016). For example, Netscape and RealNetworks, apps on Microsoft's Windows platform, were effectively extinguished by Microsoft's own rival applications, Internet Explorer and Windows Media Player. The Twitter microblogging platform released its own client applications for mobile devices, completely locking out competing client applications by third-party developers. With every major update of Apple's iOS operating system, Apple kills a number of third-party apps using its own offerings. Amazon frequently competes with third-party sellers in its marketplace by sourcing products directly from suppliers.

Complementors participating in platform markets thus routinely face threats of direct entry from platform owners. Despite its importance for innovation, entrepreneurship, and public policy, there is little empirical investigation of how complementors react to the *threat* of platform owner entry. This is largely due to the difficulty in empirically identifying the *threat* of entry separately from *actual* entry. Our research aims to bridge this gap. More specifically, we seek to understand how complementors respond to the *threat* of platform owner entry by adjusting innovation efforts and prices, and how such responses differ from the responses to *actual* entry. Moreover, besides examining whether complementors adjust the *rate* of innovation efforts when facing entry threats, we also aim to examine whether they change the *direction* of their innovation efforts—do they reallocate their development efforts to other unaffected areas?

Our research setting is the mobile app market, in which app developers typically develop mobile apps for Google's Android system and/or Apple's iOS system. We examine how app developers on Android respond to Google's entry threats into Android app markets. As direct

competitors to the mobile platform, Google and Apple often follow each other's moves, and thus Apple's direct entry into its iOS app markets would substantially increase the likelihood of Google's entry into its Android app markets. Thus, we look specifically at cases in which Apple releases apps to compete directly with developers of similar apps on its iOS system. These events change Android app developers' perception about Google's entry likelihood to the corresponding app markets on Android. This empirical design allows us to identify the threat of entry separately from actual entry.

Our data come from several sources. First, our app dataset includes approximately 200,000 apps listed in the Google Play store for use on Android. For each app, we obtain its app description, categories, release date, and its publisher name. We also collect the following observations for these apps from January 2012 to August 2015: new version release events, price change events, user ratings, and rankings. Second, we compile a list of apps and important iOS features released by Apple from 2007 to 2015, and identify 31 entry events in which Apple directly competes with app developers on iOS. We then map these events with the events in which Google releases its apps on Android. This mapping allows us to use the app markets where Apple enters *before* Google as a proxy for the markets in which Google's entry threats increase. In sum, among Apple's 31 entry events, in 5 instances, Apple's entry takes place at the same time or after Google's release of similar apps on its Android; 23 of the remaining instances take place in or before January 2012 and are excluded from our study, as we do not have observations for the period before these events. In the end, our empirical investigation focuses on the remaining 3 events. Third, one of the biggest challenges of our data construction is to identify apps that are likely to be affected by changes in Google's entry threats, as proxied by Apple's actual entry events. We use a combination of manual reading and automatic search in the Google Play store to construct this group of affected apps.

Based on a difference-in-differences empirical framework, our results show that when compared with unaffected developers' apps in the same category, app developers that experience an increase in Google's entry threat reduce innovation efforts on their affected apps; after Google actually enters, they reduce innovation efforts on affected apps further and also increase these apps' prices. However, although the entry threat dampens affected developers' innovation incentives in the affected markets, we find that they do not withdraw from the platform completely. They shift their innovation direction from affected apps to unaffected apps, as illustrated by an increase in updates on their unaffected apps during both the entry-threat and actual-entry period.

Many unobserved factors could affect both a platform owner's entry decision and app developers' innovation/pricing strategies. Through the difference-in-differences framework, our identification strategy points to the nature of unobservables that would be needed to generate our results—those that are correlated with a platform owner's entry and only appear in the affected markets. However, there is still concern whether Android app developers would perceive Apple's actual entry into its iOS markets as an indicator that Google will eventually enter into the same Android markets. Therefore, the observed effects may just reflect certain unobservables that could be correlated with both Apple's entry decision on iOS and Android app developers' behavior in the same markets on Android. To mitigate this concern, we show that the effects of Google's entry threat do not appear prior to the period when the threat happens. We also show that Apple's actual entry (used to proxy for Google's entry threat) is not correlated with Android app developers' behavior in markets where we are not supposed to observe any effects, namely those markets where Google entered before Apple so Apple's entry would not have any influence on Android app developers.

2. Related Literature

This paper builds off and contributes to several streams of literature. First, it adds to the empirical literature examining how firms react to the threat of entry. While this issue is prevalent and important for firm strategies, there is scant empirical work due to the difficulty of identifying the threat of 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 of Southwest Airline. Seamans (2012) finds that incumbent cable TV firms use upgrades to deter entry from municipal entrants. Unlike these studies that focus on how large firms respond to the threats from relatively smaller entrants, we study how small firms react to the potential entry of large firms. In addition to examining pricing, we examine how entry threats affect small firms' innovation efforts.

Our study also contributes to the literature examining the incentives and consequences of platform owners' entry into complementary markets. Most studies in this literature are theoretical and often find that this entry strategy allows a platform owner to strengthen its market power and extract more value (Whinston 1990; Economides 1998; Klein 2001; Carlton and Waldman 2002). At the same time, the action may discourage complementors from investing and innovating (e.g., Choi and Stefanadis 2001; Farrell and Katz 2000; Becchetti and Paganetto 2001; Heeb 2003;

Miller 2008; Parker and Van Alstyne forthcoming). Only a few papers empirically study this phenomenon. Gawer and Cusumano (2002) and Gawer and Henderson (2007) find in an in-depth field study of Intel that Intel tries to avoid competing directly with complementors, and it enters certain markets because it is not satisfied with complementors' products and wants to motivate them to innovate. Zhu and Liu (2016) examine Amazon's entry pattern into third-party sellers' product spaces and find that Amazon is likely to target successful products and after Amazon's entry, the affected third-party sellers are discouraged from growing their businesses on Amazon. Li and Agarwal (2016) show that Facebook's integration of Instagram has a positive effect on complementors competing with Instagram as the event expands 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.

More broadly, our work adds to the large body of literature on the relationship between competition and innovation (e.g., Schumpeter 1942; Arrow 1962; Greenstein and Ramey 1998). 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) or has no clear impact on innovation incentives (e.g., Scott 1984; Levin and Reiss 1984; Levin et al. 1985; Scherer and Huh 1992). Boone (2000) and Lee (2009) find that the relationship depends on firms' efficiency level or technological competence relative to their rivals. More recent work also finds an inverted U-shaped relationship between the two (e.g., Aghion et al. 2005). Our results show that on average app developers reduce their innovation efforts under the entry threat and reduce their innovation efforts even further under the actual entry, suggesting that greater competition reduces innovation efforts. In addition to the level of innovation efforts, our study provides evidence that competition shifts firms' innovation directions (e.g., Lerner and Stern 2012): affected app developers increase their innovation efforts on apps that are not targeted by platform owners.

3. Empirical Approach

3.1. Empirical setting

To understand how complementors respond to entry threats from a platform owner, we use the mobile app market as our research setting. In particular, we investigate how app developers on

Android react to the threats of Google's entry into a range of Android app markets. There are several features of the Android platform that make it an appealing empirical setting.

First, while Google has been developing Android as the operating system for touchscreen mobile devices, Google has also been continually introducing new mobile apps built upon Android since 2008. Based on our own data collection, Google had introduced approximately 200 mobile apps on Android by August 2015. Therefore, this provides us with an excellent setting where complementors keep facing entry threats from the platform owner.

Second, one important empirical challenge is to identify the entry threat from the many possible markets the platform owner could possibly enter. Our key idea is to identify discrete shifts in platform owner entry threat by using the entry patterns of a competing platform owner into its own complementary markets. One 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, we see two dominant mobile operating system platforms: Google's Android and Apple's iOS. As we will show later, not only do both Apple and Google enter into a range of app markets on their own platforms, but they also follow each other's moves closely. Thus, we are able to identify Google's entry threats by looking at the iOS app markets Apple has entered.

Third, the mobile market is interesting and important to examine in itself. According to a recent report by Gartner, there were about 102 billion app downloads in 2013 worldwide, leading to a global app revenue of \$26 billion; it was estimated that by 2017, the total downloads could amount to 268 billion annually, with a total revenue of \$77 billion. While the mobile app market has undoubtedly become a fertile ground that sprouts many new businesses, the competition in the mobile ecosystem is also fierce. Our study attempts to shed light on how a mobile platform owner's strategies could shape the competition and innovation landscape in its own mobile ecosystem.

3.2. Identify shifts in Google's entry threats

Few empirical studies have directly examined the effects of entry threat, largely due to the difficulty in identifying credible predictors of future entry. To predict the possible app markets Google may enter in the future for its Android platform, we utilize the app entry patterns by Apple for its iOS platform.

Since the launch of its first generation iPhone along with the iOS in 2007, Apple has been introducing a variety of standalone apps and important features for its iOS. Every time Apple

introduced a new app or iOS feature, it became a direct competitor to app developers that offer 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 suggested that it could 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 obsolete or useless on iOS.¹

We implement the following three steps to compile the list of apps introduced by Apple for its iOS. We first manually search in iTunes for all apps that indicate the seller is Apple Inc., such as iTunes U, GarageBand, and Keynote.² The entry dates of these apps are based on the first version release 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 where the acquired company was operating, then we would consider Apple as entering into the corresponding app market when the acquisition took place. However, except in the case of the acquisition of Siri Inc., we notice that most of the acquisitions by Apple are to enhance its existing apps, such as the acquisition of Locationary Inc. and Embark for its Maps app, the acquisition of Prss for its Newsstand app, and the acquisition of Beats Music for its iTunes Radio. For these instances, because Apple had already operated in the related app markets before the acquisitions, we do not include them in our list. Third, we manually read through all Apple's news articles³ to identify the brand-new features introduced by each iOS release, as they could also directly compete with some third-party app developers, such as the Flashlight feature mentioned above, the AirDrop feature which may compete with files-transferring apps, and the Guided Access feature which allows parents to restrict access to certain apps and thus could compete with many parental control apps. We use the announcement dates of these new features to define the entry dates.

We next use the same procedure to obtain the list of apps introduced by Google on Android. Then, we manually match Apple's apps and Google's apps. This mapping allows us to i) verify whether Apple and Google follow each other's moves closely regarding introducing apps on its own platform; and ii) use the app markets where Apple enters before Google as a proxy for the markets in which Google could impose greater entry threats.

¹ For example, see <http://www.cultofmac.com/231121/seven-apps-apple-killed/> for more discussions.

² However, we drop the 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.

³ All iOS release news articles can be accessed through <http://www.apple.com/pr/library/>.

Table 1 below presents the full list of apps introduced by Apple, as well as the matched Google apps. Note that although it is interesting to look at the full list of apps introduced by Google, our main interest is to understand the effect of Google's entry threats through Apple's entry patterns and how it differs from the effect of Google's actual entry. Therefore, our analysis will be restricted to the markets where Apple entered and Google either entered later than Apple or has not entered by August 2015 (the end of our sample).

Table 1 reveals some interesting entry patterns. First, if we look at the entry intensity by year, the period that sees the most intensive entry by Apple into its iOS markets is from 2009 to 2012, during which Apple entered into 23 app markets. Most of Google's entry into the same markets, on the other hand, happened from 2011 to 2014.⁴ Second, there is considerable overlap between the apps introduced by Apple and Google. More 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); for the other 31 markets Apple entered, Google entered into 25 of them (81%) by the end of our sample period. As indicated by the entry date, among the 25 overlapped app markets, Apple entered into 20 markets earlier than Google. In sum, the evidence provided by Table 1 supports our approach of using Apple's entry to predict Google's future entry, as Google does seem to follow closely Apple's app entry strategies.

As we will discuss more below, because our sample period is from 2012 to 2015, in our difference-in-differences estimation, we can only examine Apple's entry that happens after 2012, i.e. the first three entry events shown in Table 1.

3.3. Empirical framework

One identification challenge is that unobserved factors such as market opportunities could affect both a platform owner's entry decision and app developers' innovation/pricing strategies. Therefore, our empirical model is based on a difference-in-differences framework. For each of Google's entry threats (as triggered by Apple's entry events), we compare Android apps by developers that are likely to be affected by the threat (i.e. the treatment group) with Android apps by developers that may not be affected by the threat but belong to the same app category (i.e. the control group). Because our primary interest is to understand how entry threats shift both the rate

⁴ Note that we only consider entry, i.e., the first release of an app. Based on our manual reading of the news releases, both Apple and Google have continually made improvements to the apps they entered.

and direction of app developers' innovation efforts, we further decompose our treatment group into the following two groups: i) affected developers' affected apps (denoted as *Affected*); ii) affected developers' unaffected apps (denoted as *Unaffected*). Thus, our control group consists of apps developed by developers who were not affected by shifts in Google's entry threats at all. We use apps in the same app category to construct the control group, as we expect these apps may show a similar pattern in innovation/pricing as the affected apps before the entry threat.

Indexing Android app by i and time by t , we use the following as the baseline specification:

$$\begin{aligned} Outcome_{it} = & \alpha + \delta_1 * Affected_i + \delta_2 * Unaffected_i + \beta_0 * Under\ Entry\ Threat_{it} + \gamma_0 * Under\ Actual\ Entry_{it} \\ & + \beta_1 * Under\ Entry\ Threat_{it} * Affected_i + \gamma_1 * Under\ Actual\ Entry_{it} * Affected_i + \beta_2 * Under\ Entry \\ & Threat_{it} * Unaffected_i + \gamma_2 * Under\ Actual\ Entry_{it} * Unaffected_i + Control_{it} + v_i + \eta_t + \varepsilon_{it} \end{aligned} \quad (1)$$

The dependent variable ($Outcome_{it}$) is either the level of innovation a developer conducts on app i in time t or the app's price in time t . $Under\ Entry\ Threat_{it}$ turns on if it is in a period when an app i faces an increased entry threat posed by Google to its app category, but does not see Google's actual entry; $Under\ Actual\ Entry_{it}$ turns on after Google actually enters. As noted above, $Affected_i$ indicates whether an app i is affected by Google's entry threat; $Unaffected_i$ turns on if app i is not affected by Google's entry threat but developed by a developer who has some other app(s) affected by the threat. In the next section, we describe how we measure $Affected_i$ and $Unaffected_i$, and how we construct $Control_{it}$. We use v_i to indicate our use of fixed effects models in all of our analyses to control for any time-invariant differences across different apps.⁵ We employ the full set of time dummies in all analyses, as indicated by η_t . Last, because we use app-time as the unit of analysis and the innovation/pricing decisions across multiple apps developed by the same developer are correlated, standard errors are clusters at the level of developer for all of our regression analyses.

We are mostly interested in the coefficients β_1 , γ_1 , β_2 and γ_2 , as well as the difference between β_1 and γ_1 . For example, given an innovation-based dependent variable: if β_1 is negative but β_2 is positive, it suggests that under Google's entry threat, an affected developer reduces the innovation on his affected app but increases innovation on an unaffected app, relative to an

⁵ Because of the use of fixed-effect models, the direct effects of $Affected_i$ and $Unaffected_i$ cannot be estimated from the regression analysis.

unaffected developer's app in the same app category. If γ_I is negative and significantly less than β_I , it suggests that once Google actually enters, the affected app's innovation is further reduced.

4. Sample and Measures

4.1. Sample

Our dataset includes approximately 200,000 apps listed in the Google Play store for use on the Android platform. For each app, we obtain its ID number assigned by Google Play, app description, categories, release date, and its publisher ID. Our dataset also covers the following history for these 200,000 apps from January 2012 to August 2015: new version release events, price change events, user ratings, and if an app was ranked in the overall top 500, its exact ranking.

Our unit of analysis is at the app-month level. Due to our data availability, the sample period is from January 2012 to August 2015, a total of 44 months. Given our difference-in-differences research design, we could only use events that happened after 2012 to have observations for both the before- and after- periods. Thus, we are only able to use the first three entry cases listed in Table 1. Meanwhile, in our baseline sample, we only keep apps released before its matched entry threat event so that we can compare the differences of apps' innovation and price level before and after the event.

To construct our sample, we first match Android apps in our dataset to the three entry cases based on the app category. More specifically, the app category of Guided Access, Podcasts, and Flashlight is Tools, Entertainment, and Tools or Productivity⁶ respectively. Thus, apps in our dataset that belong to the same category as each of these three entry cases are selected to form the analysis sample. Second, as suggested by Bresnahan et al. (2015), one important type of apps that attract many downloads are "corporate apps," i.e., apps developed to support offline business (e.g., a banking app, an airline app, or a hotel app). The innovation activities of these apps tend to be different from other entrepreneurial apps and may not be affected by platform owner entry. Therefore, we ask three research assistants to manually eliminate these corporate apps from our sample. Third, we eliminate apps that were released after the matched entry threat, as we do not have pre-threat observations for these apps. As a result, we have 4,051 apps in the regression sample, with a total number of 165,190 observations at the app-month level. Each app enters into the sample either from January 2012 or from its release date.

⁶ Flashlight is classified into either Productivity category or Tools category.

4.2. Dependent variables

In the mobile app setting, the innovation efforts a developer exerts on an app can be examined through the frequency the developer improves the app, such as adding new features, redesigning interface, or fixing bugs. Because these updates to an existing app are often included in new version releases, we use the total number of new versions released in month t by app i (denoted as $TotalUpdates_{it}$) to capture the overall innovation efforts.

The next dependent variable we are interested in is the price of app i in month t ⁷. Although we do not have the exact monthly data on app price, we are able to extrapolate an app's price information based on our data on price change history. For example, if we observe an app had two price change events throughout the entire sample period—its price changed from \$0.99 to \$1.99 in month t and changed from \$1.99 to \$2.99 in month $t+10$, then we set its price to be \$0.99 from month 1 to month $t-1$, \$1.99 from month t to month $t+9$, and \$2.99 in and after month $t+10$.

4.3. Identify affected apps and unaffected apps by developers affected by Google's entry threats

Among the apps that are matched to each of Google's entry threats (as proxied by Apple's entry events), we need to identify apps to which Google's potential entry could create direct competition and thus which are likely to be affected by the threat (i.e. to measure the variable $Affected_i$ in specification (1)). This task proves to be challenging. We use a combination of manual reading and automatic search to address this problem. First, we have several research assistants manually read a subset of apps in our sample and identify 200 apps that are similar in functionalities as the three apps introduced by Apple.⁸ Next, we utilize Google's "similar apps" recommendation systems at the Google Play store to identify apps that are similar to these 200 apps. Although it is impossible to know the exact algorithm used by Google to determine similar apps, apps that belong to the same category, have similar keywords, have the same target country/language, and have higher trustworthiness would be more likely to be listed as similar apps.⁹ This algorithm is consistent with our definition of the *Affected* apps: if Google were to enter,

⁷ If an app's price changes within a month, we use its price at the beginning of a month.

⁸ Given the large number of apps in our dataset, it is difficult to only rely upon manual reading to identify apps affected by each entry threat.

⁹ See <https://www.quora.com/How-does-the-Google-Play-Store-determine-similar-apps> for more discussions.

it would have the most direct competition against apps with these features. To ensure we capture as many as possible apps on Android that are likely to be affected by the three entry events, we implement two rounds of search for similar apps at the Google Play store.¹⁰ The entire process allows us to identify 962 apps (out of 4,051 apps in our sample) that are likely to be affected by entry. Then, the dummy variable $Affected_i$ is equal to one if an app i belongs to these 962 apps, otherwise equal to zero. One concern is that apps from the first round search might be more similar and thus be more affected by Apple's entry than apps from the second round search. To address this concern, we test the robustness of our results by coding $Affected_i$ to be 1 for apps from the first round or from our manual reading, and coding $Affected_i$ to be 0.5 for apps from the second round search. The results with this alternative measure are consistent with the results with the baseline measure of $Affected_i$.

The next step is to identify unaffected apps published by developers affected by Google's entry threats (i.e. to measure the variable $Unaffected_i$ in specification (1)). Because we have information on the full set of apps published by each developer, if a developer has any app(s) affected by the entry threats, we define this developer as an affected developer. Then, $Unaffected_i$ turns on if an app i is not affected by the matched entry threat but developed by an affected developer. Table 2 presents the distribution of affected developers vs. unaffected developers in our sample, as well as the number of affected apps vs. unaffected apps, by each of the three Apple entry cases.

4.4. Other variables and summary statistics

The existing market competition could influence both Google's entry decision and app developers' innovation and pricing strategy. Thus, in the $Control_{it}$ vector in specification (1), we employ a variable to control for the category-level competition app i faces in month t (denoted as $Competitors_{it}$). It is measured by the number of apps that belong to the same category as the focal app i and are ranked in overall top 500 in month t . If app i belongs to more than one category, then we use the average number of top-500 apps across all its categories to measure $Competitors_{it}$. Besides controlling for the level of competition, we also compute the age of an app i in month t

¹⁰ That is, we first take each of the 300 apps and search for its similar apps as recommended by Google; we then perform another round of search for apps similar to these similar apps from the first round.

(measured in months), as an app's age could be correlated with the frequency of version release over time.

Table 3 below reports the summary statistics of the main variables used in our empirical analyses. On average, an app releases a new version for every three months. Although half of the apps in the sample have prices lower than \$0.99, some apps charge prices as high as more than \$200. The number of top-ranked competitors also varies widely across app category and time. On average, an app sees about 91 competitors in its category that are ranked in overall top 500 in a month; but in certain category there are more than 200 competitors that are ranked in overall top 500. Because the variables *TotalUpdates_{it}*, *Price_{it}*, *Competitors_{it}*, and *Age_{it}* are highly skewed, we take log transformation of these variables in the regression analyses.

5. Results

5.1. Baseline results

Table 4 below presents our baseline results based on the full sample, using a fixed-effects linear model. We choose a linear model for several reasons. First, as implied by Table 3, many apps in our sample do not have any update in many months, so nonlinear methods may lead to loss of many observations. Second, a linear model allows for easier interpretation of the implied marginal effects from the estimates. Given the way we construct the entry-threat interaction variables (*Under Entry Threat X Affected* and *Under Entry Threat X Unaffected*) and the actual-entry interaction variables (*Under Actual Entry X Affected* and *Under Actual Entry X Unaffected*), the coefficients of these variables reflect an affected developer's affected/unaffected app's changes in an outcome variable when compared with the before-threat period, relative to an unaffected developer's app.

The estimated coefficients of column (1) of Table 4 suggest that relative to an unaffected developer's app, an affected developer reduces his updates on an affected app by 3% under Google's entry threat; after Google actually enters, he reduces the updates on the affected app by 6%. The difference between the entry-threat and actual-entry interaction coefficients is statistically significant, suggesting that Google's actual entry has a greater negative effect on an affected app's innovation than an entry threat. Interestingly, our results reveal that the affected developer seems to increase his updates on an unaffected app by 3% when Google imposes the entry threat and maintains the same level of increase in updates after Google actually enters.

We next implement several additional analyses to check the robustness of our baseline results. First, 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 the complementors' innovation/pricing strategies, we augment our regressions by adding a set of linear time trends specific to each entry event. The results are reported in columns (2) of Table 4, and are consistent with our baseline results.

Second, we are concerned about multi-homing apps in our sample, i.e. apps that are developed both on iOS and on Android. After Apple enters into its iOS markets, these apps 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/pricing decisions could exhibit different patterns from the rest of apps that are only available on Android. Thus, we eliminate these multi-homing apps from the sample and report the results in columns (3) of Table 4, which are qualitatively similar to the baseline findings.

Overall, the results from columns (1) to (3) of Table 4 collectively provide some evidence that complementors on a platform do respond to both a platform owner's entry threat and its actual entry, and more interestingly, in a different way. When the entry threat from the platform owner becomes more credible, a complementor may be discouraged from innovating in the affected market because of the foreseeable competition in the future. However, it is rational not to reduce his innovation too much before he has to, as doing so could potentially lose customers and hinder his business if the entry turns out not to occur. Once the actual entry happens, because there is little chance for the complementor to compete against the platform owner, it becomes optimal for the complementor to exit from the affected market. Meanwhile, although his innovation incentives are dampened in the affected market, the complementor does not withdraw from the platform completely. Instead, after the threat occurs, he seems to shift his innovation direction from the affected market to an unaffected market, as indicated by an increase in updates in an unaffected market during both the entry threat period and the actual entry period.

We next turn to our results on how an affected app changes its price when faced with Google's entry threat and actual entry. The baseline results are presented in column (4) of Table 4, followed by two sets of robustness check in columns (5) and (6). In sum, although an affected app developer does not take much price action on its affected app when there is an entry threat, he increases the affected app price by 3% after Google actually enters, relative to an unaffected

developer's app. One plausible explanation is that, once Google actually enters, the developer of an affected app may know that the fierce competition brought by Google would make his own app unlikely to survive for very long, so he might increase the price substantially for a better exit from this affected market. On the other hand, while the developer increases his innovation on the unaffected app, he does not increase its app price to compensate for his efforts. This strategy is possibly to attract customers and grow his business in the unaffected market.

5.2. Timing falsification exercises and month-by-month effects

One concern on our empirical strategy is whether Android app developers would perceive Apple's actual entry into its iOS markets as an indicator that Google will eventually enter into the same markets. Therefore, the observed effects may merely reflect certain unobservables that could be correlated with both Apple's entry decision into its iOS markets and Android app developers' behavior in the same Android markets. In particular, Apple chose both the timing of its entry and the markets where it would enter. Some 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 its technological maturity. This would lead to a negative relationship between Google's entry threat and innovation in the affected markets. To mitigate this concern, we deepen the baseline analyses with two sets of falsification exercises. In this section, our first falsification exercises examine whether the effect shows the right timing; in the next section, our second falsification exercises investigate whether the effect shows up in the right markets.

The logic of the timing falsification exercises is that if our estimates reflect a causal relationship, the incidences of Google's entry threats (or Apple's actual entry into its iOS markets) should have no effect on affected app developers' innovation prior to the period when the threats occur. Therefore, we create a dummy "*0 Month Pre Entry Threat*" that is equal to 1 if the observation is from the month when the threat happens, a dummy "*1-3 Month Pre Entry Threat*" that is equal to 1 if the observation is from the 1st to 3rd month before the threat, and a dummy "*4-6 Month Pre Entry Threat*" that is equal to 1 if the observation is from the 4th to 6th month before the threat. We add these three dummies and their interactions with *Affected* and with *Unaffected* to our baseline specification. As shown in columns (1) to (3) of Table 5, we do not find the affected developers reduce the release of updates on their affected apps in the months leading up to

Google’s entry threat, neither do we find that the affected developers increase updates on unaffected apps before the threat happens. Columns (4) to (6) of Table 5 further employ app price as the dependent variable, which does not suggest the existence of any pre-threat trend either. This set of results provide some suggestive evidence that the exogeneity of Google’s entry threat, i.e. Google’s entry threat (as proxied by Apple’s actual entry into its iOS market) seem not driven by some omitted time-varying factors that are correlated with Android app developers’ behavior.

Building upon the timing falsification exercises above, we next decompose the time dummy *Under Entry Threat* into four time dummies that turn on in different months under the entry threat. Similarly, we also decompose “*Under Actual Entry*” into three time dummies that turn on in different months under the actual entry¹¹. This type of specification provides us a deeper look at how the effects of Google’s entry threat and actual entry vary across different periods. Results from this set of analyses are reported in Table 6. Consistent with Table 5, the coefficients of the interactions of *Affected* with all pre-threat time dummies are insignificant, so are the interactions of *Unaffected* with all pre-threat time dummies. This suggests no “pre-trend” exists before Google’s entry threat. Although the magnitude and statistical significance of the entry-threat interaction coefficients and actual-entry interaction coefficients vary across different specifications that use different months as the comparison period¹², they are largely similar to the ones observed in the baseline Table 4. Taking columns (2) and (5) for example, relative to an unaffected developer’s app, an affected developer reduces his updates on an affected app by 2% to 5% under entry threat and in the period after Google actually enters, reduces updates by 6% to 9% and increase price by 3% on the affected app; at the same time, his unaffected app sees an increase of 3% to 6% updates under entry threat and an increase of 2% to 4% updates under Google’s actual entry.

5.3. Falsification exercises using markets where Google entered before Apple

Besides the timing falsification exercises, our next set of falsification exercises seek to show that Apple’s actual entry into its iOS markets (used to proxy for Google’s entry threat) is not

¹¹ We do not include *After 10 Month Actual Entry* in this set of analyses, as there is no observation in our sample that falls into this time period.

¹² That is, in columns (1) and (4), the comparison period is the period up to the month when the threat occurs; in columns (2) and (5), the comparison period is the period up to the 4th month before the threat; in columns (3) and (6), the comparison period is the period up to the 7th month before the threat.

correlated with Android app developers' behavior where we are not supposed to observe any effects. More specifically, as shown in Table 1, we see three markets where Google entered before Apple—the maps market, the mobile wallet market (e.g., Apple's Passbook used for storing various cards, boarding passes, tickets), and the file-sharing market (e.g. Apple's AirDrop). In these markets, Android app developers would not respond to Apple's entry (which we use as a proxy for Google's entry threat in the baseline analyses), because Google had already existed in these markets when Apple's entry occurred. On the other hand, if we were to observe similar effects from Apple's entry on Android app developers' behavior as what we find in our baseline results, this could suggest that our baseline results pick up some omitted variables' effects.

The specification for this analysis can be written as follows:

$$Outcome_{it} = \alpha + \delta_1 * Affected_i + \delta_2 * Unaffected_i + \beta_0 * Under Entry Threat_{it} + \beta_1 * Under Entry Threat_{it} * Affected_i + \beta_2 * Under Entry Threat_{it} * Unaffected_i + Control_{it} + v_i + \eta_t + \varepsilon_{it} \quad (2)$$

The unit of analysis are still at the app (i) - month (t) level. As noted above, because Google entered into these markets before Apple, the direct effect of *Under Actual Entry* and its interactions with both *Affected* and *Unaffected* shown in equation (1) are not incorporated into this specification. Second, since in our baseline results we observe Android app developers respond to Google's entry threat by adjusting innovation direction but not price, we focus on logged *TotalUpdates* as the dependent variable in this set of analyses. v_i again is used to indicate our use of fixed effects models in all of our analyses, so the direct effects of *Affected* and *Unaffected* could not be estimated from the regression. We employ the same set of time dummies and control variables as in equation (1).

Likewise, we implement the same procedure to construct the analysis sample and measure the variables *Affected_i* and *Unaffected_i* as in our baseline analyses. We first match Android apps to the three Apple's entry events (Maps, Passbook, and AirDrop) based on app category. Then, within the set of apps matched to each entry event, we identify apps that are similar to the entry case and thus would belong to the “*Affected*” group using a combination of manual reading and automatic search; as long as an Android developer has any app that belongs to the “*Affected*” group, his all other apps would be considered to belong to the “*Unaffected*” group. This entire process gives us a sample of 3,272 apps with a total number of 137,893 observations for this falsification analysis.

The regression results are reported in Table 7, where column (1) shows the results based on equation (2), column (2) adds entry-specific time trends, and column (3) drops multi-homing apps. Overall, we do not find that, relative to an unaffected developer's app, an affected developer reduces his innovation on his affected app and expand his efforts on his unaffected app after Apple entered into the corresponding iOS market. This contrast with our baseline results in Table 4 boosts our confidence that Android app developers do consider Apple's moves as an indicator of Google's potential moves, and moreover, when faced with such entry threats by Google, they reduce their innovation on the affected markets and shift the efforts to the unaffected markets.

6. Conclusion

In this study, we examine the effects of a platform owner's entry threat and actual entry on complementors' behavior. Using the mobile platform Android as our empirical setting, we study how app developers adjust the *rate* and *direction* of their innovation efforts in response to Google's entry threats to the app markets vs. its actual entry. We also examine whether app developers change app prices during the entry-threat and actual-entry period. Our difference-in-differences analyses suggest that relative to an unaffected app developer's app, an affected app developer reduces its updates on an affected app by 3% under Google's entry threat; after Google actually enters, it reduces its updates by 6.6% and also increases its app price by 3%. This finding is consistent with a body of theoretical work that suggests a platform owner's entry into complementary markets could discourage complementors from investing and innovating (e.g., Farrell and Katz 2000). Different from most of the prior studies, our focus is to understand whether complementors would react in the presence of entry threat, though the actual entry has not happened. Our findings show that app developers do respond to the threat by reducing innovation, even though doing so is likely to dampen their business and lose customers. However, our empirical evidence shows that although app developers are "squeezed" by the platform owner, they do not exit from the mobile app markets completely; instead, Google's entry threats shift app developers' innovation direction from affected markets to unaffected markets. We find that relative to an unaffected app developer's app, an affected app developer increases its updates on an unaffected app by 3% under Google's entry threat, and he continues with the same rate of innovation increase after Google actually enters.

Our study has important implications for both platform owners and complementors in platform-based markets. Although complementors play an essential role in the overall health of a platform-based market, the platform owner could have incentives to enter into complementary markets and “squeeze” complementors. Such behavior may have negative consequences for the platform owner itself. Although we find complementors switch to other unaffected markets on the same platform when faced with such risks, the magnitude of the innovation increase in unaffected markets is relatively smaller than the magnitude of the innovation decrease in affected markets. It is also worth noting that our empirical evidence is drawn upon the mobile app market, where only two platform owners dominate and both have kept entering into complementary markets. In some other platform-based markets, complementors may switch to other platforms who have a better reputation for “treating complementors well.” For complementors, our finding about a shift of innovation direction caused a platform owner’s entry suggests that it might be important to develop multiple product offerings to mitigate such risks. Alternatively, complementors could focus on some non-blockbuster products that are less likely to face entry threats from the platform owner (e.g., Zentner et al. 2013).

Our study also points to many other opportunities for future research. In particular, although we find that complementors shift innovation efforts from affected markets to unaffected markets, it remains to be explored that what types of unaffected markets complementors would focus on. A related question is how such entry threat and actual entry affect complementors’ decision in launching brand-new products. Looking at how different types of complementors react to a platform owner’s entry differently could also be a fruitful avenue for future studies. Last, although a platform owner’s entry could harm complementors, its own offering might be a better alternative than third-party’s offerings. If this could attract more and more consumers to the platform, the increase in consumer base could encourage more third-party developers to enter into the platform and innovate in some new areas. Therefore, how a platform owner’s entry shapes the direction of its platform growth remains an open question.

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Table 1: List of Apple's Entry into App Markets

	Apple App	Apple Entry Date	Matched Google App	Google Entry Date	Notes
1	Guided Access	June 2012	Android restricted user activity	November, 2014	Used in the difference-in-differences analysis
2	Podcasts	June 2012			
3	Flashlight	June 2013	Flashlight	November, 2014	
4	Notes	June 2007	Google Keep - notes and lists	March, 2013	Dropped (Apple's entry date is earlier than 2012)
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	
27	Maps	June, 2012	Maps	September, 2008	Dropped (Google entered first or entered at the same time as Apple)
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)
	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	

Table 2: Number of Affected Developers vs. Unaffected Developers and Affected Apps vs. Unaffected Apps, by Google Entry Threat

	Google Entry Threat (proxied by Apple's Entry into iOS)			Total
	Flashlight	Guided Access	Podcasts	
Number of developers affected by the entry threat	299	108	135	464
Number of affected apps by affected developers	337	90	134	561
Number of unaffected apps by affected developers	229	65	107	401
Number of developers unaffected by the entry threat	1457	345	534	2227
Number of unaffected apps by unaffected developers	1952	401	736	3089

Table 3: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max	Median
TotalUpdates	165,190	0.323	0.924	0	20	0
Price	165,190	2.517	8.866	0	239	0.99
Affected apps by affected developers (denoted as <i>Affected</i>)	165,190	0.137	0.344	0	1	0
Unaffected apps by affected developers (denoted as <i>Unaffected</i>)	165,190	0.099	0.299	0	1	0
Under Entry Threat	165,190	0.581	0.493	0	1	1
Under Actual Entry	165,190	0.167	0.373	0	1	0
Competitors	165,190	91.389	31.708	10.6	237.500	85
Age	165,190	23.189	13.467	0	76	23

Table 4: Baseline results and robustness check

Dependent Variable	log(TotalUpdates)			log(Price)		
	Baseline	Add entry-specific time trends	Drop multi-homing	Baseline	Add entry-specific time trends	Drop multi-homing
	(1)	(2)	(3)	(4)	(5)	(6)
Under Entry Threat X Affected	-0.031** (0.014)	-0.031** (0.014)	-0.032** (0.016)	0.011 (0.007)	0.011 (0.007)	0.004 (0.008)
Under Actual Entry X Affected	-0.062*** (0.019)	-0.062*** (0.019)	-0.059*** (0.021)	0.029*** (0.011)	0.029*** (0.011)	0.025** (0.011)
Under Entry Threat X Unaffected	0.028** (0.011)	0.027** (0.011)	0.018 (0.012)	0.005 (0.010)	0.005 (0.010)	-0.006 (0.010)
Under Actual Entry X Unaffected	0.025* (0.014)	0.025* (0.014)	0.030* (0.016)	0.027 (0.018)	0.027 (0.018)	0.005 (0.016)
Under Entry Threat	-0.013* (0.008)	0.001 (0.008)	-0.011 (0.008)	0.001 (0.006)	0.002 (0.004)	0.003 (0.006)
Under Actual Entry	-0.056*** (0.011)	0.010 (0.013)	-0.058*** (0.012)	-0.003 (0.009)	-0.003 (0.008)	0.001 (0.010)
log (Competitors)	-0.028** (0.013)	-0.026** (0.013)	-0.030** (0.014)	0.006 (0.008)	0.006 (0.007)	0.007 (0.008)
log (Age)	-0.186*** (0.007)	-0.183*** (0.008)	-0.197*** (0.008)	0.017*** (0.006)	0.017*** (0.006)	0.019*** (0.006)
Monthly dummies	Yes	Yes	Yes	Yes	Yes	Yes
Entry event specific time trends	No	Yes	No	No	Yes	No
App fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of apps	4,051	4,051	3,462	4,051	4,051	3,462
Observations	165,190	165,190	141,063	165,190	165,190	141,063
Test of the difference between entry threat and actual entry for affected apps, p-value						
	0.008	0.008	0.035	0.016	0.017	0.008

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; columns (1) to (3) use log(TotalUpdates) as the DV and columns (4) to (6) use log(Price) as the DV; “*Affected*” is a dummy that turns on for affected apps by affected developers and “*Unaffected*” is a dummy that turns on for unaffected apps by affected developers; all columns cluster robust standard errors at the developer level; the numbers in the last row are the p-values of testing the difference between entry threat and actual entry for affected apps.

Table 5: Timing falsification exercises

Dependent Variable	log(TotalUpdates)			log(Price)		
	(1)	(2)	(3)	(4)	(5)	(6)
4-6 Month Pre Entry Threat X Affected			-0.007 (0.026)			0.004 (0.007)
1-3 Month Pre Entry Threat X Affected		-0.022 (0.026)	-0.024 (0.029)		0.010 (0.008)	0.011 (0.010)
0 Month Pre Entry Threat X Affected		-0.054* (0.028)	-0.057* (0.032)		0.010 (0.011)	0.011 (0.013)
Under Entry Threat X Affected	-0.031** (0.014)	-0.044** (0.020)	-0.046* (0.025)	0.011 (0.007)	0.015* (0.008)	0.016* (0.009)
Under Actual Entry X Affected	-0.062*** (0.019)	-0.075*** (0.023)	-0.077*** (0.027)	0.029*** (0.011)	0.033*** (0.011)	0.034*** (0.012)
4-6 Month Pre Entry Threat X Unaffected			0.001 (0.019)			-0.007 (0.011)
1-3 Month Pre Entry Threat X Unaffected		0.027 (0.019)	0.027 (0.020)		-0.008 (0.010)	-0.010 (0.013)
0 Month Pre Entry Threat X Unaffected		0.026 (0.028)	0.026 (0.028)		-0.006 (0.013)	-0.009 (0.016)
Under Entry Threat X Unaffected	0.028** (0.011)	0.038*** (0.013)	0.038** (0.015)	0.005 (0.010)	0.002 (0.012)	-0.001 (0.015)
Under Actual Entry X Unaffected	0.025* (0.014)	0.034** (0.015)	0.034** (0.016)	0.027 (0.018)	0.024 (0.021)	0.022 (0.023)
4-6 Month Pre Entry Threat			-0.034*** (0.011)			-0.002 (0.006)
1-3 Month Pre Entry Threat		-0.018* (0.009)	-0.026** (0.010)		-0.003 (0.006)	-0.003 (0.007)
0 Month Pre Entry Threat		-0.023* (0.013)	-0.030** (0.014)		-0.001 (0.008)	-0.001 (0.009)
Under Entry Threat	-0.013* (0.008)	-0.023** (0.010)	-0.036*** (0.012)	0.001 (0.006)	0.001 (0.007)	-0.001 (0.009)
Under Actual Entry	-0.056*** (0.011)	-0.060*** (0.012)	-0.073*** (0.013)	-0.003 (0.009)	-0.003 (0.010)	-0.004 (0.011)
log (Competitors)	-0.028** (0.013)	-0.020 (0.013)	-0.022* (0.013)	0.006 (0.008)	0.006 (0.007)	0.006 (0.007)
log (Age)	-0.186*** (0.007)	-0.185*** (0.007)	-0.185*** (0.007)	0.017*** (0.006)	0.017*** (0.006)	0.017*** (0.006)
Monthly dummies	Yes	Yes	Yes	Yes	Yes	Yes
App fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of apps	4,051	4,051	4,051	4,051	4,051	4,051
Observations	165,190	165,190	165,190	165,190	165,190	165,190

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; columns (1) to (3) use log(TotalUpdates) as the DV and columns (4) to (6) use log(Price) as the DV; “Affected” is a dummy that turns on for affected apps by affected developers and “Unaffected” is a dummy that turns on for unaffected apps by affected developers; for easier comparison, the baseline results are shown in column (1) and column (4), followed by two sets of timing falsification exercises; all columns cluster robust standard errors at the developer level.

Table 6: Month-by-month effects

Dependent Variable	log(TotalUpdates)			log(Price)		
	(1)	(2)	(3)	(4)	(5)	(6)
4-6 Month Pre Entry Threat X Affected			-0.007 (0.026)			0.004 (0.007)
1-3 Month Pre Entry Threat X Affected		-0.023 (0.025)	-0.025 (0.029)		0.010 (0.008)	0.011 (0.010)
0 Month Pre Entry Threat X Affected		-0.055* (0.028)	-0.058* (0.031)		0.010 (0.011)	0.011 (0.012)
1-3 Month Entry Threat X Affected	-0.028 (0.017)	-0.041* (0.023)	-0.044 (0.027)	0.013* (0.007)	0.017** (0.008)	0.018* (0.010)
4-6 Month Entry Threat X Affected	-0.024 (0.021)	-0.038 (0.026)	-0.040 (0.030)	0.013 (0.008)	0.017* (0.009)	0.019* (0.010)
7-9 Month Entry Threat X Affected	-0.009 (0.020)	-0.022 (0.025)	-0.025 (0.028)	0.011 (0.009)	0.015 (0.010)	0.017 (0.011)
After 10 Month Entry Threat X Affected	-0.039** (0.016)	-0.053** (0.021)	-0.056** (0.025)	0.009 (0.009)	0.014 (0.009)	0.015 (0.010)
1-3 Month Actual Entry X Affected	-0.051** (0.020)	-0.064*** (0.024)	-0.067** (0.028)	0.023** (0.011)	0.027** (0.011)	0.028** (0.012)
4-6 Month Actual Entry X Affected	-0.059*** (0.020)	-0.072*** (0.025)	-0.075*** (0.029)	0.032*** (0.011)	0.036*** (0.012)	0.038*** (0.012)
7-9 Month Actual Entry X Affected	-0.076*** (0.021)	-0.090*** (0.025)	-0.093*** (0.029)	0.032*** (0.011)	0.036*** (0.012)	0.037*** (0.012)
4-6 Month Pre Entry Threat X Unaffected			-0.001 (0.019)			-0.007 (0.011)
1-3 Month Pre Entry Threat X Unaffected		0.026 (0.019)	0.026 (0.020)		-0.008 (0.010)	-0.010 (0.013)
0 Month Pre Entry Threat X Unaffected		0.024 (0.028)	0.024 (0.028)		-0.006 (0.013)	-0.009 (0.016)
1-3 Month Entry Threat X Unaffected	0.046*** (0.017)	0.056** (0.022)	0.056*** (0.021)	0.004 (0.008)	0.001 (0.011)	-0.002 (0.014)
4-6 Month Entry Threat X Unaffected	0.050*** (0.016)	0.060*** (0.019)	0.060*** (0.020)	0.006 (0.009)	0.003 (0.012)	0.001 (0.015)
7-9 Month Entry Threat X Unaffected	0.023 (0.016)	0.033* (0.017)	0.032* (0.019)	-0.001 (0.011)	-0.004 (0.014)	-0.007 (0.016)
After 10 Month Entry Threat X Unaffected	0.018 (0.015)	0.028* (0.014)	0.028 (0.017)	0.007 (0.011)	0.004 (0.014)	0.001 (0.016)
1-3 Month Actual Entry X Unaffected	0.014 (0.015)	0.023 (0.016)	0.023 (0.017)	0.019 (0.017)	0.016 (0.020)	0.014 (0.022)
4-6 Month Actual Entry X Unaffected	0.032** (0.015)	0.041** (0.017)	0.041** (0.017)	0.028 (0.020)	0.025 (0.022)	0.022 (0.024)
7-9 Month Actual Entry X Unaffected	0.028* (0.016)	0.038** (0.017)	0.037** (0.018)	0.034* (0.019)	0.032 (0.021)	0.029 (0.023)
log (Competitors)	-0.025* (0.013)	-0.022* (0.013)	-0.023* (0.013)	0.006 (0.008)	0.006 (0.008)	0.006 (0.008)
log (Age)	-0.186*** (0.007)	-0.185*** (0.007)	-0.185*** (0.007)	0.016*** (0.006)	0.016*** (0.006)	0.016*** (0.006)
Monthly dummies	Yes	Yes	Yes	Yes	Yes	Yes
App fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of apps	4,051	4,051	4,051	4,051	4,051	4,051
Observations	165,190	165,190	165,190	165,190	165,190	165,190

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; columns (1) to (3) use log(TotalUpdates) as the DV and columns (4) to (6) use log(Price) as the DV; “Affected” is a dummy that turns on for affected apps by affected developers and “Unaffected” is a dummy that turns on for unaffected apps by affected developers; 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 in the table above but available upon request; all columns cluster robust standard errors at the developer level.

Table 7: Falsification exercises using markets where Google entered before Apple

Dependent Variable	log(TotalUpdates)		
	Baseline	Add entry-specific time trends	Drop multi-homing
	(1)	(2)	(3)
Under Entry Threat X Affected	0.018 (0.014)	0.017 (0.014)	-0.007 (0.019)
Under Entry Threat X Unaffected	0.017 (0.018)	0.013 (0.017)	0.002 (0.030)
Under Entry Threat	-0.034*** (0.012)	0.009 (0.012)	-0.031** (0.013)
log (Competitors)	0.030*** (0.010)	0.010 (0.009)	0.029*** (0.011)
log (Age)	-0.121*** (0.010)	-0.115*** (0.010)	-0.136*** (0.011)
Monthly dummies	Yes	Yes	Yes
Entry event specific time trends	No	Yes	No
App fixed effects	Yes	Yes	Yes
Number of apps	3,272	3,272	3,272
Observations	137,893	137,893	137,893

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; “*Affected*” is a dummy that turns on for affected apps by affected developers and “*Unaffected*” is a dummy that turns on for unaffected apps by affected developers; all columns cluster robust standard errors at the developer level.