A platform for change? The impact of core component innovations on complementors' actions in a platform-based ecosystem

Shiva Agarwal
The University of Texas at Austin, McCombs School of Business
2110 Speedway Stop B6300 Austin, TX 78712-1282
Tel: (1) 512 232 5862
Email: shiva.agarwal@mccombs.utexas.edu

Ram Ranganathan
The University of Texas at Austin, McCombs School of Business
2110 Speedway Stop B6300 Austin, TX 78712-1282
Tel: (1) 512 471 2844
Email: ram.ranganathan@mccombs.utexas.edu

Keywords: platforms, ecosystems, innovation, adaptation, competition

(Authors contributed equally and are listed in alphabetical order)

Working paper: Please do not cite, post or distribute

A platform for change? The impact of core component innovations on complementor actions in a platform-based ecosystem

ABSTRACT

We examine the consequences of ongoing innovations to a platform firm's core components, on the subsequent choices of its complementors. Our central thesis is that core innovations are a double-edged sword in ecosystems. While they boost value creation by enhancing recombination opportunities to generate novel complementarities, they also erode existing complementors' positions by enabling new entrants and imposing adaptation costs. Importantly, such tensions can trigger complementors to join competing platforms, thus blunting the platform's competitive differentiation. We demonstrate support for these mechanisms in the smartphone ecosystems, using a difference-in-differences design and novel iOS release notes data that reveal core component innovation information. Our findings provide a fresh evolutionary perspective on platforms and underscore the path-dependent pressures to co-innovation even in highly modular interorganizational contexts.

INTRODUCTION

Platform-based firms are now ubiquitous across the economic landscape, accounting for seven out of the top ten most valuable companies globally[1]. From pioneers such as Apple and Google in smartphones, and Amazon and Alibaba in retailing, platform-based businesses have become prominent in a wide range of sectors, including social media (e.g., Facebook and Twitter), transportation (e.g., Uber and Lyft), lodging (e.g., AirBnB and VRBO), workplace communications (e.g., Slack and Azure), payments (e.g., Stripe and Paypal), and more recently, cryptocurrency (e.g., Coinbase and Binance). Platform-based ecosystems have witnessed dramatic economic success because they are able to spur a vast array of external complementors to develop innovations that build on a set of core "platform" components (Fang, Wu and Clough, 2020; Jacobides, Cennamo, & Gawer, 2018; Kapoor, 2018). These complementary innovations generate positive cross-side network effects that induce end-users to join the platform (Katz and Shapiro, 1985). Indeed, research has inextricably tied the competitive advantage of a platform firm to both the size of these network effects (i.e., the number and variety of complementary innovations), as well as its timing advantage in generating them (Parker and Van Alstyne, 2005; Zhu and Iansiti, 2012; Barach, Kaul, Leung and Lu, 2019).

However, despite the widespread success of platform-based ecosystems, a fundamental tension and potential limitation to the platform-based way of coordinating surfaces when a platform firm innovates and alters the core components that complementors build on (Wareham et al., 2014; Kapoor and Agarwal, 2017). Because complementors develop their products to align with a set of core platform components, they benefit when these components remain stable over time. Stability enables complementors to continuously adapt in an environment where the interdependencies with the platform are held constant, thus learn and improve their offerings to enhance end-user and ultimately ecosystem performance. But maintaining such stability constrains the platform firm's response to shifts in market conditions or user preferences, and limits its ability to capitalize on new technological developments. When the platform firm does respond to such shifts by innovating and

[1] In January 2020, these seven firms represented more than $6 trillion in market value (Cusumano, Yoffie and Gawer, 2020), a figure that exceeds the GDP of any country other than the United States and China.

transforming its core platform components, existing complementors may face both adaptation hurdles as underlying interdependencies shift (Kapoor and Agarwal, 2017; Pierce, 2008; Levinthal, 1997), as well as competitive challenges from new complementor firms who can capitalize on the opportunities presented by core component innovations to enter the ecosystem. Critically, these tensions are heightened when competing platform-based ecosystems exist, because switching to an alternate platform may become appealing for impacted complementors. Such migration is consequential because it diminishes both the focal platform's value proposition for end-users as well as the distinctiveness of its network effects vis-à-vis competing platforms, thus diluting the likelihood that there will be a winner-take-all outcome (Eisenmann et. al, 2006; Cusumano et al., 2019).

How do these challenges to existing complementors' technological and competitive environments posed by core component innovations, affect their actions and engagement on the platform? Our paper examines this important research question that has the potential to enhance our understanding of the limitations of platform-based organizations. While prior scholarship on platforms has stressed the importance of pricing, fees and information control as strategic levers to kickstart network effects in platforms and solve the "chicken-and-egg problem" (e.g. Hagiu, 2009; Boudreau, 2010), we know little about how the challenges posed by the ongoing evolution of platform to the sustainability of the platform firm's network effects. Compared to traditional firms, these challenges are more palpable in platform-based ecosystems because of the inherent organizational tradeoffs platform firms make to rapidly generate network effects. At the heart of platform firms' network advantage vis-à-vis traditional ways of organizing, is their ability to externalize large scale innovation across numerous independent complementor firms, outside of a formal authority structure (Gulati et al., 2012), yet without incurring substantial coordination overheads (Parker et al, 2016). Underscoring the importance of attracting and managing such complementors without relying on traditional hierarchical structures, Parker et al. (2016) note, "[f]rictionless entry [for complementors] is a key factor in enabling a platform to grow rapidly" (pg. 25). To minimize the overheads involved in adding and monitoring new complementors, platform firms in digital ecosystems leverage smart contracts and software development kits (SDK) with application programming interfaces (API) that serve as standardized communication pathways (typically referred to as "interfaces") with the core platform components they control (Argyres, 1999; Barach, Kaul, Leung and Lu, 2019). However, in contrast with traditional dyadic co-innovation organizational arrangements such as R&D alliances, where knowledge exchange routines cater to specific bilateral partnerships (Dyer and Singh, 1998), in platforms these generic pathways are equally accessible to all current and potential complementors who must utilize them to generate unique recombinations. Although this makes platforms more scalable and modular than traditional interorganizational collaboration forms (Baldwin and Clark, 2000), this very same exchange mode–i.e., standardized, generic interfaces- that facilitates "frictionless entry", also creates the abovementioned challenges for the platform's evolution. The scale and scope of complementors makes it impractical for the platform firm to coordinate the core component changes using traditional mechanisms such as co-development (e.g. joint ventures or R&D alliances), or at the extreme, vertical integration (Dyer, 1997; Afuah, 2001; Teece, 1986; Williamson, 1971).

In our theoretical arguments, we elaborate on the above tensions and advance the idea that the ongoing innovations in the platform's core component act a double-edged sword. On the one hand, they increase the potential for novel complementarities, by fomenting fresh co-innovation opportunities for existing complementors as well as new complementors, thus boosting overall value creation through network effects. However, on the other hand, core component innovations also diminish the value that existing complementors can appropriate, precisely by enabling new complementor entrants to compete, and by imposing additional costs of adapting an existing complement to a new set of standardized rules. We argue that as a result of these tensions, core component innovations can trigger complementors to diversify[2] into a competing platform, thus diminishing a key source of the platform's differentiation.

We test our hypotheses on the Apple iOS ecosystem and the competing Google Android ecosystem between 2011 and 2016. Our unique dataset leverages generational core component innovations that are manifested in Apple's software development kit (SDK) and application

[2] Platform scholars commonly use the term multihoming to refer to complementor's diversifying into the competing platform. We have used these terms interchangeably throughout the paper.

programming interface (API) release notes. We are able to specifically track which core component interfaces are used by each complementor, whether the complementor responds to Apple's core innovation changes by introducing corresponding innovations using the altered component, and also whether the complementor introduces a similar innovation on a competing platform. Using a difference-in-differences design, we find strong evidence that is consistent with our theorized mechanisms. Our results and additional analyses also show that the consequences of changes in the platform's core components have important economic implications for platform firms. Notably, complementors (Apps) with a greater revenue potential and a higher user engagement in the focal platform (Apple) demonstrated a higher likelihood of diversifying to the competing platform (Android). We find that average user engagement declines by almost nine percent in the three-month period following these changes.

Our paper makes several important contributions to the strategy literature at the intersection of technological change, innovation and ecosystems. First, we contribute to the emerging literature on platforms by underscoring the evolutionary challenges of co-innovation even in a highly modular platform-based interorganizational context. Our findings highlight that a platform-based approach of organizing, which relies on a platform firm orchestrating alignment through a standardized set of ecosystem rules for all complementors, may face limits to its effectiveness. While a majority of studies examining platform-based ecosystems focus on the challenges of generating network effects in ecosystems either during its emergence and nascency (e.g. Hannah and Eisenhardt, 2018), or by using strategic pricing (e.g., Eisenmann et al., 2006) or by selectively opening up its core components (e.g., Parker and Van Alstyne, 2018), our paper demonstrates the challenges a platform firm faces in sustaining these network effects over time. While standardized interfaces may help in scaling up the platform and enabling initial network effects, we show that these interfaces pose challenges in sustaining these network effects over generations of core component innovations.

Second, in contrast with most research that theorizes about network effects in the aggregate, our paper deconstructs these network effects by showing that these challenges stem from the heterogeneity of complementors, which is rooted in their idiosyncratic, path-dependent choices on a particular regime of platform rules. Because these choices create interdependencies with the rules, a change in these rules imposes adaptation costs that are asymmetric across complementors.

Third, our findings also illustrate the joint effects of both intra and inter-platform competition by showing that complementors' adaptation and redeployment decisions take into account both the competitive conditions and adaptation costs within the platform as well as the opportunities presented by cross-platform diversification. Even though prior research has suggested that multihoming can result in lower complementor performance (e.g. Cennamo, Ozalp and Kretschmer, 2018) and can diminish the strength of the network effects (Cusumano, Gawer and Yoffie, 2019), our paper is one of the first to examine the antecedents to such multihoming decisions.

Lastly, we also depart from the typical characterization of the platform owner as a highly rational designer of platform rules and governance mechanisms to demonstrate the negative consequences of the platform firm's core innovations. Overall, our findings strongly suggest that contrary to conventional wisdom, platform-based contexts are not necessarily "winner-take-all" markets. The evolution of the platform and the need for even a leading platform firm (as is the case in our context) to alter its core components, can open up opportunities for competing platforms and indeed more traditional non-platform-based organizations to devise appropriate governance structures and rules in order to create comparable network effects.

THEORETICAL BACKGROUND

We first elaborate the challenges of designing a platform, then outline how contemporary platform firms attempt to solve this challenge, and finally turn our attention to examining the particular co-evolutionary tensions posed by such solutions in order to derive testable hypotheses.

The design of platform-based ecosystems: Modular components, APIs and SDKs

Platform-based ecosystems constitute a distinct class of business ecosystems wherein transactions between two (or more) sets of actors (e.g., iOS App providers and smartphone users, merchants and consumers, enterprises and providers of software modules) are intermediated by a "platform" (Kapoor and Agarwal, 2017). In recent years, the term platform has become synonymous with the notion of a digital technological solution to the problem of organizing innovative activity efficiently across a large number of disparate (i.e., vertically disconnected) actors. Although such platform-based solutions can be engineered collaboratively across affected actors – for example, as in open standards development in SSOs (Ranganathan and Rosenkopf, 2014) – of particular interest to our theorizing herein is the subset of platform-based ecosystems where the platform is devised and controlled by a single firm, commonly referred to as a platform firm (or alternatively as a hub firm or a platform leader) (Gawer and Cusumano, 2002). In particular, the cross-side or indirect network effects that are generated by the activities and contributions of third-party complementor firms, are responsible in large part for the market success of leading platform firms (Zhu and Iansiti, 2019).

Because platform-based ecosystem contexts can be subject to winner-take-all competitive pressures and timing advantages, platform designs need to enable large numbers of independent complementor firms to rapidly join the ecosystem and generate complementary innovations, with minimal coordination overheads or delays. At the same time, the platform's uniqueness, and indeed its competitiveness as an organizing form, rests on the differentiation provided by these complementary innovations compared to competing platforms. Importantly, dyadic inter-firm collaborations (e.g., equity agreements, joint ventures) that are established modes of facilitating knowledge sharing and interactions to discover unique complementarities (Dyer and Singh, 1998; Gulati and Singh, 1998), are not scalable with regard to time pressures or governance costs. In other words, platforms must be designed to induce many complementors to enter the platform with unique offerings, but without incurring substantial coordination costs that such collaborations might normally entail in traditional ways of organizing.

While early work in the economics literature on platforms and two-sided markets focused on establishing the importance of the price mechanism in attracting complementors to join platforms (e.g., Hagiu, 2006; Economides and Katsamakas, 2006), more recent research in strategic management has taken seriously the role of the platform's architecture, and in particular the role of modularity and how platform firms manage interdependencies between their platforms and their complementors (e.g.

Kapoor and Agarwal, 2017; Kapoor, 2018; Jacobides et al., 2018; Helfat and Raubitschek, 2018; Baldwin and Clark, 2000; Baldwin, 2021)[3].

Most basically, platform firms such as Apple, Google and Slack, first create a core set of modular components (core components), that constitute the platform-specific building blocks for complementors to develop their innovations on (Kapoor and Agarwal, 2017). Each core component or module encapsulates a distinct set of functions or activities that are essential to the platform. The platform firm must then devise a solution to enable downstream complementors in the ecosystem to recombine these components, with the objective of discovering and realizing unique complementarities (Ganco, Kapoor and Lee, 2020). However, as discussed, because the particularities of the platform context render piecemeal and customized arrangements to relay proprietary platform-specific knowledge to individual complementors infeasible, platform firms devise a set of standardized interfaces (i.e., rules of exchange) for *any* complementor to join the platform and utilize these components. These rules, that are referred to as software development kits (SDKs) or application program interfaces (APIs), are essentially well-codified, predictable pathways over which the platform-firm allows controlled access to its core functions. This solution embodies the central tenets of modularity (Baldwin and Clark, 2000), wherein each component or module encloses a set of highly interdependent activities inside of it, while limiting interdependencies with other areas of the ecosystem by creating "thin" interfaces that constitute the crossover points between components (Sanchez and Mahoney, 1996).

Indeed, modular solutions with SDKs and APIs are now prominent in almost every platform-based business. For instance, in Apple's iOS platform (as well as in the competing Android platform), APIs allow complementors to design Apps that can not only access the basic features of Apple devices such as sound, images, geolocation and haptics (i.e., touch and motion) but also access services to manage security and privacy, retrieve advanced user information, and communicate with other Apps

[3] The notion of modularity, dating back to Simon (1962), is "a continuum describing the degree to which a system's components can be separated and recombined, and it refers both to the tightness of coupling between components and the degree to which the 'rules' of the system architecture enable (or constrain) the mixing and matching of components" (Schilling (2000):p.312).

and devices (e.g., Bluetooth headsets, Apple Watch etc.). Uber's API for Business allows enterprises to access services for billing, reporting and user management while their APIs for drivers allow access to trip data, payments and ratings. Similarly Google's APIs for Maps and YouTube allow third party complementors to embed and recombine navigation and video capabilities into their applications and websites, while Amazon's AWS Marketplace APIs provide sellers on Amazon with tools to customize and better market their product offerings.

Given these common platform design solutions, we now turn our attention to elucidating the fundamental co-evolutionary tensions that are precipitated when the platform firm alters its core components and consequently the standardized interfaces with which these components connect to the ecosystem's complementors.

Why platform designs must evolve and change

An important assumption that is implicit in our preceding discourse on platform design and indeed in the research on ecosystem and platforms, is that highly rational platform firms endowed with superior capabilities can choose the "optimal" attributes to architect a platform solution that creates a sustainable competitive advantage (Hagiu, 2014; Parker et al., 2016; Iansiti and Levin, 2002; Teece; 2018). For instance, research suggests that platform firms can enhance performance by overcoming typical issues related to strategic tradeoffs, positioning, pricing or sharing value with complementors (Cennamo and Santalo, 2013; Cennamo and Santalo, 2015). The platform design problem is viewed as one pertaining to strategic foresight, environment scanning and market sensing, with firms that possess the right set of capabilities avoiding common pitfalls (Cennamo and Santalo, 2015) and thereby performing better (Teece, 2018).

While these perspectives are no doubt insightful in prescribing normative attributes for platform leaders, it is also equally reasonable to consider platform firms as subject to the same constraints of bounded rationality as traditional organizations (Simon, 1955). In other words, even a highly capable platform firm will likely find it challenging to architect a "one-shot" stable platform design that can not only account for the current, but also possible future states of the ecosystem's environment. Most basically, a platform firm's design must evolve and change in unforeseen directions for a variety of reasons. First, the platform must be responsive to changing demand conditions, both as end users with different preferences join at different times (e.g., Rietveld and Eggers, 2018), and as the size of network effects obtained in different parts of the platform varies over time (Panico and Cennamo, 2022). For instance, the platform firm may need to innovate in order to open up areas of the ecosystem that have an insufficient number of complementors, or where complementor innovation has declined over time.

Second, the platform must also respond to competitive pressures when new ecosystems, devised on divergent governance rules or design parameters, offer greater opportunities for complementors, and ultimately superior value for end users. As Helfat and Raubitschek (2018) point out, "as a consequence of the pace of change and the pressure of competition, platform leaders must continually innovate and redesign", and that these redesigns can be "extremely complex tasks given the number of actors involved, the multi-faceted characteristics of these ecosystems, and high uncertainty". Indeed, recent research recognizes these competitive pressures and suggests that even platforms that have a significant first mover advantage in generating network effects may not be guaranteed a "winner-take-all" outcome (Cennamo and Santalo. 2013; Keith and Rahmandad, 2019).

Lastly, the platform must incorporate innovations in underlying technologies that have the potential to dramatically improve the performance of the ecosystem. For instance, Apple's implementation of fingerprint and face recognition technologies in its devices, or its inclusion of a magnetometer for navigation, mapping and gaming, were not predictable when the first iPhone was commercialized in 2007. Notably, these changes also required corresponding alterations to its architectural design and component interface rules. Relatedly, shifts in the firm's strategy spurred by product innovations outside the platform are ultimately interdependent with its choices on the platform. For instance, the introduction of Apple Watch required the creation of new core components in iOS to support it. Similarly, the introduction of AirPods – wireless headphones – required the firm to innovate on a new chipset (the Apple W1) that then had performance implications for the entire ecosystem.

HYPOTHESES DEVELOPMENT

Adaptation of complementary innovations to core component innovations

What are the consequences of the evolution of the platform on its complementors? Specifically, when the platform owner introduces core component innovations, how do complementors respond? To examine this question, we first distinguish between *existing* and *new* complementors by observing that innovations in core components are more likely to unlock *new* complementarities in the ecosystem. For instance, innovations introduced by Apple in the form of accelerometers, pedometers and gyroscopes dramatically opened up the innovation space for gaming Apps such as Pokemon Go that rely on augmented reality (AR). Similarly, the introduction of the Apple Watch created new opportunities for health Apps that could use vital health statistics data in innovative ways. Importantly, in the absence of core component innovations, as a platform matures, end-users may become locked in to using specific complementors' products because of network effects, thereby limiting their engagement with the rest of the ecosystem. In such maturing platforms, new complementor firms may be deterred from entry because they are unlikely to be able to introduce a differentiated offering that can take market share away from established complementors. But core component innovations can help solve this problem – such innovations are analogous to technology "shocks" because they alter the landscape of innovation possibilities for both existing and new firms. Thus, new complementor firms may be able to enter the ecosystem by introducing a complement that takes advantage of the core component innovation. Furthermore, because both the number of complements and the diversity among complements are important drivers of platform success (Boudreau, 2012), we would expect platform firms to introduce innovations specifically targeting areas of the ecosystem where complementors are more entrenched, or where the rate of innovation in complements is comparatively low. Thus, we hypothesize:

Hypothesis 1a: New complementors will respond to innovation in a platform-firm's core components by entering the platform with complements that build on these components.

As reasoned above, an existing complementor firm may also respond to core component innovations in order to enhance its established complement, capture new complementarities and ultimately ward off potential entrants. However, a more basic rationale has to do with the idea that decomposing a complex system into perfect modules is not always feasible, as systems often have interdependencies spanning across modules (Simon, 1962; Baldwin and Clark, 2000). Specifically, because core components are highly interdependent with the rest of the ecosystem, a change in one or more core components is likely to affect the performance of numerous existing complementors (Kapoor and Agarwal, 2017). These complementors, including those that do not see obvious value in enhancing their offering, may be forced to make adjustments to their complements that incorporate interdependencies and thus changes in these core components. Thus, we hypothesize:

Hypothesis 1b: Existing complementors will respond to innovation in a platform-firm's core components by enhancing complements to build on these components.

The effect of within platform co-evolutionary tensions on cross-platform diversification

How do these dynamics of competitive entry by new complementors and ongoing adaptation by existing complementors, in response to core component innovations, affect the distinctiveness of the platform's network effects? Recall that from the platform owner's perspective, the sustainability of its advantage crucially depends on its superior ability to lock-in complementor firms into its ecosystem vis-à-vis competing platform firms. However, the challenge for the platform firm is that it has very little control on the actions of its complementor firms, particularly outside of its ecosystem, because it lacks formal authority over them (Kende 1998, Morris and Ferguson 1993, Shapiro and Varian 1998, West 2003). In contrast, in traditional supply chains, a firm may enter into exclusive agreements with suppliers or distributors that prohibit them from forging contemporaneous alliances with the firm's competitors. But because in platform-based businesses such agreements are likely to deter entry by complementors and thereby dampen the creation of network effects, complementors are not legally bound to a particular ecosystem, and are free to diversify (i.e., multihome) to different competing platforms.

Moreover, the platform firm cannot rely on traditional interfirm informal governance modes, where repeated interactions, as well as partner-specific routines, capabilities and experiences, might have helped weather conflicts as a result of coordination failures (Gulati, Lavie and Singh, 2009; Zollo, Reuer and Singh, 2002). Indeed, our exposition here suggests that complementors in the platform context are not really partners in the strict sense, but more akin to anonymous transactional actors. Additionally, in traditional alliance-based settings, the innovating firm could choose to invest in a limited set of partners to help them adapt to core innovations (Dyer, 1997), or at the extreme vertically integrate to overcome coordination failures (Afuah, 2001; Teece, 1986; Monteverde and Teece, 1982; Williamson, 1971). However, in platforms, such strategies are less feasible because of the scale and scope of complementors, and the breadth of associated knowledge and investments required. Indeed, it may be problematic for platform firms to identify the adverse impacts of core innovations *even* after they have been made (Kapoor and Agarwal, 2017).

When the platform firm introduces a core component innovation, it creates two types of challenges for existing complementors that utilize the component. We argue that these challenges are likely to increase the likelihood that the complementors will diversify to a competing platform. First, as discussed above, component innovation will spur entry by new complementor firms that will then compete with existing complementor firms for their end-users. While several established complementors may be well-positioned to respond to such entry, we would nevertheless expect competitive pressures to reduce economic benefits for at least a subset of complementors, compared to complementors that are unaffected by the component innovation. In particular, for complementors that face the greatest increase in competition from new entrants, the option of cross platform diversification is likely to be the most salient (Lang and Stulz, 1994; Giustiziero, Kaul and Wu, 2019).

Second, complementors whose innovations are more interdependent with core components, are likely to face heightened adaptation challenges. Although we would expect affected complementors to attempt to adapt to component innovations (as argued in Hypothesis 1b), the high interdependence, or tight coupling between the complementor's design choices and the platform's architecture, will reduce the effectiveness of such adaptations (Levinthal, 1997). Essentially, for complementors with greater levels of interdependencies, changes in few design parameters are unlikely to yield the required performance gains (Kapoor and Agarwal, 2017). These architectural challenges are well established in the literature on technological change and adaptation (e.g., Henderson and

Clark, 1990). On the contrary, complementors whose innovations are less interdependent with the altered component (loosely coupled) – indeed at the extreme unaffected by the innovation – are more likely to be able to successfully redesign their complement. We would therefore expect those complementors who are more interdependent with the platform's altered core component to be more likely to diversify into a competing platform.

Overall, we expect both the above theoretical mechanisms to affect complementors' responses to the platform owner's component innovation such that:

Hypothesis 2: Existing complementors whose complements build on core components that change are more likely to enter a competing platform.

METHODOLOGY

Empirical Setting and Data

Our context for the study is Apple's iOS ecosystem, where Apple is the platform owner and the App developers are complementors that participated in the iOS ecosystem between 2011 and 2016. The setting provides a relevant and feasible empirical context to study the effect of the platform's core innovation changes on the complementors' actions for various reasons. First, the iOS ecosystem represents one of the largest and most valuable business ecosystems, with App Store revenue estimated to be more than $20bn in 2016. Second, hundreds of thousands of Apps (i.e., the complementary innovations introduced by the complementors) actively participate in the iOS ecosystem, thereby providing us an opportunity to examine our hypotheses on complementors' actions on a large scale. Third, Apple periodically upgrades its platform with component innovations, thus creating multiple punctuated episodes of architectural changes in core platform components. Finally, because Apple provides detailed publicly available documentation for each innovation, we can systematically observe and track the specific components in which the innovation occurred.

We assembled a unique dataset by integrating data from multiple sources. First, we gathered information about the API usage by Apps on the iOS platform from a leading analytics firm.[4] This

[4] This firm is well established and provides its data to many established such as Amazon, Intel, and Adobe.

dataset captures a variety of attributes of Apps that entered the iOS ecosystem since 2011, including the specific iOS platform APIs they use. Second, we obtained data on Apps that entered the competing platform (Android) during this period. Finally, we hand-collected information on APIs that Apple innovated on in every new iOS release by parsing release notes as described below.

The technological architecture of the iOS platform

The iOS platform provides access to multiple functions and services to complementors, including basic computing technology, navigation, camera, and advanced technologies such as accelerometer and haptics. App developers integrate these functionalities into their Apps using APIs. APIs are the modular interfaces, developed and made accessible by Apple, that allow developers to connect their Apps to the iOS platform. These APIs simplify programming tasks by abstracting away from the underlying implementation of the platform and only exposing objects or actions that the developers need as they build their applications. For example, an App developer can access the GPS functionality of the iOS platform through a set of APIs called CoreLocation without knowing exactly how the functions are assembled and implemented in the iOS platform. Thus, APIs are critical conduits for App developers to access core functions and features that they recombine to innovate and create complementary innovations.

Each API is communicated to the complementor community with a document (a standard description) called the API specification. This specification describes the detailed steps developers can follow in order to use a particular function of the core component. However, any change in the technological architecture of the iOS platform, including innovations to core components, necessarily predicates changes in the APIs that need to be communicated to the App developers. Apple communicates such changes in APIs through documents called "Release notes". To tabulate APIs that were changed in a particular iOS platform version, we downloaded all the archived release notes from Apple's developer library (these corresponded to iOS versions 3.0 to 9.2). We then matched the list of APIs that Apple innovated on, to the APIs that were used by Apps in our dataset to construct the dependent and independent variables as we describe below.

Sample construction

We began by obtaining information on a cross-section of Apps released between 2012 and 2016 with listed API usage information[5]. From this sample, we excluded Apps that were missing data on one or more required variables. Additionally, in our empirical setting, there are a large number of Apps that are not actively used by users, or, at the extreme, never downloaded at all. Because including such Apps in the analysis could create spurious results and because they are economically less relevant, we filtered out those Apps that did not receive any reviews or receive any user ratings during their lifetime. We also removed "dead" Apps – i.e., Apps not updated in the twelve months before the introduction of the platform's core component changes. Our final sample consisted of 177,813 Apps.

Research design and empirical models

To test hypotheses 1a and 1b, we need to be able to measure how innovations in the core components of the platform, as manifested in Apple's iOS APIs, cause corresponding changes in API usage in both new as well as existing complements. Here, because complementors (i.e. the App developers) choose to incorporate specific APIs into their programs, our main identification challenge is to account for unobserved factors that may influence App developers' API usage decisions. To overcome this challenge, we use a difference-in-differences (DID) design where the launch of a new generation of the iOS platform by Apple marks an event that demarcates the pre and the post periods. For our DID analysis, we identify the treated group as the set of APIs that were changed during a new iOS release, and the control group as the set of APIs that were unchanged. In our dataset, we observed five episodes of platform core component changes corresponding to five new iOS versions and therefore we created different treated and control groups for each of these episodes. The level of analysis for testing hypotheses 1a and 1b is API-month. We record observations on each App that uses either treatment group or control group APIs from six months prior (the pre period) to six months after (the post period) the new iOS version is announced. The corresponding empirical

[5] We limited our sample to this specific period because in our dataset, API usage availability after 2016 is sparse.

specifications to test Hypotheses 1a (#New apps installing the API) and1b (#Existing Apps installing the API) are as follows:

$$New\ apps(installing\ the\ API) = \delta_1 * Treated\ API * Post + \delta_2 * Post + \delta_3 * API\ \mathrm{id} + \gamma * Time + control\ variables + residual$$

$$Existing\ apps\ (installing\ the\ API\ ) = \delta_1 * Treated\ API * Post + \delta_2 * Post + \delta_3 * API\ \mathrm{id} + \gamma * Time + control\ variables + residual$$

Note that the above specification includes API and period fixed effects, denoted by *API id* and *Time*, respectively. The coefficient of the *Post* variable captures the overall usage trend across all APIs occurring after the changes to the core components of the iOS platform.[6] The key variable of interest in both specifications is the interaction term δ_1, which captures the difference between the new Apps (or existing Apps) that install and use the APIs that Apple innovated on in a new version of the iOS platform, and the new Apps (or existing Apps) that install and use the APIs that Apple did not innovate on. The period fixed effect controls for potential time trends. We estimate these models using Ordinary least squares (OLS) regressions.[7]

To test Hypothesis 2, we need to be able to examine how innovations in Apple's iOS APIs, cause trigger existing complementors to diversify to a competing platform. Similar to Hypotheses 1a/b, we use a DID design to test Hypothesis 2, but with some distinctions. Here, the treated group is the set of Apps which use APIs that Apple innovated on in a new iOS release. The control group is the set of Apps which use APIs that were unchanged in a new iOS release. The level of analysis for testing this hypothesis is App-month. We begin observing each App six months before the new version of the platform is announced, and end the observation window six months after. For Apps that diversify, we end the observation window at the month of entry into the competing platform. Our empirical specification is as follows:

[6] Note that because API fixed effects capture the time-invariant differences across APIs in their propensity to be installed by various Apps, the main effect of Treated API is dropped in the regression model.
[7] OLS was preferred to count-based models based on both the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). OLS models also had a higher R-square value. Nevertheless, we also conducted additional robustness checks using non-linear count models, including fixed-effects Poisson and Poisson quasi-maximum likelihood estimators. Results from these models were consistent with our results from the OLS models.

$$Multihoming = \delta_1 * Treated\ App * Post + \delta_2 * Post + \delta_3 * App\ Id + \gamma * Time + residual$$

In the above specification, App-fixed effects and time-fixed effects are included and denoted by *App Id* and *Time*, respectively. The key variable of interest is the coefficient for the interaction term, i.e., δ_1, which captures the difference between the likelihood that treated Apps will diversify as compared to that of the control group Apps, after the changes ushered in by the new iOS platform version. The coefficient for *Post* captures the overall trend that is occurring in the control group across two periods. The App-level fixed effects capture time-invariant differences across Apps in their propensity to multi-home. We employ a linear probability model (LPM) for estimation. The LPM has been extensively used to avoid interaction interpretability issues with nonlinear models (Hoetker, 2007).[8]

Measures

Dependent variables: Corresponding to the empirical specifications above, for the first set of hypotheses 1a and 1b, we constructed two dependent variables - *New Apps (API install)* and *Existing Apps(API install)*. These respectively measure the extent to which a focal API is used by the new Apps entering the iOS platform, and the extent to which a focal API is used by existing Apps already on the platform. The variable *New Apps (API install)*$_{it}$ is measured as the number of new Apps that installed the focal API *i* in the given month *t*. Similarly, the variable *Existing Apps(API install)*$_{it}$ is measured as the number of existing Apps that installed the focal API *i* in the given month *t*.

For hypothesis 2, which examines the extent to which complementors multi-home, we needed to determine which iOS Apps multihomed to the competing Android platform and when. We first used the App's and the developer's names to match the available Apps across both platforms over time. We then coded whether a focal App entered the Android platform in a given month or not. The variable *Multihoming*$_{it}$ takes the value of 1 if a focal App *i* entered Android in month *t*, and 0 otherwise.

Independent variables: Corresponding to the above empirical specifications, for the first set of hypotheses 1a and 1b, our main independent variables are *Treated APIs* and *Post. Treated APIs* is a dummy variable that represents the APIs that Apple innovated on in new iOS releases. *Treated API*$_{it}$

[8] We also test the robustness of the model using conditional logit regression.

takes the value of 1 if the API *i* was modified with the launch of a new generation of the iOS platform within the *t-6 and t+6* 12-month time window, and 0 otherwise. Similarly, the variable *Post* is a dummy variable that takes the value 1 if a new iOS generation was launched within six months of a given time *t*. For the second hypothesis, our main independent variables are *Treated App* and *Post*. The variable *Treated* App_{it} takes the value of 1 if any of the APIs the focal app *i* uses is modified with the new generation of the iOS, within the *t-6 and t+6* time window, and 0 otherwise. The coding for the variable *Post* is consistent with the first set of hypotheses.

Control Variables: We control for many observable characteristics of Apps that may affect our dependent variables of interest. First, the variable *Avg Rating*, measured as the consumer rating received by an App, averaged across all Apps that use a focal API, accounts for quality differences. Second, we control for differences in business models of Apps using the APIs, with two variables *Avg In-App purchases* and *Avg Price*. The variables *Avg In-App purchases* and *Avg Price* are measured as the proportion of Apps with in-App purchases and the average price of the Apps that use the focal API, respectively. Third, we control for differences in demand conditions using the variable *Avg Review Count,* measured as the number of reviews received by Apps, averaged across all Apps that use a focal API. Lastly, we also control for differences in the Apps' content rating, usage of platform components, and complexity using the variables *Avg Content Rating, Avg Platform Component usage* and *Avg Size* (using download size), respectively. Descriptive statistics and correlations are reported in Tables 1, 2 and 3.

(Insert Tables 1, 2 and 3 here)

RESULTS

We test hypotheses 1a and 1b by examining the extent to which new and existing Apps use those APIs that are innovated on by Apple as part of a new version of the platform's iOS core components. We report the results of these tests in Tables 4 (new Apps) and 5 (existing Apps). In Table 4, Model 1 includes only the independent variables *Treated APIs, Post* and the interaction term between them. Model 2 is the full model that includes all the control variables. As reported in Model 2, the coefficient for the interaction term is positive (b=1,425.10, p-value < 0.01) and consistent with hypothesis 1a that new complementors will respond to innovation in a platform-firm's core components by entering the platform with complements that build on these components. Effectively, for each API that is innovated on by Apple, ~ 1425 new Apps that enter the ecosystem incorporate the API.[9]

One concern with DID is that observed results might be driven by spurious differences in the trend between the treatment and the control groups. To alleviate this concern, we conducted a placebo test where we moved the observation window to three months before the introduction of the new generation of the iOS platform (i.e., from [t-6, t+6], to [t-9, t+3]). In Model 3, we present the results of this test - the coefficient for the interaction term with the placebo shock is *negative* (b=-867.11, p-value < 0.01, indicating that there is no evidence for a DID effect outside the defined treatment period and thus increasing confidence in our results in Model 2. We discuss the remaining models (4-8) in a subsequent section on robustness checks (they are included in Table 4 to facilitate visual comparisons).

(Insert Table 4 here)

Table 5 reports analogous models with existing Apps to test Hypothesis 1b. Model 9 includes only the independent variables. Model 10 is the full model that includes all controls. As reported in Model 10, the coefficient for the interaction term between *Treated APIs* and *Post* is positive (b=1,425.39, p-value < 0.01), consistent with our argument that existing complementors will respond to innovation in a platform's core components by enhancing complements to build on these components. Effectively, for each API that is innovated on by Apple, ~1425 existing Apps incorporate the API into their design.[10] Identical to the regressions with new Apps, Model 11 reports the results of a placebo test to rule out any spurious differences in the trend between the treatment and control groups. The coefficient for the interaction term with the placebo shock is *negative* (b=-1,152.287, p-value <0.01), indicating that there is no evidence for a DID effect outside the defined treatment period, and increasing confidence in our results. We discuss models 12-16 in the robustness section.

(Insert Table 5 here)

[9] Because on average, 39,564 Apps enter the iOS ecosystem every month during our observation window, this coefficient translates into a 3.6% increase to this baseline number, that is spurred by innovations in core components.

[10] Because on average, in a given month, 296,977 existing Apps install APIs that they haven't built on before, this coefficient translates into a 0.5% increase in this baseline number, that is spurred by innovations in core components.

In Hypothesis 2, we argued that the innovation in the platform's core components also disrupts existing complementors, such that Apps which build on core components that change are more likely to enter a competing platform . Table 6 shows the results for the models used to test this hypothesis. We begin with a linear probability model reported in Model 17. The coefficient for the interaction term between *Treated Apps* and *Post* is positive (b=0.009, p-value < 0.01), suggesting that Apps are 0.9 percentage points more likely to multihome when core components that they build on undergo change. Although this may seem small, note that the unconditional probability of Apps multihoming is 6.5 percent. Thus, the effect captures a 13.66 percentage increase over this baseline. Again, we tested to ascertain whether our results were driven by spurious trend differences between the treated and control groups by interacting *Treated Apps* with *Placebo shock* in Model 18.[11] The coefficient of the interaction term between the *Treated Apps* and *Placebo Shock* is negative, suggesting no evidence that the results are not driven by the hypothesized treatment of core component innovations.

(Insert Table 6 here)

Robustness checks

The validity of the DID regressions relies on meeting the parallel trends assumption, which requires a similar pre-shock trend for the treatment and the control group. We tested for the parallel trend assumption for the DID models used for Hypotheses 1a (and 1b) by plotting the difference between the average number of new Apps (and existing Apps) that use the treated group APIs and those that used the control group APIs (Figures 1 and 2). A visual inspection suggests that the parallel trend assumption was not satisfied for either new or existing Apps because the difference between the two groups is not stable pre-treatment. We dealt with this potential violation in multiple ways. First, we followed the approach recommended by Angrist and Pischke (2009, p-178) and explicitly controlled for the trend in a fully-flexible model (Model 4, Table 4, and Model 12, Table 5) by including an interaction between *Treated APIs* and *month fixed-effect*, before and after treatment. (Mora and Reggio, 2015). The results are consistent with Model 2, Table 4 for H1a, and Model 10, Table 5 for H1b.

[11] We coded placebo shock consistent with Hypothesis 1a and 1b.

We also tested for the parallel trend assumption for Hypothesis 2 by plotting the difference between the number of treated group and control group Apps that entered the competing platform. As shown in Figure 3, the plotted line suggests that the difference between the groups is not entirely stable pre-treatment although there is no clear trend. In any case, we conducted a similar robustness check by including the interaction between *Treated Apps* and *month-fixed effects*. As shown in Model 19 in Table 6, the results are consistent with those in Model 17 and Hypothesis 2.

(Insert Figures 1, 2 and 3 here)

Second, we also conducted a sensitivity analysis to understand how the pre-treatment parallel trend violation would bias our results using the "honest approach" (Rambachan and Roth, 2019). This technique allows us impose various restrictions on the possible differences in trends between the treated and control groups and then draw corresponding conclusions. We bound the differences in trends between the two groups for the pre and post-treatment periods using the following formula:

$$\Delta^{sD} = \{\delta : |(\delta_{t+1} - \delta_t) - (\delta_t - \delta_{t-1})| \leq M$$

Where δ_t refers to the difference in trends between the treated and control group at period t and M governs the possible error of the linear extrapolation. In the special case, where M = 0, $\Delta^{sD}\ (0)$, the difference between the treatment and control groups is exactly linear. Unfortunately, the data itself cannot provide any upper bounds on the parameter M. Therefore, using this approach, we assess the robustness of our results for various points of M. To pick a value for M, we use the point estimates and the variance-covariance matrix in the pre-policy period. Assuming that error terms are jointly normally distributed, we calculate the median of average (absolute) deviations from the trend in the pre-policy period. The corresponding sensitivity plots are illustrated in Figure 4.

(Insert Figure 4 here)

For Hypothesis 1a, this approach leads to the value of M = 2, suggesting that results for Hypothesis 1a are robust to allow for violation in trends up to twice as big as the maximum violation in the pre-treatment period. Similarly, for Hypotheses 1b and 2, the value of M = 1.75, suggesting that results are robust to allow for violation in trends up to 1.75 times as big as the maximum violation in the pre-treatment period. Overall these tests suggest that our results are reasonably robust to the plausible violation of the parallel trend assumption.

Third, we conducted additional robustness checks to rule out any differences between the treatment and the control group that could bias our results, by using propensity score matching to match the treatment and control groups (Rosenbaum and Rubin,1983). For each observation in the treatment group, we used the nearest-neighbor matching (NNM) estimator to search for the most similar observation in the control group. For Hypotheses 1a and 1b, we matched the APIs based on the average ratings, in-app purchases, price, download size, content rating, review count, and use of platform components. For Hypothesis 2, we matched the Apps based on the month of entry in the platform, average consumer rating, content rating, total API usage, download price, download size, in-app purchase, category, review count, and whether Apple promoted them. Figures 5 and 6 plot the kernel densities of the propensity scores for treatment and control groups before and after matching.

(Insert Figures 5 and 6 here)

The effectiveness of our matching procedure can be deduced from the increased similarity in kernel densities between the groups after matching. Furthermore, the variable ratio test, which assesses the ratio of variance in covariates for the treated group over the control group, indicates balance across the matched sample: Rubin's B (at 22.7 for Hypotheses 1a and 1b, and 18.6 for Hypothesis 2) and Rubin's R (at 0.6 for Hypothesis 1a and 1b, and 0.64 for Hypothesis 2) were within recommended limits (Rubin, 2001). As reported in Models 5 (Table 4), 13 (Table 5), and 20 (Table 6), our regression results on the matched sample continue to be consistent with our hypotheses.

Additionally, we ran models using continuous treatment variables that allowed us to assess whether the *extent* of disruption, as reflected in the total number of API changes impacting an App in the treatment group, correspondingly impacted the dependent variables of interest. As reported in Models 6 (Table 4), 14 (Table 5), and 21 (Table 6), our regression results using continuous treatment continue to be consistent with our hypotheses.

Next, we checked whether our results were robust to the specification of the treatment window by reducing it from +/- six months to +/- three months before/after releases of the new iOS platform versions. These results, shown in Models 7 (Table 4), 15 (Table 5) and 22 (Table 6) continue to be consistent with our hypotheses. We also checked whether our multihoming results for Hypothesis 2 might be asymmetrically driven by one or a few episodes of change, particularly given that the competing Android platform might offer greater opportunities for App developers in the latter time periods. To assess this concern, we ran regressions for each of the iOS versions 6-9 separately. The results, shown in Models 23-26 (Table 7), remain consistent with Hypothesis 2.

(Insert Table 7 here)

Finally, we also checked whether our results are robust to alternate specifications. For Hypotheses 1a and 1b, we used the natural log of the number of new and existing Apps; results for these tests are reported in Models 8 (Table 4), and 16 (Table 5), and are consistent with our hypotheses. For Hypothesis 2, we used conditional logit models; results for both binary and continuous treatment are reported in Models 27 and 28, respectively in Table 8, and continue to support hypothesis 2.

(Insert Table 8 here)

Mechanism test for multihoming

In hypothesis 2, we argued that ongoing innovations in the platform's core components reduce the attractiveness of the platform for existing complements for two reasons – 1) increased competition from new complements that enter the platform and 2) increased adaptation challenges because of interdependencies with core components. We tested these specific mechanisms through two additional analyses that are shown in Table 9. First, we measured the increase in competition from new complements by counting the total number of new Apps that entered the platform in a focal App's category and included a three-way interaction between *Treated App, Post,* and *New Apps* variables. As reported in Model 29 in Table 9, the coefficient for the three-way interaction terms is positive (0.001, p-value < 0.01), indicating that the likelihood of treated Apps multihoming after API innovations increases when it faces greater competition from new entrants. Second, we measured the adaptation challenges faced by an App by quantifying its interdependencies with core components as the extent of its usage of various core component APIs. We interacted the variable *Platform component usage* with variables *Treated App* and *Post.* As reported in Model 30, the coefficient for the interaction term is positive (0.003, p-value < 0.01), indicating that the likelihood of treated Apps multihoming after API innovations is higher when their design uses a greater number of core component APIs.

(Insert Table 9 here)

Assessing the economic impact of multihoming on the platform

We also assessed the economic impact of multihoming for the focal platform firm – i.e., Apple - by first examining the revenue generation potential of those Apps that are more likely to enter the Android platform following changes in the iOS components that they use. We considered both modes by which Apps generate revenue within the Apple ecosystem: (1) price, that the App charges to the users to download and use the app, and, (2) in-app purchases, i.e., whether the App offers additional services or content that users can buy as they use it. It is important to note that both these modes of revenue generation are economically vital for Apple because it charges fees in the range of 15%-30% on all sales that Apps make. To assess the likelihood of Apps with these two modes of revenue generation multihoming after changes to iOS components, we interacted the two corresponding variables (i.e., *Price* and *In-app purchases*) with the *Post* and *Treated App* variables. These results, reported in Table 10 in Models 30 and 31, show that Apps with higher prices and those that offer in-app purchases are both more likely to multi-home following the changes to iOS components that they use. These findings suggest that the complementor diversification across platforms, spurred by core component innovations, can have significant economic consequences for the platform owner.

Second, because the cross-side network effects (and not simply revenues) created by complementors are vital for the platform's growth, we also assessed the impact of multihoming on user engagement. We measured user engagement by the number of reviews that an App receives in a given month. We then interacted this monthly measure of user engagement with *Post* and *Treated App* variables and found that Apps with greater user engagement are more likely to enter the competing platform after changes to core iOS components they use (Model 32, Table 10).

(Insert Table 10 here)

Finally, we also examined the net effect of the new Apps entering the focal platform and existing Apps multihoming to the competing platform by comparing the platform-level user engagement for the focal platform three months before and after the introduction of each new version of the iOS core components. We measured the platform-level user engagement as the average number of reviews received by an App in a given month. As shown in Table 11, the average user engagement declined by 8.6 percent over this six-month period. The decline in user engagement is most likely driven by the dual effect of core component changes: new apps need time to generate user engagement and existing apps with higher user engagement are multihoming to the competing platform.

(Insert Table 11 here)

DISCUSSION

As firms rapidly shift from product-based to platform-based strategies, they are increasingly reliant on complementors to co-create value (Wareham et al., 2014; Baldwin, 2018; Gawer and Henderson, 2007; Van Alstyne et al., 2016). In such platform-based ecosystems, the platform firms provide the core technological components and the complementors innovate using these components (McIntyre and Srinivasan, 2017). Because the network effects generated from the availability and variety of such complements helps the ecosystem attract and grow users, the success of platform firms is heavily reliant on the active engagement and related innovations of complementor firms (Eisenmann et al., 2011; Iansiti and Levin, 2004). In competitive settings, a particular platform firm's network advantage critically depends on its superior ability (vis-à-vis other platform firms) to externalize large scale innovation across these independent firms, outside of a formal authority structure (Gulati et al., 2012), yet without incurring substantial transaction costs in the process (Parker et al, 2016). To accomplish this, most platform firms rely on standardized interfaces and technology-based solutions such as Application Programming Interfaces (APIs) to enable complementors to recombine their core technology on a massive scale. These solutions allow the platform firm to manage the network of complementors without incurring substantial negotiation, monitoring and coordination costs typically faced in traditional organizational arrangements (e.g. Argyres, 1999).

Against the backdrop of these widely touted merits of platform-based ecosystems, our study was motivated on a fundamental tension that remains unaddressed in strategy research on ecosystems and platforms: how does the instability precipitated by the platform firm's ongoing innovations to its core platform components, alter existing complementors' technological and competitive environments, and, consequently, how do these dynamics affect their actions and engagement on the platform? This tension is rooted in our observation that the standardized rules or uniform digital interfaces between platform firm and complementors, are more akin to what we see in marketplace contexts, where complementarities are generic and static, and where explicit coordination is therefore unnecessary. However, this is at odds with both the theory of ecosystems and their compositions in practice. Platform-based ecosystems have been conceptualized in the literature as ongoing organizing contexts that are characterized by "non-generic complementarities" that require explicit coordination to achieve appropriate alignment across relevant actors (Jacobides et al., 2019; Adner, 2017). In these conceptualizations, as Jacobides et al. (2018) underscore, "[M]odularization and the subsequent reduction of frictional transaction costs are more likely to lead to the emergence of markets. For ecosystems to [continue to] be useful, there must also exist a significant need for coordination that cannot be dealt with in markets, but which also does not require the fiat and authority structure of a central actor" (Jacobides et al., 2018: pg. 2260). These notions are indeed mirrored in practice; even in ecosystems with standardized rules of interaction (for e.g., Android, Apple iOS or Slack), complementors are heterogeneous, and are required to make "some [distinctive] investment that is not fully fungible" within the framework of the platform's rules and interfaces in order to create value for end consumers (Jacobides et al., 2018: pg. 2265). At the same time, they must adapt in an environment where the platform firm retains flexibility to augment these core components and rules in order to respond to changing technology and/or market conditions (Kapoor and Agarwal, 2017).

We argued that the above considerations open up the possibility that a contemporary platform-based approach of organizing, which relies on a platform firm orchestrating alignment through a standardized set of ecosystem rules for all complementors, faces limits to its effectiveness. While standardized solutions allow the platform firm to generate large-scale network effects without incurring significant transaction costs, the challenge of coordinating to generate *non-generic* complementarities remains (Jacobides et al., 2018; Adner, 2017). On the one hand, the complementors that participate in the ecosystem need to make non-fungible investments within the framework of the platform's rules and interfaces to create value, and depend on the stability of these rules and indeed the predictability of their own competitive conditions to appropriate value. But, on the other hand, the platform firm needs to continuously adapt its core components to respond to changing technology, demand and competitive conditions (Kapoor and Agarwal, 2017). As Helfat and Raubitschek (2018) note, "as a consequence of the pace of change and the pressure of competition, platform leaders must continually innovate and redesign…extremely complex tasks given the number of actors involved, the multi-faceted characteristics of these ecosystems, and high uncertainty" (Helfat and Raubitschek (2018), p. 1391). This, in turn, limits the effectiveness of the platform's standardized interfaces as a coordinating mechanism. Therefore, in this paper, our goal was to shed light on these limits by assessing the impact of the ongoing evolution of a platform's core components on the subsequent choices made by complementors participating in its ecosystem.

We tested our arguments in the context of Apple's iOS ecosystem, where Apple periodically introduces innovations in the core components of the iOS platform. Our unique dataset and DID design allowed us to precisely identify those core components of the platform that were altered with the introduction of new generations of iOS and also identify those complementors (i.e., the Apps) that were impacted by the changes. We found that the evolution and the ongoing innovations of these core components act as a double-edged sword for the platform owner. On the one hand, changes in the core components increased the potential for novel complementarities and thereby triggered existing complementors to innovate to respond to the opportunities. On the other hand, they also dampened the value that existing complementors could appropriate, precisely by enabling new complementor entrants to compete and by imposing additional costs of adapting an existing complement to an altered set of standardized rules. However, the implication of these dynamics is particularly concerning for platform firms as we found that existing complementors that face greater adaptation challenges and more intense competition diversified into competing platforms. Moreover, the likelihood of such diversification was significantly higher for complementors with higher revenue generating potential and greater user engagement, indicating a tangible economic impact. Thus the platform firm's key source of differentiation – the variety and uniqueness of its complementors that constitutes its network advantage – is blunted by these complementor moves.

Our paper contributes to the emerging literature on platform-based ecosystems as well as the literature on technology management. First, we highlight the limits of standardized rules and interfaces used by platform firms to generate network effects. We show that even standardized rules, when changed, can create significant adaptation hurdles for the complementors and ultimately spur them to diversify to a competing platform. Indeed, our findings underscore the strategic implications of the platform's design and the extent to which its architecture is truly modular and stable. The platform firm's design challenge is to identify specific modules and interfaces that correspond to core functions so as to minimize cross modular interdependencies, enable the discovery of novel complementarities and facilitate rapid innovation by third-party complementor firms. However, we highlight that this design problem is not simply a technical one, but one that has substantial strategic implications. A well-designed set of modules and interfaces will allow a diverse set of complementors with heterogeneous innovation capabilities to devise complementary innovations that substantially boost the ecosystem's value creation potential. Concomitantly, such a design will also allow the platform firm to protect and control its critical intellectual property, yet sustain participation and investments by complementor firms (Wareham, Fox and Giner, 2014). Conversely, an inferior design may either stymie growth by creating more complex interdependencies that are difficult for complementors to navigate, or limit the innovation performance of complementors altogether and motivate them to explore alternate, competing platforms.

Second, while the primary focus of the extant literature on platforms has been on the generation of network effects during the nascent stages of a platform, our results highlight the challenges associated with maintaining these network effects over subsequent phases. Indeed, our findings call into question the notion that network effects protect established platform firms' competitive advantages. As Cusumano et al (2020) note, "strong network effects, have been increasingly difficult to attain because of multihoming (the ability of platform users and complementors to access more than one platform for the same purpose)" (Cusumano, Yoffie and

Gawer, 2020: p.30). Our paper shows the underlying drivers of multihoming, and consequently the loss of network effects, are in part driven by the changes made by the platform owner over time. In doing so, we also respond to calls for studying evolving platform governance strategies over time (Rietveld and Schilling, 2021).

Third, we also contribute to the modularity literature by showcasing the evolutionary dynamics and challenges of co-innovation even in highly modular inter-organizational contexts where modularity, in theory, is supposed to buffer the effects of technological change (Baldwin, 2022; Baldwin and Clark, 2000). Our paper highlights that modular solutions, even well designed ones as is the case with Apple – a clear industry leader, are imperfect.

Finally, we contribute to the literature on technology management by highlighting how the evolution of one technology can affect related innovations that leverage that technology. Overall, our findings have an important managerial implication. They strongly suggest that contrary to conventional wisdom, platform-based contexts are not necessarily "winner-take-all" markets. The evolution of the platform and the need for even a leading platform firm to alter its core components, can open up opportunities for competing platforms and indeed more traditional non-platform based organizations with hybrid solutions to devise appropriate governance structures and rules in order to create comparable, differentiated network effects.

Limitations and directions for future research

The findings of this study are subject to several limitations that provide opportunities for future research. First, the empirical context for the study is a single platform. While the iOS platform is one of the most valuable platforms globally, with Apple being one of the most successful platform owners, the validity of our findings should be examined in other settings.

Second, the peculiarity of our empirical context imposes specific boundary conditions. Since the iOS platform is the leading platform in the smartphone industry, the findings might not be generalizable to platforms that are not leaders in their industry. Future work can therefore shed greater light on how complementors' actions in response to core component innovation are also shaped by the competitive positioning of the focal platform. Another important boundary condition for our findings is that the smartphone industry is dominated by two platforms. Therefore, the validity of our findings in contexts with more than two platforms needs to be established. Future work can study contexts with more than two platforms to understand how fragmented competition among platforms might shape complementor reactions to changes in core platform components.

Third, our findings are based on an innovation platform where complementors use the platform components to develop their products. It will be fruitful for future work to explore the implications of platform-level innovations on peer-to-peer transaction platforms such as Venmo and Uber.

Finally, in our empirical setting, core component innovations were not pre-coordinated with the complementors because Apple is highly secretive about its technological development and did not provide advance information about upcoming changes to App developers. However, in other platform settings, such as Microsoft Windows, platform firms coordinate changes with complementors by providing access to core component innovations prior to the actual release.

Despite these restrictions stemming from our choice of empirical context, this study is among the first to shed light on the limitations of the platform-based approach of organizing co-innovation that is reliant on standardized interfaces and rules. While on the one hand, standardized interfaces help in kickstarting network effects, on the other hand they also pose challenges in maintaining those network effects as the platform owner needs to innovate the core components in order to continue to grow and develop the ecosystem.

REFERENCES

Adner R. 2017. Ecosystem as structure: an actionable construct for strategy. *Journal of Management*, *43*(1):39-58.

Adner R, Kapoor R. 2010. Value creation in innovation ecosystems: How the structure of technological interdependence affects firm performance in new technology generations. *Strategic. Manage. J.*, *31*(3):306-333.

Afuah, A., 2001. Dynamic boundaries of the firm: are firms better off being vertically integrated in the face of a technological change?. *Academy of Management Journal*, 44(6), pp.1211-1228.

Agarwal S, Kapoor, R. 2022. Value Creation Tradeoff in Business Ecosystems: Leveraging Complementarities While Managing Interdependencies. *Organization Science*.

Angrist JD, Pischke JS. 2009. Mostly harmless econometrics: An empiricist's companion. *Princeton university press*.

Argyres, NS. 1999. The impact of information technology on coordination: Evidence from the B-2 "Stealth" bomber. *Organization Science*, 10(2), 162-180.

Baldwin CY & Clark KB. 2000. Design rules: The power of modularity (Vol. 1). MIT press.

Baldwin CY. 2012. Organization design for business ecosystems, *Journal of Organization Design*, 1(1).

Baldwin CY. 2021. Platform systems vs. step processes—The value of options and the power of modularity. Design rules, 2: 19-073.

Barach MA, Kaul A, Leung MD, Lu S. 2019. Strategic redundancy in the use of big data: Evidence from a two-sided labor market. *Strategy Science,* 4(4), 298-322.

Boudreau, K. 2010. Open platform strategies and innovation: Granting access vs. devolving control. *Management Science*, 56(10), 1849-1872.
Boudreau K. 2012. Let a thousand flowers bloom? An early look at large numbers of software App developers and patterns of innovation. *Organization Science*, 23(5): 1409-1427.
Cennamo, C., & Santalo, J. 2013. Platform competition: Strategic trade-offs in platform markets. *Strategic management journal*, 34(11):1331-1350.
Cennamo, C., & Santaló, J. 2015. How to avoid platform traps. MIT Sloan Management Review, 57(1), 12.
Cusumano, M., Yoffie, D., & Gawer, A. (2020). The future of platforms. *MIT Sloan Management Review*.
Cennamo C, Ozalp H & Kretschmer, T., 2018. Platform architecture and quality trade-offs of multihoming complements. *Information Systems Research*, 29(2): 461-478.
Dyer, J.H., 1997. Effective interim collaboration: how firms minimize transaction costs and maximise transaction value. *Strategic Management Journal*, 18(7), pp.535-556.
Dyer, J.H. and Singh, H., 1998. The relational view: Cooperative strategy and sources of interorganizational competitive advantage. Academy of management review, 23(4), pp.660-679.
Economides, N, Katsamakas, E. 2006. Two-sided competition of proprietary vs. open source technology platforms and the implications for the software industry. *Management science*, 52(7):1057-1071.
Eisenmann T, Parker G, & Van Alstyne, MW. 2006. Strategies for two-sided markets. *Harvard business review*, 84(10): 92.
Eisenmann T, Parker G, Van Alstyne M. 2011. Platform envelopment. *Strategic management J.32*(12), 1270-1285.
Fang, T.P., Wu, A, Clough, D.R.. 2021. Platform diffusion at temporary gatherings: Social coordination and ecosystem emergence. *Strategic Management Journal*, 42(2):.233-272.
Ganco, M., Kapoor, R., & Lee, G. K. (2020). From rugged landscapes to rugged ecosystems: Structure of interdependencies and firms' innovative search. Academy of Management Review, 45(3), 646-674.
Gawer A, Cusumano M. 2002. *Platform leadership: How Intel, Microsoft, and Cisco drive industry innovation* (Vol. 5: 29-30). Boston, MA: Harvard Business School Press.
Gawer A, Henderson R. 2007. Platform owner entry and innovation in complementary markets: Evidence from Intel. *Journal of Economics & Management Strategy*, *16*(1):1-34.
Giustiziero G, Kaul A, Wu B. 2019. The dynamics of learning and competition in Schumpeterian environments. *Organization Science*, (4):668-93.
Gulati R, Puranam P, Tushman M. 2012. Meta-organization design: rethinking design in interorganizational and community contexts. *Strategic Management Journal*, 33(6):571-586.
Gulati, R., & Singh, H. (1998). The architecture of cooperation: Managing coordination costs and appropriation concerns in strategic alliances. Administrative science quarterly, 781-814.
Gulati R, Lavie D & Singh H., 2009. The nature of partnering experience and the gains from alliances. *Strategic management journal*, 30(11):1213-1233.
Hagiu A. 2007. Merchant or two-sided platform?. *Review of Network Economics*, 6(2).
Hagiu, A., 2009. Two-sided platforms: Product variety and pricing structures. *Journal of Economics & Management Strategy*, 18(4), pp.1011-1043.
Helfat, C. E., & Raubitschek, R. S. (2018). Dynamic and integrative capabilities for profiting from innovation in digital platform-based ecosystems. *Research policy*, 47(8), 1391-1399.
Hannah, D.P., Eisenhardt, K.M. 2018. How firms navigate cooperation and competition in nascent ecosystems. *Strategic Management Journal*, 39(12), 3163-3192.
Henderson, R. M., & Clark, K. B. (1990). Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. *Administrative science quarterly*, 9-30.
Hoetker G., 2007. The use of logit and probit models in strategic management research: Critical issues. *Strategic management journal*, 28(4):331-343.
Iansiti M, Levien R. 2004. *The keystone advantage: what the new dynamics of business ecosystems mean for strategy, innovation, and sustainability*. Harvard Business Press.
Jacobides M, Cennamo C, Gawer A. 2018. Towards a theory of ecosystems. *Strat. Manag. Jour.*, *39*(8): 2255-2276.
Kapoor R. 2018. Ecosystems: broadening the locus of value creation. *Journal of Org. Design*, *7*(1), p.12.
Kapoor R, Agarwal S. 2017. Sustaining superior performance in business ecosystems: Evidence from application software developers in the iOS and Android smartphone ecosystems. *Org. Science*, *28*(3): 531-551.

Katz, M.L. and Shapiro, C., 1985. Network externalities, competition, and compatibility. *The American economic review*, 75(3), pp.424-440.
Keith, D.R, Rahmandad, H.2019. Are On-Demand Platforms Winner-Take-All Markets?. *Academy of Management Proceedings*, 1.
Lang LH, Stulz RM. 1994. Tobin's q, corporate diversification, and firm performance. *Journal of political economy*, 102(6). 1248-1280.
Levinthal, D. A. (1997). Adaptation on rugged landscapes. Management science, 43(7), 934-950.
McIntyre DP, Srinivasan A. 2017. Networks, platforms, and strategy: Emerging views and next steps. *Strategic management journal*, *38*(1): 141-160.
Mora R, Reggio I. 2015. didq: A command for treatment-effect estimation under alternative assumptions. *The Stata Journal*, 15(3).796-808.
Morris CR, Ferguson CH. 1993. How architecture wins technology wars. *Harvard Business Review*, 71(2): 86-96.
Monteverde, K., & Teece, D. J. (1982). Supplier switching costs and vertical integration in the automobile industry. The Bell Journal of Economics, 206-213.
Parker G, Van Alstyne M. 2005. Two-sided network effects: A theory of information product design. *Management science*, *51*(10): 1494-1504.
Parker GG, Van Alstyne MW & Choudary SP. 2016. *Platform revolution: How networked markets are transforming the economy and how to make them work for you*. WW Norton & Company.
Pierce, L., 2009. Big losses in ecosystem niches: How core firm decisions drive complementary product shakeouts. Strategic Management Journal, 30(3), pp.323-347.
Panico, C., & Cennamo, C. (2022). User preferences and strategic interactions in platform ecosystems. Strategic Management Journal, 43(3), 507-529.
Rambachan A, Roth J. 2019. An honest approach to parallel trends. Working Paper.
Ranganathan, R. and Rosenkopf, L., 2014. Do ties really bind? The effect of knowledge and commercialization networks on opposition to standards. *Academy of Management Journal*, 57(2), pp.515-540.
Rietveld J, & Eggers JP. 2018. Demand heterogeneity in platform markets: Implications for complementors. *Organization Science*, 29(2):304-322.
Rietveld J, Schilling MA. 2021. Platform competition: A systematic and interdisciplinary review of the literature. *Journal of Management*, 47(6),1528-1563.
Sanchez R. & Mahoney JT. 1996. Modularity, flexibility, and knowledge management in product and organization design. *Strategic management journal*, 17(S2):63-76.
Schilling M. 1999. Winning the standards race: Building installed base and the availability of complementary goods. *European Management Journal*, *17*(3):265-274.
Schilling M. 2002. Technology success and failure in winner-take-all markets: The impact of learning orientation, timing, and network externalities. *Academy of Management Journal*, *45*(2):387-398.
Shapiro C, Varian HR. 1998. Information Rules: A Strategic Guide to the Network Economy. *Harvard Business School Press*: Cambridge, MA.
Simon HA. 1955. A behavioral model of rational choice. *The quarterly journal of economics*, 69(1), 99-118.
Simon HA. 1962. The architecture of complexity. *Pro-ceedings of the American Philosophical Society,* 156: 467–482
Teece DJ. 1986. Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research policy*, 15(6), 285-305.
Teece DJ. 2018. Profiting from innovation in the digital economy: Enabling technologies, standards, and licensing models in the wireless world. Research policy, 47(8), 1367-1387.
Van Alstyne MW, Parker GG & Choudary SP. 2016. Pipelines, platforms, and the new rules of strategy. *Harvard business review*, 94(4): 54-62.
Wareham J, Fox P, Cano Giner J. 2014. Technology ecosystem governance. *Organization Science*, *25*(4):1195-1215.
West J. 2003. How open is open enough?: Melding proprietary and open source platform strategies. *Research policy*, 32(7): 1259-1285.
Williamson, O. E. (1971). The vertical integration of production: market failure considerations. The American Economic Review, 61(2), 112-123.
Zollo M, Reuer JJ & Singh H. 2002. Interorganizational routines and performance in strategic alliances. *Organization science*, 13(6):701-713.
Zhu F, Iansiti M. 2012. Entry into platform-based markets. *Strategic Management Journal*, *33*(1):88-106.

FIGURES AND TABLES

Figure 1: New Apps installing SDKs (Difference between treated and control groups)

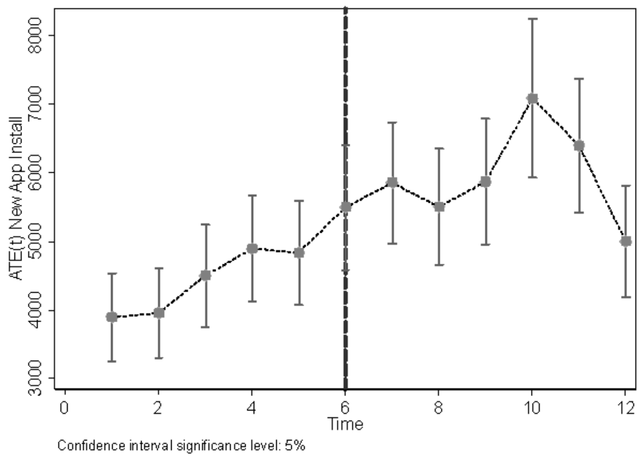


Figure 2: Existing Apps installing SDKs (Difference between treated and control groups)

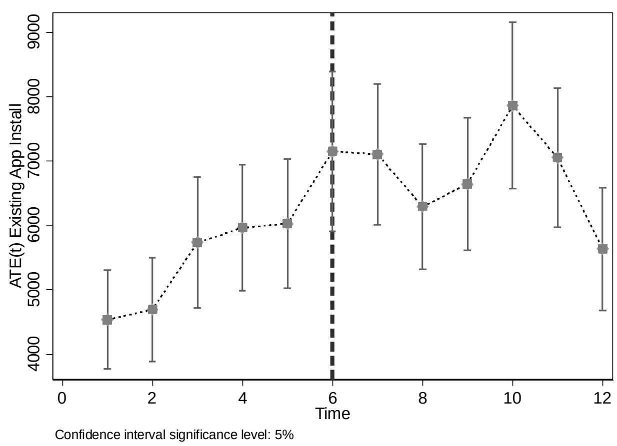


Figure 3: Percentage of Apps multihoming before and after the change

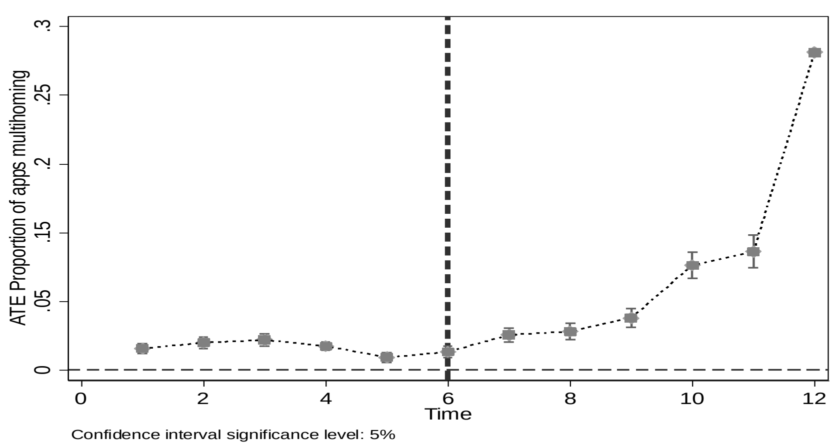
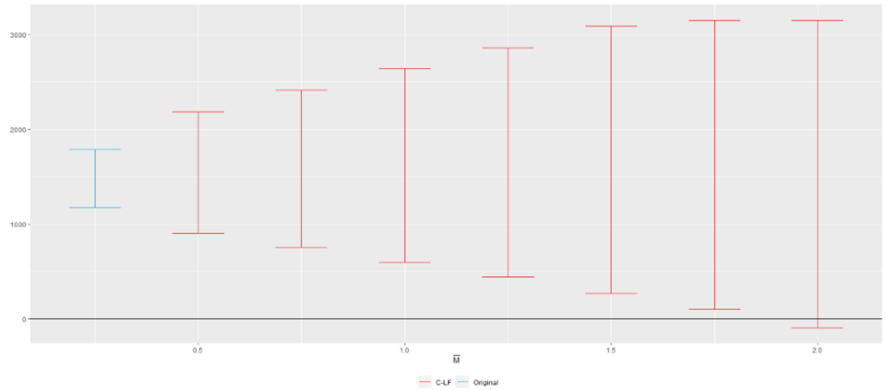
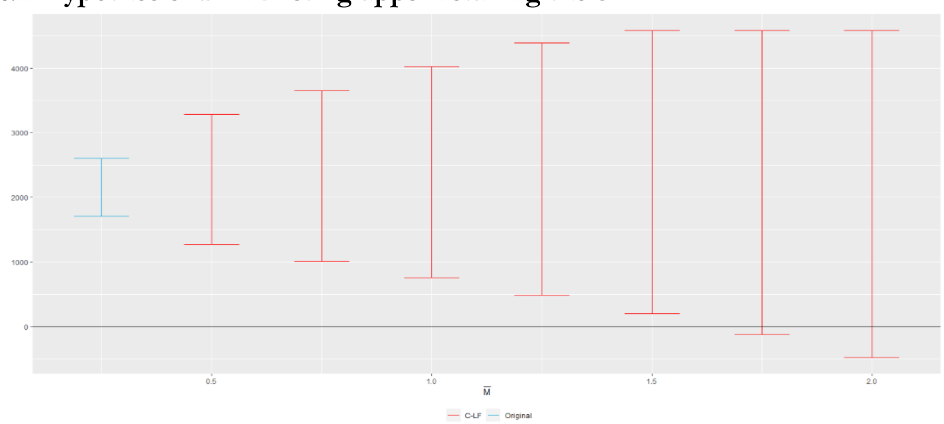


Figure 4: Sensitivity graph for violation of parallel trend assumption, applying the method from Rambachan and Roth (2019).

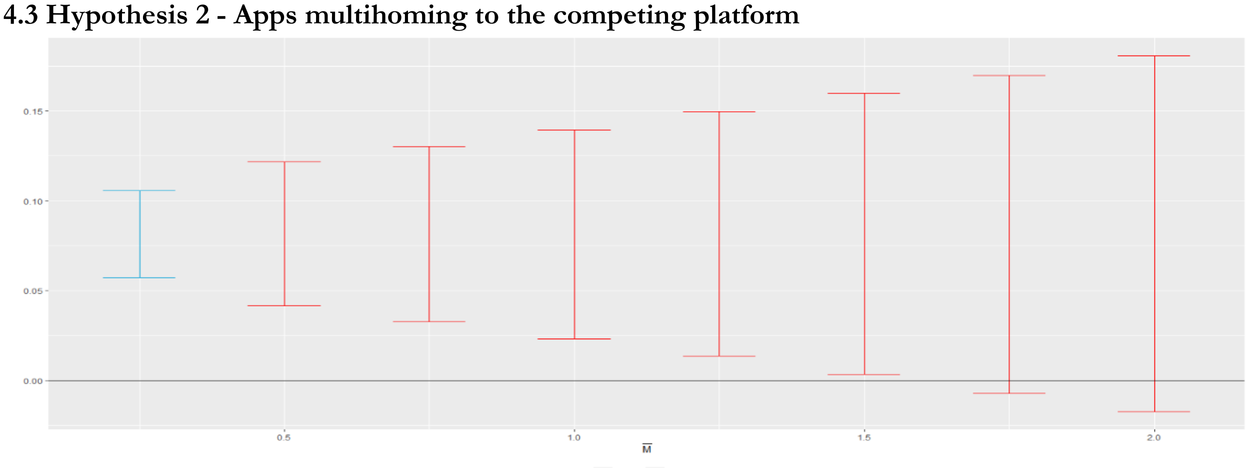
4.1 Hypothesis 1a - New apps installing the SDK



4.2 Hypothesis 1b - Existing apps installing the SDK



4.3 Hypothesis 2 - Apps multihoming to the competing platform



Notes: The graph plots the confidence interval for the treatment effect of changes in platform core components for the corresponding dependent variable allowing for a non-linearity in differential trends in the post-treatment period that is about $\overline{M}$ times the maximum observed non-linearity in the pre-treatment period.

Figure 5: Propensity score of treatment (APIs that are changed) and control groups (APIs that were not changed) before and after matching

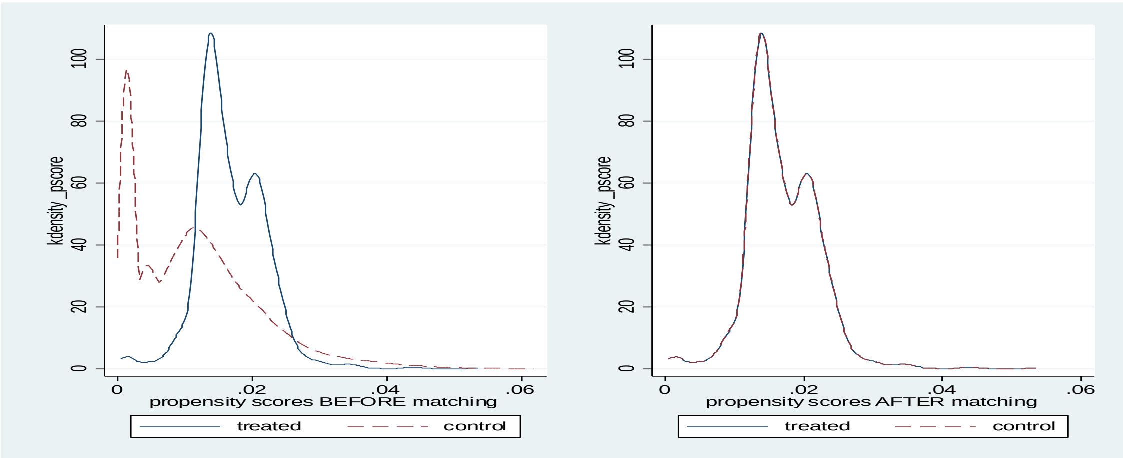


Figure 6: Propensity score of treatment (Apps using changed APIs) and control (Apps not using changed APIs) groups before and after matching

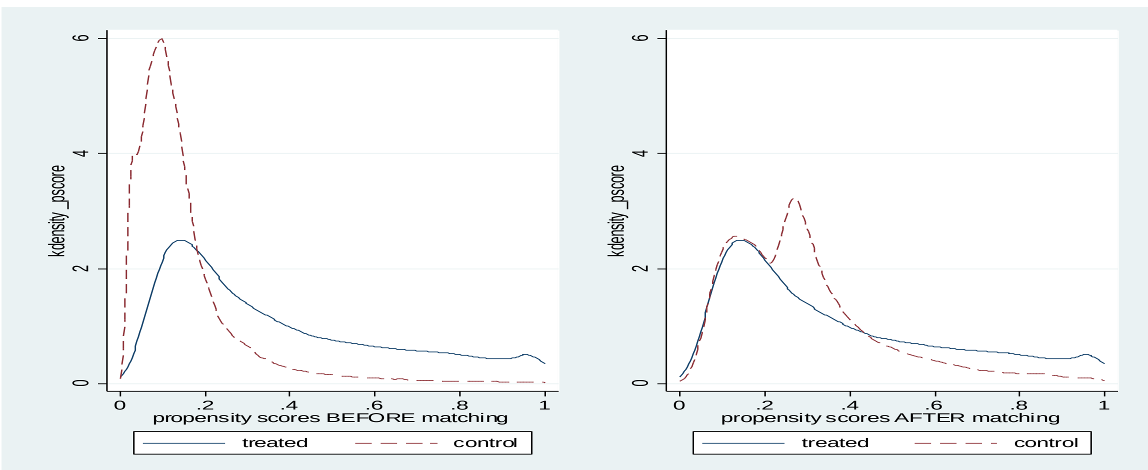


Table 1: Descriptive statistics and Correlation for Hypothesis 1b (New Apps API install)

#	Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10
1	New app (API install)	1480.15	1131.73	1.000									
2	Treated API	0.01	0.11	0.575	1.000								
3	Post	0.54	0.50	0.013	-0.006	1.000							
4	Avg Rating	2.87	1.75	0.072	0.058	0.024	1.000						
5	Avg In-App	0.39	0.39	0.041	0.044	-0.018	0.265	1.000					
6	Avg Review Count (1000s)	0.61	6.84	-0.007	-0.004	-0.002	0.059	0.049	1.000				
7	Avg Size	54.63	65.39	-0.001	-0.005	0.027	0.215	0.153	0.111	1.000			
8	Avg Price	2.32	248.62	0.000	0.000	-0.005	0.004	0.004	0.000	-0.001	1.000		
9	Avg Content Rating	197.66	122.01	-0.008	-0.022	0.012	0.079	0.027	0.028	0.131	-0.002	1.000	
10	Avg Platform Component	0.86	0.42	-0.004	0.009	0.011	0.051	0.116	0.031	0.116	0.001	0.031	1.000

Table 2: Descriptive statistics and Correlations for Hypothesis 1b (Existing Apps API install)

#	Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10
1	Existing app (API Install)	1733.15	1354.43	1.000									
2	Treated API	0.01	0.11	0.567	1.000								
3	Post	0.54	0.50	0.011	-0.006	1.000							
4	Avg Rating	2.87	1.75	0.071	0.058	0.024	1.000						
5	Avg In-App	0.39	0.39	0.039	0.044	-0.018	0.265	1.000					
6	Avg Review Count (1000s)	0.61	6.84	-0.006	-0.004	-0.002	0.059	0.049	1.000				
7	Avg Size (MB)	54.63	65.39	0.002	-0.005	0.027	0.215	0.153	0.111	1.000			
8	Avg Price	2.32	248.62	0.000	0.000	-0.005	0.004	0.004	0.000	-0.001	1.000		
9	Avg Content Rating	197.66	122.01	-0.006	-0.022	0.012	0.079	0.027	0.028	0.131	-0.002	1.000	
10	Avg Platform Component	0.86	0.42	-0.004	0.009	0.011	0.051	0.116	0.031	0.116	0.001	0.031	1.000

Table 3: Descriptive Statistics and Correlations for Hypothesis 2 (Apps multihoming)

S.No.	Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10	11
1	Multihoming	0.03	0.16	1.000										
2	Treated App	0.01	0.08	-0.005	1.000									
3	Post	0.55	0.50	0.003	0.002	1.000								
4	Review count (1000s)	0.07	0.72	-0.009	-0.003	0.004	1.000							
5	In-app	0.39	0.49	-0.067	-0.059	0.027	0.062	1.000						
6	Price	1.24	299.82	0.001	0.000	0.000	0.000	0.002	1.000					
7	Size(MB)	50.53	90.70	-0.025	0.006	0.010	0.045	0.172	0.000	1.000				
8	Content Rating	172.68	147.39	-0.008	0.017	0.002	0.015	0.027	-0.002	0.059	1.000			
9	Avg Rating	2.51	3.32	-0.002	0.001	0.001	0.239	0.016	0.000	0.034	0.003	1.000		
10	Promoted	0.00	0.03	-0.002	-0.002	0.001	0.113	0.020	0.000	0.068	0.004	0.037	1.000	
11	Use platform component	0.75	0.43	-0.057	-0.008	0.023	0.018	0.078	-0.001	0.093	0.010	0.008	0.014	1.000

Table 4: New Apps installing the APIs, before and after the change (API Fixed Effect OLS)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	W/o control	Full Model	Placebo	Time-interaction	Matching	Continuous treatment	3-month window	Log DV
Post	24.150	53.129		38.545	1,297.304	66.416	2.109	0.284
	(1.629)	(6.401)		(4.788)	(386.109)	(7.837)	(4.014)	(0.011)
Treated API# Post	1,419.523	1,425.097		2,751.328	1,510.148		1,020.945	0.181
	(146.387)	(146.612)		(494.387)	(224.890)		(100.347)	(0.034)
Total API						-0.066		
						(0.322)		
Total API# Post						0.933		
						(0.330)		
Post_Placebo			-30.660					
			(3.813)					
Treated API# Post Placebo			-1,152.287					
			(98.666)					
Avg Rating		-1.853	-2.074	-0.959	-203.234	-2.331	-0.731	0.053
		(0.169)	(0.178)	(0.149)	(73.286)	(0.198)	(0.105)	(0.001)
Avg In-App		-4.436	-4.013	-2.800	86.009	-4.706	-0.755	0.105
		(0.692)	(0.676)	(0.685)	(315.360)	(0.687)	(0.472)	(0.005)
Avg Review Count (1000s)		-0.007	0.017	0.017	8.940	0.021	0.003	-0.003
		(0.025)	(0.024)	(0.017)	(9.940)	(0.019)	(0.017)	(0.000)
Avg Size (MB)		-0.023	-0.019	-0.028	-9.134	-0.020	-0.017	-0.001
		(0.009)	(0.009)	(0.016)	(1.919)	(0.008)	(0.003)	(0.000)
Avg Price		0.000	-0.000	-0.000	0.375	-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)	(0.590)	(0.000)	(0.000)	(0.000)
Avg Content Rating		-0.000	0.001	-0.001	-1.033	0.001	-0.003	-0.000
		(0.002)	(0.002)	(0.002)	(1.625)	(0.002)	(0.001)	(0.000)
Avg platform component		-4.167	-3.153	-2.764	306.240	-3.292	0.303	-0.078
		(0.802)	(0.745)	(0.905)	(321.356)	(0.727)	(0.629)	(0.006)
Constant	123.315	186.344	208.568	182.883	5,668.491	186.639	147.538	2.243
	(1.337)	(3.113)	(3.139)	(2.239)	(532.957)	(2.875)	(3.388)	(0.008)
API FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	221,655	221,655	221,655	221,655	23,956	221,655	128,804	221,655
R-squared	0.100	0.113	0.080	0.350	0.459	0.027	0.156	0.168
Number of APIs	13,936	13,936	13,936	13,936	2007	13,936	13,936	13,936

Robust standard errors in parentheses

Table 5: Existing Apps installing the APIs before and after the change (API Fixed Effect OLS)

VARIABLES	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	W/o control	Full model	Placebo	Time interaction	Matching	Continuous treatment	3-month window	Log DV
Post	25.044	20.654		29.833	-978.140	33.823	-31.017	0.131
	(2.169)	(7.737)		(6.077)	(440.843)	(8.393)	(7.451)	(0.011)
Treated API * Post	1,419.632	1,425.388		407.187	1,602.677		1,117.190	0.200
	(178.491)	(179.270)		(60.077)	(291.609)		(144.598)	(0.035)
Total API						-0.089		
						(0.363)		
Total API * Post						1.027***		
						(0.317)		
Post_Placebo			-30.660					
			(3.813)					
Treated API*Post Placebo			-1,152.287					
			(98.666)					
Avg Rating		-2.327	-2.074	-1.140	-282.591	-2.801	-1.148	0.076
		(0.199)	(0.178)	(0.176)	(89.205)	(0.231)	(0.135)	(0.001)
Avg In-App		-2.482	-4.013	-1.378	432.380	-2.754	1.363	0.145
		(0.959)	(0.676)	(0.914)	(401.160)	(0.951)	(0.685)	(0.005)
Avg Review Count		-0.000	0.017	-0.000	-19.151	0.028	-0.003	-0.001
		(0.029)	(0.024)	(0.000)	(14.552)	(0.025)	(0.025)	(0.000)
Avg Size		-0.027	-0.019	-0.000	-9.931	-0.025	-0.018	-0.000
		(0.016)	(0.009)	(0.000)	(3.285)	(0.015)	(0.004)	(0.000)
Avg Price		-0.001	-0.000	-0.001	-2.563	-0.001	-0.001	-0.000
		(0.000)	(0.000)	(0.000)	(1.365)	(0.000)	(0.000)	(0.000)
Avg Content Rating		-0.003	0.001	-0.003	-1.587	-0.002	-0.007	-0.000
		(0.003)	(0.002)	(0.003)	(1.986)	(0.003)	(0.002)	(0.000)
Avg Platform Component		-3.319	-3.153	-2.727	384.333	-2.454	0.264	-0.109
		(1.032)	(0.745)	(1.087)	(379.127)	(0.942)	(0.806)	(0.005)
Constant	147.501	222.018	208.568	217.941	6,963.587	222.338	198.390	2.351
	(1.696)	(3.684)	(3.139)	(2.680)	(664.035)	(3.438)	(5.402)	(0.007)
R^2	0.064	0.074	0.080	0.285	0.388	0.020	0.079	0.195
API FE	YES	YES	YES	YES	YES	YES	YES	YES
Time Dummies	YES	YES	YES	YES	YES	YES	YES	YES
Total Observation	224,595	221,655	221,655	221,655	23,956	221,655	121,021	221,655
Number of APIs	13,936	13,936	13,936	13,936	2007	13,936	13,936	13,936

Robust standard errors in parentheses

Table 6: Apps multihoming before and after the API changes – LPM regression

	(17)	(18)	(19)	(20)	(21)	(22)
VARIABLES	Main Model	Placebo	Time interaction	Matching	Continuous	3-month window
Post	0.025		0.026	-0.017	0.026	0.349
	(0.001)		(0.001)	(0.000)	(0.001)	(0.005)
Treated App* Post	0.009		0.026	0.028		0.258
	(0.003)		(0.003)	(0.001)		(0.057)
Treated App (continuous)*Post					0.002	
		-0.002			(0.000)	
Post_Placebo		(0.001)				
		-0.006				
Treated App*Post_Placebo		(0.007)				
		0.0563				
Constant	0.045	(0.001)	0.045	0.037	0.0442	0.043
	(0.001)		(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.036	0.034	0.038	0.064	0.036	0.038
App Fixed effect	YES	YES	YES	YES	YES	YES
Time Dummies	YES	YES	YES	YES	YES	YES
Observations	1,871,739	1,871,739	1,871,739	890,509	1,871,739	1,871,739
Number of Apps	177,813	177,813	177,813	81,300	177,813	177,813

Robust standard errors in parentheses

Table 7: Apps multihoming before and after API changes: regressing each iOS version separately

	(23)	(24)	(25)	(26)
VARIABLES	iOS 9	iOS 8	iOS 7	iOS 6
Post	0.043	0.149	0.139	0.174
	(0.001)	(0.002)	(0.002)	(0.002)
Treated App#Post	0.020	0.129	0.227	0.119
	(0.001)	(0.008)	(0.036)	(0.068)
Constant	-0.0148	-0.032	-0.037	-0.028
	(0.000)	(0.001)	(0.001)	(0.001)
R^2	0.013	0.045	0.039	0.052
App Fixed Effect	YES	YES	YES	YES
Time Dummies	YES	YES	YES	YES
Observations	757,674	301,002	360,885	329,298
Number of Apps	68,090	29,903	36,610	31,982

Robust standard errors in parentheses

Table 8: Conditional Logit model for testing Apps multihoming before and after API changes

VARIABLES	(27)	(28)
Treated App	-0.315	
	(0.038)	
Post	21.853	22.046
	(0.060)	(0.042)
Treated App# Post	1.163	
	(0.084)	
Treated App (continuous)		-0.180
		(0.008)
Treated App (continuous)# Post		1.014
		(0.102)
Total New Apps (in 1000s)	-0.357	-0.349
	(0.020)	(0.022)
Review count (in 1000s)	0.023	0.029
	(0.005)	(0.010)
In-App purchases	-0.968	-1.010
	(0.058)	(0.064)
Price	-0.053	-0.078
	(0.031)	(0.030)
Average Rating	-0.000	-0.000
	(0.000)	(0.000)
Content Rating	-0.000	-0.000
	(0.000)	(0.000)
Promoted by Apple	-0.245	-0.217
	(0.442)	(0.489)
Use platform component	-0.797	-0.789
	(0.052)	(0.056)
Download Size	-0.000	-0.000
	(0.000)	(0.000)
Category Dummies	Yes	Yes
Observations	25,895	25,895
Number of Apps	25,895	25,895

Robust standard errors in parentheses

Table 9: Mechanism tests for Hypothesis 2: Competition and Adaptation costs

VARIABLES	(29) New entrant	(30) Platform component
Post	0.025	0.041
	(0.000)	(0.001)
Treated App# Post	0.009	0.012
	(0.003)	(0.006)
Post# New entrant	-0.002	
	(0.000)	
Treated App# Post# New entrant	0.001	
	(0.000)	
Post# Use platform component		-0.037
		(0.001)
Treated App# Post# Use Platform component		0.003
		(0.000)
Constant	0.045	0.045
	(-0.001)	(-0.001)
Observations	1,871,739	1,871,739
Number of Apps	177,813	177,813

Robust standard errors in parentheses

Table 10: Economic effect of multihoming of Apps

VARIABLES	(31) In-app purchases	(32) Price	(33) User Engagement
Post	-0.006	-0.017	-0.008
	(0.001)	(0.000)	(0.001)
Treated App# Post	0.022	0.028	0.012
	(0.001)	(0.001)	(0.001)
Post# New entrant	-0.002		
	(0.000)		
Post# In-app purchases	-0.020		
	(0.001)		
Treated App# Post# In-app purchases	0.009		
	(0.001)		
Post# Price		-0.001	
		(0.000)	
Treated App# Post# Price		0.001	
		(0.000)	
Monthly Review			-0.000
			(0.000)
Treated App#Monthly Review			0.001
			(0.001)
Post# Monthly Review			0.001
			(0.000)
Treated App# Post # Monthly Review			0.008
			(0.003)
Constant	0.036	0.037	0.017
	(0.001)	(0.001)	(0.001)
Observations	1,871,739	1,871,739	289,827
Number of Apps	177,813	177,813	56,844

Robust standard errors in parentheses

Table 11: Overall effect on user engagement

	# of Observations	Mean	Std. Err.	Std. Dev
Post-shock	12	16.305	0.899	3.115
Pre-shock	12	17.837	0.575	1.991
Difference		-1.532	1.067 (p-value = 0.08)	