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Threat of platform-owner entry and complementor responses: Evidence from the mobile app market

Wen Wen[1] | **Feng Zhu**[2]

[1]McCombs School of Business, University of Texas at Austin, Austin, Texas

[2]Harvard Business School, Harvard University, Boston, Massachusetts

Correspondence
Feng Zhu, Harvard Business School, Harvard University, Boston, MA 02163.
Email: fzhu@hbs.edu

Funding information
Harvard Business School; the NET institute

Abstract

***Research Summary*:** This paper studies the impact of platform-owner entry threat on complementors in platform-based markets. We examine how app developers on the Android mobile platform adjust innovation efforts (rate and direction) and value-capture strategies in response to the threat of Google's 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. However, their incentives to innovate are not completely suppressed; rather, they shift innovation to unaffected and new apps. Given that many apps already offer similar features, Google's entry threat may thus reduce wasteful development efforts. We discuss the implications of these results for platform owners, complementors, and policy makers.

***Managerial Summary*:** We examine one prevalent source of conflict: platform owners' entry into complementary product spaces. We show that app developers on Google's Android system are strategic and nimble actors. They respond to the threat of Google's entry by adjusting both value-creation and value-capture strategies. We also show that platform owners could use direct entry to shape innovation directions and encourage variety of complements. Overall, on the one hand, Google's entry may have pushed complementors into other areas (which might be less lucrative) and strengthened its position in the mobile market. On the other hand, the entry may have reduced wasteful production efforts in the development of redundant

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applications. The overall welfare implication is thus ambiguous.

KEYWORDS

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

1 | INTRODUCTION

Platforms are becoming increasingly influential in our economy. On these platforms, a wide range of small firms, often referred to as *complementors*, leverage platform resources to offer complementary products or services to prospective end users. Although these complementors are value-creation partners of platform owners (e.g., Kapoor, 2013), many of them are concerned that platform owners may imitate them and enter their product spaces with similar offerings. For example, with every major update of Apple's iOS operating system (OS), 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 it is competing against them.

Unlike the traditional R&D collaboration settings in which firms do not solely rely on partners for value creation, most complementors in platform-based markets have to form ties with platform owners to create value and often have a limited number of platforms to choose from. Meanwhile, because large platform owners can favor their own offerings through bundling or prominent displays, their entry into a product space could significantly affect complementors' ability to create and capture value (e.g., Bakos & Brynjolfsson, 2000; Farrell & Katz, 2000; Parker & Van Alstyne, 2017; Zhu & Liu, 2018). As a result, platform owners' use of their market power with respect to other firms in their ecosystems has become a hotbed of policy debate. One example is the recent investigation of Amazon by the European Union regarding whether it unfairly uses the data of third-party complementors on its platform to decide which markets to enter.[1]

Despite the policy and managerial implications of the tension between platform owners and complementors, the related literature is still nascent, with only a few empirical papers on the drivers and consequences of value appropriation by platform owners (e.g., Edelman & Lai, 2016; Gawer & Cusumano, 2002; Gawer & Henderson, 2007; Li & Agarwal, 2017; Zhu & Liu, 2018).[2] One important but unexplored question is whether and how complementors adjust value-creation and value-capture strategies when the *threat* of platform-owner entry increases. The conventional view suggests that complementors should not react until the actual entry takes place (Goolsbee & Syverson, 2008). This is because it is often risky and difficult to redeploy and reconfigure resources (Harrigan, 1980). If complementors react too early and the actual entry turns out not to happen, it would impose substantial costs on the complementors. However, a competing view is that complementors should react

[1]See, for example, https://www.nytimes.com/2018/09/19/technology/amazon-europe-margrethe-vestager.html, accessed November 2018.

[2]Note that the tension between platform owners and complementors does not have to arise from direct competition. Platform owners, for example, may seek to capture more value by squeezing complementors (e.g., see the Taylor Swift and Spotify case as well as Facebook's use of virtual currency credits and 30% cut from its game developers: https://www.theverge.com/2017/6/9/15767986/taylor-swift-apple-music-spotify-statements-timeline and https://techcrunch.com/2012/10/05/more-competitors-smarter-gamers-expensive-ads-less-virality-mobile/). Direct entry of platform owners is one of the most threatening and visible ways of squeezing complementors and is thus often the focus of policy debate.

from the onset of the process (i.e., when the entry threat increases but the actual entry has not yet happened), as they could gain competitive advantages early and smooth out the costs of transitioning over time.

In this paper, we take a first step toward evaluating complementors' ex ante actions in response to a platform owner's potential entry. Focusing on settings where a platform owner has gained enormous market power, we investigate how complementors adjust innovation and pricing strategies in the presence of the platform owner's entry threat. Our theoretical framework is motivated by the entry-threat literature (e.g., Goolsbee & Syverson, 2008; Prince & Simon, 2015; Seamans, 2012) and the competition-driven repositioning literature (e.g., de Figueiredo & Silverman, 2007; George & Waldfogel, 2006; Wang & Shaver, 2014). Our central hypothesis is that once a platform owner has strong market power, the average complementor will accommodate the platform-owner entry threat by reallocating innovation efforts from affected areas to unaffected areas. Meanwhile, in the affected areas, it will focus on short-term profits in its value-capture efforts. We also predict significant heterogeneity in complementors' accommodation responses according to the popularity of their products: when the threat of platform-owner entry increases, complementors may *increase* innovation on affected products if these products have a large user base. They use this response to position themselves either as strong competitors should the platform owner choose not to enter or as attractive acquisition targets if it does.

The empirical context for testing our hypotheses is 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 threat to enter Android app markets, Android app developers adjust not only app prices but also the rate and direction of innovation. As direct competitors in the mobile platform space, Google and Apple often follow each other's moves. Apple's direct entry into an iOS app market therefore substantially changes Android app developers' perceptions of the likelihood of Google's entry into the corresponding Android app market. Thus, to capture Google's entry threat to various mobile app markets, we look at instances in which Apple released its own apps on its iOS system but Google had not yet entered in the equivalent market on Android. 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 84% of the time, Google entered the same app space. Among those instances, Apple entered before Google 80% of time.

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 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 innovation on affected apps by 5.1% and increase these apps' prices by 1.8%. They do not, however, abandon the platform; rather, when the entry is imminent, they shift innovation efforts to unaffected markets, manifested in a 4% increase in updates on existing apps and a 3% to 10% increase in the introduction of new apps. Consistent with our hypothesis, developers that have popular products being affected by an entry threat react differently from other affected developers: they increase innovation by 7.8% for affected apps and 15% for unaffected apps.

1.1 | Related literature

Our paper contributes to several streams of literature. First, it adds to an emerging body of research on firm strategies in platform-based markets (e.g., Cennamo & Santalo, 2013, 2015; Claussen, Essling, & Kretschmer, 2015; Eisenmann, Parker, & Van Alstyne, 2011; Kretschmer & Claussen, 2016; McIntyre & Srinivasan, 2017; Panico & Cennamo, 2015; Parker & Van Alstyne, 2005; Rochet & Tirole, 2003; Zhang, Li, & Tong, 2018; Zhu & Iansiti, 2012). A small number of empirical studies concern platforms' boundary decisions and focus on the consequences of platform-owner entry into complementary markets (e.g., Edelman & Lai, 2016; Li & Agarwal, 2017; Pierce, 2009; Wan & Wu, 2017; Zhu & Liu, 2018). Our study differs from existing studies in two important ways. First, focusing on complementors' ex ante responses to platform-owner entry, we highlight that instead of waiting until the actual entry takes place, they may adjust their competitive strategies early in the process. More broadly, our focus on the effects of entry threat provides a better understanding of the overall effects of entry. If we were to only estimate the effects of actual entry, which is typically the focus of previous empirical studies on platform-owner entry, we would miss the responses before the actual entry and thus underestimate the total effects of entry. Second, while our study is consistent with prior literature in finding that the average complementor's innovation incentive drops in affected areas, it is—to the best of our knowledge—among the first to show that complementors shift innovation efforts to other areas on the same platform, a finding with interesting policy implications: in many platform markets, the complementors' side is characterized by free entry, which is well known to lead to social inefficiency (e.g., Berry & Waldfogel, 1999; Dixit & Stiglitz, 1977; Hsieh & Moretti, 2003; Spence, 1976a, 1976b). When consumers derive little additional benefit from more entrants, the additional resources used to develop these products are wasted. Platform owners' entry threats may help reduce this wasteful expenditure of effort and push complementors to explore other important areas.

Our study also contributes to the empirical literature on how firms react to entry threat (e.g., Goolsbee & Syverson, 2008; Prince & Simon, 2015; Seamans, 2013). A large body of strategy literature has examined firms' ex post responses to entry (e.g., Casadesus-Masanell & Zhu, 2010; Lieberman, 1987, 1989; McCann & Vroom, 2010; Simon, 2005); however, the empirical literature on firms' ex ante responses to entry is relatively scant (e.g., Ethiraj & Zhou, 2019; Goolsbee & Syverson, 2008; Wilson, Xiao, & Orazem, 2017), partly due to the difficulty of empirically identifying the threat of entry separately from actual entry. Most entry-threat studies focus on how firms respond to threats from comparable or smaller entrants, where both entry deterrence and entry accommodation motives could exist. Seamans (2013) finds that incumbents may use low prices to deter entry, particularly in environments with asymmetric information. Other entry-deterrence strategies include early technology adoption, excess capacity investment, and quality improvement. Hamilton and McManus (2009), using the infertility market as their empirical context, find that early adoption of new technology may delay the entry of rival firms. Seamans (2012) reports that incumbent cable television firms use upgrades to deter municipal entrants. Dafny (2005) and Ellison and Ellison (2011) find nonmonotonic relationships between incumbents' incentives to deter entry and market potential in the hospital procedure and pharmaceutical markets, respectively.

One important challenge in this body of research is the difficulty in distinguishing between entry deterrence and entry accommodation motives. As highlighted in the literature (e.g., Prince & Simon, 2015), incumbent firms reduce product quality under entry threat either to cut costs to deter entry or else to adapt to the new competitive environment by shifting from certain quality dimensions to other dimensions. One notable feature of our context is that given a platform owner's enormous market power, it is almost impossible for complementors to deter platform-owner entry. With very little deterrence motive, we have a relatively clean context in which to study small firms' entry accommodation strategies. Further, in contrast to other studies that find that entry threat reduces prices, we show that the average small firm increases prices because, faced with the entry threat of a powerful firm, it may decide to focus on short-term value-capture strategies.

Last, our work adds to the limited literature on competition-driven repositioning, particularly those studies that examine how the competition created by a powerful entrant affects incumbents' positioning strategies (e.g., de Figueiredo & Silverman, 2007; George & Waldfogel, 2006; Seamans & Zhu, 2017; Wang & Shaver, 2014, 2016). Unlike most of the existing studies that only examine firms' product differentiation strategies as a response to intensified competition, our study seeks to understand how firms adjust both innovation and pricing strategies, emphasizing the need to coordinate various actions to accommodate competition from a powerful entrant. Moreover, consistent with prior literature that speculates on the heterogeneity of response across firms of varying competitive strength (e.g., Wang & Shaver, 2014), we document that popular complementors react to competition in a way that is distinct from average complementors: while they strengthen product offerings in alternative (unaffected) markets, as do average complementors, they increase innovation efforts in affected markets during the entry-threat period, which is contrary to average complementors' reaction. This result highlights that firms may not have uniform positioning strategies and that optimal actions depend upon idiosyncratic investments in affected markets, potential exit options, and resource constraints.

2 | THEORY AND HYPOTHESES

2.1 | Complementors' innovation strategies in response to platform-owner entry threat

Platform owners' entry into complementary markets has the potential to allow them to strengthen their market power and extract more value (e.g., Carlton & Waldman, 2002; Economides, 1998; Whinston, 1990). It may also unleash fierce competition against existing third-party complementors for several reasons.[3] First, platform owners' products may be better in quality. This is particularly true for digital platforms: the platform owner's access to the platform's technical details may allow it to offer products that function better because they are more platform-compatible. Second, platform owners often subsidize product adoption in complementary markets (Heeb, 2003), but many third-party complementors rely solely on their products for revenue and cannot afford to give products away. Platform owners' products may therefore be more appealing to consumers due to lower adoption cost. Third, one common practice by platform owners is to bundle their complementary products into their platforms. Famous examples include Microsoft's bundling of Internet Explorer and Windows Media Player into its Windows OS. Due to lower search costs and easier access, consumers may prefer adopting these products instead of the ones offered by third parties (Tirole, 2005). In some cases, it is almost impossible to remove these bundled options from the platform, so consumers would have less incentive to adopt additional products with similar features. For example, when Apple bundled its native Flashlight app into its iOS OS, which consumers could access with just a swipe and a tap, there was little reason for adopters to waste additional storage and screen space for another third-party Flashlight app. For all these reasons, it is often difficult for complementors to

[3]We acknowledge that not all platform owner entry is successful. Because we focus on complementors' *ex ante* reactions to potential platform-owner entry, the underlying assumption for our argument is that complementors perceive the platform owner entry as likely to take a substantial market share. This assumption tends to hold for reasons mentioned here.

compete directly against platform owners in the same product spaces. Zhu and Liu (2018), examining the pattern of Amazon's entry into third-party sellers' product spaces, find that once Amazon offers certain products, the affected third-party sellers are likely to stop offering them.

The competition-driven repositioning literature (e.g., de Figueiredo & Silverman, 2007; Menon & Yao, 2013) has highlighted three major factors that could affect a firm's decision on whether to stay in or move away from a market affected by competition: (a) the profitability in the affected market, (b) the profitability in an alternative market, and (c) a firm's strategic flexibility and repositioning costs. Although the competition caused by an entrant reduces the profitability of the affected market, a variety of factors, such as a low level of asset redeployability, domain-specific proprietary knowledge, and investments in customer and distribution networks in the affected market, could heighten exit barriers and render repositioning too costly (Decker & Mellewigt, 2007; Harrigan, 1980; Harrigan, 1985). Similarly, the costs associated with learning and acquiring new resources (e.g., intellectual property, customers) in the alternative market could increase the entry barriers and reduce the profitability in that market. If the repositioning costs are too high and/or the net profits from the alternative market are too low, firms may be unwilling to withdraw from the affected market, even if they suffer declining business. In short, in deciding whether to reposition, firms need to weigh the losses in the affected market against the efforts required to reconfigure resources and activities to an alternative market.

When faced with a powerful competitor, many small firms, being strategically oriented and nimble, may choose to lessen the competitive pressure by repositioning away from the affected market (e.g., Li & Zhou, 2017; Piezunka, Katila, & Eisenhardt, 2018; Tirole, 1988). In line with this argument, George and Waldfogel (2006) find that following the introduction of *The New York Times* into local markets, local newspapers shift their product offerings by including more local but less national coverage. de Figueiredo and Silverman (2007) show that the entry of Hewlett-Packard into certain laser printer segments increases the exit rate of firms already in those segments. Wang and Shaver (2014) show that due to the competitive pressures created by the entry of a dominant firm, small firms abandon their positioning and differentiate away from the dominant firm.

In our context, when the entry of the platform owner is imminent, complementors may shift innovation efforts to reposition away from the affected market. We define a complementor's *innovation effort* as the rate at which a complementor develops its products. Depending upon their technological capability and the external competitive environment, complementors could focus on either refining existing products or expanding product variety to conduct innovation. Because the entry of the platform owner may take significant market share in the affected market, the benefits to complementors of continuing to work in that market are likely to be significantly reduced. Meanwhile, as highlighted by the platform literature (e.g., Tiwana, 2015), platform-based markets often have diverse customer needs, thereby providing many opportunities for complementors to enter into a variety of product market spaces. Particularly for digital platform markets, it is relatively easy for complementors to redeploy their existing resources and skills to develop products for other markets. Due to the relatively low entry barriers in such markets, the net benefits of developing products for alternative markets tend to outweigh the net benefits of staying in the affected market. As a result, complementors may accommodate platform-owner entry by diverting innovation efforts to unaffected areas (e.g., Lieberman, Lee, & Folta, 2017). Innovation stimulated by platform-owner entry can take different forms, such as improving existing products (i.e., product refinements) or introducing brand-new products (i.e., product expansions).

More importantly, we expect such diversion of innovation efforts to take place even though the actual entry has not yet occurred. First, because of the expected erosion in profit in the affected area, complementors would want to establish competitive positions in unaffected areas as early as possible. Second, product development is time-consuming, so starting early could smooth out development costs over time. Indeed, Goolsbee and Syverson (2008) and Prince and Simon (2015) both find that incumbent firms may start accommodating entrants when the threat of entry increases.

Hypothesis 1 (H1). *Following an increase in platform-owner entry threat, complementors will shift innovation efforts from affected to unaffected market segments.*

2.2 | Complementors' pricing strategies in response to platform-owner entry threat

Studies often examine firms' repositioning response in isolation. However, as suggested by the literature (e.g., Seamans & Zhu, 2017; Wang & Shaver, 2016), firms may in fact coordinate multiple responses to competition. We expect complementors not only to respond through product innovation but also to adjust their pricing strategies as a joint decision to accommodate platform-owner entry, for the following reasons. First, pricing strategies have been widely recognized as a competitive tool deployed in response to entry threat and actual entry (e.g., Prince & Simon, 2015; Seamans & Zhu, 2014). Second, innovation activities and pricing are interlinked as firms create value through innovation and capture it through pricing. It is natural to expect that firms will capture value differently after they change their value-creation strategies.

Most of the literature focuses on entry deterrence as the mechanism to explain pricing responses, with only a few exceptions looking at entry accommodation. Frank and Salkever (1997) show that following the entry of generic drugs, brand-name drugs increase their prices. The authors suggest that the entry of generic drugs leads price-sensitive buyers to shift to generics, so brand-name producers accommodate such entry by exploiting price-insensitive buyers. Thomas (1999), too, suggests that incumbents may increase prices as part of their accommodation strategy in response to competitor entry.

In platform-based markets, many complementors may price their products low, hoping to grow through network effects or positive word-of-mouth to maximize long-term profits. Should a platform owner enter, its bundling strategy and/or price advantage would make it almost futile for complementors to fight. Therefore, complementors who may not expect to survive in the market for too long will begin to focus on maximizing short-term profits. Complementors capturing value through ads or add-on sales may find that selling their products directly for a fee becomes an attractive business model because it generates immediate returns. By charging a higher price, a complementor can exploit the customers who value that complementor's products most and thus are insensitive to price change (e.g., Frank & Salkever, 1997). Taking OS software as an example, even if an OS provider is about to enter a software application market, a complementor's software may offer some unique functions. Such differentiation allows the complementor to charge more to those consumers who value the differences. Similarly, if consumers need to upgrade their OS to enjoy new applications to be offered by the OS provider, complementors could also increase prices to exploit consumers who do not upgrade and therefore will not have access to the OS provider's apps. Meanwhile, if complementors begin to reposition away from the affected market, such changes may require resources. The revenue from a price increase in the affected market could ease the transition.

Hypothesis 2 (H2). *Following an increase in platform-owner entry threat, complementors will increase their prices in the affected market segment.*

2.3 | Heterogeneity in complementor respaonses

Recent platform literature has highlighted that complementors with different sizes of user bases may be affected by platform-owner entry differently (e.g., Li & Agarwal, 2017). Motivated by this stream of literature, we seek to understand how complementors respond to the threat of platform-owner entry if their affected products have a large user base.

We argued above that when platform-owner entry threat increases, average complementors may expect less benefit from developing products in the affected area, so they reduce development efforts. Complementors that have popular products being affected by entry threat, however, may still see some benefit from improving these affected products—at least during the entry-threat period—for the following reasons. First, while platform owners could develop products internally to enter a market, another viable strategy would be through acquisitions, as acquisitions allow platform owners to tap new technical knowledge and obtain new products or users rapidly (Graebner, Eisenhardt, & Roundy, 2010; Kaul & Wu, 2016; Lee & Lieberman, 2010). For example, Google acquired about 50 software application companies from 2007 to 2015 to develop its mobile business. Apple acquired Siri to enter the virtual assistant market on its iOS platform. Facebook acquired Instagram to enter the photo-sharing app market. When platform owners decide which products to acquire, the ones with a large user base often become the top choices, particularly for markets subject to network effects. For instance, one major driver behind Microsoft's purchase of Skype (instead of another Internet communications company) was Skype's large user base.[4] Similarly, the acquisition of WhatsApp by Facebook was largely because it had the fastest-growing user base in the messaging and Voice over IP app space.[5] As a result, complementors with affected popular products may focus on becoming attractive acquisition targets as an alternative response to the platform owner's potential entry (Graebner & Eisenhardt, 2004).[6] Due to the great information asymmetry between acquirers and targets (Capron & Shen, 2005), these complementors may improve their affected products aggressively to signal their potential (Zott & Huy, 2007). Second, although it is nearly impossible to deter platform-owner entry, complementors may have incentives to accelerate innovation on these popular products to lock in as many users as possible before entry takes place. This serves to strengthen their market positions if entry does not occur (Goolsbee & Syverson, 2008) or, if it does, to render them attractive targets for acquisition. In sum, due to potential benefits that only complementors with popular products can enjoy, we expect them to increase innovation efforts before the actual entry.

> **Hypothesis 3 (H3)**. *Following an increase in platform-owner entry threat, complementors that have popular products being affected will increase innovation in both the affected and unaffected market segments.*

We also expect complementors with popular products affected by entry threat to take less aggressive pricing action during the entry-threat period. First, as indicated in the literature (e.g., Simon, 2005), firms that are more vulnerable to competitors' entry would respond with more aggressive pricing strategies. With a large installed base and positive word of mouth, complementors with popular

[4]Source: https://www.businessinsider.com/why-microsoft-bought-skype-an-insider-explains-2011-5, accessed November 2018.

[5]Source: https://www.businessinsider.com/why-facebook-buying-whatsapp-2014-2, accessed November 2018.

[6]In fact, for many entrepreneurs, "getting bought out *is* the exit strategy: Work your butt off, sell big, pop some champagne, pack up the office and go figure out your next big idea." (Source: https://www.tonygreenberg.com/save-entrepreneur-big-business-keeps-buying-startups-killing-em-2/, accessed November 2018.)

products are less vulnerable than other complementors; therefore, they are under less pressure to increase prices to secure short-term profits. Second, as argued above, complementors with popular products may accommodate platform-owner entry by capturing customers early and becoming attractive acquisition targets. Increasing price would reduce their popularity and hence the likelihood of being acquired.

> **Hypothesis 4 (H4)**. *Following an increase in platform-owner entry threat, complementors that have popular products being affected will not take any price action during the entry-threat period.*

3 | EMPIRICAL DESIGN

3.1 | 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 mobile devices. According to our collected data, it has also introduced approximately 200 mobile apps on Android between 2008 and 2015. Thus, this is a market in which complementors keep facing entry threats from the platform owner.

Second, our research design calls for identifying which market is threatened by platform-owner entry by using the patterns of entry exhibited by 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, not only do the two dominant platform providers, Apple and Google, enter a range of app markets on their own platforms but Google also follows Apple's moves closely. Thus, we can identify increases in Google's entry threat by looking at which iOS app markets Apple enters.

Third, because mobile devices and their associated apps have become a central part of everyday life, the mobile market is interesting and important to examine in itself (e.g., Kapoor & Agarwal, 2017).[7] In addition to being 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.

3.2 | 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 iOS. With each one, Apple became a direct competitor of developers that offer similar apps 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,

[7] Kapoor and Agarwal (2017) focus on cross-platform performance heterogeneity, while we focus on within-platform variation by comparing threatened app firms to control app firms. The approach allows us to control for platform-specific effects such as ecosystem complexity.

observers suggested that music-streaming apps such as Spotify and Pandora could be rendered much less popular on iOS.[8]

We use the following three steps to compile a list of apps introduced by Apple for iOS. First, we manually search its App Store for all apps that indicate the seller was Apple, such as iTunes U, GarageBand, and Keynote.[9] We take the first version release date as the entry date.

Second, we search the SDC Merger and Acquisitions Database to identify mobile app companies Apple acquired: If Apple had not already entered an app market in which the acquired company was operating, we considered it to have done so via the acquisition. However, with the exception of 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 service. Because Apple had already operated in the related app markets before these acquisitions, we do not include them in our list.

Third, we manually examine all Apple press releases[10] 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, which could compete with file-sharing apps, and the Guided Access feature, which could compete with parental control apps. We use the announcement dates of these new features to define their entry dates.[11]

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 that Apple enters before Google as a proxy for the markets in which Google's entry threat has increased.

The matching of Apple and Google apps reveals some interesting entry patterns. First, as shown in Table S1, the most intensive entry by Apple into its iOS markets takes place between 2009 and 2012, when it entered 23 app markets. Most of Google's entries into the same markets, on the other hand, took place between 2011 and 2014.[12] 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 S1). Of the other 31 markets Apple entered, Google had entered 26 (84%) by the end of our sample period. As indicated by the entry date, among the 26 overlapped app markets, Apple entered 21 (80%) earlier than Google. Thus, the evidence supports our use of Apple's entry to predict Google's future entry.

Because our sample period is from 2012 to 2015, in our difference-in-differences estimation, we can only examine Apple entry events that occur after 2012; that is, the three events listed in Table 1. In all three cases, the apps released by Apple and Google are offered free to users.

[8]For more discussion, see http://www.cultofmac.com/231121/seven-apps-apple-killed/, accessed June 2018.

[9]We exclude apps that have to be used in conjunction with Apple's desktop apps (such as Logic Remote) or are clearly used to support Apple's hardware products (such as AirPort Utility). On the other hand, for apps such as Garage Band, although Apple had offered a desktop version prior to a mobile version, we consider the introduction of the mobile version as an entry event, as the mobile version often offers many essential new features and technically differs from its desktop counterpart.

[10]All iOS release news articles can be accessed through http://www.apple.com/pr/library/, accessed June 2018.

[11]There could be a lag between the announcement date and the actual release date for some of those features. We use the announcement date as it marks the first day the public learns about Apple's move into a certain app market.

[12]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.

TABLE 1 Apple entry events and matched Google entry events used in the main analysis

Apple app	Apple entry date	Matched Google app	Google entry date
Guided Access	June 2012	Android restricted user activity	November 2014
Podcasts	June 2012	Google Podcasts	June 2018
Flashlight	June 2013	Flashlight	November 2014

3.3 | Empirical framework

For each Google entry threat (triggered by an Apple entry event), 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 we seek 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 (*ADAA*) and (b) affected developers' unaffected apps (*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 category to construct the control group because we expect these apps tend to show similar patterns in innovation and pricing before the entry threat.

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

$$\begin{aligned} Outcome_{it} = \ & \beta_0{}^{*} Under\,Entry\,Threat_{it} + \gamma_0{}^{*} Under\,Actual\,Entry_{it} \ + \ \beta_1{}^{*} Under\,Entry\,Threat_{it}{}^{*} ADAA_i \\ & + \gamma_1{}^{*} Under\,Actual\,Entry_{it}{}^{*} ADAA_i + \beta_2{}^{*} Under\,Entry\,Threat_{it}{}^{*} ADUA_i \\ & + \gamma_2{}^{*} Under\,Actual\,Entry_{it}{}^{*} ADUA_i + Control_{it} + v_i + \eta_t + \varepsilon_{it} \end{aligned} \tag{1}$$

The dependent variable ($Outcome_{it}$) is either the developer's level of innovation efforts for app i in month t or the app's price in month t. As implied by Table 1, many apps experience both an entry-threat period and a period in which Google had entered. Given the different competitive environment across the two periods, app developers may behave differently. Following other studies of entry threat (e.g., Goolsbee & Syverson, 2008; Prince & Simon, 2015), we use two time dummies to distinguish these two periods: $Under\ Entry\ Threat_{it}$ equals 1 in the period during which app i faces an increased entry threat to its app category but does not face Google's actual entry, and 0 otherwise; $Under\ Actual\ Entry_{it}$ equals 1 after Google actually enters and 0 otherwise. $ADAA_i$ 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 with some other app being affected (the next section describes 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, such as any attributes specific to an app as well as any of its developer's attributes that could be correlated with the outcome variables and Apple's entry patterns. Meanwhile, v_i also absorbs the direct effects of $ADAA_i$ and $ADUA_i$. We also use a full set of month dummies in all analyses, 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 regression analyses.

4 | SAMPLE AND VARIABLES

4.1 | Sample

Our dataset, which is directly obtained from a mobile app analytics company, includes approximately 200,000 randomly selected Android apps listed in the Google Play store for the U.S. market. 110,000 (about 58%) of them were active as of August 2015 and form our initial sample. Our dataset captures 7% of all active apps listed in Google Play as of August 2015.[13] The comparison of the top 10 app categories of our sample with statistics provided by an independent data source, AppBrain, suggests a significant overlap. 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) the exact ranking for any app that was ranked in the top 500 in its category or among all apps.

Given our difference-in-differences research design and the data availability, we focus on the three events listed in Table 1. The apps Apple released in these three events—Guided Access, Podcasts, and Flashlight—belong to the Tools, Entertainment, and Tools or Productivity categories, respectively.[14] Our analysis sample therefore only consists of Android apps in these categories. Second, because the difference-in-differences estimation requires a comparison before and after the entry threat, we could only use apps released before the matched entry-threat events. This has further reduced the sample to about 4,800 apps. Third, one frequently downloaded type of app is “corporate apps”—such as banking apps, airline apps, or hotel apps—developed to support offline businesses (Bresnahan, Orsini, & 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 approximately 800 corporate apps from the analysis sample. In the end, we have 3,986 apps in the regression sample, with 162,473 observations at the app-month level.

4.2 | Variables

For our first dependent variable, in the baseline models, we measure a developer's innovation efforts by the frequency of app updates released by the developer, such as adding new features, redesigning the interface, and fixing bugs. Because the unit of analysis is at the application-month level and 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 innovation. Our measure of innovation efforts is consistent with a body of literature that uses app updates to capture digital innovation in similar settings (e.g., Boudreau, 2012; Tiwana, 2015). The high technological agility of digital products and equivocal customer needs suggest innovation in such a setting requires numerous experimentations and product refinements (Yoo, Lyytinen, Boland Jr., & Berente, 2010). In this trail-and-error-based innovation process, what matter are the ongoing experimentations tried by the developer; even an incremental refinement of the product could potentially address certain customer needs (Nelson, 1995; Tiwana, 2015). Therefore, it is important to incorporate both major and minor updates to measure the innovation efforts exerted by a developer.[15] Another advantage of using the frequency of

[13]According to AppBrain, about 1.6 million apps were active in Google Play as of August 2015. This suggests our initial data sample (110,000 apps) captures 7% of these apps.

[14]Flashlight is classified into both the Productivity and the Tools categories.

[15]We acknowledge that major and minor updates may require different levels of innovation efforts. To examine how developers respond to Google's entry threat by adjusting their more significant innovation efforts (i.e., major updates), we later implement the analyses by using the number of major updates as the dependent variable and obtain similar results.

TABLE 2 Number of affected apps versus unaffected apps

	Google entry threat			
	Flashlight	**Guided Access**	**Podcasts**	**Total**
# of affected apps by affected developers (ADAA)	251	48	79	378
# of unaffected apps by affected developers (ADUA)	191	53	67	311
# of apps by unaffected developers	2054	432	811	3,297

updates as the dependent variable is that it allows for an analysis at the app level, enabling us to look at how developers adjust their innovation efforts across different apps when Google's entry threat increases. That said, because app updates only capture one facet of innovation—product refinements, we also implement the analyses at the developer level and measure developer's innovation efforts by using the rate of product expansions, that is, the introduction of new apps. Our second dependent variable is the price of app i in month t. If an app's price changes within a given month, we use its price at the beginning of a month.

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.[16] 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 the same category and that have similar keywords and the same target country/language would be more likely to be listed as similar apps.[17] 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) directly affected by entry. Consequently, the dummy variable $ADAA_i$ equals 1 if app i is one of these 378 apps, and 0 otherwise. If a developer has any app(s) affected by 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, 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 measure it 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 to find apps similar to app i.[18]

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

[16]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.

[17]For more information, see https://www.quora.com/How-does-the-Google-Play-Store-determine-similar-apps, accessed June 2018.

[18]Our approach to measuring competition on the basis of Google's "similar apps" recommendation is consistent with other studies on mobile apps, for example, Kesler, Kummer, and Schulte (2017).

TABLE 3 Summary statistics

Variable	Obs.	Mean	*SD*	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

technological maturity or opportunities, which could, in turn, be correlated with both Apple's and Google's decisions on which markets to enter.

4.3 | Summary statistics

In Table 3, we report summary statistics for the variables. On average, an app is updated every 3 months. Although half cost less than \$1, some cost over \$200.[19] The level of competition varies widely. On average, about 0.8% of apps in the same category directly compete with a focal app, but that can go as high as 7%. Because the variables $Updates_{it}$ and $Price_{it}$ are highly skewed, we use their log transformations in the regression analyses.

5 | RESULTS

5.1 | 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.[20] The coefficients in Column (1) suggest that, under Google's entry threat, an affected developer significantly reduces its updates on an affected app by 5.1% relative to an unaffected developer's app, whereas after Google actually enters, the affected developer significantly reduces updates on the affected app by 7.9%. Given that on average, an app is updated every 3 months, the estimated effects suggest that a developer would make an update on an app every 98 days under entry threat and make an update every 101 days after the actual entry. 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 an app market, the affected developer significantly increases updates on unaffected apps by 4.3% 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 decisions and app developers' innovation strategies, we

[19]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 90th percentile of *Price*). The results are qualitatively the same.

[20]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.

TABLE 4 Baseline results and robustness check

Dependent variable	log(Updates) Baseline (1)	Add entry-specific time trends (2)	Drop apps by multi-homing developers (3)	log(Price) Baseline (4)	Add entry-specific time trends (5)	Drop apps by multi-homing developers (6)
Under Entry Threat × 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 × 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 × 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 × 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^2	0.049	0.050	0.053	0.005	0.005	0.005

Notes: Robust standard errors in parentheses and clustered at the developer level. 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.

Abbreviations: ADAA, affected developers' affected apps; ADUA, affected developers' unaffected apps.

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 may respond to Google's entry threat differently from the rest of the developers. Thus, we run another robustness check using the subsample that eliminates all multi-homing developers' apps.[21] The results, shown in Column (3) of Table 4, are similar to the baseline results.

Overall, the results in Columns (1)–(3) of Table 4 provide evidence that complementors on a platform do respond to a platform owner's entry threat. They are discouraged from innovating in the affected market. They do not, however, withdraw from the platform completely but rather shift innovation efforts to unaffected markets. These results support H1. It is also interesting that as actual entry occurs and the competition becomes real, complementors reduce innovation efforts to a greater extent, perhaps because the expected benefit from innovating in the affected areas would decrease even further.

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% when entry threat increases and by 3.7% after Google actually enters, relative to the prices of unaffected developers' apps. Both effects are statistically significant with p values of .005 and .008, respectively. Given the high price elasticity of demand for mobile apps,[22] even such small change could lead to a significant loss of customers in the long run, which suggests that complementors indeed focus more on short-term profits after Google's entry threat increases.[23] Interestingly, although they increase innovation for unaffected apps, they do not increase the prices. This seems largely consistent with our argument: in order to build a competitive position in unaffected markets, complementors should focus on improving the products but maintain a similar price in order to stimulate demand.

5.2 | Falsification exercises

5.2.1 | Timing falsification exercises

An important assumption of our difference-in-differences approach is that the treatment and control groups exhibit similar trends during the pre-entry-threat period. We implement a timing falsification exercise to investigate whether this assumption holds. In particular, we create three dummies that indicate different periods for months leading up to Google's entry threat: *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 dummies and their interactions with *ADAA* and with *ADUA* to the baseline specification. If the

[21]In a later section, we discuss further how and why multi-homing developers may react differently from single-homing developers. We also compare the main regression coefficients for multi-homers vs. single-homers. The result is consistent with our expectations.

[22]As suggested by Ghose and Han (2014), on average a 10% price change may lead to a 37% change in demand for apps in Google Play. This observation is also consistent with the anecdotal evidence that more and more app developers tend to offer free apps due to the high elasticity of the demand (e.g., Flurry, 2013).

[23]Note that developers of apps with in-app purchases option might change the in-app purchase prices under entry threat and we do not have data to capture this effect. As a result, our baseline estimate in Table 4 may be a lower bound of the overall pricing effect. As shown below, using the paid-app subsample, we find that developers significantly increase the price of affected apps by 6.5% after Google's entry threat increases and by 9.5% after Google's actual entry. Given the high price elasticity of demand, this greater price change further supports the argument that as entry threat increases, developers choose to focus more on short-term gains at the cost of losing many customers in the long run.

treatment and control groups have parallel trends before Apple's entry, the coefficients of these interaction should remain statistically insignificant.

We also decompose the time dummy *Under Entry Threat* into four time dummies that equal 1 in different months under the entry threat, and similarly decompose *Under Actual Entry* into three time dummies that equal 1 in different months after the actual entry. The variables of interest are again the interactions between these post-threat time dummies and *ADAA*/*ADUA*. 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 S2 report the results of including only the post-threat time 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 S2, the estimated coefficients for the interactions with *1–3 Month Pre-entry Threat* suggest that the affected developers take little action 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 due to the use of different months as the comparison periods,[24] they are qualitatively consistent with those in Table 4. Overall, these results suggest that the treatment group and the control group exhibit similar trends with regard to updates and price prior to the increase in the entry threat; the results also boost our confidence that shifts in app developers' behavior are caused by entry threats.

5.2.2 | Falsification exercises using markets that Google entered before Apple

Our baseline model assumes that Apple's entry caused changes to affected Android developers' actions. To boost our confidence in this assumption, we next implement a falsification exercise that uses markets that Google had already entered before Apple's entry. In these markets, because Google had already entered, these developers should not respond after Apple's entry. However, if certain unobservables, such as the maturity of the market, lead to both Apple's entry and changes in Android developers' behavior, we would observe similar responses in those markets as in the main analysis.

As shown in Table S1, there are three markets that Google entered before Apple: maps, mobile wallets (e.g., Apple's Passbook, used for storing credit cards, boarding passes, and tickets), and file-sharing (e.g., Apple's AirDrop). Apps in these markets are therefore used in this analysis, with the following specification:

[24]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.

$$\begin{aligned} Outcome_{it} = {} & \beta_0{}^* Under\ Entry\ Threat_{it} + \beta_1{}^* Under\ Entry\ Threat_{it}{}^* ADAA_i \\ & + \beta_2{}^* Under\ Entry\ Threat_{it}{}^* ADUA_i + Control_{it} + v_i + \eta_t + \varepsilon_{it} \end{aligned} \tag{2}$$

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 S3 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 specifications but with *log(Price)* as the dependent variable. Overall, we do not find significant reactions by affected developers to Apple's entry, which suggests 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 in our main analysis sample.

5.3 | Use of different control groups

In addition to our timing falsification results, which reinforce our confidence in the parallel trends assumption, we implement a "coarsened exact matching" (CEM) procedure (e.g., Blackwell, Iacus, King, & Porro, 2009; Iacus, King, & Porro, 2012) to construct a control group that is similar to the treatment group prior to Apple's entry, both in terms of absolute levels and trends in key attributes. We identify a control app for each treatment app based on the following covariates: (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) during the pre-threat period; and (d) age up to the month in which the threat occurs. We anticipate 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. Based on the covariates and the corresponding buckets,[25] 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 × 2) apps and 43,256 app-month observations. The results, as shown in Table S4, are qualitatively similar to our baseline results.

The consistency of the CEM procedure depends on the "selection-on-observables" assumption. However, the likelihood of "treatment"—that is, an app facing an entry threat—could be determined by some unobserved factors. We use 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 also interested in entering later but had not entered yet. The assumption is that markets Apple entered later share similar (unobserved) characteristics with markets Apple entered earlier and thus are more comparable than markets Apple never entered. In other words, 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

[25]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 we define these buckets, but it is available upon request.

Guided Access market as the treatment sample and the Flashlight market as the control sample.[26] It is worth noting that for this matching strategy, 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, and 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. As shown in Table S5, the signs of the interaction terms *Under Entry Threat* × *ADAA* and *Under Entry Threat* × *ADUA* are as expected but with larger magnitudes than the baseline results, possibly due to a different comparison group.

5.4 | 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 entry into iOS markets could make Android users aware of these apps and interested in downloading them from Android. 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. We think this is unlikely, as most users of one mobile platform would not follow what is happening on another platform. That said, to address this 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. We 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 S6, where we use the linear probability model to estimate the same baseline specification and robustness checks as in Table 4.[27] The negative coefficients for both *Under Entry Threat* × *ADAA* and *Under Actual Entry* × *ADAA* do not support this alternative hypothesis. Moreover, the positive and significant coefficients for *Under Entry Threat* × *ADUA* and *Under Actual Entry* × *ADUA* suggest frequent updating of unaffected apps by 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 (in Table S7) are qualitatively similar to those in Table 4. Examining updates reveals some difference in the magnitudes of the coefficients of the Guided Access and Flashlight markets, respectively. This might be due to differences in these markets' technical features: Guided Access could be more complex and therefore require more effort and more frequent updating than Flashlight; thus, developers of Guided Access apps may be more sensitive to changes in their competitive environment.

Third, in our baseline measure for *Updates*$_{it}$, we consider all types of version releases. One concern is that some of these releases could be relatively major, such as adding new functions and revamping the user interface, while others are relatively minor, such as adding patches and fixing bugs. However, it is extremely hard to identify which releases are major or minor. Although one possible way is to use the version number to identify major versus minor updates, this is subject to important limitations, as developers determine version numbers arbitrarily and differ considerably in what they

[26]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 completely different categories and may not be comparable.

[27]We use the linear probability model to ease the interpretation of interaction variables. In our analysis, more than 90% 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.

consider a major or minor release. That said, for robustness, we use the <major> field[28] in a version number to count the major releases of app i in month t (denoted as $MajorUpdates_{it}$) and use this as the dependent variable. The results (see Table S8) are qualitatively similar to the baseline results.

Fourth, our hypothesis is that as Google's entry threat increases, app developers are likely to prefer value-capture strategies that allow them to maximize short-term profits. That is, they are likely to increase app prices to capture value immediately, rather than using ads/in-app purchases to capture value over time with more uncertainty or offering the app free initially to build word of mouth and then capture value from future users. Although our dataset does not contain information on whether an app has ads or in-app purchases, we implement the following analysis to further explore the pricing results. Relative to the paid business model, developers under the ads/in-app purchase business model may face greater difficulty in increasing app price, as this would involve a change in business model. Developers under the paid model may have greater flexibility to increase app price to capture value immediately. Thus, when entry threat increases, we might see greater price action for developers under the paid model. To test this prediction, we restrict the sample to apps that were paid for at least 1 month prior to the treatment and rerun the baseline analysis. As shown in Table S9, we find that these developers significantly increase the price of affected apps by 6.5% after facing the entry threat (as compared to 1.8% in the baseline result in Table 4). After Google's actual entry, the price of affected apps becomes 9.5% higher than in the pre-threat period (as compared to 3.7% in Table 4). Their innovation efforts, however, decrease by a similar amount as in the baseline result.

Fifth, about 14% of the baseline sample developers publish apps for both Android and iOS (i.e., multi-homers). We expect that they may have stronger responses to Google's entry threat than developers who develop apps only for Android (i.e., single-homers) for the reasons that follow. Due to the difficulty of developing apps across different digital platforms, developers who choose to multi-home may have higher technological capability than single-homing developers (e.g., Cennamo, Ozalp, & Kretschmer, 2018). Meanwhile, multi-homers may also possess more resources than single-homers, as they are generally more attractive and have larger user base (e.g., Bresnahan et al., 2015). Such characteristics indicate that when entry threat increases, multi-homing developers can adapt to the changing market environment more easily and be more agile in diverting their innovation efforts. As a result, they may shift innovation to unaffected areas to a greater extent than single-homers and, at the same time, implement a greater increase in app prices in affected areas. To test this hypothesis, we split our sample into a subsample of single-homing developers (with 3,425 apps) and a subsample of multi-homing developers (with 561 apps). Then, we rerun the main specifications for each subsample and compare the main coefficients. As shown in Table S10, multi-homers reduce innovation and increase prices more on the affected apps than do single-homers under entry threat. Although we see a greater increase in innovation on unaffected apps by multi-homers during the entry-threat period, this result should be interpreted with caution: when entry threat increases, the affected multi-homers may shift innovation to some unaffected apps on iOS, which we are unable to capture due to the unavailability of the data on iOS. As a result, the estimated effect on the unaffected apps on Android may only capture the lower bound of the total effect of entry threat on unaffected apps by multi-homers.

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. The results are presented in Tables S11 and S12 and are largely similar to the baseline results.

[28]As defined by Android, the release version number should follow the format <major>.<minor>.<point>. For more details, see https://developer.android.com/studio/publish/versioning.html, accessed June 2018.

5.5 | The impact of entry threat on new app introduction

Thus far, we have focused on how developers change their innovation efforts 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 efforts. We expect that Google's entry threat 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 on the introduction of *similar apps*, we again use Google's "similar apps" search to identify apps in our sample that are likely to be affected by the three entry events. We obtain release dates to compute the number of 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 1. Taking Figure 1a as an example, the average number of new Flashlight-related apps released per month was 38 before the threat, but only 10 during the

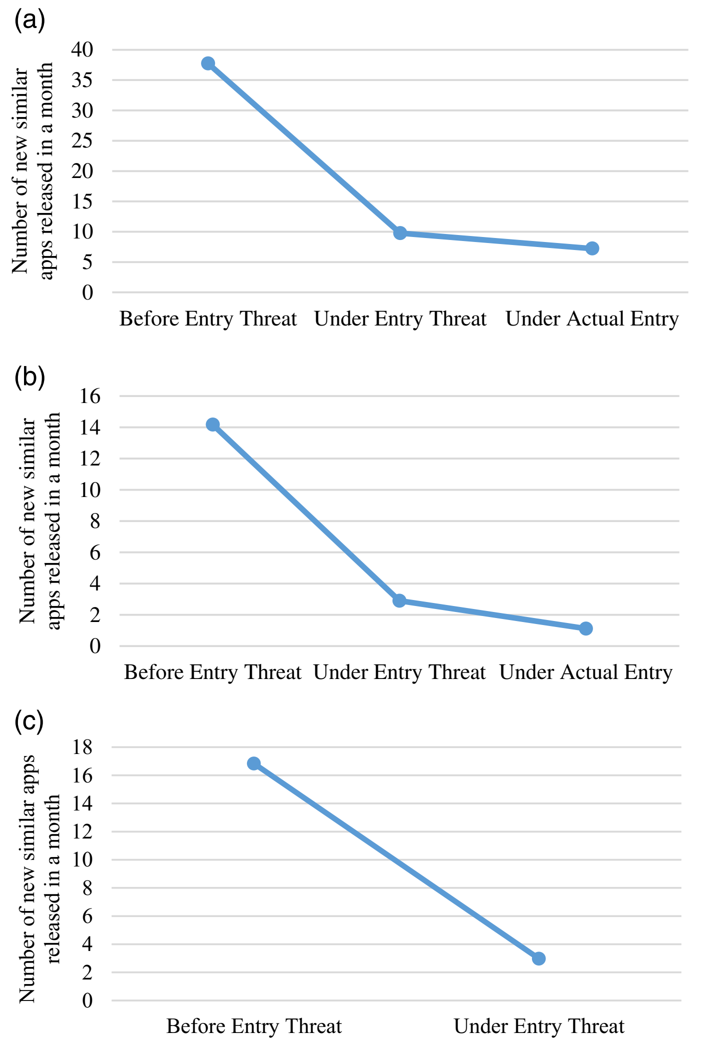

FIGURE 1 (a) Average number of new similar apps during the before-threat, entry-threat, and actual-entry periods: Flashlight. *Notes*: The *t*-test statistic for the mean difference in number of new similar apps between the before-threat and entry-threat (actual-entry) periods is 2.272 (1.791) with *p*-value .001 (.04). (b) 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 entry-threat (actual-entry) periods is 3.447 (2.198) with *p*-value .001 (.02). (c) Average number of new similar apps during the before-threat and entry-threat periods: Podcasts. *Notes*: Because we do not observe Google's actual entry by the end of our sample, 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 entry-threat periods is 4.922 with *p*-value .001

entry-threat period, and only 7 after the entry. The *t* tests show that the mean difference between the before-threat and entry-threat periods is statistically significant. Figure 1b,c show 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 H1, which hypothesizes that developers' incentives to release new apps are depressed when entry threat increases.

We next investigate how entry threats and actual entry influence the introduction of new *unrelated apps*. Unlike the baseline analysis above, the unit of analysis for this exercise 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 the number introduced by developers that are not affected (the control group). While in our baseline analysis, we are able to 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:

$$\begin{aligned}\log\left(Number\ of\ New\ Unrelated\ Apps_{jt}\right) = {} & \beta_0{}^{*}\,Under\ Entry\ Threat_t + \gamma_0{}^{*}\,Under\ Actual\ Entry_t \\ & + \beta^{*}\,Under\ Entry\ Threat_t{}^{*}Affected\ Developer_j \\ & + \gamma^{*}\,Under\ Actual\ Entry_t{}^{*}Affected\ Developer_j + Control_{jt} \\ & + v_j + \eta_t + \varepsilon_{jt}\end{aligned} \tag{3}$$

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 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.[29] We again use a fixed-effects model (as indicated by v_j) to control for any developer-specific attributes that could be correlated with the introduction of new unrelated apps and Apple's entry patterns. Similar to our baseline specification, we also incorporate a full set of month dummies (as indicated by η_t). One potential concern is that more-experienced developers may introduce more apps, and at the same time, they may be more likely to work in the markets Apple tends to enter (e.g., markets with greater opportunities). Thus, in *Control*$_{jt}$, we use developer *j*'s age in month *t* to proxy for a developer's experience. Robust standard errors are clustered at the developer level.

In Columns (1), (2), and (3) of Table 5, we report the results for each entry event. 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%. Once Google does enter that market, the affected developer keeps up a similar rate of introducing new unrelated apps. The results for the Guided Access and Podcasts markets[30] are similar. As in our baseline analysis, we test the robustness of the results by excluding multi-homing developers. The results, shown in Columns (4)–(6), are largely consistent with those in Columns (1)–(3). These results further support H1.

[29] *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 entry events.

[30] Because Google had not entered the Podcasts market by the end of our sample period, we cannot estimate the coefficient of *Under Actual Entry* × *Affected Developer* for this event.

TABLE 5 Effect of Google's entry threat on introduction of new unrelated apps

	log(Number of New Unrelated Apps)					
	Baseline sample			Drop apps by multi-homing developers		
Dependent variable	Flashlight (1)	Guided Access (2)	Podcasts (3)	Flashlight (4)	Guided Access (5)	Podcasts (6)
Under Entry Threat × 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 × 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^2	0.063	0.071	0.066	0.068	0.075	0.073

Notes: Robust standard errors in parentheses and clustered at the developer level. *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 entered into the Podcasts market by the end of our sample period, we cannot estimate the coefficient of *Under Actual Entry* × *Affected Developer* for this event.

5.6 | Exploring heterogeneity

We next study how complementors change innovation efforts and prices on apps that are popular and affected by platform-owner entry threat. As in our baseline analysis, this analysis is at the app level. We consider an app is popular if it had been ranked in the top 500 across all categories at any time prior to Google's entry threat.[31] Then, within these popular apps, we identify the set of popular apps that are affected by Google's entry threat (i.e., the *ADAA* group) and these app developers' other popular apps that are unaffected (i.e., the *ADUA* group); our control group thus consists of the rest of popular apps by unaffected developers. The baseline result is presented in Column (1) of Table 6. Consistent with H3, a developer *increases* the updates of its affected popular app by 7.8% under threat of entry. However, 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 developer also significantly increases innovation on other unaffected popular apps under entry threat and maintains that level after Google actually enters. The magnitude is also worth noting—a 15–19% increase for the entry-threat and actual-entry periods, which is significantly greater than the 4% increase observed in baseline results.

Column (4) of Table 6 further investigates these developers' pricing strategies. Unlike developers with an average app, these developers do not raise their affected app's price when entry threat increases. After the actual entry, however, the price goes up by 4.1%, an increase similar to that of developers with an average app. We extend this analysis by using the same set of robustness checks

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

TABLE 6 Responses from developers with popular apps

	log(Updates)			log(Price)		
Dependent variable	**Baseline (1)**	**Add entry-specific time trends (2)**	**Drop apps by multi-homing developers (3)**	**Baseline (4)**	**Add entry-specific time trends (5)**	**Drop apps by multi-homing developers (6)**
Under Entry Threat × ADAA	0.075	0.070	0.083	0.002	0.003	0.003
	(0.037)	(0.037)	(0.043)	(0.011)	(0.011)	(0.012)
Under Actual Entry × ADAA	0.005	0.002	0.009	0.040	0.040	0.027
	(0.052)	(0.052)	(0.060)	(0.024)	(0.023)	(0.020)
Under Entry Threat × ADUA	0.170	0.169	0.142	−0.030	−0.029	−0.033
	(0.035)	(0.034)	(0.034)	(0.021)	(0.021)	(0.026)
Under Actual Entry × ADUA	0.190	0.190	0.171	−0.008	−0.009	−0.028
	(0.050)	(0.049)	(0.051)	(0.032)	(0.032)	(0.034)
Under Entry Threat	−0.105	−0.076	−0.090	0.012	0.012	0.017
	(0.031)	(0.031)	(0.035)	(0.012)	(0.010)	(0.012)
Under Actual Entry	−0.164	−0.046	−0.122	−0.009	−0.022	0.003
	(0.045)	(0.053)	(0.062)	(0.025)	(0.023)	(0.023)
Competitors	−3.390	−2.880	−9.833	−6.541	−6.404	−10.906
	(7.735)	(7.915)	(9.368)	(5.191)	(5.105)	(6.469)
Age	−0.004	−0.006	−0.005	−0.000	0.001	−0.000
	(0.002)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)
Monthly dummies	Yes	Yes	Yes	Yes	Yes	Yes
App fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of apps	341	341	245	341	341	245
Observations	14,409	14,409	10,340	14,409	14,409	10,340
Adjusted R^2	0.097	0.098	0.111	0.007	0.008	0.011

Notes: Robust standard errors in parentheses and clustered at the developer level. 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.

Abbreviations: ADAA, affected developers' affected apps; ADUA, affected developers' unaffected apps.

as in our baseline sample analysis and report the results in the other columns of Table 6. They are all largely consistent with the baseline results in Columns (1) and (4).

One interesting question to explore is whether developers whose popular apps are all affected respond to entry threat in a different way from developers who have a portfolio of other unaffected popular apps. We expect that the former may have greater incentive to signal their innovation potential and seek exit strategies when the threat of entry increases, as they are affected more. On the other hand, developers with a portfolio of other unaffected apps could shift to the other apps more easily since such portfolio already exists (e.g., Lieberman et al., 2017). Thus, they are less likely to focus on improving the affected products when entry threat increases. To test this hypothesis, we split the sample into a subsample of developers whose apps are all affected and a subsample of developers who have a portfolio of other unaffected apps. The results, as shown in Table S13, are largely consistent with our speculation. In particular, the size of increase in innovation on affected apps during the threat period for developers whose apps are all affected is twice the size for developers who also have other apps. We do not observe any price action during the entry-threat period for either type of developer.

We also explore, among these popular apps, how multi-homers react to entry threat differently from single-homers. Table S14 presents the comparison of the estimated coefficients for the subsample of single-homers versus the subsample of multi-homers. The single-homers significantly increase updates on the affected apps by 8.7% during the entry-threat period, whereas the multi-homers only increase updates by 3.7%, and this magnitude is not statistically significant. However, multi-homers increase updates on the unaffected apps by 32% during the entry-threat period, compared with an increase of 15% by single-homers. This result seems consistent with our view that multi-homers are nimbler, so when the threat of entry increases, they tend to shift to other unaffected apps to strengthen their market positions instead of focusing on improving the affected apps for a potential exit.

6 | CONCLUSION

Digitalization has led to the emergence of platforms in a wide range of industries, including Airbnb in accommodations, Uber in transportation, Alibaba and eBay in retail, and General Electric in industrial equipment. By providing efficient matching or development kits, such platforms have significantly lowered the barriers for many small firms or individuals to innovate and connect with consumers. However, there can be conflicts between platform owners and firms in their ecosystems. The impact of those conflicts on firms' incentives to innovate has captured regulators' attention and resulted in policy interventions.

We examine one prevalent source of conflict: platform owners' entry into complementary product spaces. Unlike prior studies, ours empirically investigates whether complementors react to entry threats—that is, before the actual entry. Our core argument is that complementors, as strategic and nimble actors, may take actions to accommodate platform-owner entry early in the process. The focus on threats contributes to the debate on whether complementors should respond early to the potential entry of the platform owner. It also underscores the importance of taking entry threat into account when studying market entry: as firm responses can take place well before the actual entry, by not taking the effect of entry threat into account, the impact of market entry might be underestimated. Our results also add to the literature on competition-driven repositioning by highlighting the importance of considering a combination of firm actions as joint responses and heterogeneity among firms. We find that complementors respond to competition by adjusting both value-creation and value-capture strategies: when platform-owner entry threat increases, complementors reduce innovation efforts in affected markets but increase innovation efforts in unaffected markets; meanwhile, they focus on short-term profits by increasing prices in affected markets. We further show the different responses between complementors with popular products and the ones with average products, suggesting that withdrawing from the affected markets during the threat period may not necessarily be the optimal action for all types of complementors.

Our study has important implications for both complementors and platform owners. The finding on a shift of innovation direction caused by platform-owner entry threat suggests that it might be important for complementors to develop multiple product offerings to mitigate such risks. Alternatively, complementors could focus on some nonblockbuster products that are less likely to face entry threats from the platform owner (e.g., Zentner, Smith, & Kaya, 2013). Moreover, we highlight that a complementor's user base could be an important determinant of the optimal strategy to pursue under platform-owner entry threat. Average complementors may need to reallocate R&D efforts from affected areas to other areas early and exploit customers by increasing prices. Complementors with popular products, however, may enjoy a few benefits from devoting more efforts to innovation in the affected areas, at least during the threat period.

Although complementors are essential to the health of a platform-based market, a platform owner could have incentives to enter complementors' markets. A body of literature has identified certain conditions in which profit-maximizing platform owners may want to imitate successful complementors and enter their product spaces (e.g., Farrell & Katz, 2000; Jiang, Jerath, & Srinivasan, 2011; Parker & Van Alstyne, 2017). Our results suggest that complementors are sensitive to the potential for such competition. As a result, platform owners may need to carefully manage their relationships with complementors and use a variety of mechanisms to provide enough incentives for complementors to innovate on the platform. This view is consistent with the observations of scholars on Intel, which uses entry mostly to motivate complementor innovation in areas it is not satisfied with (Gawer & Cusumano, 2002; Gawer & Henderson, 2007). More importantly, our findings suggest that platform owners could use direct entry to influence the overall innovation directions of the platform ecosystem. For example, it may be effective to use entry to reduce product redundancy in certain complementary markets. Likewise, platform owners could also use entry as part of their standardization strategy for certain areas so that complementors could focus on building products or services on the standardized components. Overall, we find that on the one hand, Google's entry pushed complementors into other areas (which might be less lucrative) and strengthened its position in the mobile market. On the other hand, the entry has reduced wasteful production efforts in the development of redundant applications. The overall welfare implication is thus ambiguous.

One interesting question is the extent to which our results can be replicated in settings in which small firms face an entry threat from a behemoth firm (instead of a platform provider). Although small firms might exhibit similar behavior in such scenarios, a few important features pertaining to platform-based markets make the relationship between a platform owner and its complementors unique. First, while faced with potential competition from the platform owner, most complementors also solely rely upon the platform owner for value creation and value capture. In a traditional competitive environment, on the other hand, the behemoth would only be viewed as a competitor. Second, given a large platform owner's market power and product advantages, it is nearly impossible for complementors to deter or to compete with it. For these reasons, complementors may be particularly sensitive to signals that indicate platform-owner entry into their product spaces and, accordingly, take preemptive actions to accommodate it from the start. Moreover, in contrast to a behemoth, which would only focus on its own market share and profitability in its own product space, a platform owner needs to maintain the long-term health of its entire ecosystem. Our results have particularly important implications for platform owners, as we show that platform-owner entry may be used to shape innovation directions and encourage variety. That said, we do believe that firm responses to an entry threat from a behemoth firm is worthy of future investigation.

6.1 | Limitations and future research

Given our research design and data availability, we are able to study the effects of entry threat by investigating three entry events rather than one, as commonly leveraged in other studies (e.g., Edelman & Lai, 2016; Li & Agarwal, 2017). Although these three markets differ substantially, we obtain consistent results by looking at them together and separately, thereby improving the generalizability of our results. Yet, one limitation of our study is that we are unable to study Apple's entry events prior to 2012 into markets where Google had not yet entered. If data allow, more studies are needed to investigate whether our results could represent complementors' strategic responses to these earlier events. Meanwhile, one important direction for future research could be to examine how complementors respond differently based on market characteristics and the platform owner's competitive advantages, such as whether complementors perceive that the platform owner holds significant advantages over themselves if it chooses to enter. This could have important implications for platform owners regarding which markets they may choose to enter.

As revealed by our data, Google has introduced approximately 200 mobile apps on Android between 2008 and 2015. Due to our focus on complementors' ex ante responses to a platform owner's potential entry, we do not use most of these events to study Android developers' ex post responses to Google's actual entry. One avenue for future research could be to leverage this intensive entry pattern to understand not only complementors' strategic actions when faced with a platform owner who has acute incentives to enter but also how the responses differ from those in a setting where a platform owner is committed to not entering too many complementary markets.

Our empirical results suggest that on average, multi-homing developers tend to display a stronger response in affected areas when entry threat increases, as their higher technological capability and resources may allow them to adapt to the changing environment faster and more efficiently. However, among multi-homers in our setting, there are two types: (a) multi-homers who have apps on iOS affected by Apple's actual entry and equivalent apps on Android affected by Google's entry threat, and (b) multi-homers who only have apps on Android affected by Google's entry threat and no equivalent affected apps on iOS. Because the influence of the platform owners on the former type is greater than on the latter, the former may devote more resources to unaffected areas, so the overall effect on unaffected apps may be stronger on the first type than on the second. Unfortunately, we are unable to test this hypothesis because we do not have data on iOS and thus do not know whether a multi-homer belongs to the first type or second. However, we believe this could be an interesting direction for future research.

In this study, we focus on settings where platform owners have gained enormous market power. When a platform owner does not have strong market power, we may expect different dynamics between the platform owner and complementors: in this case, on one hand, the platform owner may need to enter more complementary markets to stimulate demand for the platform; on the other hand, it would be more important for the platform owner to refrain from entering and "play nicely" with complementors so that the entire ecosystem could grow. Thus, one interesting stream of future research could be to investigate the strategic interactions between a platform owner and complementors when the platform owner lacks strong market power.

Another interesting question is to what extent our results can be generalized to other industries. For industries characterized by low exit/entry barriers, we expect our results may hold—when there is a threat from a platform owner to a complementary market, firms may tend to move away from the affected market. However, in industries where there are high exit/entry barriers and thus repositioning is difficult, firms may need to implement other strategies (such as cost-cutting and product differentiation) in the affected area to accommodate platform-owner entry and increase their long-term survival chances.

Our empirical design hinges on the predictability of Google's entry based on Apple's entry but is agnostic to the motivations for Apple's entry and Google's imitation.[32] As suggested in the literature, the motivation of platform-owner entry is multifaceted. Platform owners could use entry to capture more value, strengthen their market position through tying, motivate complementors to innovate by introducing competition, or provide better experiences to consumers (e.g., Bennett & Pierce, 2016; Gawer & Cusumano, 2002; Gawer & Henderson, 2007; Yoffie & Kwak, 2006). Future research could seek to identify such motivations through qualitative approaches.

Finally, platform owners' own offerings might be significantly better than third parties' offerings in some cases. If these superior offerings could attract more consumers to the platform, that could 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.

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ORCID

Wen Wen https://orcid.org/0000-0002-8086-6386
Feng Zhu https://orcid.org/0000-0002-3034-6876

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[32]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 the 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. For details, see https://www.ftc.gov/news-events/press-releases/2013/12/android-flashlight-app-developer-settles-ftc-charges-it-deceived, accessed June 2018. All of our results continue to hold when we exclude flashlight apps.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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