Platform Entry and Innovation: The Role of Adjustment Costs in Shaping Complementor Innovation Strategies

INTRODUCTION

Platforms compete both with other platforms as well as their own complementors (Kretschmer, Leiponen, Schilling, & Vasudeva, 2020). Prior research has highlighted heterogenous effects of platform entry on complementors' subsequent innovation. Focusing on within-platform dynamics following platform entry, prior research has identified contradictory findings: first, platform entry increases the rate of complementor innovation in affected areas (Foerderer, Kude, Mithas, & Heinzl, 2018) and second, platform entry decreases the rate of complementor innovation in affected areas (Wen & Zhu, 2019). This study attempts to resolve this tension (Rietveld & Schilling, 2021) by highlighting complementor adjustment costs in shifting innovation efforts as a driver of these potential outcomes. In this paper, we build on prior literature by theorizing and empirically testing cross-platform entry effects, by examining the extent to which complementors' adjustment costs to redeploy innovation efforts to competing platforms affect their response to entry on a focal platform. We find that complementors with lower adjustment costs shift their innovation activity to a competing platform while complementors with higher adjustment costs are confined to innovation attempts on the focal platform.

Platforms benefit from orchestrating complementor activity (Gawer, 2014; Tiwana, Konsynski, & Bush, 2010). One manner to orchestrate complementor activity is platform entry directly into complementor market niches (Gawer & Henderson, 2007). Platforms enter in order to capture value in a target domain proven by complementors and hence direct innovation efforts of complementors. Platforms may enter successful (Zhu & Liu, 2018) or saturated (Wen & Zhu, 2019) complementor domains, pushing complementors to direct effort to unaffected areas (Wen & Zhu, 2019). Platforms may also decide to enter to raise the attention, of both the end-users and complementors, towards a targeted domain. Signaling the presence of opportunities for further innovation on the platform, such entries will have attention-spillover effects from which complementors can benefit (Hukal, Henfridsson, Shaikh, & Parker, 2020). While this literature has focused on both negative and positive implications of platform entry, its focus on within-platform response has limited our understanding of cross-platform complementor responses. First, we have a limited understanding regarding resource redeployment following entry which could engender complementors' innovation on competing platforms as a reaction to entry. Innovation on competing platforms enables benefiting from additional userbase as well as the heterogenous resources of other platforms (Wan, Wang, & Liu, 2020) to compensate for part of the lost value of complementors following platform entry. Second, complementor-specific attributes may affect the choice of complementors regarding redeployment of their innovative resources across different domains of the focal and the competing platforms.

We hypothesize that complementors' adjustment costs for enabling innovation on a competing platform can affect both the change in their innovative activity on their affected and unaffected products on the focal platform, as well as their strategy regarding their subsequent innovative activity on the focal as well as the competing platforms. More specifically, we hypothesize that complementors with high adjustment costs will increase their innovative activity on affected products on the focal platform. Moreover, complementors with low adjustment costs will exit their affected products from the focal platform. Furthermore, we posit that in face of entry, complementors with low adjustment costs will redeploy innovative effort to a competing platform.

Our empirical setting is the mobile apps platforms including Apple Store and Play Store. We use a difference-in-differences empirical design, exploiting an entry by Apple in

2017. Apple entered its complementors domain for file organizing in the App Store in September 2017 by releasing the "Files" application – a file explorer and cloud storage management product. Focusing on this entry, we analyze the change in innovative activity of the full sample of applications in the "Utilities" category of App Store, in which Apple released its application. We conduct application-level analyses on both affected and unaffected products of treated developers as well as a developer-level analysis. We investigate complementor behavior on App Store (focal platform) and Play Store (competing platform). We use developers' (i.e., complementors) prior multihoming experience in Play Store as a proxy for the extent of their adjustment costs when increasing activity on the competing platform and find evidence for the proposed hypothesis. At the product level, we find that following the entry, previously single-homed developers with applications only in the App Store (i.e., developers with high adjustment costs to competing platforms) keep active, and release more updates on, their applications which were affected by Apple's entry. On the contrary, previously multihomed developers with applications in both App Store and Play Store (i.e., developers with low adjustment costs) exit their affected products from App Store and do not innovate on them. More popular apps are also more likely to remain active and receive updates. Furthermore, previously multihomed complementors (low adjustment cost complementors) redeploy part of their resources to Play Store by updating their existing applications and releasing new products on that platform. This supports the argument that complementors with low adjustment costs exert more innovative effort on a competing platform following entry on the focal platform.

This study contributes to the literature on platform innovation strategy. We highlight heterogeneity in complementor innovation outcomes in response to platform entry in the context of digital platforms. We reconcile findings in prior research which showed that platform entry both increases and decreases complementor innovation in affected areas following platform entry. Complementors' adjustment costs guide their innovation strategies on the focal and the competing platforms in response to direct competition from a focal platform. As a result, this study expands our understanding of both intra and inter-platform innovation dynamics.

BACKGROUND & THEORY

Platform Entry & Complementor Responses

Platforms govern the creation and distribution of value in the ecosystem and among platform members (Kretschmer et al., 2020). This can be achieved through different means, such as competition or cooperation among complementors, or between them and the platform provider (Kretschmer et al., 2020), with each having specific tradeoffs. Platforms are also concerned with enabling interactions among participating parties, i.e., their end-users and complementors (Anderson Jr, Parker, & Tan, 2014; Gawer, 2014; Tiwana et al., 2010; Yoo, Henfridsson, & Lyytinen, 2010). Platforms may decide to do so indirectly by providing complementors with incentives to operate and lowering their entry and participation costs (Gawer & Henderson, 2007), by means such as disclosing IP to foster innovation (Gawer & Henderson, 2007; Miller & Toh, 2020). Following the same line of logic, platforms may be hesitant to govern interactions directly by entering their complementors domain, as this can discourage them from further engagement (Gawer & Henderson, 2007). That said, the act of entry has itself been identified as a tool which can, in addition to other mechanisms, be adopted by platforms to directly govern complementors' activities. Platforms can use this strategy to achieve different goals, with each differing in the type of response subsequently received from complementors (He, Peng, Li, & Xu, 2020).

One reason for platforms to enter is to enjoy rents in profitable niches and encourage complementors to shift effort to other areas. Prior studies have argued that platforms may strategically decide to enter complementors' domain to appropriate rents (Farrell & Katz, 2000; Huang, Ceccagnoli, Forman, & Wu, 2013). In particular, platforms may choose successful domains to enter (Zhu & Liu, 2018) to capture the existing value and strengthen their market position (Wen & Zhu, 2019), similar to a vertical integration approach (Zhu & Liu, 2018). Following such an entry, end-users will perceive first-party complements (i.e., those offered by platform itself) to be of higher quality, thus resulting in higher demand and increased popularity for the platform-owned complements (Zhu & Liu, 2018). For instance, He et al. (2020) find that in the e-commerce context, orders set for complementors' products following entry will experience a huge decrease in volume, as opposed to an increase in the orders received by platform's offerings in the same domain. Similarly, Zhu and Liu (2018) find evidence for loss of value for complementor-offered products in Amazon marketplace. Similarly, such entries will also result in complementors' focus being redirected to other domains of complements which are unaffected by the entry. For instance, in their empirical analysis of Google's entry into Play Store, Wen and Zhu (2019) find that complementors (i.e., application developers) engage less with their affected products and instead, shift their attention and value creation activities towards new or unaffected apps in the same focal platform. Complementors will also engage in rent-seeking from their affected complements by means such as increasing prices on their affected complements to capture value in the short run (Wen & Zhu, 2019).

On the contrary, platforms may decide to enter to raise attention, of both end-users and complementors, towards the targeted domain. Such an entry can, therefore, serve as an enabling mechanism and provide additional innovation opportunities for complementors in the affected domain (Boudreau, 2012; Brown & Eisenhardt, 1995; Hukal et al., 2020; March, 1991). Platform providers can use entry as a governance tool (Gawer & Henderson, 2007) to create or signal the presence of additional opportunities for their complementors to be used for further value creation (Hukal et al., 2020). In that respect, platform entry is argued to have attention spillover effects from which complementors can benefit by further innovating in the affected domain (Hukal et al., 2020). Foerderer et al. (2018) find that, following Google's release of Google Photos in its Play Store platform, complementors increased engagement, value creation, and innovation in the "Photo" product category of the platform (i.e., the domain affected by entry). Such attention spillover effect is observed in other contexts as well: for instance Li and Agarwal (2017) observe a similar effect whereby complementor engagement increased following Facebook's entry into photo sharing application domain by acquiring Instagram.

Scope of Complementors' Response to Entry

As discussed, extant findings on complementors' response to entry in terms of their post-entry innovative choices within the focal platform are inconclusive (Rietveld & Schilling, 2021), whereby both positive (Foerderer et al., 2018; Li & Agarwal, 2017) and negative (Wen & Zhu, 2019) subsequent engagement of complementors in the affected domains of the focal platform have been observed. In that respect, we have limited understanding regarding attributes which can explain complementors' post-entry resource redeployment within the focal platform. One reason for the existence of this gap can be the approach taken by extant literature in studying complementor response to entry which is limited in terms of scope. While prior studies on platform entry have contributed to our understanding of how complementors may react to entry in terms of their redeployment of innovative resources across different domains within the focal platform, we know much less about resource redeployment following entry which could cross the boundaries of the focal platform. Platform complementors' innovative strategy need not be confined to a single platform, as they can direct their innovative resources to multiple platforms simultaneously. According to resource redeployment literature, resource holders can redeploy them from one context of use to another given the respective opportunity costs of the choices (Folta, Helfat, & Karim, 2016; Levinthal & Wu, 2010; Lieberman, Lee, & Folta, 2017). In the case of platform complementors, redeploying part of their innovative resources to competing platforms can help them gain access to the additional userbase as well as heterogenous resources of other platforms (Wan et al., 2020).

Studying the redeployment of innovative resources to competing platforms, as a potential response strategy of complementors to entry, is important for several reasons. First, it can compensate, at least in parts, for the lost value of complementors due to the entry. As discussed earlier, platform entry can appropriate part of complementor-owned value in the affected domains (Wen & Zhu, 2019). Following entry, the platform owner increases its bargaining power against complementors, in response to which complementors will decide to react. A well-known response in extant literature is that complementors will redeploy their innovative resources into other settings in the focal platform (Ceccagnoli, Forman, Huang, & Wu, 2012; Huang et al., 2013) such as domains which are unaffected by platform entry (Wen & Zhu, 2019). Hence, the direct change in the domain and context of value creation in the focal platform can provide potential revenue for complementors to compensate for part of their lost value in the affected domains. Similarly, redeployment of resources to the more distant unaffected domains of competing platforms can provide complementors with the same. Second, resource redeployment to competing platforms can also help mitigate the risk of future potential entries of the focal platform. Literature on platform entry suggests that platforms might enter additional domains in future as well (Wen & Zhu, 2019). Therefore, while a response strategy of directly changing the domain and context of value creation in the focal platform by complementors can account for some of the losses due to entry (Gawer & Henderson, 2007; Wen & Zhu, 2019), the mere act of resource redeployment within the same focal platform may not be enough to fully address the threats posed by entry.-Hence, while extant literature has mostly studied complementors' post-entry innovative choices within the scope of the focal platform as their response strategy and the outcome of interest, we argue that a more comprehensive view incorporating both the focal and the competing platform can help shed light on mechanisms driving complementors innovative effort following entry.

Factors Shaping Complementor Response & Resource Redeployment

While redeployment exhibits the above-discussed benefits, investing effort in a competing platform can have heterogenous outcomes, as it can be both detrimental and beneficial to the subsequent performance of the complementors. Wan et al. (2020) found that it can increase complementors' overall performance, with the increase in performance being amplified for complementors with lower performance. On the contrary, Cennamo, Ozalp, and Kretschmer (2018) argue that marginal performance of complementors who engage in value creation on multiple platforms would decrease, with them having lower quality in the platforms they have subsequently redeployed resources to, compared to the focal one which they originally offered their complements on. Therefore, when considering within- or cross-platform resource redeployment as a potential response strategy for complementors, it is important to study the factors which can influence their practice.

A central driver of the ability to redeploy resources across contexts is adjustment costs (Helfat & Eisenhardt, 2004), which condition intertemporal economies of scope: adjustments costs capture the frictions in resource transfer driven by the difficulty of adapting resources from one context to another. Thus, lower adjustment costs facilitate resource redeployment (Dickler & Folta, 2020) . In the context of platforms, the costs that a complementor must incur in order to operate in additional platforms are an important determinant of a complementor's choice for doing so as well as their subsequent performance (Cennamo et al., 2018). The degree of differences between the focal and competing platforms, and the desired level of conformity by the complementor to each of them, is one factor which can affect such costs (Cennamo et al., 2018). Platforms differ in their core functions (Anderson Jr et al., 2014; Zhu & Iansiti,

2012) and full compliance with the competing platforms requires platform-specific investments by complementors to match with their distinct technological infrastructures (Anderson Jr et al., 2014; Claussen, Kretschmer, & Stieglitz, 2015; Tiwana, 2015). Moreover, while there is fungibility for similar complements in an ecosystem, the original complement might still be more tailored to a focal platform (Jacobides, Cennamo, & Gawer, 2018; Jacobides, Knudsen, & Augier, 2006). Adjustment costs would therefore offset, in part, the benefits which could be derived from redeploying resources to competing platforms, such as accessing additional userbases (Wan et al., 2020). Consistent with this argument, higher costs associated with operating in competing platforms will negatively affect the propensity of complementors' engagement in it (Wan et al., 2020).

The amount of specific investments required for a competing platform is one attribute which can affect the adjustment cost which a complementor must incur. Chen, Yi, Li, and Tong (2021) argue that in case of high complexity of the destination ecosystem (i.e., the one into which a complementor would be redeploying resources) complementors would be less likely to join that . Technological differences between a focal and a competing destination platform in an industry is one dimension in which this complexity can be defined. To make this more precise, consider the example of adjustment costs in the context of mobile phone platforms such as iOS and Android. In this context, a developer (i.e., complementor) would incur high adjustment costs when redeploying resources from one platform to the other, given the totally different software- as well as hardware-related infrastructures required for developing an application (i.e., complement) in either platform. Whereas one can develop an Android application by knowing programming languages such as Java and having either a Linux-, Windows-, or Mac-based machine, a developer needs to have knowledge of Swift programming language, an almost totally different development platform, as well as a Mac-based machine to be able to offer a proper complement for the iOS platform.

Complementor Response Contingent on Adjustment Costs

We have argued that adjustment costs associated with the resource redeployment to competing platforms are important in that they influence complementors' innovation strategy. In particular, opportunity costs govern redeployment choices, as non-scale free resources limit the number of simultaneous uses of a given resource (Levinthal & Wu, 2010). Idiosyncratic characteristics of complementors, such as their experience with the different attributes of competing platforms (Chen et al., 2021), may affect the level of adjustment costs that each complementor would incur while redeploying resources to a competing platform. Therefore, given the difference in adjustment costs across different complementors, we can expect heterogeneity in their practice of redeployment strategy as a response to entry. Complementors with lower associated adjustment costs would find it easier and less costly to redeploy their resources to the competing platform. Given the arguments mentioned on benefits of redeploying resources to competing platforms in response to platform entry, we argue that, in case of low adjustment costs for complementors, they would redeploy more of their resources to the competing platform.

On the contrary, in case of high adjustment costs, we expect complementors' reaction to be different: the adjustment cost of redeploying resources to a competing platform can offset its expected benefits. Complementors affected by entry are confronted with the threat of losing revenue and userbase and would look for strategies which can quickly compensate for those. High adjustment costs would discourage complementors from deciding on redeploying their resources to competing platforms, as this would offset the potential profits which they could gain from it. Moreover, entry can signal complementors regarding the emergence of additional opportunities for value appropriation (Hukal et al., 2020) by means such as increased demand-side attention (Li & Agarwal, 2017). Therefore, entry can encourage complementors to leverage their existing product-market domain which is affected by entry and engage more in the focal platform (Foerderer et al., 2018; Li & Agarwal, 2017). Therefore, given both the available opportunities in the focal platform and the costs associated with resource redeployment to competing platforms, complementors who need to incur high adjustment costs would keep redeploying their resources within the focal platform rather than the competing ones, as the latter would require high adjustment costs to appropriate value from (Wan et al., 2020). Summarizing the above arguments, we would arrive at the following hypothesis:

Hypothesis: Faced with platform entry, complementors with low adjustment costs will shift innovation efforts to a competing platform relative to innovating on the focal platform, whereas complementors with high adjustment costs will focus innovation efforts on the focal platform.

METHODOLOGY

Context

We rely on the mobile application platforms of Play Store (offering Android-based applications) and App Store (offering iOS-based applications) as the context for the empirical analysis in this study. Mobile application markets have been already used in research for analyzing platform entry (Foerderer et al., 2018; Wen & Zhu, 2019). Using this context can have several benefits for this study. First, it adds to the validity of the current study as it is based on a well-known and identified context. Second, it will allow us to compare results with those of the previously conducted empirical analysis and to see whether results can be replicated or differences and heterogeneities in findings would be observed.

For the purpose of this study, we will use Apple App Store (from now on referred to as App Store) and Google Play Store (from now on referred to as Play Store) as the focal and competing platforms respectively. The broad range of applications (i.e., products) and developers (i.e., complementors) in the two stores, the history of platform entries, and the rich and historical data available for the two makes them appropriate choices for the purpose of this empirical analysis.

Platform Entry

The platform entry we analyze is Apple's introduction of the "Files" app on its App Store. Apple announced the entry in June 2017 and released the application on the App Store in September 2017[1]. Per Apple's announcement, "Files" was aimed at improving user experience in exploring and accessing files, as well as enhancing use of cloud storage services, such as iCloud, OneDrive, Google Drive, Dropbox, etc., and some other features. A description of this application and associated notes about its release are provided in online Appendix D[2].

The mobile apps setting and the "Files" application in particular are appropriate choices to capture platform entry due to several institutional factors. First, the app was embedded in the iOS operating system, thus a high majority of iPhone users had access to it shortly following the release. Moreover, the released product is core to the platform and easily accessible to platform users. Second, there is clear information regarding the announcement and actual entry by the platform. Apple holds an annual conference around June each year, called Apple Worldwide Developers Conference ("WWDC"). Apple announces news regarding its products and services, including new product releases and software updates in this conference. The WWDC 2017 was held on June 5th, 2017, and Apple announced its plan for releasing the "Files" application[3]. The fact that the news regarding the entry was provided to developers approximately 100 days before the actual entry (which did not happen before September 19,

[1] Apple did not enter Google's Play Store with its "Files" app.
[2] We have moved some of the complementary content including figures and part of tables to the online Appendix due to space constraints which will become available with the paper.
[3] The full list of changes announced by Apple in the conference are included in online Appendix E.

2017), provides a good opportunity to study the effect of entry on developers' reaction both after the entry news, as well as following the release of the app[4] (i.e., actual act of entry).

Empirical Strategy

We use a difference-in-differences experimental design to test the hypothesis. We carry out the analyses at the application (or product) level and at the developer (or firm) level. First, we identify treated applications (those applications that are directly affected by Apple entry) and control applications (comparable applications that are not directly affected by Apple entry). Apple released the "Files" application in the "Utilities" category of the App Store. We use a word-embedding approach[5] to run text analysis over the description of all applications in the "Utilities" category in the App Store to find those applications that are similar to the focal application. We measure applications' similarity with the focal "Files" application by calculating the Word Mover's Distance (WMD) for the description of each application and that of the "Files" application.[6] The text-analysis is run on all applications in the "Utilities" category which have English descriptions available- We then read the descriptions for the top 100 similar applications identified by the text-analysis in order to ensure they were correctly identified.

Using text-analysis for identifying the treated applications has both benefits and shortcomings compared to other methodologies adopted by extant literature. One approach is

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[4] The earliest time developers were informed about the application release was a few hours before the conference and not before that.

[5] Word embedding is a technique to transform text and convert them into a form processable by machine. The transformation technique makes analysis on the text possible. Word embedding can capture similarity and relationship of words together as well as their context in a document.

[6] We use the WMDSimilarity function from the "gensim" package using Python programming language. Word Mover's Distance (WMD) learns words' representations from local co-occurrences in sentences by using the results of word-embedding techniques such as word2vec which is suitable for large datasets. According to WMD, embedded word vectors have meaningful distances. It considers text documents as "weighted point cloud of embedded words". The distance between two text documents is then calculated as "the minimum cumulative distance" that words from one document need to "travel" to match exactly those of the other document (Kusner, Sun, Kolkin, & Weinberger, 2015).

to use platform-generated “similar apps” functionality. The benefit of this approach is that the target set of apps is identified by the platform rather than choices of the researcher. However, the “similar apps” functionality displays only a small subset rather than all of applications which are similar to the focal one, and not all of shown applications are closely similar. Furthermore, the “similar apps” functionality only displays applications which are contemporaneously active on the platform, while other applications might have exited the platform in the past. This could bias the sample by confining it to applications which have remained active following the entry, and we show that keeping an application active is a key strategic choice of a firm. Another approach is to apply manual analysis on the descriptions of the applications. Manual approach can be more accurate compared to relying solely on a text-analysis algorithm. However, it is not scalable enough to be used over a large sample such as all applications in a target category, which is why it can only be applied to a subset of units. Therefore, we leverage the text-analysis algorithm by applying it over the full sample of applications, and then do manual reading on the top similar applications to ensure their similarity with the focal “Files” application.

We run three sets of analyses to test the hypothesis. First, we run application-level analyses to test the effect of platform entry on firm innovation strategies for treated applications on the focal platform. Second, we run application-level analysis on the unaffected applications of the developers on both App Store and Play Store to examine their actions with respect to their other applications. Finally, we run developer-level analysis to study new application release on both platforms.

Analysis 1: Developers’ Response on Affected Applications

For the application-level (i.e., product-level) analysis, we form a treatment group consisting of the top 100 most similar applications to the focal one based on their similarity scores to the "Files" application which constitutes the focal entry event. We obtain the list of applications in the treatment group using text-analysis. The control group is subsequently formed using applications from the same category, with details on the Coarsened Exact Matching to create a control group below. Using same-category applications for the control group provides comparable set of applications which can be used to control for attributes like those of the treated applications, such as market size and target customers. The timeframe of analysis is from December 2016 until January 2018, or 14 months. December 2016 to May 2017 are the six months before the entry was announced (in June 2016) and constitute the pre-treatment period. The remaining 8 months constitute the post-treatment period. Platform entry took place in September 2017. In this fast-paced industry of digital goods, the chosen timeframe provides sufficient time to observe the effects of both the announcement as well as the actual act of entry.

The first analysis examines the reaction of developers on their treated application, i.e., how they change their behavior on the affected applications. For the difference-in-differences (DID) approach, we first conduct a Coarsened Exact Matching (Blackwell, Iacus, King, & Porro, 2009) between the treatment and control applications based on their important attributes in the pre-treatment period, including their (1) update frequency in Play Store and App Store, (2) multihoming status (i.e., whether they were already released on Play Store or not), (3) active status in App Store (i.e., how long the application was active in the pre-treatment period), (4) age, (5) average rating, (6) average number of users who rated them, and (7) multihoming status of their developers (i.e., whether the developer already had any applications in Play Store). Matching based on these factors enable forming the appropriate strata of treatments and controls which are similar in their pre-treatment trends. Therefore, it enables establishing parallel pre-treatment trends in the two groups as a required condition for using the difference-in-differences design. The results for the imbalance scores before and after the matching are provided in the online Appendix, Tables A1 and A2. The matching results in 86 and 17808 matched treated and control applications, respectively. Table A3 shows the distribution of these applications with respect to the prior multihoming status of their developers.

Having the matched applications from the two groups, we will use model 1 for our DID analysis.

$$Outcome_{it} = \beta_0 + \boldsymbol{\beta_1}.Treatment_i.Post_t + \beta_2.Moderator_i.Post_t + \boldsymbol{\beta_3}.Treatment_i.Moderator_i.Post_t + \delta_i + \delta_t + \epsilon_{it} \qquad (1)$$

, with variables of interest explained in detail below. Given the timeframe of the study, there will be 14 observations for each application corresponding to each month in the timeframe of the study, making up 250,516 observations in total for the 17,894 matched applications in treatment and control. Variables are defined and measured as stated below.

Dependent Variables. $Outcome_{it}$ captures three dependent variables of interest. These are (1) the number of updates which application *i* received in month *t*, as a measure of innovation in the affected domain, (2) the active/inactive status of application *i* in month *t* in the App Store (i.e., the focal platform), which captures the possible exit of affected applications, and (3) the multihoming status of application *i* in month *t* in the Play Store (i.e., the competing platform), which captures whether the application is actively published in the competing platform or not. An application marked as active (in either the focal or the competing platform) is one which is published by the respective developer and is available to all users for access. An inactive application is unpublished, meaning that it is no longer accessible for users to view or download. Summary statistics for dependent variables across the three sets of analysis are included in Table 1.

TABLE 1: Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max	Median
Application-Level Analysis: Analysis 1						
Variable	Observations	Mean	Std. Dev.	Min	Max	Median
Active Status	250,516	0.92	0.28	0	1	1
Update Count	250,516	0.02	0.19	0	9	0
Application's Multihoming Status	250,516	0.06	0.23	0	1	0
Application-Level Analysis: Analysis 2 - Unaffected Applications in App Store						
Variable	Observations	Mean	Std. Dev.	Min	Max	Median
Active Status	1,612,897	0.86	0.34	0	1	1
Update Count	1,612,897	0.27	0.15	0	18	0
Application-Level Analysis: Analysis 2 - Unaffected Applications in Play Store						
Active Status	360,528	0.99	0.12	0	1	1
Update Count	360,528	0.01	0.14	0	4	0
Developer-Level Analysis: Analysis 3						
Variable	Observations	Mean	Std. Dev.	Min	Max	Median
New Releases on Play Store	46,276	0.0077	0.16	0	26	0
New Releases on App Store	46,276	0.15	1.88	0	189	0

Treatment and Post-Entry Variables. $Treatment_i$ is a dummy variable equal to 1 if application *i* is identified as treated by entry, and 0 otherwise. $Post_t$ is a dummy variable equal to 1 if the observation is in the post-treatment timeline (i.e., after June 2017, when the entry was announced) and 0 otherwise.

We also differentiate between low-adjustment-cost and high-adjustment-cost developers. Developers' adjustment cost is proxied by their prior engagement with the competing platform. Developers who already have applications in Play Store (i.e., the competing platform) would incur low adjustment costs in case they decide to redeploy their resources to it by releasing new applications or more updates on their existing applications, compared to developers who have no prior experience in engaging with the competing platform. This is the case since the two platforms are highly different in terms of their technological infrastructure. Therefore, a developer with prior experience in working with the competing platform would possess the required knowledge and hardware for further innovation on that, either in the form of new application release or updating the previously released ones. In that respect, prior engagement with the competing platform serves as a good proxy for measuring the adjustment costs of developers. In that sense, we label developers who have released applications in the competing platform as “low-adjustment-cost” developers, and those with no prior engagement with the competing platform as “high-adjustment-cost” ones.

Moderators. As part of the robustness checks, we also use the complementor adjustment cost, which is measured as discussed above, as a moderator in addition to the sub-sample analysis which will follow. This will be explained later in the robustness check analysis.

Fixed effects and error term. Application and time fixed effects are captured by δ_i *and* δ_t respectively. The inclusion of app fixed effects accounts for any time-invariant application-level characteristics, such as developer firm quality, size, headquarters location, etc. The inclusion of time fixed effects accounts for dynamic shocks applicable across different apps, such as seasonality, other changes taking place on the platforms and in the industry app industry, etc. Also, the post-entry and treatment dummies are excluded from the model since they are captured by the fixed effect terms (Foerderer, 2020; Zhang, Li, & Tong, 2020). The error term is represented by ϵ_{it}.

TABLE 2: Update and Exit of Complementors on Affected Products on the Focal Platform – Main Effects

	Full Sample	High Adjustment Cost Developers	Low Adjustment Cost Developers	Full Sample	High Adjustment Cost Developers	Low Adjustment Cost Developers	Full Sample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Updates on App Store	Updates on App Store	Updates on App Store	Keep Active	Keep Active	Keep Active	MH to Play Store
Treated Application X Post	0.0658***	0.1010***	0.0118	-0.0449***	0.0009	-0.115***	-0.0021
	(0.0172)	(0.0225)	(0.0255)	(0.0128)	(0.0153)	(0.0239)	(0.0022)
Constant	0.0972***	0.1370***	0.0359***	1***	1***	1***	0.0883***
	(0.0022)	(0.0029)	(0.0033)	(0.0016)	(0.0019)	(0.0031)	(0.0002)
Observations	250,516	190,848	59,668	250,516	190,848	59,668	250,516
R-squared	0.013	0.019	0.006	0.121	0.139	0.098	0.004
Number of Applications	17,894	13,632	4,262	17,894	13,632	4,262	17,894
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
App FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Results. The results for the main effects on the update and exit of treated apps are presented in Table 2. Updates are a common measure to study innovation in digital settings (Wen & Zhu, 2019). Moreover, applications exit, identified by their active/inactive status, allows us to investigate the mechanism we argue is at play, namely, redeployment costs. We find economically and statistically significant rates of updates and exits of treated applications. Following the announcement of entry in June 2017, treated apps were more likely to exit by 0.045 percentage points (i.e., ~5% exit rate given the pre-treatment baselines) compared to untreated apps as shown in model 4, suggesting that the entry forced some of the complementor-developed products to leave the market. However, on average, treated apps were more likely to receive updates after the entry by 0.066-points (model 1), on a pre-treatment baseline of 0.02 for updates, suggesting more than a three-fold increase in the update rate of treated applications as the effect size is three-times higher than the baseline. Finally, there is neither a strong nor significant effect regarding the multihoming status of the treated apps to the competing platform (i.e., Play Store), as shown by model 7, suggesting that developers do not tend to redeploy their resources to the competing platform to multihome their treated applications to a competing platform following the entry. These general results suggest that, in the face of entry, heterogenous effects could be observed for treated applications, with some exiting the platform while others may be subject of innovative activity.

Apart from the effects observed in the full sample, an important remaining question is whether the observed effects are the same across all developers. The theorized hypothesis claims for heterogeneity in complementors' response given their adjustment costs to the competing platform. More precisely, the argument is that we should observe lower engagement with the focal platform by developers with low adjustment costs, as opposed to those with high adjustment costs who are expected to exert more effort on the focal platform following platform entry. We test for this argument by separately comparing the behavior of low and high adjustment cost developers with respect to their update and exit behavior on their applications which are affected by entry. To test this empirically, we separate the matched applications based on the adjustment cost of their developers which is proxied by their prior engagement with the competing platform as discussed earlier. Table A3 in the online Appendix shows the distribution of applications with respect to the multihoming status of their developers. Models 2, 3, 5, and 6 in Table 2 include the regression results based on separate samples of low and high adjustment cost developers. The results show evidence for heterogeneity in how the adjustment cost of developers affect their resource redeployment choices: High Adjustment Cost firms invest on the treated apps in the focal platform while Low Adjustment Cost firms are more likely to exit their treated applications. We further analyze these patterns in more detail based on the type of response.

Exiting Treated Applications. Considering the full sample, applications which are treated by entry display a large and significant exit behavior following entry, with an approximate 5% higher exit rate compared to untreated apps in the same category. The effect is much stronger for applications with low-adjustment-cost developers, with the effect rising to more than 11% decrease in active apps given the pre-treatment baseline. Figure F1 in the online Appendix shows that this effect is observed following the actual entry, i.e., after month 3 (i.e., September 2017), meaning that the exit did not happen after the announcement was made but started right after the entry and even escalated until several of months later. Moreover, the actual monthly treatment effect on the exit is much stronger in months after the entry (e.g., ~18% exit in month 4) compared to the average effect captured by the diff-in-diff estimate (i.e., ~11% in model 6). The effect is however not significant for high-adjustment-cost developers, as shown in model 5. Table B1 in online Appendix includes further information on some of the treated applications which exited the focal platform following entry[7].

Innovation and updates on Treated Applications. Table 2, model 2 on applications with high-adjustment-cost developers shows a significant and stronger positive effect compared to model 1 which was on the whole sample, while model 3 is not significant. This suggests that the observed effect on the increased update of treated applications is coming from high-adjustment-cost developers and not low-adjustment-cost ones. Figure F1 in online Appendix shows the significant and strong monthly effect on update by high-adjustment-cost developers from which three main implications can be derived. First, some developers have used the post-announcement until pre-entry period as a time period to keep innovating on their affected apps to be readier at the time of actual entry. For instance, the monthly treatment effect is around 0.05-points in month 3 which is not statistically significant but compared to the baseline pre-treatment update ratio of 0.02 and the observed trend, indicates that some developers already started to update their affected applications. Second, this increase becomes stronger following the actual entry, with an effect of around 0.2-points in month 4. This is a highly substantial increase in updates given the pre-treatment baseline. Third, the pattern of increase in the number of updates remains statistically significant, and strong in terms of size, at least until month 7 (i.e., until 7 months following the announcement) which indicates more

[7] Comparing this information with the description and feature set of Apple's "Files" application shows that developers decide to exit applications similar to the "Files" rather than keeping them active. Our interviews with experienced iOS developers, as well as our review of professional online iOS forums show that, contrary to conventional wisdom, keeping applications active even when not publishing updates for them, is not costless for developers. Low-quality applications could receive negative ratings from users and undermine developers' reputation. Moreover, platforms could mandate developers to occasionally publish updates to comply with additional terms and policies which may be introduced by the platform. As one developer mentioned, "… we do not have the resources to be updating all the time to comply with changing policy in the future …". Active applications should adhere to both the current as well as upcoming platform rules, provide support for all users who have installed the app, and respond to raised issues and users' comments which all require resource allocation.

of a longstanding effect as opposed to a random increase in the updates. Low-adjustment-cost developers, on the other hand, do not display such a trend. Table B2 in online Appendix displays some information regarding the added features and improvements mentioned by developers who released updates for their treated applications following entry. Investing effort towards improving functionality and features, as well as stability of applications which are treated by entry, can be inferred from the release notes.

In sum, these findings are consistent with our predictions that complementors with low adjustment costs to innovate on other domains will find it easier and more accessible to innovate elsewhere and would hence be more likely to decrease their innovative effort on the treated applications on the focal platform. On the contrary, developers with no prior experience with the competing platform (high adjustment cost developers) find it more costly to redeploy their resources and move to other platforms and domains and would therefore stick with their available options in the focal platform. Therefore, the latter group would not exit their treated applications, but instead increase their innovative effort on affected domains.

Multihoming the Affected App. As results in Table 2 suggest, there is no evidence to suggest developers would redeploy their resources to multihome their treated applications to the competing platform, i.e., Play Store. While some developers have increased their engagement with treated apps on the focal platform, they did not multihome such applications to the competing platform. High adjustment costs associated with multihoming these applications to a totally different technological platform, as well as the expectation of Google entering the same domain in future (Wen & Zhu, 2019), discourages developers from exerting effort into multihoming an already affected application.

Analysis 2: Developers' Response on Unaffected Applications

The second analysis studies the effect of entry on the other applications which developers may hold on the focal and competing platforms. While the entry effect on treated applications sheds some light on our understanding of complementors' reaction to entry, it is likely this is not what their response to entry will be confined to: they may redeploy resources to innovate on the unaffected applications. We study the change in the same variable, yet on a different sample, i.e., the other applications which the developers might be already hosting in the focal and competing platforms. These applications are called unaffected applications by treated developers, meaning that while they are not directly affected by the focal platform's entry, their developers are the same ones as in the prior analyses of treated applications. Therefore, while developers might react to entry partly through their treated applications, they might also respond by changing behavior on their other, unaffected applications. We analyze both the unaffected applications which complementors have on App Store as well as those on Play Store, i.e., the competing platform.

Unaffected Applications on App Store. For the unaffected application analysis, we follow an approach similar to that of the treated applications. The main difference, however, is in the formation of treatment and control groups. While in the treated application analysis the treated applications were identified directly using the text analysis on their own descriptions, here the treatment group should be formed based on the developer of treated applications, by analyzing whether the respective developer has had a treated application or not.

We first created treatment and control groups from all developers in the category affected by entry, i.e., the "Utilities" category in App Store. To do so, we conducted the word-embedding text analysis (the same approach used in Analysis 1) on applications in the Utilities category in May 2017, i.e., the month before the announcement of entry[8]. Next, top 200 applications in terms of their similarity score to the focal app were chosen as those affected by entry. Subsequently, we formed a treated-developer group from developers of these top 200 affected apps, and a controlled-developer group from those who owned none of the top 5000 applications given their similarity scores[9]. The reason for not including the developers of the top 5000 similar applications in the controlled-developer group is to avoid adding the other possibly treated apps which might be among them, and not captured in the top 200 ones, to the control group. This ensures the accuracy of the control group. Next, we created the main application-level treatment group based on all unaffected applications by treated developers, and the application-level control group based on the unaffected applications by untreated developers. We conducted coarsened exact matching similar to the previous analysis. We ended up having 322,580 matched unaffected applications on App Store. The summary statistics for dependent variables is reported in Table 1.

[8] We identify the treated and control developers by analyzing applications at the time of treatment rather than in the beginning of the pre-treatment period which is six-months before that. The reason is that the treatment status of developers could change in the pre-treatment period as they might develop new treated applications or deactivate their treated applications which could lead to their placement in the wrong group.

[9] Given having 90,000 applications, eliminating the top 5,000 to have a more accurate control group is not problematic to the sample size.

TABLE 3: Update and Exit Behavior of Complementors on Unaffected Products on the Focal Platform

	Full Sample	High Adjustment Cost Developers	Low Adjustment Cost Developers	Full Sample	High Adjustment Cost Developers	Low Adjustment Cost Developers
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Active	Active	Active	Updates	Updates	Updates
Unaffected Application from Treated Developer X Post	0.0634***	0.0781***	-0.0125**	0.0007	-0.0057	0.0337*
	(0.0039)	(0.0049)	(0.0061)	(0.0071)	(0.0076)	(0.0186)
Constant	0.946***	0.940***	0.974***	0.108***	0.0706***	0.302***
	(0.0004)	(0.0005)	(0.0006)	(0.0007)	(0.0008)	(0.002)
Observations	1,612,897	1,112,430	500,467	1,612,897	1,112,430	500,467
R-squared	0.156	0.167	0.105	0.007	0.005	0.021
Number of Applications	322,580	222,486	100,094	322,580	222,486	100,094
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
App FE	Yes	Yes	Yes	Yes	Yes	Yes

Exit of Unaffected Apps on App Store. Results for the treatment effect on the active status of unaffected applications for low and high adjustment cost developers on focal platform are provided in Table 3. Consistent with predictions, high-adjustment-cost treated developers are more likely to keep their applications active on the focal platform by ~7%, with effects being much larger in subsequent months following the treatment as the monthly effects in Figure F3 in Appendix suggest. However, low-adjustment-cost developers were less likely to do so, as they deactivate their applications in later months. Model 3 in Table 3 shows a significant decrease in the active ratio of unaffected applications by low-adjustment-cost developers. Together, these findings suggest that while high adjustment cost developers would be more likely to keep their applications active on the focal platform, those with low adjustment costs are likely to exit them.

Update on the Unaffected Apps on App Store. Models 4, 5, and 6 in Table 3 display results for this analysis. While low-adjustment-cost developers did not increase innovation on their treated applications, and were more likely to exit on those, they increased innovation on unaffected applications as shown in Model 6. This suggests an almost 28% increase on updates in the application-quarter level. On the other hand, high-adjustment-cost developers, who were previously shown to be displaying a huge increase in innovative effort on their treated applications, do not display a significant change in terms of their innovative behavior on their unaffected applications on the focal platform. This suggests that when the entry increases the potential interest for exerting higher innovative effort on the treated applications, high-adjustment-cost developers will be more likely to focus their innovative effort on the treated applications rather than shifting innovation to their unaffected products.

TABLE 4: Update and Exit Behavior of Complementors on Existing Products on the Competing Platform

	(1)	(2)
VARIABLES	Updates	Active
Unaffected Application from Treated Developer X Post	0.0154*	0.0127**
	(0.0096)	(0.0051)
Constant	0.0437***	1***
	(0.0013)	(0.0007)
Observations	360,528	360,528
R-squared	0.014	0.042
Number of Applications	30,044	30,044
Month FE	Yes	Yes
App FE	Yes	Yes

Unaffected Applications on Play Store. We run the same analysis on applications in the Play Store as the competing platform. This analysis would, by design, be limited to applications developed by low-adjustment-cost developers. The approach is the same as the previous analysis on unaffected applications on App Store. From 212 applications by treated and 71,548 by untreated developers on Play Store, the matching provides 183 and 29,861 matched applications in each group, i.e., 30,044 applications in total. Regression results are in

Table 4. Consistent with the proposed hypothesis, treated developers will increase their innovation on their unaffected applications in the competing platform and would be less likely to exit them. Together, these findings suggest that low adjustment cost developers will redeploy more of their resources to other unaffected applications in their portfolio, including those they have on the competing platform. This would not be perceived favorably by the focal platform and is an undesired side-effect of entry, as it encourages developers to redeploy their innovative resources to a competitor.

Analysis 3: Developer-Level Analysis

In the third and last analysis, we analyze the behavior of treated developers directly. Developer-level analysis further allows to probe the mechanism of resource redeployment as we observe firm behavior on the overall portfolio of products. We use the group of treated and controlled developers formed in Analysis 2. We match developers in the treatment and control groups based on their key pre-treatment attributes, including number of new apps they released in both stores and the total number of their applications. Matching based on these controls for their previous innovative effort and disparity in their number of applications. The matching results in 11,569 matched developers across the treatment and control groups.

The dependent variables of interest in this study are the number of new applications released by developers in the focal and competing platforms. The timeframe of this analysis is from December 2016 until November 2017 and the observations are in developer-quartile level (i.e., each developer in every 3-months), as it would make more sense to study the new application release behavior in longer periods. The distribution of developers given their prior multihoming behavior is in Table A4.

TABLE 5: New Application Release of Complementors on the Focal and Competing Platforms

	Full Sample	High Adjustment Cost Developers	Low Adjustment Cost Developers	Full Sample	High Adjustment Cost Developers	Low Adjustment Cost Developers
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	New Apps on Play Store	New Apps on Play Store	New Apps on Play Store	New Apps on App Store	New Apps on App Store	New Apps on App Store
Treated Developer X Post	0.0210	0.000357	0.0661**	0.182	0.0824	0.154
	(0.0139)	(0.0146)	(0.0332)	(0.312)	(0.442)	(0.127)
Constant	0.0274***	-0	0.127***	0.953***	1.095***	0.435***
	(0.00155)	(0.00144)	(0.00492)	(0.0348)	(0.0437)	(0.0188)
Observations	46,276	36,776	9,500	46,276	36,776	9,500
R-squared	0.005	0.001	0.049	0.009	0.010	0.021
Number of Developers	11,569	9,194	2,375	11,569	9,194	2,375
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Developer FE	Yes	Yes	Yes	Yes	Yes	Yes

New releases on Play Store. Table 5 includes the regression results for this analysis. In terms of developers' new application release on Play Store as the competing platform, a significant increase is observed for low-adjustment-cost developers following entry. Model 3 suggests ~0.06-point increase in the number of new applications released on Play Store. Given the pre-treatment baseline of 0.025, this effect suggests more than double increase in the number of new application releases. Figures C1 and C2 in the online Appendix show the quarterly treatment effect for the full sample and low-adjustment-cost developers respectively. The main effect is coming from low-adjustment-cost developers, where in the first quarter following the announcement, there is a huge effect of ~0.1-point increase in new application release. No effect is observed for high-adjustment-cost developers. These findings suggest that low adjustment cost developers increase their innovation on the competing platform by redeploying their resources to it following entry, while high adjustment cost ones do not, given the high costs associated with that. Moreover, as analysis 2 suggested earlier they rather invest more on their treated applications in the beginning, and subsequently on the unaffected products, all in the same focal platform where they would not incur adjustment costs.

New releases on App Store. There is no significant effect observed on new application release on the focal platform, i.e., App Store. The effect size, however, is rather large for low-adjustment-cost developers although it is not statistically significant (model 6, Table 5). Figure C3 in online Appendix shows that this effect is observed in the first quarter following entry which is the same as the time in which new applications were released on Play Store by same low-adjustment-cost developers. Our complementary qualitative analysis suggests that these new apps on App Store are mostly those which were released earlier by their developers on Play Store. Therefore, part of low-adjustment-cost developers have developed the same applications for both platforms yet released them first on Play Store as the competing platform and then on the focal one. These results together with those of prior two analyses confirm that the amount of exerted innovative effort by low-adjustment-cost developers on new app releases, which require higher level of innovative resource allocation compared to updates on existing ones, is higher on the competing platform. Together with their act of exiting on both affected and unaffected applications on the focal platform, these findings suggest that, following entry, low adjustment cost developers will redeploy more of their innovative resources into the competing platform.

Robustness Checks

We test alternative methods for estimating results in an effort to show the robustness of the findings to different statistical approaches. We conduct the analysis on same measures across all three sets of analyses using Poisson, Logit, and Probit regressions. We use Poisson regression to estimate the effect of entry on the continuous measures, which are the updates of affected and unaffected applications as well as the number of new applications released by developers on the focal and competing platforms. Furthermore, the measure for active status of applications in platforms is a dichotomous measure. Hence, we also estimate results using Logit and Probit regressions for this dependent variable. Results in Tables F6, F7, F8, and F9 in online Appendix display results using these estimation methods for the 3 sets of analysis. Results suggest that the estimates are robust to all these alternative measures and in some cases, they increase the statistical significance as well.

Moreover, we have reported results on samples of low and high adjustment cost developers separately. We alternatively use the low-adjustment-cost as a moderator and estimate the results on the full sample. Results in tables F10, F11, and F12 report results using this approach for all analyses. Our reported findings are robust to this approach as well.

DISCUSSION AND CONCLUSION

In this study we analyzed the reaction of complementors to platform entry. Consistent with the proposed hypothesis, we found a clear heterogeneity in terms of complementors' response to entry based on their adjustment cost. While complementors with high adjustment costs are more likely to stick to the focal platform and innovate on their applications following entry, those with lower adjustment costs to competing platforms redeploy more of their resources to unaffected domains in both the focal and competing platforms. The latter group do this by innovating more on unaffected applications as well as releasing new ones on both platforms, with a higher focus on the competing one. The reason is that they would incur much less adjustment cost for redeploying their resources, compared to high adjustment cost developers, and would therefore benefit more from redeploying their innovative resources to the competing platform.

These findings have several implications for both theory and practice. First, they suggest that entry can be a double-edged sword for an entering platform. On one hand, entry can increase the innovation on the target domain and improve the quality of complements by forcing some to exit and incentivizing innovation on those remaining. The entry can also motivate complementors to innovate more on their other products. On the other side, complementors with low adjustment costs to competing platforms will be inclined towards shifting their innovative effort to them. This undesired side-effect of entry has two important attributes to consider. First, the low adjustment cost developers who shift part of their innovative effort to the competing platform also happen to be more experienced and have larger portfolio of complements. Second, their increased innovation on the competing platform is not only confined to their existing portfolio of products on that platform, but also takes the form of introducing new complements which requires higher allocation of innovative resources. This suggests that entry, while having some desired outcomes for the platform, could be motivating a group of big and important complementors to increase their engagement on the competing platforms. Moreover, there are implications for complementors and competing platforms as well. High adjustment cost complementors can learn from the agility of low-cost ones by trying to decrease their adjustment cost to competing platforms to be more prepared for potential entries in future. As for the competing platforms, the increased innovation of low adjustment cost complementors on them in the face of entry from other platforms can provide an opportunity for them to capture more value, by investing in ways which can decrease the adjustment cost of complementors in the market and economize resource redeployment for them.

This research contributes to literature on platforms and innovation management by highlighting the heterogeneity in innovation strategy of complementors in response to platform competition in the context of digital platforms. Moreover, it provides evidence for the argument that complementors' adjustment cost affects their allocation of innovative resources both on the focal and the competing platforms in response to direct competition from a focal platform.

It also identifies an undesired outcome of entry in that it can have nuanced effects at the same time for the focal platform in terms of its complementors' innovation strategy and resource redeployment.

Finally, there are ways to improve and extend this research. First, there is still more that can be done on identifying the mechanisms driving the results, where qualitative data, such as interviews with developers who were affected by entry, can be helpful. Furthermore, future research can study other factors which could explain other heterogeneities in complementors' responses. For instance, another attribute which can shape complementor response could be the governance mode of the platform. For instance, entry of Microsoft (as a proprietary platform) vis-à-vis Ubuntu (as an open-source distribution of Linux) into the same product domain may be based on different intentions, and be differently perceived, and subsequently responded to, by complementors. Therefore, the question to ask would be whether complementors' response to entry is different given the monetization, governance, and openness strategies of the entering platform.

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