Sustaining Superior Performance in Business Ecosystems: Evidence from Application Software Developers in the iOS and Android Smartphone Ecosystems

Rahul Kapoor
The Wharton School
University of Pennsylvania
3620 Locust Walk, Philadelphia
PA 19104-6370, USA
Email: kapoorr@wharton.upenn.edu

Shiva Agarwal
The Wharton School
University of Pennsylvania
3620 Locust Walk, Philadelphia
PA 19104-6370, USA
Email: shivaaga@wharton.upenn.edu

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ABSTRACT

We study the phenomenon of business ecosystems in which a platform firm orchestrates the functioning of the ecosystem by providing a platform and setting the rules for other complementor firms to participate in it. We develop a theoretical framework to explain how the structural and evolutionary features of the ecosystem may shape the extent to which participating complementor firms can sustain their superior performance. The structural feature, which we refer to as ecosystem complexity, is a function of the number of unique components or subsystems that interact with the complementor's product. We incorporate the evolutionary features by considering the role of generational transitions initiated by platform firms over time as well as the role of complementors' ecosystem-specific experience. Evidence from Apple's iOS and Google's Android smartphone ecosystems supports our arguments that higher ecosystem complexity helps app developers sustain their superior performance, and that this effect is stronger for more experienced firms. In contrast, platform transitions initiated by Apple and Google make it more difficult for app developers to sustain their performance superiority, and that this effect is exacerbated by the extent of ecosystem complexity. The study offers a novel perspective on how the performance of complementor firms in business ecosystems may be shaped by the rules and actions of the central platform firms.

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Introduction

There is increasing recognition within the strategy field that the locus of value creation has shifted from focal firms to business ecosystems (Iansiti and Levien, 2004; Teece, 2007; Baldwin, 2012; Adner et al., 2013). Business ecosystems encompass different types of firms offering complementary products and who are connected through an underlying technical architecture. Often, such contexts are characterized by a firm that orchestrates the functioning of the ecosystem by providing a platform and setting the rules for other complementor firms to participate in it. Scholars exploring this phenomenon have tended to focus on the strategies and performance of platform firms (e.g., Gawer and Henderson, 2007; McIntyre and Subramaniam, 2009; Eisenmann et al., 2011; Zhu and Iansiti, 2012). Much less attention has been devoted to understanding the performance of the complementor firms who are critical to the value creation within the ecosystem.

In this study, we focus on the performance of complementor firms within an ecosystem. Specifically, we study the extent to which a high performing complementor can sustain its superior performance within an ecosystem. While sustainability of superior performance is a critical goal for managers and has been an important line of inquiry for strategy scholars (e.g., Porter, 1985; Rumelt et al., 1991), it is becoming increasingly difficult for firms to realize it (Wiggins and Ruefli, 2002; D'Aveni et al., 2010; McGrath, 2013). In the context of business ecosystems, sustainability of complementors' superior performance has important implications not only for the complementors but also for the platform firms whose performance is tied to that of their complementors.

To unpack the drivers of sustainability, we first consider the structure of the complementor's interdependence with other actors in the ecosystem. We characterize this structural feature based on the number of unique components or subsystems that interact with the complementor's product. For example, in the iOS smartphone ecosystem orchestrated by Apple (the platform firm), an application software (app) developer firm (the complementor) is interdependent on the specific handset and operating system combination offered by Apple. In contrast, in the Android smartphone ecosystem orchestrated by Google, an app developer is interdependent on many unique handset and operating system combinations offered by firms such as HTC, LG, Motorola and Samsung. We use the notion of ecosystem complexity to characterize this difference in the structure of interdependence for complementor firms. We then consider the role of generational transitions initiated by platform firms over time (e.g., introduction of new generation of operating system) as well as the role of complementors' ecosystem-specific experience.

Drawing on the evolutionary economics perspective (e.g., Nelson and Winter, 1982, 2002; Gavetti and Levinthal, 2004), we theorize performance dynamics among complementor firms to be shaped by firms searching for superior performance configurations as well as imitating the strategic configurations of higher performing firms (Levinthal, 1997; Rivkin, 2000; Zott, 2003; Lenox et al., 2006). We argue that greater ecosystem complexity makes it much more difficult for follower firms to search for configurations that yield superior performance and to imitate the configurations of the leader firms. Hence, complementor firms will find it easier to sustain their success when ecosystem complexity is high than when it is low.

We also argue that while experience in an ecosystem in general facilitates learning, generational transitions initiated by the platform firms typically requires complementors to reconfigure their products and may reduce the value of their accumulated learning. As a result, complementors' ability to sustain their superior performance will be facilitated by their experience and will be hampered by platform transitions. Finally, we consider how these effects are impacted by ecosystem complexity. We argue that higher ecosystem complexity will be associated with greater learning opportunities, and therefore, the benefit of experience will be greater when ecosystem complexity is high than when it is low. In contrast, during platform transitions, higher ecosystem complexity would make it more difficult for complementors to reconfigure and sustain their superior performance. Hence, the negative effect of such transitions on the sustainability of complementors' superior performance will be stronger when ecosystem complexity is high than when it is low.

We test our arguments on app developers that participate in Apple's iOS and Google's Android smartphone ecosystems within the U.S. market. The context provides a valuable opportunity to study complementors' performance dynamics in ecosystems with varying levels of complexity and subject to frequent platform transitions. The diversity in handsets and operating systems among the user base makes the Android ecosystem much more complex for app developers than the iOS ecosystem. While the contrast between iOS and Android is stark, we also observe varying levels of complexity within the Android ecosystem over time. In addition, we observe three episodes of platform transitions that entail major updates to the handset and the smartphone operating system.[1]

We assembled a unique panel dataset of top-performing app developers in the iOS and Android smartphone ecosystems over the two-year period from January 2012 to January 2014. To gain insights into the challenges of developing apps and competing in the iOS and the Android ecosystems, we also interviewed several executives and engineers from app developer firms. The analysis is based on the extent to which app developers sustain their superior performance by observing whether their apps continue to be in the top performance stratum in a given ecosystem (i.e., Top 500 apps by revenue). The research setting is hypercompetitive and, on average, a firm sustains its superior performance for only six months. Moreover, once a firm exits the top performance stratum in a given ecosystem, the likelihood of reappearance in the stratum is very low. Only 14% of exit events are followed by re-entry in the top performance stratum. Finally, 64% of top-performing firms participate in both the iOS and Android ecosystems, which helps us address endogeneity concerns due to firms self-selecting into a given ecosystem.

We find that higher ecosystem complexity increases app developers' likelihood of sustaining their performance superiority. However, generational transitions initiated by platform firms impede app developers' ability to sustain their superior performance, and that this effect is exacerbated by the extent of ecosystem complexity. Finally, we find that experience within an ecosystem helps app developers sustain their superior performance, and that this beneficial effect is more pronounced at higher levels of complexity.

[1] While smartphone is the dominant hardware for Android and iOS operating systems, these operating systems are also used in other hardware categories such as tablets and e-readers. In this study, we focus on the performance dynamics of app developer firms within only the Android and iOS smartphone ecosystems.

The study, while limited to a specific empirical context, offers one of the first detailed accounts of the drivers of complementors' performance within an ecosystem. A key aspect of the study is to characterize the structure of interdependence for complementor firms in terms of ecosystem complexity and show that this characterization helps explain the drivers of value appropriation among firms. We also illustrate how platform transitions and complementors' ecosystem experience impact the ease with which complementors can sustain their performance advantage, and how these effects vary at different levels of ecosystem complexity. In so doing, the study contributes to the emerging literature stream examining the challenges and opportunities faced by complementor firms in business ecosystems (e.g., Boudreau, 2010; Kapoor, 2013; Kapoor and Lee, 2013). By linking ecosystem-level complexity with firm-level search processes, the study is also among the first to offer systematic empirical evidence on one of the key tenet (i.e., the role of complexity on firm performance) within the evolutionary economics perspective of firms (e.g., Levinthal, 1997; Rivkin, 2000; Lenox et al., 2010). Finally, our findings contribute to the literature on the persistence of superior firm performance (e.g., Wiggins and Ruefli, 2002, 2005; D'Aveni et al., 2010) by highlighting how the specific features of the business ecosystem can impact sustainability of superior performance among complementor firms.

Literature Review and Hypotheses Development

There is growing recognition within the strategy field that firms are operating in the context of business ecosystems in which value is created through a network of firms offering complementary products and services. Often, business ecosystems are orchestrated by firms such as Apple, Cisco, Google, Intel, Microsoft, and SAP, which provide the central technological platform and set the rules for how complementor firms participate in it (e.g., Gawer and Cusumano, 2002; Iansiti and Levien, 2004). Scholars studying this phenomenon have explored how platform firms compete and manage their interdependence with complementors (e.g., Schilling, 2002; Gawer and Henderson, 2007; Boudreau, 2010; Eisenmann et al., 2011; Zhu and Iansiti, 2012). The emphasis has been on explaining how firms can create a platform, attract users and complementors, and achieve market dominance. Hence, the research so far has tended to focus on the strategies and performance of the unitary actor that orchestrates the business ecosystem. Much less attention has been devoted to understanding the performance consequences for complementors who typically represent a vast majority of firms in the ecosystem and who are critical to the total value created by the ecosystem.

In this study, we focus on the performance of complementor firms. In particular, we consider the problem of sustaining superior performance, and we explore the extent to which a high performing complementor can sustain its performance advantage within an ecosystem. Sustainability of superior performance is an important goal for managers (e.g., Porter, 1985), and it has been studied extensively by strategy scholars (e.g., Rumelt et al., 1991; Teece, 2007). However, recent empirical evidence suggests that it is becoming increasingly difficult for firms to sustain their superior performance (Wiggins and Ruefli, 2002; 2005; McGrath, 2013). For example, drawing on a comprehensive database of 40 industries from 1974 to 1997, Wiggins and Ruefli (2005) found that periods of persistent superior performance among firms have decreased over time. They found that this pattern is not only limited to high-technology or manufacturing industries but is also prevalent across a broad range of industries. Moreover, several scholars have underscored in general a lack of understanding of the reasons why the persistence of superior performance varies across different types of firms and industry environments (McGahan and Porter, 1997; Hoopes et al., 2003; D'Aveni et al., 2010). We theorize how complementor's sustainability of superior performance is impacted by two key features of the ecosystem.

First, we consider the structure of complementor's interdependence with other actors in the ecosystem based on the number of unique components and subsystems that interact with a complementor's product. We refer to this structural feature as ecosystem complexity. The greater the number of unique components and subsystems that interact with a complementor's product, the greater is the degree of ecosystem complexity faced by the complementor. Hence, depending on the architecture of the ecosystem, the same complementor may be subject to varying degrees of complexity across two different ecosystems (e.g., an app developer in iOS and Android smartphone ecosystems), or two different complementors may be subject to varying degrees of complexity within the same ecosystem (e.g., an app developer and a handset manufacturer within the Android smartphone ecosystem).[2] Figure 1 illustrates our approach of considering varying levels of ecosystem complexity faced by a complementor through a simple schema.

(Insert Figure 1 about here)

Second, we consider the evolutionary shifts in the ecosystem as a result of generational transitions initiated by platform firms (e.g., new generations of gaming consoles introduced by Sony, Nintendo, or Microsoft). These transitions represent a common means by which platform firms compete and create value over time. From a complementor's perspective, however, they necessitate significant adaptation, as complementors reconfigure their products to leverage the performance improvements accorded by the new generation of the platform.

We derive predictions regarding how structural complexity and platform transitions within an ecosystem impact a complementor's ability to sustain its superior performance. Given the importance of experience in shaping firms' performance outcomes across different types of industry environments (Dutton and Thomas, 1984; Balasubramanian and Lieberman, 2010), we also consider the effect of complementor's ecosystem experience across varying degrees of ecosystem complexity.

Our theoretical predictions stem from the evolutionary economics perspective of firms (e.g., Nelson and Winter, 1982, 2002; Levinthal, 1997; Gavetti and Levinthal, 2004). Drawing on this perspective, we consider the dual search processes of innovation and imitation as shaping performance dynamics among firms (e.g., Zott, 2003; Lenox et al., 2006). The first process, innovative search, is characterized by firms searching for superior solutions to a given problem and improving their performance over time (e.g., Levinthal, 1997). The second process, imitative search, represents firms'

[2] Since our emphasis in this paper is to explore the performance outcomes of complementor firms, we are considering the local structural complexity that the complementor firm is subjected to in a given ecosystem. A separate characterization can entail the complexity of the entire ecosystem. Note also, as these examples illustrate, ecosystem complexity that a given complementor is subjected to could be driven by the number of *actors* producing variants of the same *component*. It could also be driven by the underlying technical architecture such that a given complement may vary in the number of components that it interacts with. Our empirical context presents a nice setting in which ecosystem complexity is driven by the former while controlling for the latter.

attempting to imitate other high performing firms (e.g., Rivkin, 2000). We assume that complementor firms are continuously searching for superior performance configurations within an ecosystem. While search processes for complementors with inferior performance (follower firms) are more likely to be characterized by some combination of innovative and imitative search, the search processes for complementor firms with superior performance (leader firms) are more likely to be characterized by innovative search. We first explore the role of ecosystem complexity in impacting complementors' ability to sustain superior performance. We then examine the role of complementors' experience and platform transitions and how they interact with ecosystem complexity.

Ecosystem Complexity

To explain how ecosystem complexity influences complementor firms' sustainability of superior performance, we need to understand how ecosystem complexity impacts the search processes of firms in the ecosystem. As ecosystem complexity increases, complementors need to optimize their products so as to account for greater interdependence between their products and other components or subsystems within the ecosystem. For example, in our empirical context, the large variety of the handset and operating system combinations subjected app developers to significantly greater complexity in the Android ecosystem than in the iOS ecosystem. During our interviews, many executives and engineers from app developer firms emphasized this difference. The quote below from an engineer elucidates the difference:

> "We need to test our app on different OEM devices likes Samsung, HTC to make sure our app works on different Android devices.[3] This creates a lot of work for developer and testing teams. iOS does not have any such issue…this is our biggest technological challenge with Android."

From a theoretical perspective, greater ecosystem complexity subjects complementors to numerous interrelated design choices and decision variables (i.e., creates high level of interdependence). Under these conditions, the search for superior performance configuration by follower firms is difficult (e.g., Levinthal, 1997). This is because a high level of interdependence increases the number of possible

[3] OEM stands for Original Equipment Manufacturer. In our empirical context, it is used to refer to handset manufacturers.

combinations of decisions, which makes the search process intractable. Moreover, even if a follower firm is able to innovate and identify a higher performance configuration, it is more likely that the configuration represents a local optimum and may not lead to superior performance. Further, greater complexity also makes it difficult for follower firms to search by incrementally changing their decision variables. In enhancing the performance of one variable, managers often inadvertently undermine the performance of other variables.

Beyond searching for superior configurations through innovation, followers can also imitate leader firms. When ecosystem complexity is high, the focal firm with the leadership position is also protected against imitation in two ways. First, follower firms will find it difficult to decipher the exact configuration of the leader firm (Lippman and Rumelt, 1982; Rivkin, 2000). Second, even if a follower attempts to replicate the exact configuration of the leader, greater complexity will help sustain the leader's superior performance. This is because a small error in imitation will generate large penalties in performance when there is a high level of interdependence among design choices (Rivkin, 2000).

Finally, the leader firm can also sustain its performance by continuously searching for superior performing configurations. However, such a search process is prone to errors, and the firm can unknowingly end up in a lower performance configuration (Harrison and March, 1984, Knudsen & Levinthal, 2007). The high level of interdependence among design choices can help leader firms avoid such errors. Under such conditions, configurations that lead to superior performance tend to be less correlated (Levinthal, 1997). A small change in a given configuration can lead to substantially different performance outcomes. This reduces the likelihood of leader firms selecting an inferior alternative (Knudsen & Levinthal, 2007). As a result, a focal complementor that is subject to a high level of ecosystem complexity and that has already achieved superior performance is less likely to erroneously move towards a lower performance configuration.

In summary, ecosystem complexity acts as a buffer for complementors with superior performance by making it more difficult for other complementors to search for or imitate higher performance configurations and by reducing the likelihood of leaders' search processes erroneously moving them toward lower performance configurations. Accordingly, we predict:

> *Hypothesis 1: A complementor firm will be more likely to sustain its superior performance when ecosystem complexity is high than when it is low.*

Ecosystem Experience

A complementor firm's experience within an ecosystem can also play a significant role in its ability to sustain superior performance. Experience within an ecosystem will help confer several types of learning-based advantages on leader firms. Experience facilitates the development and improvement of routines, making search more reliable (i.e., less prone to mistakes) (Nelson and Winter, 1982; Katila and Ahuja, 2002). Experience also helps improve the efficiency of leader firms' search processes by reducing the cost of experimentation and, hence, making it less costly for firms to innovate over time (Zott, 2003).

In addition to the abovementioned learning-by-doing advantages, an important type of learning-based advantage in business ecosystems is what Rosenberg (1982) referred to as learning-by-using. This type of learning-based advantage is not a function of the experience in developing and producing the product *per se*, but rather of the experience in the product's utilization by its users. Rosenberg (1982) provided a detailed account of learning-by-using in the aircraft engine industry and conjectured that this type of learning is especially important in systemic industries such as electric power generation, telephones, and computers, where the use of the product is influenced by its interaction with other components and subsystems. In such industry contexts, it is very difficult for firms to know in advance how the product will perform during use and, hence, user experience plays a vital role in helping firms innovate and improve their products over time.

In our interviews, a senior engineer from an app developer firm elaborated on the importance of experience-based benefits through both learning-by-doing and learning-by-using:

> "Experience plays a critical part in our product lifecycle. From pure engineering perspective…most of the knowledge and skills are acquired through the development efforts over time. It is not easily accessible from outside-firm sources, and it [is] essential for building a high quality, user delightful application…The application keeps evolving at design and feature level,

through responding to user feedbacks and data. Engineering team also benefits from this mostly capturing edge cases which is rarely producible in the internal environment."

Finally, experience in an ecosystem enables leader firms to accumulate knowledge-based assets. Follower firms imitating such assets will be subject to time compression diseconomies (Dierickx and Cool, 1989), making it easier for the leader firms to sustain their performance superiority. Hence, experience in an ecosystem is likely to confer a high performing complementor with both learning-by-doing and learning-by-using advantages as well as make it more difficult for followers to replicate its knowledge-based assets. Accordingly, we predict:

Hypothesis 2: The greater the complementor's ecosystem experience, the more likely the complementor will sustain its superior performance within the ecosystem.

We next explore the extent to which a complementor firm's experiential advantage within an ecosystem is impacted by the level of ecosystem complexity. Greater complexity among design choices is associated with steeper learning curve that makes it more difficult for followers to catch up with experienced leaders (Balasubramanian and Lieberman, 2010). In addition, the greater the degree of ecosystem complexity that a focal firm's product is subjected to, the more uncertain will be the interactions between the product and the rest of the system and, hence, the more valuable will be learning-by-using. Finally, time compression diseconomies associated with the followers' imitation of assets accumulated by the leader firms are also likely to increase in ecosystem complexity (Pacheco-de-Almeida, 2010). Hence, we expect that complementors' ecosystem experience would be more valuable in sustaining their superior performance when ecosystem complexity is high than when it is low:

Hypothesis 3: The positive effect of a complementor's ecosystem experience on the sustainability of its superior performance will be stronger when ecosystem complexity is high than when it is low.

<u>Generational Transitions by Platform Firms</u>

Finally, we consider the impact of generational transitions initiated by platform firms on the complementors' ability to sustain their superior performance. Transitioning to a new platform generation is an important mode by which platform firms compete and create value. New platform generations typically offer improvements in existing functionality and also add new functionality. In so doing, they alter the interactions among components and subsystems within the ecosystem (Venkatraman and Lee, 2004; Ansari and Garud, 2009; Adner and Kapoor, 2010). This renders the strategic configurations of the high performing complementor firms from the previous platform generation less effective. Put at a more abstract level, the fitness landscape (i.e., mapping between strategic configurations and performance) is re-specified (Levinthal, 1997). For example, when Apple introduced the new mobile operating system named iOS 6, some of the music apps stopped working. After updating to the new operating system, many users found that their music data had disappeared. Application developers had to optimize and retest their apps with the new operating system to ensure smooth functioning of their apps. During our interview, a senior engineer from an app developer firm also elaborated on this challenge:

> "Although OS upgrades do a good job of the issue of backward compatibility, but the new OS will depreciate some APIs from the older version.[4] If the apps are using the API from the older version, it is going to crash. Further, we also try to use latest APIs in the new OS. If the user tries to run the latest APIs on the older version, the app is going to crash."

In another interview, a cofounder of a leading app developer firm discussed how a recent transition in iOS impacted the functioning of his firm's app:

> "In iOS 7 [released in September 2013], Apple changed some parts of the background infrastructure [API] the way an app interacts with the operating system, in order to enhance the graphics on its new hardware. And because of this change, our app literally stopped working on the new version, when it was working perfectly in the previous version."

Hence, while platform transitions are important for sustaining technological progress within an ecosystem, they may present challenges for complementors to sustain their superior performance:

> *Hypothesis 4: Generational transition initiated by the platform firm will make it more difficult for the complementor firm to sustain its superior performance within the ecosystem.*

In the face of a platform transition, complementors need to adapt so as to identify new strategic configurations that can yield high performance. We now consider how ecosystem complexity affects

[4] API stands for application program interface. In the context of smartphone ecosystems, these are software protocols provided by platform firms such as Apple and Google for app developers to create apps for their platforms.

these firms' ability to adapt — i.e., we explore the interaction between platform transitions and ecosystem complexity. When ecosystem complexity is low (i.e., products offered by complementors are subject to fewer technological interactions within the ecosystem), adaptation through local search performed in the neighborhood of a firm's previous configuration is effective (Levinthal, 1997). Hence, a complementor with a superior performance configuration in the previous platform generation will find it relatively easier to identify a high performance configuration in the new platform generation. In contrast, when ecosystem complexity is high, adaptation through local search is not very effective. Successful adaptation would require a greater degree of change (i.e., often referred to as a long jump on a fitness landscape). However, at the same time, a high degree of interdependence among firms' choices makes such a large-scale change very risky, as a small error or miscalculation can result in subpar performance (Henderson and Clark, 1990). Therefore, we predict:

> *Hypothesis 5: The negative effect of platform transition on the sustainability of a complementor's superior performance will be stronger when ecosystem complexity is high than when it is low.*

Methodology

We explore our arguments in the context of the iOS and Android smartphone ecosystems within the U.S. market. The focal complementor firms are application software developers who were able to attain superior performance in these ecosystems from January 2012 to January 2014. Smartphones based on iOS and Android operating systems represent more than 90% of the U.S. smartphone installed base during the study period. Both Apple and Google provide a daily list of Top 500 apps by revenue. We use that information to identify the focal firms. The context is hypercompetitive, where hundreds of thousands of app developers are frequently introducing new apps or improved versions of their existing apps. Such high intensity of competition makes it very difficult for app developers to sustain their superior performance, even for a few months.

This setting also provides a natural experiment in which we can observe two ecosystems with varying levels of complexity for the app developers within the same industrial context. This difference arises primarily due to the difference in the strategies used by Apple and Google for controlling and governing their respective ecosystems. Apple's strategy is often described as a closed strategy, as it exercises strong control over the entire ecosystem, with the objective of providing high quality experience to the user (Ghazawneh and Henfidsson, 2013). Most notable is Apple's strict control and ownership of both the handset and the iOS operating system. In contrast, Google's strategy is premised on Android as an open-source operating system, which allows its development and distribution by various original equipment manufacturers (OEMs) such as HTC, LG, and Samsung. This has resulted in the Android ecosystem being more fragmented. Hence, an app in the Android ecosystem interacts with multiple specialized handset and operating system combinations offered by various OEMs. As a result, an app developer firm in the Android ecosystem operates in a relatively more complex ecosystem compared to the one operating in the iOS ecosystem. The two ecosystems also collectively underwent three episodes of platform transitions during our observation period, which allowed us to examine the impact of platform transition on complementors.

Data

The primary sources for our data are App Annie (www.appannie.com) and appFigures (www.appfigures.com), two of the leading analyst firms in the mobile computing sector. App Annie has been tracking and archiving information related to all the applications developed on iOS and Android platforms since 2009. Its data is extensively used by app developers, venture capital firms, and financial analysts. Similarly, appFigures has developed a comprehensive database of all apps in the iOS and Android ecosystems since 2009. We used appFigures as a supplementary data source in order to validate the data received from App Annie and to also extend the data to incorporate a more recent time frame.[5] Note that both App Annie and appFigures do not generate their own data, but accumulate daily data from Google Play and Apple iTunes over time and offer their users easy-to-use tools for analyzing trends.

[5] Originally, App Annie was the primary source of data for the paper. We had received data from App Annie from January 2012 to June 2013. We subsequently received data from appFigures that allowed us to extend the timeline to January 2014.

The dataset comprises information on app developers whose apps attained top-ranking positions by revenue (i.e., Top 500) in either the iOS or Android ecosystem from January 2012 to January 2014. The revenue distribution for smartphone apps is heavily skewed. For example, based on a recent survey of more than 10,000 app developers, it was found that the top "1.6% of developers make multiples of the other 98.4% combined" (VisionMobile, 2014).[6] Therefore, having an app in the Top 500 list offers clear evidence of performance superiority among hundreds of thousands of app developers. Such a list is also keenly followed by industry observers and analysts as a reference for successful app developers.

The majority of firms whose apps appear in the Top 500 list do not stay in that list for more than six months, a finding that is consistent with the context being hypercompetitive. Unpacking such finer-grained performance dynamics requires choosing an observation window that is shorter than the annual window typically employed in strategy research (D'Aveni et al., 2010). We chose the period of observation to be a given month that would allow us to explain greater variance in the app developer's sustainability of superior performance without being subject to exogenous intermittent fluctuations in the Top 500 ranking associated with daily or weekly observations. This required aggregating the daily revenue rank data obtained from App Annie and appFigures into monthly data. Because of the skewness of the distribution of revenues across the Top 500 apps, taking a simple average of apps' daily ranks to compute monthly ranks is problematic. To adjust for this skewness, we followed a procedure guided by prior research.

Researchers have attempted to infer revenue and sales data from rank data by conducting experiments, collaborating with focal firms, or using publicly available information (e.g., Brynjolfsson, Hu, and Simester, 2003; Chevalier and Goolsbee, 2003; Garg and Telang, 2013). These studies have found that the relationship between revenue (or sales) and rank closely follows a Pareto distribution according to which:

$$revenue = b * (rank)^{-a} + \in$$

[6] The report is available at http://www.developereconomics.com/reports/developer-economics-q3-2014/.

where b is the scale parameter that is a function of the total revenue and a is the shape parameter of the underlying distribution that drives the difference in revenues across ranks. Moreover, the shape parameter for the Pareto distribution has been found to be proximate to 1. For example, in a recent study by Garg and Telang (2013), shape parameters for the iOS and Android apps were estimated to be between 0.86 and 1.16. Hence, to account for the Pareto distribution in our data, we assume the daily revenue for an app in the Top 500 list to be inversely proportional to its rank.[7] Further, we assume the scale parameter for each ecosystem to be constant during a given month. This allows us to calculate an app's monthly revenue rank for both the iOS and the Android ecosystems.

In addition to data on app developers whose apps achieved a Top 500 rank by revenue, we also obtained monthly data on the total number of apps and firms within each category of apps (e.g., games, social networking, productivity). We supplemented data from App Annie and appFigures with data from firms' websites and LinkedIn (www.linkedin.com) to gather information on the number of employees and firms' participation in businesses other than smartphone apps. We contacted some firms that had missing data via e-mail. To measure ecosystem complexity faced by app developers within the Android ecosystem, we obtained data on the monthly share of the U.S. installed base for each of the smartphone OEMs from comScore (www.comscore.com). The final dataset comprises 12,720 monthly observations from 1,533 app developer firms.

Measures

Dependent variable: We examine the sustainability of superior performance for app developers by observing whether their apps continue to be among the Top 500 apps by revenue in the iOS or Android ecosystem. For about 80% of the cases, a firm had a single app in the Top 500 list in the same month. Since our level of analysis is a firm and not an app, if a firm had more than one app in the Top 500 list,

[7] Note that the inversely proportional relationship between app revenue and rank also follows from Zipf's law that is frequently used to approximate actual data from rank data in physical and social sciences.

we treated those cases as a single firm-level observation.[8] Similar to Wiggins and Ruefli (2002, 2005) and Hermelo and Vassolo (2010), we consider a firm's superior performance to be eroded if it exits the superior performance stratum (i.e., the Top 500 list). In order to ensure that the exit is somewhat persistent rather than intermittent, we use a window of three months to record the exit event (i.e., firm's app is not present in the Top 500 list for three consecutive months after being in that list in the previous month). Hence, a firm is assumed to sustain its superior performance if its app continues to be in the Top 500 list in at least one of the following three months. We also performed sensitivity checks by using windows of two and four months.

On average, an app developer firm remains in the Top 500 list for a longer duration in the Android ecosystem (7 months) than in the iOS ecosystem (5 months). Moreover, in the iOS ecosystem, about half of the firms exit the Top 500 list in less than two months, whereas in the Android ecosystem, this duration is about five months. This pattern is consistent with our prediction in Hypothesis 1.

Independent variables: Complexity has been defined and measured in many different ways across different scientific fields (Lloyd, 2001). This is because no single approach can capture what scientists from different fields mean by complex (Page, 2010). In general, most definitions and associated measures consider complexity based on the difficulty of describing or creating an object, or based on the degree of organization with respect to the object (e.g., structural linkages between parts of a system). Our measure of ecosystem complexity needs to account for the structural interdependencies that an app developer is subjected to within a smartphone ecosystem. Therefore, our approach here is consistent with characterizing complexity in terms of the degree of organization. It is also consistent with the formal theoretical literature in strategy using NK models (i.e., N elements and K interactions) that we extensively draw upon in our theorizing. In the context of business ecosystem, the greater the diversity of components and subsystems that a complementor is interdependent on, the greater is the ecosystem

[8] In such cases, we used the higher ranking app to create app-level control variables.

complexity.[9] For smartphone ecosystem, the most obvious interdependencies for an app developer are with respect to the operating system and the handset. Hence, the greater the diversity of operating system and handset configurations that an app developer is subjected to, the greater is the ecosystem complexity. As Apple controls both the operating system and handset, an app developer in the iOS ecosystem interacts only with the unitary configuration. In the case of the Android ecosystem, although the core operating system is designed by Google, each smartphone OEM customizes the operating system and the handset. As a result, an app developer in the Android ecosystem interacts with handset and operating system configurations from many different OEMs. We use a Simpson index-based measure to characterize this diversity in the operating system and handset configurations faced by the app developer (Page, 2010).[10] The measure *ecosystem complexity* is the sum of the squares of the monthly shares of the U.S. installed base for smartphone OEMs in an ecosystem.[11] The measure takes a value of 1 for the iOS ecosystem and ranges from 0.28 to 0.40 for the more complex Android ecosystem. We multiplied the measure by -1 so that higher values indicate higher ecosystem complexity.

We measured *ecosystem experience* as the total number of months that a firm gained experience in a given ecosystem. To obtain this measure, we first identified the month in which the firm introduced

[9] Note that greater diversity in components or subsystems is not a sufficient condition for greater complexity, rather greater diversity coupled with interdependencies among components results in greater complexity. This is also consistent with the dictionary definition of complex – "composed of many interconnected parts" (http://dictionary.reference.com/browse/complex).
[10] An alternative could be a measure based on the Shannon index. The two indices differ with respect to the relative weights that they ascribe to each OEM's user base. The Simpson index uses the proportion of each OEM's installed base as weights to calculate the weighted arithmetic mean of the share of installed base for each OEM. The Simpson index thus gives higher weights to the OEMs which have high installed base. In contrast, the Shannon index uses weights based on natural logarithm of the proportion of installed base of each OEM and thus ascribes relatively higher weights to the OEMs with the low installed base. Hence, the measure is somewhat inconsistent with the fact that app developers focus most of their efforts on OEMs with high installed base. The Simpson index measure is also mathematically identical to the popular Herfindahl index used in economics and management literature to measure industry concentration based on the sales of different firms within an industry.
[11] Note also that our measure is based on the share of OEMs installed base and not the share of their sales. This is because the market for apps is not only confined to new smartphones being sold but it also encompasses existing smartphones being used. As an additional alternative measure, we could have also used a count-based measure of the number of Smartphone OEMs or the number of the different types of smartphones in a given ecosystem. However, in our interviews, industry participants repeatedly asserted that their firms focus their app development efforts on the small subset of more commonly used handsets. For example, in Android, they consistently referred to focusing their efforts on 6-8 leading smartphones from multiple OEM firms. The Simpson index-based measure helps to account for this concentration effect.

its first app in the ecosystem (i.e., month of entry) and then computed the number of months between the observation month and the month of entry.

We identified the effect of *platform transition* using a dummy variable that takes a value of 1 if a new generation of smartphone operating system was introduced within the prior three months. The reason for the three-month window is that it often takes users several weeks to adopt the new generation of operating system and a similar time frame for app developers to adapt and reconfigure their apps. During the period of study, there were two major platform transitions in the iOS ecosystem (launch of iOS 6 in September 2012 and launch of iOS 7 in September 2013) and one major transition in the Android ecosystem (launch of the Jellybean 4.1 operating system in July 2012). Although Google officially launched Jellybean 4.1 in July 2012, it became available to the majority of U.S. consumers through the different OEMs only in December 2012. We verified this information by searching for news articles discussing the launch of Jellybean 4.1 by OEMs such as Samsung, HTC, and Motorola, often with new generations of handsets. Hence, for the Android ecosystem, we considered the period of platform transition to last from January to March 2013.

To ensure that our coding of these platform transitions matches with our theoretical premise of challenges faced by complementors during such episodes, we used data from Google Trends for searches made on Google in the U.S. with the search term “app not working.”[12] Figure 2 plots the normalized weekly trend of search volume from January 2012 to January 2014. It shows clear instances of peaks during the months in which new generations of operating system are introduced within the iOS and Android ecosystems. Hence, these trends confirm our coding schema and provide evidence of the challenges faced by app developers during periods of platform transitions.

(Insert Figure 2 about here)

Control variables: We controlled for a number of covariates that may influence an app developer’s ability to sustain its superior performance. We used the total number of employees as a proxy

[12] Results can include searches containing "app" and "not working" in any order. Other related terms may be included in the search results, like "music app not working."

for *firm size* and used this variable to control for scale-related effects. Data on the total number of employees was collected from the firm's website or LinkedIn. For those firms for which this information was not available, we contacted them via e-mail and received a 78% response rate.

About 64% of firms in the sample participated in both the iOS and Android ecosystems. Participation in both ecosystems may create challenges with respect to resource allocation over time. We controlled for this effect through the variable *dual participation,* which takes a value of 1 if the firm had an app in both the iOS and Android ecosystems in a given month and 0 otherwise. We also controlled for the firm's presence in businesses other than smartphone apps. The variable *other online business* takes a value of 1 if a firm participated in other web-based businesses like an e-commerce or a social networking website. The variable *other offline business* takes a value of 1 if the firm's scope of businesses expanded beyond the internet domain, such as game consoles, brick and mortar retail, etc.

App developers often try to gain visibility by providing free apps. We controlled for this effect through a dummy variable *Top 500 free ranking* that takes a value of 1 if any of the apps developed by the firm were also part of the Top 500 ranking based on the number of downloads for free apps in a given month. We also controlled for the overall quality of firms' apps by using data on consumer ratings received by all apps developed by the firm until March, 2014. We are unable to observe the change in ratings for all apps over time. Hence, we used a time-invariant firm-level control to capture firm-level differences in app quality. Consumers can rate an app from 1 to 5 stars, with 5 being the highest quality. The variable *firm app rating* is the average rating of all apps developed by the firm as of March, 2014. We also controlled for the *price* of the focal app that is in the Top 500 list (by revenue). For the few firms that had more than one app in the Top 500 list in the same month, we used the price for the app with the higher rank.

Firms predominantly offered apps in a specific category such as games, music, social networking or productivity. We controlled for this category-level heterogeneity through category fixed effects and other category-level time-varying controls.[13] A firm can continue to have its apps in the Top 500 ranking if there is a high level of demand for a particular category of apps in which the firm is active in. We account for this possibility using the variable *apps in top 500*, which is the total number of apps from the focal firm's app category in the Top 500 list in a given month. While the context in general is hypercompetitive, there may be differences in the competitive intensity across categories over time. We included two variables to account for these differences. First, we included the total number of *new apps* that were introduced in a category in a given month. This variable captures apps launched by both new and existing firms. Second, we included the total number of *new firms* that entered the category in a given month. The two variables are log-transformed to account for skewness.

Analysis

We tested our hypotheses using discrete time event history analysis to estimate the rate at which app developers exit the superior performance stratum. This approach is consistent with prior studies which have focused on studying the sustainability of firms' superior performance (e.g., Wiggins & Ruefli, 2002, 2005; Hermelo & Vassolo, 2010). Many firms in our sample did not exit the superior performance stratum during the observation period. Hence, our data is right censored. Event history models are well suited to account for right-censored observations (Allison, 1984). Since we are studying only those firms that made it to the Top 500 ranking and were subjected to the risk of exiting the superior performance stratum, our data does not have left censoring. Some firms in our sample entered the superior performance stratum before the start of the observation period. Hence, our data is left truncated. We checked for potential biases due to left truncation through additional robustness checks. We did this by including observations only for firms whose apps entered the Top 500 list after January 2012 or for firms that participated in the iOS or Android ecosystems from January 2012 onward, regardless of when their apps made it to the Top 500 list. We report these analyses in the robustness checks section.

[13] In the few cases where firms offered apps in multiple categories, we used information for the highest ranking app to calculate values for the category-level control variables.

We constructed data in the long form to account for time-varying covariates. We used the Cox proportional hazards model, a robust technique for hazard rate analysis that does not require making an additional assumption about the shape of the baseline hazard, which may be increasing, decreasing, constant, or non-monotonous (Cox, 1975). This helps address concerns with respect to incorrect distributional assumptions yielding biased estimates (Blossfeld and Rohwer, 2002), and the choice of parametric specification based on observed data generating inconsistent results (Carroll and Hannan, 2000). Further, we tested for proportionality hazard assumption by checking if the slope of the regression equation of scaled Schoenfeld residuals on time is nonzero for full model as well as for all predictor variables (Grambsch and Therneau, 1994). We found that the proportionality hazard assumption was not satisfied for *Top 500 free ranking* and *price* variables. To overcome this issue, we followed the recommended approach in the literature by including interaction terms between time (in months) and the respective variables to allow for different effects of these variables at different points in time. As a robustness check, we also performed our estimations using the piecewise constant model with month-specific effects. The estimates from these models were consistent with those obtained from the Cox model.

Results

We report the summary statistics and correlations between our covariates in Table 1. We report the results from the Cox model in Table 2. The model estimates the hazard rate that a firm exits the superior performance stratum and, hence, its inability to sustain its superior performance. The reported coefficients can be exponentiated to obtain hazard ratios, which are interpreted as the multiplier of the baseline hazard of the firm exiting the superior performance stratum when the variable increases by one unit (Allison, 2001). An increase in hazard can also be interpreted as shortening the time period for which a firm sustains its superior performance. All standard errors reported were corrected for non-interdependence across multiple observations faced by the same firm by clustering observations for each firm. Model 1 is a baseline model. In Models 2, 3, and 4, we include ecosystem complexity, ecosystem experience, and platform transition to test Hypotheses 1, 2, and 4, respectively. In Model 5, we include the interaction term between ecosystem complexity and ecosystem experience to test Hypothesis 3. In Model 6, we include the interaction term between ecosystem complexity and platform transition to test Hypothesis 5. Model 7 is the fully specified model.

(Insert Tables 1 and 2 about here)

In Hypothesis 1, we predicted that higher ecosystem complexity will be associated with greater likelihood of complementor firms sustaining their superior performance. This prediction was supported in all of the models (Models 2, 5, 6, 7). The coefficient for *ecosystem complexity* is negative and statistically significant (p-value < 0.01). Hence, higher ecosystem complexity is associated with lower likelihood of app developer exiting from the superior performance stratum. In considering the magnitude of estimated coefficient in Model 2, we find that an increase in ecosystem complexity by one standard deviation reduces the app developer's likelihood of exiting the superior performance stratum by 19%.

In Hypothesis 2, we predicted that firms with greater experience within the ecosystem will be more likely to sustain their superior performance. We find support for Hypothesis 2, as the coefficient for *ecosystem experience* is negative and statistically significant in Models 3, 5, and 7 (p-value < 0.01). Hence, higher ecosystem experience is associated with lower likelihood of an app developer exiting from the superior performance stratum. In considering the magnitude of estimated coefficients, an increase in an app developer's experience by one standard deviation (16 months) decreases its likelihood of exiting the superior performance stratum by 11%.

In Hypothesis 4, we predicted that generational transitions initiated by platform firms will make it more difficult for complementors to sustain their superior performance. We find support for this prediction as the coefficient for *platform transition* is positive and statistically significant in Models 4, 6, and 7 (p-value < 0.01). In considering the magnitude of estimated coefficient in Model 4, we find that an app developer's likelihood of exiting the superior performance stratum increases by about 38% during the platform transition.

In Hypothesis 3, we predicted that the effect of complementor's ecosystem experience on the sustainability of its superior performance will be moderated by ecosystem complexity such that the effect will be stronger when ecosystem complexity is high than when it is low. We find support for Hypothesis 3, as the coefficient for the interaction term between ecosystem complexity and ecosystem experience is negative and statistically significant ($p < 0.10$) in both Models 5 and 7. Therefore, the effect of ecosystem experience on lowering the likelihood of an app developer's exit from the superior performance stratum is stronger when ecosystem complexity is high than when it is low. Figure 3 illustrates this interaction effect by plotting the predicted hazard of an app developer's exit as a function of ecosystem experience and ecosystem complexity based on the estimates in the fully specified model (Model 7) and holding all other variables at their mean values. High and low ecosystem complexity refers to values of one standard deviation above and below the mean. The interaction effect seems to be more pronounced at lower levels of experience.

(Insert Figure 3 about here)

Finally, the coefficient for the interaction term between ecosystem complexity and platform transition is positive and statistically significant in both Model 6 and Model 7 ($p < 0.05$). Hence, we find support for Hypothesis 5 that platform transitions make it more difficult for complementors to sustain their superior performance when ecosystem complexity is high than when it is low. This interaction effect can be clearly seen in Figure 3 with the slope of predicted hazard of exit being much steeper for the high level of ecosystem complexity.

Robustness checks

We conducted a number of additional checks to establish the robustness of our findings. The results from the robustness checks are reported in Tables 3 and 4. First, in our main results, we considered a firm to be in the superior performance stratum if its app appeared in the Top 500 list by revenue, and we used a three-month observation window to assess whether the firm sustains its superior performance or not. To ensure that our results are not sensitive to these choices, we used a higher performance threshold based on a firm's app in the Top 250 list by revenue (Model 8), and we also used windows of two and four months (Models 9 and 10). The coefficient estimates for all the three models continue to support our predictions.

(Insert Table 3 about here)

Second, in order to account for firms self-selecting into the iOS or Android ecosystems, we estimated a model by including data for only those firms that participated in both ecosystems. The coefficient estimates are reported in Model 11 and exhibit very similar patterns as our main results. The only exception was that the interaction term between ecosystem complexity and ecosystem experience is marginally insignificant (p-value = 0.115). In order to ensure that the significant effect of app developers' ecosystem experience is not simply an artifact of their general experience with apps, we performed a supplementary analysis on these firms that participated in both ecosystems. We controlled for the app developers' general experience – the total number of months that an app developer has been active in the smartphone app market for iOS and Android apps. The results are reported in Model 12. While the coefficient for general experience is significant, the coefficient for ecosystem experience remains significant and is of the similar magnitude as in the main results. Note also that the magnitude of the coefficient for ecosystem experience is more than twice as that of the coefficient for general experience. Hence, this check helps to reinforce that complementor firms' experiential benefit has a strong ecosystem-specific component.

Some firms in our sample entered the superior performance stratum before the start of the observation period. Hence, our data is left truncated. We tested for any potential biases due to left truncation by only including observations for those firms whose apps appeared in the Top 500 list after January 2012 (Model 13). Additionally, we ran a model (Model 14) by only including observations for those firms that entered these ecosystems from January 2012 onwards, regardless of when their apps made it to the Top 500 list. The coefficient estimates are qualitatively similar as our main results with the exception of the interaction term between ecosystem complexity and firm experience exhibiting similar magnitude and sign, but the estimates are not precise enough for statistical significance. This is possibly due to the fact that these estimations are based on a smaller sample and that too of younger app developer firms.

Another potential concern with the analysis could be that our measure for ecosystem complexity, based on the OEMs' installed base, does not account for the diversity of handset configurations within OEMs. For example, in the case of iOS ecosystem, the measure remains constant throughout the observation period and does not capture differences with respect to the types of phones, especially does with different screen sizes (e.g., iPhone 4s and 5). For an app developer, screen size in addition to OEM operating system configuration can be an important driver of the variety of the handset and operating system combinations that their app interacts with. While designing an app, the developer needs to carefully ensure that its app fits and works seamlessly across the different screen sizes of the different OEMs (Panzarino, 2012). Hence, we explore the robustness of our results by including a finer-grained measure of ecosystem complexity based on the number of unique OEM firm and screen size combinations.

Further, since the measure of ecosystem complexity is significantly correlated with the type of platform (i.e., iOS or Android), it might be capturing some unobserved differences with respect to platform firms' strategies or user-characteristics across these platforms. These differences may impact the relative ease with which app developer firms can sustain their superior performance in a given ecosystem, and may make some of our inferences problematic. To address this possibility, we obtained detailed data on installed base of handsets and user characteristics from comScore. comScore conducts a monthly survey of about twelve thousand U.S. smartphone users and collects data on their handset profiles, user demographics and the app usage patterns. The survey data for each month is then adjusted to account for national demographics. Due to cost constraints, we were able to obtain this data only for the period from Jan' 2012 to May' 2013.

We used the information on screen size and OEM type in the comScore survey dataset to calculate the finer-grained measure of ecosystem complexity. The use of this measure also allows us to control for the focal platform. The variable *iOS* takes the value of 1 if the app developer is participating in the iOS platform and 0 if it is participating in the Android platform. We mean centered the ecosystem complexity measure to address multicollinearity with the *iOS* variable. Finally, we also control for differences in app usage behavior for the two platforms as it can be an important driver of app developers' ability to sustain its performance in the specific ecosystem. The variable *App download* measures the percentage of users who download 5 or more apps in a given month in the focal platform. In addition, we also control for the differences in age and gender as these two demographic characteristics can drive differences in user preferences for various apps. The variables *Female user* and *Age* measure the percentage of female users and the percentage of users of age between 18 to 45 years, respectively, for the focal platform in a given month. We report the results in Table 4.

(Insert Table 4 about here)

Model 15 is used to test the direct effects of the predictor variables with the new measure of ecosystem complexity and with additional controls for user characteristics. Model 16 includes the additional control for the focal platform. The coefficient estimates for the direct effects of the predictor variables are significant and consistent with our predictions. Models 17 and 18 also include the interaction terms. The coefficients for the interaction term between ecosystem complexity and platform transition are consistent with our main results with the coefficient being statistically significant in Model 17 but insignificant in Model 18 (p-value = 0.198). The coefficients for the interaction term between ecosystem complexity and experience have the expected sign but the standard errors are not precise to offer any statistical significance. This is likely because of fewer observations and limited time period for the observation window. Overall, these additional analyses help to establish the robustness of our findings and give us greater confidence in our inferences.

Discussion

In this study, we focus on the emergent phenomenon of business ecosystems in which value is created through a network of firms offering complementary products and services. We explore how the structural and evolutionary features of the ecosystem shape the extent to which complementor firms can sustain their superior performance. We use the notion of ecosystem complexity to characterize the structure of the complementors' interdependence with other actors in the ecosystem. We incorporate the evolutionary features of the ecosystem by considering the impact of platform-level transitions and firm-level experience on the complementors' ability to sustain their performance superiority.

We test our arguments on app developers in Apple's iOS and Google's Android smartphone ecosystems from January 2012 to January 2014. During the period of study, both of these ecosystems were populated by hundreds of thousands of app developers that offered a wide variety of specialized software applications to smartphone users. The stark contrast between Apple's "closed" model and Google's "open" model, in addition to several episodes of platform transitions initiated by these firms, allowed us to examine how ecosystem complexity and platform transitions impacted the ease with which complementors such as app developers could sustain their superior performance within an ecosystem. Consistent with our arguments, we find that higher ecosystem complexity helps app developers sustain their superior performance and that this effect is stronger for more experienced firms. In contrast, platform transitions make it more difficult for app developers to sustain their performance superiority, and this effect is exacerbated by the extent of ecosystem complexity.

Our study's findings make important contributions to the emerging literature streams in strategy on business ecosystems, platforms, and persistence of superior performance. Scholars studying business ecosystems have focused on the coordination and technological challenges with respect to complementors and the resulting implications for firms' organizational choices and value creation (e.g., Iansiti and Levien, 2004; Adner and Kapoor, 2010, 2014; Kapoor and Lee, 2013; Kapoor, 2013). Scholars studying platforms have focused on the strategies used by platform firms to attract complementors and to compete against rival platforms (Gawer and Cusumano, 2002; Gawer and Henderson, 2007; Boudreau, 2010;

Eisenmann et al.; Zhu and Iansiti, 2012). While these literature streams have shifted the theoretical emphasis from industries and products to business ecosystems and platforms, the primary mode of inquiry is to illustrate how firms manage their interdependence with complementors so as to create and appropriate value.

In this study, we focus on the other side of the phenomenon and illustrate how complementors' value appropriation is shaped by the structural and evolutionary features of the business ecosystem. Our findings have implications for both platform firms such as Apple and Google that set the rules and own the core technological platform and complementors such as app developers that follow the rules and leverage the technological platform. We show how the choices made by the platform firms (e.g., Apple's closed model and Google's open model) may play a significant role in the ability of complementors to appropriate value over time. In addition, while major technological changes within the platform are important for sustaining the progress of the business ecosystem over time, we show that these changes can disrupt members who are leaders within specific market niches. At the same time, platform transitions provide opportunities for other complementors in the ecosystem to gain leadership. Hence, we shed light on the challenges and the trade-offs that platform firms and complementors face in their quest for superior performance over time.

The study is also among the first to provide systematic empirical evidence regarding the role of complexity on firm performance as theorized within the evolutionary economics perspective. While scholars have drawn on a variety of theoretical approaches to model firms' search processes and their performance outcomes at different levels of complexity (e.g., Levinthal, 1997; Rivkin, 2000; Siggelkow and Rivkin, 2005), empirical evidence regarding the role of complexity on firm performance has been somewhat lacking (Lenox et al. (2010) is an important exception). We show that complexity plays an important role in sustaining superior performance in business ecosystems, and its impact is especially strong for more experienced firms and during periods of platform transitions.

Finally, our findings also offer important implications for the literature stream examining persistence of superior performance. There is growing evidence that it is becoming increasingly difficult for firms to sustain their superior performance over time (Wiggins and Ruefli, 2002, 2005; D'Aveni et al., 2010; McGrath, 2013). However, the underlying drivers of this trend are not well understood, nor are the reasons why the persistence of superior performance varies across different types of firms and industry contexts (McGahan and Porter, 1997; Hoopes et al., 2003; D'Aveni et al., 2010). We contribute to this literature stream by generating and validating some theoretical mechanisms regarding why firms' ability to sustain their superior performance may be influenced by the structural and evolutionary features of the business ecosystems. Knowledge of such relationships can help managers devise strategies (e.g., frequency and nature of competitive moves, resources reconfigurations) that exhibit a superior fit with their business environment (e.g., Young et al., 1996; Lee et al., 2010). We also offer an empirical contribution to this literature stream and reaffirm the need to go beyond annual datasets that are typically used in the strategy literate to shorter temporal windows, such as months or quarters. We show that such finer-grained observational periods can be more useful in deciphering performance dynamics in high velocity environments than the more aggregated annual data.

The findings and the inferences from the study are subject to a number of caveats that offer opportunities for future research. First, they are limited to a single empirical setting, and their validity needs to be established across other contexts. Second, our measure of superior performance based on the Top 500 list by revenue, although widely accepted as a proxy for competitive superiority in our empirical setting and consistent with the strategy literature, may not represent true economic performance for complementors. Finally, our dataset is limited to only 25 months, and while we observe significant fluctuations within the competitive landscape over this relatively short period, we are unable to draw inferences over longer time frames.

Despite these and other limitations, the study offers one of the first explorations of how business ecosystems influence performance dynamics among complementors. By drawing on arguments from the evolutionary economics perspective and by linking ecosystem-level effects with firm-level search processes of innovation and imitation, we show how they explain the extent to which firms can appropriate value within an ecosystem over time.

References

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

Adner, R., & Kapoor, R. 2014. Innovation Ecosystems and the Pace of Substitution: Re-examining Technology S-curves. *Strategic Management Journal*.

Adner, R, Oxley, J, & Silverman, B. 2013. Collaboration and Competition in Business Ecosystems. *Advances in Strategic Management*, **31**: 9-18

Allison P.D. 1984. *Event History Analysis: Regression for Longitudinal Event Data. Sage:* Beverly Hills, CA.

Allison P.D. 2000. *Survival analysis using the SAS system: A practical guide.* SAS Institute: Cary, NC.

App Annie. 2014. App Annie Index – Market Q1 2014: Revenue Soars in the United States and China. http://blog.appannie.com/app-annie-index-market-q1-2014/ (6 January 2015)

Ansari, S., & Garud, R. 2009. Inter-generational transitions in socio-technical systems: The case of mobile communications. *Research Policy*, **38**(2), 382-392.

Balasubramanian N., & Lieberman M.B.2010.Industry learning environments and the heterogeneity of firm performance. *Strategic Management Journal*, **31**(4): 390-412.

Baldwin, C. Y. 2012. Organization Design for Business Ecosystems. *Journal of Organization Design*, **1**(1): 20-23

Blossfeld HP, Rohwer G. 2002. *Techniques of Event History Modeling. New Approaches to Causal Analysis* (2nd edition). Lawrence Erlbaum Associates: Hillsdale, NJ.

Boudreau, K. 2010. Open platform strategies and innovation: Granting access vs. devolving control. *Management Science*, **56**(10), 1849-1872.

Brynjolfsson, E., Hu, Y.J., & Smith, M.D.2003.Consumer surplus in the digital economy: estimating the value of increased product variety at online booksellers. *Management Science*, **49**(11): 1580-1596.

Caroll GR, Hannan MT. 2000. *The Demography of Corporations and Industries.* Princeton University Press: Princeton, NJ.

Chevalier J., & Goolsbee A. 2003. Measuring prices and price competition online: Amazon.com and BarnesandNoble.com. *Quantitative Marketing and Economics*, **1**(2): 203 – 222.

Cleves M.A., Gould W.W., & Gutierrez R.G. 2008. *An Introduction to Survival Analysis Using Stata.* Stata Press: Texas.

Cox D.R. 1975. Partial likelihood. *Biometrika*, 62: 269–276.

D'Aveni R.A. 1994. *Hypercompetition: Managing the Dynamics of Strategic Maneuvering.* Free Press: New York:.

D'Aveni R.A., Giovanni B.D., & Smith K.G. 2010. The age of temporary advantage. *Strategic Management Journal*, **31**(13): 1371 – 1385.

Dierickx I., & Cool K.1989. Asset stock accumulation and sustainability of competitive advantage. *Management Science*, **35**(12): 1504-1511

Dutton J.M., & Thomas A.1984. Treating progress functions as a managerial opportunity. *Academy of Management Review*, **9**(2): 235 – 247

Eisenmann, T., Parker, G., & Van Alstyne, M. 2011. Platform envelopment. *Strategic Management Journal*, **32**(12), 1270-1285.

Garg R., & Telang R. 2013. Inferring app demand from publicly available data. *MIS Quarterly*, **37** (4): 1253-1264

Gavetti G., & Levinthal D.A. 2004. The strategy field from the perspective of management science: divergent strands and possible integration. *Management Science*, **50** (10): 1309 – 1318

Gawer A., & Cusumano M.A. 2002, *Platform Leadership: How Intel, Microsoft, and Cisco Drive Industry Innovation*. Harvard Business School Press : Boston, MA.

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

Ghazawneh A., & Henfridsson O. 2013. Balancing platform control and external contribution in third-party development: the boundary resources model. *Information System Journal***, 23**(2): 173-192.

Grambsch PM, Therneau TM. 1994. Proportional hazards tests in diagnostics based on weighted residuals. *Biometrika***, 81**(3): 515‑526

Harrison, J. R., & March, J. G. 1984. Decision making and postdecision surprises. *Administrative Science Quarterly***, 29**(1): 26-42.

Henderson, R. M., & Clark, K. B. 1990. Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. *Administrative science quarterly*, **35**(1): 9-30

Hermelo F.D., & Vassolo R. 2010. Institutional development and hypercompetition in emerging economies. *Strategic Management Journal***, 31**(13): 1457 – 1473.

Hoopes, D. G., Madsen, T. L., & Walker, G. 2003. Guest editors' introduction to the special issue: why is there a resource based view? Toward a theory of competitive heterogeneity. *Strategic Management Journal*, **24**(10): 889-902.

Kapoor, R. 2013. Collaborating with complementors: What do firms do? *Advances in Strategic Management*, **30**: 3-25.

Kapoor, R., & Lee, J. M. 2013. Coordinating and competing in ecosystems: How organizational forms shape new technology investments. *Strategic Management Journal*, **34**(3), 274-296.

Iansiti M., & Levien R. 2004. *The Keystone Advantage: What the New Dynamics of Business Ecosystem Mean for Strategy, Innovation, and Sustainability***.** Harvard Business School Press: Boston: MA.

Katila R., & Ahuja G. 2002. Something old, something new: a longitudinal study of search behavior and new product introduction. *Academy of Management Journal*, **45**(6): 1183 – 1194.

Knudsen, T., & Levinthal, D. A. (2007). Two faces of search: Alternative generation and alternative evaluation. *Organization Science*, **18**(1), 39-54.

Lee C., Venkatraman N., Tanriverdi H., & Iyer B. 2010. Complementary-based hypercompetition in the software industry: Theory and empirical test, 1980-2002. *Strategic Management Journal***, 31**(13): 1431-1456.

Lenox M.J., Rockart S.F., & Lewin A.Y. 2006. Interdependency, competition, and the distribution of firm and industry profits. *Management Science***, 52**(5): 757 – 772

Lenox M.J., Rockart S.F., & Lewin A.Y. 2007. Interdependency, competition, and industry dynamics. *Management Science***, 53**(4): 599-615.

Lenox M.J., Rockart S.F., & Lewin A.Y. 2010. Does interdependency affect firm and industry profitability? An empirical test. *Strategic Management Journal***, 31**: 121-139.

Levinthal D.A. 1997. Adaptation on rugged landscapes. *Management Science***, 43**(7): 934 – 950.

Lippman, S. A., & Rumelt, R. P. 1982. Uncertain imitability: An analysis of interfirm differences in efficiency under competition. *The Bell Journal of Economics*, 418-438.

Lloyd, S. 2001. Measures of complexity: a nonexhaustive list. *IEEE Control Systems Magazine***, 21**(4):7-8.

McGahan, A. M., & Porter, M. E. 1997. How much does industry matter, really?. *Strategic Management Journal*, **18**(6): 15-30.

McGrath R.G. 2013.*The end of competitive advantage: How to keep your strategy moving as fast as your business.* Harvard Business Review Press: Boston, MA.

McIntyre D. P, & Subramaniam M. 2009. Strategy in network industries: a review and research agenda. *Journal of Management*, **35**(6): 1494- 1517.

Nelson R.R., & Winter S.G. 1982. *An Evolutionary Theory of Economic Change***.** Belknap Press: Cambridge, MA.

Nelson R.R., & Winter S.G. 2002. Evolutionary theorizing in economics. *Journal of Economic Perspectives*, **16**(2): 23 – 46.

Pacheco-de-Almeida G. 2010: Erosion time compression, and self-displacement of leaders in hypercompetitive environments. *Strategic Management Journal*, **31**(13): 1498 – 1526.

Panzarino M. 2012. Developer say iPhone 5's large screen poses some challenges, especially without a device to test apps. http://thenextweb.com/apple/2012/09/13/developers-say-iphone-5s-larger-screen-poses-challenges-especially-without-device-test-apps/ (13 September, 2012)

Page, S. E. 2010. *Diversity and complexity*. Princeton University Press: Princeton, NJ.

Porter M. E. 1985. *Competitive strategy: Creating and sustaining superior performance*. The Free Press: New York.

Posen H. E., Lee J., & Yi S. 2013. The power of imperfect imitation. *Strategic Management Journal*, **34**(2): 149-164.

Rivkin J. 2000. Imitation of complex strategies. *Management Science***, 46**(6): 824 – 844.

Rivkin J. 2001. Reproducing knowledge: replication without imitation at moderate complexity. *Organization Science***, 12**(3): 274 – 293.

Rosenberg N. 1982**.** *Inside the black box: Technology and economics*. Cambridge University Press.

Rumelt, R. P., Schendel, D., & Teece, D. J. 1991. Strategic management and economics. *Strategic Management Journal***, 12**(S2), 5-29.

Schilling M.A. 2002. Technology success and failure in winner-take-all markets: the impact of learning orientation, timing, and network externalities. *Academy of Management Journal,* **45**: 387 – 398.

Sigglekow N., & Rivkin J.W. 2005. Speed and search: designing organizations for turbulence and complexity. *Organization Science***, 16**(2): 101-122.

Teece D.J. 2007. Explicating dynamic capabilities: the nature of microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, **28**(13): 1319 – 1350.

Venkatraman, N., & Lee, C. H. 2004. Preferential linkage and network evolution: A conceptual model and empirical test in the US video game sector. *Academy of Management Journal***, 47**(6): 876-892.

Wiggins R.R., & Ruefli T.W. 2002. Sustained competitive advantage: temporal dynamics and the incidence and persistence of superior economic performance. *Organization Science***, 13**(1): 81 – 105.

Wiggins R.R. & Ruefli T.W. 2005. Schumpeter's ghost: is hypercompetition making the best of times shorter? *Strategic Management Journal***, 26**(10): 887 – 911.

Young G., Smith K.G., & Grimm C.M. 1996. 'Austrian' and industrial organization perspectives on firm-level competitive activity and performance. *Organization Science***, 7**(3): 243 – 254

Zhu F., & Iansiti M. 2012. Entry into platform-based markets. *Strategic Management Journal*, **33**(1): 88-106.

Zott C. 2003. Dynamic capabilities and the emergence of intra-industry differential firm performance: Insights from a simulation study. *Strategic Management Journal***, 24**(2)**:** 97 – 125

Figure 1: Simple schema illustrating varying levels of ecosystem complexity for a complementor. Each circular node represents a specific component or subsystem that interacts with the complementor's product in an ecosystem.

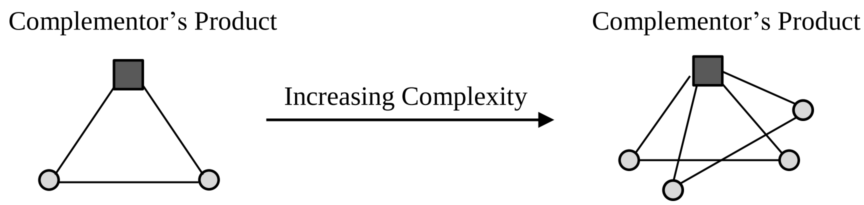

Figure 2: Normalized weekly trend of Web search in the U.S. on Google for the term "app not working." (Data source: Google Trends; http://www.google.com/trends/)

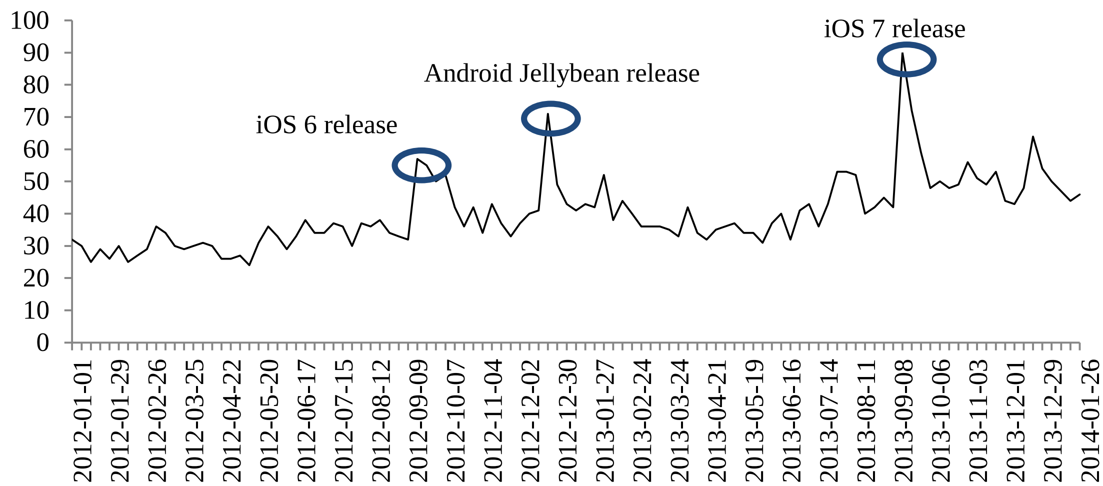

Figure 3: Graphical plots of the interaction effects

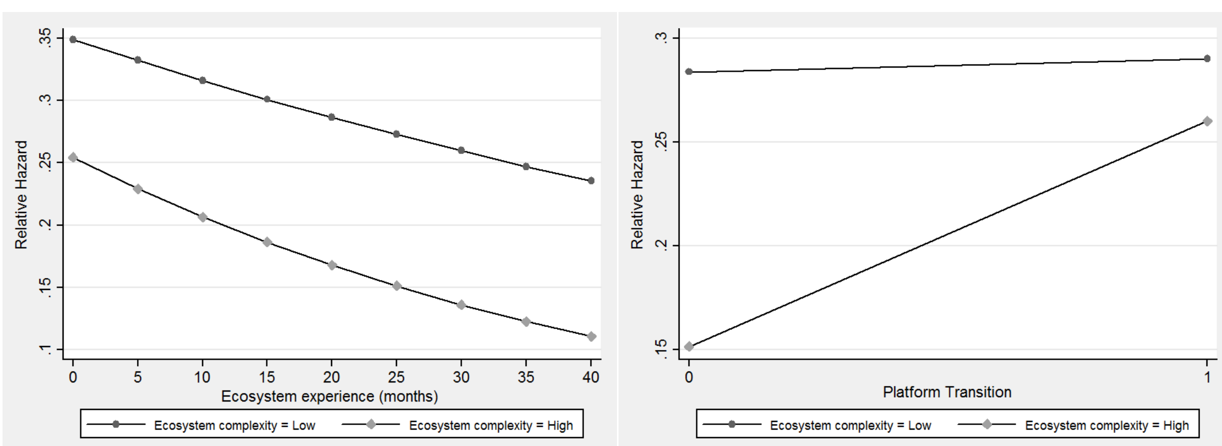

Table 1: Descriptive statistics and correlations

Variable	Mean	Std. Dev.	Ecosystem complexity	Ecosystem experience	Platform transition	New apps	New firms	Apps in Top 500	Firm size	Other Online business	Other Offline business	App price	Firm app rating	Top 500 free app	Dual parti-cipation
Ecosystem complexity	-0.665	0.341	1.000												
Ecosystem experience	22.343	16.063	-0.530	1.000											
Platform transition	0.178	0.382	-0.142	0.128	1.000										
New apps	7.842	0.974	-0.137	0.065	0.108	1.000									
New firms	6.351	0.769	-0.034	-0.017	0.067	0.952	1.000								
Apps in Top 500	198.842	162.808	0.063	-0.086	0.051	0.764	0.714	1.000							
Firm size (employees)	620.432	1790.673	-0.043	0.162	0.000	-0.055	-0.068	-0.066	1.000						
Other online business	0.587	0.492	-0.029	0.095	0.013	-0.038	-0.044	-0.011	0.230	1.000					
Other offline business	0.300	0.458	-0.032	0.118	0.007	-0.063	-0.092	-0.069	0.398	0.293	1.000				
App price	3.555	30.865	-0.042	0.028	0.000	-0.082	-0.092	-0.103	0.010	0.008	0.040	1.000			
Firm app rating	4.008	0.489	0.248	-0.293	-0.025	0.167	0.162	0.220	-0.228	-0.139	-0.180	0.010	1.000		
Top 500 free app	0.558	0.497	-0.173	0.155	0.009	0.115	0.123	0.133	0.075	0.027	-0.048	-0.101	0.012	1.000	
Dual participation	0.625	0.484	0.124	0.030	0.007	0.121	0.141	0.196	0.150	0.203	0.174	-0.027	-0.044	0.076	1.000

Correlations greater than 0.01 or smaller than -0.01 are significant at $p < 0.05$, N= 12,720

Table 2: Cox proportional hazards estimates for firms exiting the superior performance stratum

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Ecosystem complexity		-0.634***			-0.572***	-0.682***	-0.630***
		(0.116)			(0.168)	(0.124)	(0.168)
Ecosystem experience			-0.007***		-0.026***		-0.026***
			(0.002)		(0.007)		(0.008)
Platform transition				0.321***		0.727***	0.793***
				(0.075)		(0.244)	(0.249)
Ecosystem complexity*Experience					-0.015*		-0.016**
					(0.008)		(0.008)
Ecosystem complexity* Transition						0.651**	0.762**
						(0.297)	(0.304)
New apps	0.066	-0.397**	0.194	0.023	-0.287*	-0.392**	-0.279*
	(0.146)	(0.168)	(0.145)	(0.149)	(0.168)	(0.169)	(0.169)
New firms	-0.171	0.206	-0.268	-0.111	0.161	0.201	0.150
	(0.185)	(0.206)	(0.182)	(0.188)	(0.202)	(0.207)	(0.203)
Apps in Top 500	0.003	0.005	0.002	0.001	0.004	0.004	0.003
	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)
(Apps in Top 500)^2	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm size (employee)	-0.012***	-0.012***	-0.011***	-0.012***	-0.011***	-0.012***	-0.011***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Other online business	-0.207***	-0.214***	-0.201***	-0.207***	-0.210***	-0.213***	-0.209***
	(0.066)	(0.065)	(0.066)	(0.066)	(0.064)	(0.065)	(0.064)
Other offline business	0.105	0.121	0.102	0.107	0.124*	0.122	0.126*
	(0.078)	(0.076)	(0.078)	(0.077)	(0.075)	(0.076)	(0.075)
Dual participation	-0.430***	-0.389***	-0.422***	-0.424***	-0.366***	-0.389***	-0.366***
	(0.065)	(0.065)	(0.065)	(0.065)	(0.064)	(0.065)	(0.064)
Firm app rating	-0.085	-0.020	-0.128**	-0.078	-0.071	-0.019	-0.069
	(0.057)	(0.057)	(0.056)	(0.056)	(0.055)	(0.057)	(0.055)
Top 500 free app	-0.666***	-0.793***	-0.601***	-0.672***	-0.710***	-0.797***	-0.716***
	(0.094)	(0.098)	(0.095)	(0.094)	(0.097)	(0.098)	(0.097)
Top 500 free app*time	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
App price	0.040	0.009	0.058	0.039	0.029	0.007	0.027
	(0.047)	(0.048)	(0.046)	(0.047)	(0.046)	(0.048)	(0.046)
App price*time	0.002	0.002	0.001	0.001	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Category fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total observations	12,720	12,720	12,720	12,720	12,720	12,720	12,720
Total firms	1533	1533	1533	1533	1533	1533	1533
Total exit events	1,791	1,791	1,791	1,791	1,791	1,791	1,791
Log likelihood	-10,935.71	-10,913.76	-10,927.44	-10,928.48	-10,891.25	-10,908.47	-10,885.81

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 3: Robustness checks

	Model 8 (Top 250 ranks)	Model 9 (2-month)	Model 10 (4-month)	Model 11 (common firms)	Model 12 (general experience)	Model 13 (post-Jan'12 Top rank)	Model 14 (post-Dec'11 entry)
Ecosystem complexity	-0.493**	-0.570***	-0.624***	-0.682***	-0.490**	-0.421**	-0.709***
	(0.208)	(0.164)	(0.173)	(0.209)	(0.222)	(0.175)	(0.257)
Ecosystem experience	-0.032***	-0.025***	-0.024***	-0.028***	-0.021**	-0.005	-0.052***
	(0.008)	(0.007)	(0.008)	(0.009)	(0.010)	(0.009)	(0.018)
Platform transition	0.857**	0.580**	0.801***	0.722**	0.722**	0.672**	0.995**
	(0.381)	(0.228)	(0.268)	(0.294)	(0.294)	(0.269)	(0.443)
Ecosystem complexity*Experience	-0.021**	-0.016**	-0.014*	-0.015	-0.016	-0.004	-0.029
	(0.009)	(0.008)	(0.008)	(0.010)	(0.010)	(0.009)	(0.021)
Ecosystem Complexity* Transition	0.945**	0.527*	0.728**	0.675*	0.679*	0.636*	0.987*
	(0.433)	(0.278)	(0.324)	(0.360)	(0.360)	(0.326)	(0.516)
New apps	-0.372*	-0.314*	-0.310*	-0.234	-0.195	0.133	0.011
	(0.193)	(0.162)	(0.172)	(0.229)	(0.227)	(0.173)	(0.317)
New firms	0.272	0.260	0.157	0.044	0.022	-0.350*	-0.143
	(0.249)	(0.191)	(0.208)	(0.267)	(0.265)	(0.199)	(0.376)
Apps in Top 500	0.017**	0.003	0.003	0.004	0.003	-0.002	0.013
	(0.007)	(0.006)	(0.007)	(0.010)	(0.010)	(0.007)	(0.012)
(Apps in Top 500)^2	-0.000**	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm size (employee)	-0.006**	-0.012***	-0.011***	-0.010***	-0.010***	-0.007**	-0.024
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.016)
Other online business	-0.129*	-0.200***	-0.210***	-0.198**	-0.194**	-0.138**	-0.264***
	(0.073)	(0.061)	(0.065)	(0.079)	(0.079)	(0.063)	(0.097)
Other offline business	-0.022	0.141*	0.093	0.127	0.137	0.137*	0.255**
	(0.083)	(0.074)	(0.077)	(0.085)	(0.086)	(0.072)	(0.128)
Dual participation	-0.215***	-0.333***	-0.392***			-0.293***	-0.176*
	(0.074)	(0.062)	(0.065)			(0.064)	(0.102)
Firm app rating	-0.041	-0.070	-0.067	-0.002	-0.004	-0.002	0.027
	(0.066)	(0.054)	(0.057)	(0.072)	(0.073)	(0.053)	(0.087)
Top 500 free app	-0.470***	-0.647***	-0.728***	-0.767***	-0.775***	-0.581***	-0.770***
	(0.140)	(0.096)	(0.099)	(0.117)	(0.117)	(0.098)	(0.187)
Top 500 free app*time	0.001*	0.001***	0.001***	0.002***	0.002***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
App price	0.056*	0.049	0.034	-0.063	-0.053	0.095**	0.063
	(0.034)	(0.044)	(0.047)	(0.058)	(0.059)	(0.043)	(0.073)
App price*time	-0.000*	0.001	0.002	0.007**	0.007*	0.000	0.002
	(0.000)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)
General experience					-0.008**		
					(0.004)		
Category fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total observations	6,785	12,720	12,720	10,010	10,010	6,578	3,675
Total firms	1042	1533	1533	997	997	1325	662
Total exit events	1,034	2,013	1,658	1,243	1,243	1,442	620
Log likelihood	-5,700.77	-12,265.69	-10,069.45	-7,297.72	-7,294.45	-7,864.84	-3,000.25

* p<0.1; ** p<0.05; *** p<0.01

Table 4: Robustness checks (Alternative complexity measure)

	Model 15	Model 16	Model 17	Model 18
Ecosystem complexity	-1.067**	-1.066**	-1.760**	-1.502*
	(0.511)	(0.512)	(0.789)	(0.818)
Ecosystem experience	-0.014***	-0.015***	-0.015***	-0.015***
	(0.003)	(0.003)	(0.003)	(0.003)
Platform transition	0.316***	0.274**	0.002	0.075
	(0.116)	(0.117)	(0.181)	(0.192)
Ecosystem complexity*Experience			-0.004	-0.005
			(0.020)	(0.020)
Ecosystem Complexity* Transition			7.320**	5.026
			(3.336)	(3.906)
New apps	0.186	0.099	0.104	0.077
	(0.257)	(0.263)	(0.263)	(0.265)
New firms	-0.289	-0.157	-0.215	-0.157
	(0.277)	(0.290)	(0.283)	(0.291)
Apps in Top 500	-0.003	-0.002	-0.000	-0.001
	(0.011)	(0.011)	(0.011)	(0.011)
(Apps in Top 500)^2	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Firm size (employee)	-0.010**	-0.010**	-0.010**	-0.010**
	(0.004)	(0.004)	(0.004)	(0.004)
Other online business	-0.247***	-0.248***	-0.250***	-0.249***
	(0.087)	(0.087)	(0.087)	(0.087)
Other offline business	0.025	0.028	0.027	0.029
	(0.104)	(0.104)	(0.104)	(0.104)
Dual participation	-0.416***	-0.412***	-0.415***	-0.413***
	(0.103)	(0.103)	(0.103)	(0.103)
Firm app rating	-0.158**	-0.152*	-0.156*	-0.153*
	(0.080)	(0.080)	(0.080)	(0.080)
Top 500 free app	-0.763***	-0.768***	-0.771***	-0.773***
	(0.113)	(0.114)	(0.115)	(0.115)
Top 500 free app*time	0.002*	0.002*	0.002*	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
App price	0.002	-0.000	0.001	-0.001
	(0.053)	(0.053)	(0.053)	(0.053)
App price*time	0.015***	0.015***	0.015***	0.015***
	(0.006)	(0.006)	(0.006)	(0.006)
User characteristics				
Female users[a]	5.194	3.211	5.409	4.134
	(3.831)	(3.906)	(3.819)	(3.990)
Age(18-45)[a]	4.335	1.231	2.133	0.936
	(3.015)	(3.303)	(3.109)	(3.298)
App download (>5 per month)[a]	5.283*	-1.825	4.721*	0.579
	(2.769)	(3.996)	(2.735)	(4.458)
iOS		0.356**		0.217
		(0.179)		(0.211)
Category Fixed effects	Yes	Yes	Yes	Yes
Total observations	8,742	8,742	8,742	8,742
Total firms	1099	1099	1099	1099
Total exit events	1,010	1,010	1,010	1,010
Log likelihood	-6,127.13	-6,125.26	-6,125.03	-6,124.54

[a]Variables are in percentage of total subscribers. * p<0.1; ** p<0.05; *** p<0.01