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Three Essays On Interfirm Interdependence And Firm Performance

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Abstract
This dissertation explicitly examines the structure of interdependencies that firms are subjected to within a platform-based ecosystem and its implications for firm performance. Two theoretical themes emerge from this dissertation: (1) a firm's interdependence with other actors in the ecosystem matters both for its performance and the sustainability of its superior performance; and (2) a manager's understanding of these interdependencies can have significant implications on firm performance and the choice of governance structures. The first essay explores how a firm's innovation differs with respect to its interdependence with various elements of the ecosystem and examines its implications on the innovation's commercialization success. The core set of data is based on all the apps that were launched in the Apple iPhone ecosystem from 2008 to 2013. The results suggest that firms can enhance the value of their innovation by drawing on the broader set of complementary technologies that are available in the ecosystem. But, these complementarities also subject firms to an array of bottlenecks limiting their innovation's value creation. The second essay examines how ecosystem-level interdependencies affect the extent to which firms can sustain their value creation in a platform-based ecosystem. The analysis is based on a panel dataset of top-performing app developers in the iOS and Android ecosystems from January 2012 to January 2014. The results suggest that a firm's ability to sustain its superior performance is facilitated by the technological interdependence faced by its innovation within an ecosystem and the experience gained within the ecosystem, but hampered by technological transitions initiated by the central firm. The third essay addresses the performance consequences of misrepresentation of interdependence structures in the alliance context using an agent-based simulation. The results suggest that the misrepresentation of interdependence structures plays an important role in determining performance consequences of various governance modes to manage the alliance relationship. Specifically, overrepresentation of interdependence structures requires fully integrated or more hierarchical governance modes, whereas underrepresentation of interdependence structures requires more decentralized governance modes. Collectively, these essays contribute to the literature on ecosystems and alliances, shedding new light on the role of structure of interdependence ins shaping firm's performance.

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Shiva Agarwal

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THREE ESSAYS ON INTERFIRM INTERDEPENDENCE AND FIRM PERFORMANCE

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ABSTRACT

THREE ESSAYS ON INTERFIRM INTERDEPENDENCE AND FIRM PERFORMANCE

Shiva Agarwal

Harbir Singh & Rahul Kapoor

This dissertation explicitly examines the structure of interdependencies that firms are subjected to within a platform-based ecosystem and its implications for firm performance. Two theoretical themes emerge from this dissertation: (1) a firm's interdependence with other actors in the ecosystem matters both for its performance and the sustainability of its superior performance; and (2) a manager's understanding of these interdependencies can have significant implications on firm performance and the choice of governance structures. The first essay explores how a firm's innovation differs with respect to its interdependence with various elements of the ecosystem and examines its implications on the innovation's commercialization success. The core set of data is based on all the apps that were launched in the Apple iPhone ecosystem from 2008 to 2013. The results suggest that firms can enhance the value of their innovation by drawing on the broader set of complementary technologies that are available in the ecosystem. But, these complementarities also subject firms to an array of bottlenecks limiting their innovation's value creation. The second essay examines how ecosystem-level interdependencies affect the extent to which firms can sustain their value creation in a platform-based ecosystem. The analysis is based on a panel dataset of top-performing app developers in the iOS and Android ecosystems from January 2012 to

January 2014. The results suggest that a firm's ability to sustain its superior performance is facilitated by the technological interdependence faced by its innovation within an ecosystem and the experience gained within the ecosystem, but hampered by technological transitions initiated by the central firm. The third essay addresses the performance consequences of misrepresentation of interdependence structures in the alliance context using an agent-based simulation. The results suggest that the misrepresentation of interdependence structures plays an important role in determining performance consequences of various governance modes to manage the alliance relationship. Specifically, overrepresentation of interdependence structures requires fully integrated or more hierarchical governance modes, whereas underrepresentation of interdependence structures requires more decentralized governance modes. Collectively, these essays contribute to the literature on ecosystems and alliances, shedding new light on the role of structure of interdependence ins shaping firm's performance.

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1. INTRODUCTION

The strategy literature has long explored how firms generate rents by combining resources that lie outside their boundaries (e.g., Dyer and Singh, 1998; Gulati 1998). The bulk of the attention has been on the bilateral nature of interdependence, such as those between buyers and suppliers. However, in today's world, with the rising prominence of ecosystems often fueled by technology platforms, the nature of interdependence between firms is becoming increasingly multilateral, involving a network of suppliers and complementors (Teece 2007; Adner and Kapoor, 2010; Kapoor and Lee 2013; McIntyre and Srinivasan 2017). In this dissertation, I focus on this emergent phenomenon of platform-based ecosystems and examine how the structure of multilateral interdependencies shapes firms' value creation. Scholars in economics and strategy have studied platform-based ecosystems primarily through theories of direct and indirect network effects, where the main line of inquiry has been to understand how the platform firm orchestrates interactions between different players (e.g., Katz and Shapiro, 1986; Schilling, 2000; Evans, 2003; Rochet and Tirole, 2003, 2006; Armstrong, 2006). While complementor firms are considered key enablers of value creation in these ecosystems, their strategies and performance have been largely understudied (Kapoor, 2013; McIntyre and Srinivasan, 2017). This dissertation focuses on complementor firms participating in platform-based ecosystems and explores how the structure of technological interdependencies with respect to platform and other elements in the ecosystem impact their performance.

Two theoretical themes emerge from this dissertation: (1) a firm's interdependence with other actors in the ecosystem matters both for its performance and the sustainability of its superior performance; and (2) a manager's understanding of these interdependencies can have significant implications on firm performance and the choice of governance structures to manage these interdependencies. The dissertation comprises three essays. The first essay focuses on complementors participating in platform-based ecosystems via their innovations. It considers the structure of complementors' innovations with respect to the platform and other complements in the ecosystem. It introduces the notion of connectedness to refer to the extent to which a given innovation interacts with the platform (i.e., platform connectedness) and also with the other complements in the ecosystem (i.e., complement connectedness). For example, while all software applications (apps) launched by developers on the iPhone platform interact with the iPhone's core mobile computing module, there is considerable variation in terms of whether they interact with the iPhone's other components (e.g., camera,GPS, accelerometer), as well as with other complementary apps (e.g., Google Maps, Dropbox, Facebook). The core set of data for this first essay is based on all the apps that were launched in the Apple iPhone ecosystem from 2008 to 2013 within the U.S. market. The results suggest that firms can enhance the value of their innovations by drawing on the broader set of complementary technologies that are readily available in the ecosystem. Still, these complementarities also subject firms to an array of bottlenecks that limit their innovations' value creation.

The second essay examines how ecosystem-level interdependencies affect the extent to which complementor firms can sustain their performance in a platform-based ecosystem. In this chapter, I offer a novel perspective on firms' ecosystem-level interdependencies that is rooted in the structural and evolutionary features of the ecosystem. The structural feature is based on the technological interdependence between firms' products and other components of the ecosystem. I incorporate the evolutionary feature by taking into account the technological transitions initiated by the central firm that governs the ecosystem and the experience gained by complementors within an ecosystem over time. The analysis is based on a unique monthly panel dataset of top-performing app developers in the iOS and Android ecosystems from January 2012 to January 2014. The results suggest that a firm's ability to sustain its superior performance is facilitated by the technological interdependence faced by its innovation within an ecosystem and its experience gained within the ecosystem, but hampered by technological transitions initiated by the central firm.

The third essay takes a more behavioral perspective and examines the implications of an incorrect understanding of interdependence structures. Specifically, it uses an agent-based simulation model to gain insights into the behavioral biases that may exist when interdependent firms form strategic alliances. The model simulates managers' understanding of underlying task interdependencies within an alliance under different levels of complexity and governance modes. The findings suggest that the misrepresentation of interdependence structures plays an important role in determining performance consequences of various governance modes to manage the alliance relationship. Specifically, I find that overrepresentation of the interdependence structures requires fully integrated or more hierarchical governance modes, whereas underrepresentation of the interdependence structures requires more decentralized governance modes. Additionally, I find that the complementary effect of both types of misrepresentation and governance modes on exploration and coordination can explain the performance differences of various governance modes.

2. TWO FACES OF VALUE CREATION IN BUSINESS ECOSYSTEMS: LEVERAGING COMPLEMENTARITIES AND MANAGING INTERDEPENDENCIES

INTRODUCTION

There is increasing recognition among strategy scholars and practitioners that firms are dependent on their ecosystems for creating value from their innovations (Iansiti and Levien, 2004; Adner and Kapoor, 2010, Kelly, 2015). In many cases, the basis of value creation in ecosystems involves a platform that serves as a foundation upon which other firms can build complementary products or services (i.e., complements). Scholars have explored this phenomenon primarily from a perspective of a platform firm, emphasizing how platform-based architectures encourage innovations by complementor firms and enhance the overall value proposition of the platform (e.g., Baldwin and Clark, 2000; Gawer and Cusumano, 2002; Evans et al., 2008). While having a large number of complementors innovating around a platform is uniformly acknowledged as an important driver of the platform's success, the implications for complementors themselves participating in these ecosystems with their innovations remain less clear. There are often significant differences in the extent to which a given innovation is commercially successful in an ecosystem (Adner and Kapoor, 2010), and yet, what makes a complementor's innovation successful in a platform-based ecosystem is not well understood.

In this study, we start with the premise that a given innovation does not stand alone. Rather it is connected with other elements in the ecosystem that impacts its value creation (Rosenberg, 1982; Hughes, 1983; Adner and Kapoor, 2010; 2016). We draw on this premise and take the perspective of a complementor firm innovating around a platform to explain the commercial success of its innovation. To do so, we introduce the notion of connectedness to refer to the extent to which a given innovation interacts with the platform (i.e., platform connectedness) and also with the other complements in the ecosystem (i.e., complement connectedness). For example, while all software application (apps) launched by developers on the iPhone platform interact with iPhone's core mobile computing module, there is considerable variation in terms of whether they interact with iPhone's other components (e.g., camera, GPS, accelerometer), as well as with other complementary apps (e.g., Google Maps, Dropbox, Facebook).

On the one hand, higher connectedness may allow the innovation to leverage a broader set of complementarities in the ecosystem. Firms will be able to enhance the value of their innovations by drawing on complementary technologies that are readily available in the ecosystem (Teece, 2006; Kapoor and Furr, 2015). On the other hand, it may subject the innovation to an array of interdependencies that may limits its value creation. An innovation that is interdependent on other complementary technologies may not achieve its desired functionality either because of the challenges in managing the interdependencies (Henderson and Clark, 1990; Kapoor and Agarwal, 2017), or because of being subject to the bottlenecks that may arise with respect to other complementary technologies in the ecosystem (Ethiraj, 2007; Adner and Kapoor, 2010; 2016). In the context of platform-based ecosystems, these challenges are especially salient when there is a change in the platform architecture triggered by platform firms through the introduction of a new platform generation.

We explore our arguments in the context of Apple's iPhone ecosystem between 2008 and 2013 within the U.S. market. This context provides a relevant and important opportunity to study the commercialization success of complementors' innovations in a platform-based ecosystem. The focal firms are app developers launching their apps for the iPhone. The iPhone ecosystem represents one of the largest and most valuable business ecosystems with the App Store revenue estimated to be more than $10B in 2016. Hundreds of thousands of app developers participate in this ecosystem by frequently launching new apps. Moreover, apps launched by developers vary in terms of leveraging both the iPhone components and other complementary apps, providing us with significant variance to test our predictions with respect to platform and complement connectedness. Finally, we are able to exploit yearly changes in the iPhone platform through Apple's introduction of new platform generations to consider the commercialization challenges that app developers may face with the new generation of the platform.

The analysis is performed on a newly assembled dataset of 249,305 iPhone apps launched by 20,391 developers with detailed information on the focal app and the app developer, along with novel measures for each of the app's platform and complement connectedness. An app's successful commercialization is measured based on the likelihood of it being listed in the Top 500 list by revenue (e.g., Kapoor and Agarwal, 2017; Davis et al., 2016). The Top 500 list is an important indicator of an app's successful commercialization as apps that make it into this list represent approximately 95 percent of the total revenue generated by apps in the iPhone ecosystem (SensorTower, 2016). Such a list is also keenly followed by industry observers and analysts as a reference for successful apps. We find that higher platform connectedness and higher complement connectedness is associated with a higher likelihood of app's successful commercialization. However, the benefit of platform connectedness is negated during the initial period of the new iPhone generation. In contrast, the benefit of complement connectedness with respect to iPhone's generational evolution is much more nuanced. The benefit is strengthened when Apple introduces the new platform generation and if the complements that the focal app is connected to have *low* platform connectedness whereas it is weakened when Apple introduces the new platform generation and if the connected complements themselves have *high* platform connectedness.

These findings highlight the two facets of value creation in ecosystems, and the implications for complementor firms innovating around a platform. Firms in platform-based ecosystems can enhance the value of their innovations by leveraging a broad array of platform components and other complements. However, this interconnected architecture of value creation can subject the firm to challenges with respect to managing the technological interdependencies especially when there is a new platform generation. Further, the distinction between platform connectedness and complement connectedness helps in explaining the puzzling difference within innovations with high complement connectedness. Our results suggest that the technological interdependencies due to complement connectedness have a negative impact on the innovation's commercialization only when the connected complements themselves have high platform connectedness. In contrast, when the connected complements have low platform connectedness, the new platform generation actually facilitates the innovation's commercialization. In so doing, the study contributes to the emerging literatures on ecosystems and platforms, examining both the opportunities and the challenges faced by complementors in creating value from their innovations (e.g., Boudreau, 2010; Ceccagnoli et al., 2012; Kapoor, 2013; Kapoor and Lee, 2013; Altman, 2016; Cennamo, Gu, and Zhu, 2016; Zhu and Liu, 2016; Kapoor and Agarwal, 2017). More broadly, the study contributes to the complementary assets framework (Teece, 1986) that has been instrumental in explaining innovators' commercialization outcomes. As Teece (2006) points out in his reflection of the original article, the extant literature has been somewhat limited in its examination of complementarities, confining them to enterprise-level value chains (i.e., manufacturing, sales, marketing, and distribution), and not considering complementarities within the broader ecosystem (Adner and Kapoor, 2010, 2016; Kapoor and Furr, 2015). Our findings offer compelling evidence of how such complementarities impact the innovation's commercial success. Moreover, while the extant literature has emphasized the usefulness of specialized complementary assets for innovators to benefit from their innovations, we show that in the context of platform-based ecosystems, even generic complementary assets (i.e., platform, complements) can influence innovators' value creation and appropriation.

INNOVATION IN PLATFORM-BASED ECOSYSTEMS

A platform-based ecosystem encompasses a central platform firm and a network of complementor firms who build products around the platform. A platform represents an underlying technical architecture that acts as a foundation upon which other firms can develop their products, and offer them to the users.[1] Gawer (2014) highlights two distinct approaches to studying platforms in the extant literature. One approach focusses on platforms as creating value through network effects or multisided markets (e.g., Katz and Shapiro, 1986; Schilling, 2002; Eisenmann et al., 2006; Rochet and Tirole, 2003; Armstrong, 2006). The other approach focusses on platforms as technical architectures that facilitate innovation by complementors within the ecosystem (Gawer and Cusumano, 2002; Baldwin and Woodard, 2009; Boudreau, 2010). Scholars from both streams of research have considered the focal platform or the focal platform firm as the primary object of attention. While these scholars have also acknowledged the role of complementors and their innovation in driving platform's success, there has been in general a lack of emphasis in examining the outcomes of complementors and their innovations. There are often significant differences in the extent to which a given innovation is commercially successful in an ecosystem (Adner and Kapoor, 2010), and yet, what makes a complementor's innovation successful in a platform-based ecosystem is not well understood.

[1] In this paper, the focus is primarily on platforms that provide a foundation upon which other firms develop complementary products (e.g., platforms focusing on enterprise software, genomics, smart homes, internet of things), and not on platforms that purely facilitate transactions between buyers and sellers (e.g., eBay. Amazon).

An emerging stream of work has started paying attention to complementors, which are critical to value creation within the platform-based ecosystem (e.g., Kapoor, 2013; Kapoor and Agarwal, 2017; Boudreau, 2010, 2012; Altman 2016; Cennamo, Gu, and Zhu, 2016; Zhu and Liu, 2016). While scholars have started shedding some light on the complementors' strategies and performance, they have largely been agnostic to the technological interactions that exist between a complementors' innovation and other elements of the ecosystem. In this study, we focus on complementors' innovation and the vast array of its technological interactions within the ecosystem. For example, an app in the iPhone ecosystem can interact with multiple components from the iPhone (e.g. camera, GPS, accelerometer) as well as with other apps from the ecosystem (e.g. Google maps, Facebook, Dropbox). We use the notion of connectedness to refer to these technological interactions of a complementor's innovation with the platform (i.e., platform connectedness) and other complements (i.e., complement connectedness). We explore how an innovation's platform connectedness and its complement connectedness shape its commercialization success within the ecosystem.

For the platform connectedness, we consider the level of hierarchy within the platform architecture. In addition to being a modular system, a platform is also a hierarchical system and can be decomposed into core and optional components. There are some components in the platform that represent the core architecture of the platform, and all the complements participating in the ecosystem leverage these core components. In other words, firms develop their products using the core components of the platform. The rest of the components are optional, and complements may (or may not) leverage them. For example, in the video game ecosystem, the console consists of the central processing unit (CPU), the graphics processing unit, the memory controller, and the video decoder. These are the core components of the console that enable games developed by third-party developers to be played on the console. In addition to the core components, the console also provides access to a number of optional components (such as motion detectors, camera, and Bluetooth) that game developers can leverage to enhance features of their games. The game developers use the core components, and may also use some of the optional components, to develop different games for the console users. Such an architectural hierarchy that involves core and optional platform components exists in many settings such as in the cases of computing hardware, enterprise software, genomics technologies and mobile payments. We consider this characterization of the platform to understand variation in ways a complementor's innovation can be connected with the platform.

In addition to platform connectedness, we also examine the role of complement connectedness in impacting an innovation's commercial success. The extant literature has considered the interaction between the platform and the complements primarily through the theoretical lens of indirect network effects (e.g., Schilling, 2002; Zhu and Iansiti, 2012). However, complements in an ecosystem can be connected not only with the platform but also with the other complements in the ecosystem. For example, the Uber app in the smartphone ecosystem is connected with Google Maps for its navigation purposes. Figure 2.1 illustrates the two types of connectedness that we consider in this study using a simplified schema. We now explore how the nature of connectedness for the focal innovation within the ecosystem may affect its commercialization success.

Insert Figure 2.1 about here

Platform Connectedness

We consider an innovation as having high platform connectedness if it leverages the optional components of the platform in addition to the core module of the platform. For example, in the iPhone ecosystem, the 'QR reader' app that allows scanning of QR codes, barcodes, and documents through the app has high connectedness with the iPhone platform as it leverages the core mobile computing module as well as the camera, one of the optional components provided by the smartphone. The optional components provided by the platform represent a set of complementary technologies that firms can combine with their focal innovation, and achieve superior functionality without having to invest in those technologies internally. Moreover, users are generally familiar with platform components, and hence, may not face adoption challenges for innovations high platform connectedness. Finally, access to these components can also facilitate experimentation by providing the innovating firm with new options with respect to the functionality at little or no cost. Hence, we expect that innovations with greater platform connectedness will be more likely to achieve successful commercialization:

H1 - The greater is the innovation's platform connectedness, the higher will be the likelihood of its successful commercialization.

Complement Connectedness

We consider an innovation as having high complement connectedness if it interacts with other complements in the ecosystem. For example, in the iPhone ecosystem, the "National Park" app, provided by National Geographic Society, has high complement connectedness, as it leverages the Google Map app to provide navigation facility to its users. Prior work in strategy has considered how complements enhance the value of the platform for the user through indirect network effects (e.g., Schilling, 2002; Zhu and Iansiti, 2012). We argue that such network externalities can not only exist between a platform and complements, but can also exist between complements.

The focal innovation that is connected to other complements in the ecosystem might be more valuable as users can derive additional benefits from combining the functionalities of the complements with the focal innovation. Such connections can also provide the focal innovation with access to the installed bases of the connected complements. Further, having access to the specialized technologies provided by external complements can increase the combinatorial set for experimentation and learning for the focal innovation and thus, can facilitate commercialization. Finally, developing the complementary technologies on one's own can be costly and uncertain. By leveraging the readily available complementary technologies provided by other firms, firms can also avoid commercialization setbacks that can be associated with the launch of new innovations within an ecosystem (Adner and Kapoor, 2010; Kapoor and Furr, 2015). Accordingly, we suggest that:

H2 - The greater is the innovation's complement connectedness, the higher will be the likelihood of its successful commercialization.

Effect of platform evolution (generational change)

We now consider how the effect of platform and complement connectedness on an innovation's commercialization success might be impacted by the introduction of the new generation of the platform. Transitioning to a new platform generation is an important mode by which platform firms compete and create value over time. New platform generations typically offer improvements in existing functionality as well as add new functionality. In so doing, they alter the interfaces through which the complements interact with the platform (Venkatraman and Lee, 2004; Ansari and Garud, 2009; Adner and Kapoor, 2010; Kapoor and Agarwal, 2017). Hence, a new platform generation may represent the instance of an architectural change as discussed by Henderson and Clark (1990) but at the level of the ecosystem, where the core design concepts and the associated knowledge are not overturned but there is a change in the nature of the interactions between the platform and the complements. This, in turn, might affect the commercialization success of innovations that are technologically connected with the platform for their functioning.

The connectedness between an innovation and a platform creates interdependence that needs to be managed proactively. Traditional coordination mechanisms such as hierarchy and ongoing communications associated with firms are typically absent in platform-based ecosystems. The platform firm often relies on the core technical architecture to frame interactions and to coordinate activities among complementors (Gawer and Cusumano, 2002). This is achieved through the design of the platform interfaces that provide complementors with access to the platform's core and optional components. The platform firm coordinates activities within the ecosystem by managing these interfaces so as to ensure coherent working of the ecosystem. As firms build their innovations using the components provided by the platform, they repeatedly interact with the platform through these interfaces. To maximize value creation, they design their innovation specific to the interfaces provided by the platform. They develop skills and processes specific to the interfaces provided by the platform. This designing of the innovation and routinization of processes specific to the interfaces and the platform context can also be referred to as 'structural embeddedness' of firms in the platform (Karim, 2012).

When an innovation has a high level of connectedness with the platform, its commercialization may be hampered by the newness of the platform generation. Users may face challenges as they adopt the focal innovation during a period when there is significant uncertainty regarding the overall architecture of the platform. From the perspective of the innovating firm, while higher platform connectedness allows for the leveraging of additional functionality accorded by the platform firm, it also imposes greater technological interdependencies that have to be carefully managed during a period of generational transition within a platform (Kapoor and Agarwal, 2017). Such additional challenges faced by the users and innovators during a period of generational transition may limit the commercialization success of those innovations with high platform connectedness. Hence, we hypothesize the following:

H3 - The effect of platform connectedness on the innovation's commercialization success will be moderated by platform's generational evolution such that the effect will be less positive when the platform generation is new than when it is mature.

The new generation of the platform not only affects innovations that have high connectedness with the platform, but it can also affect innovations that are connected with other complements in the ecosystem. On the one hand, the interdependent complements enhance the value of the focal innovation; on the other hand, they can also act as bottlenecks constraining its successful commercialization especially during technology transitions (Adner and Kapoor, 2010; 2016). For example, Gawer and Henderson (2007) show that the performance of Intel's microprocessor was constrained by the bottleneck in the peripheral complements that supplied data to the microprocessor. Similarly, in the semiconductor lithography equipment industry, the commercialization success of innovations was negatively impacted by the technological bottlenecks in the mask and the resist complements (Adner and Kapoor, 2016). Such constraints that limit the commercialization success of an innovation are likely to be most prominent in a platform-based ecosystem when a new generation of platform is introduced.

In addition, it is likely that as the connected complements evolve in the face of platform transitions, so will the technological interfaces between the focal innovation and those complements. Thus, the focal innovation needs to adapt not only to the changes made in the new generation of the platform but also to the changes that the connected complement makes in response to the new platform generation. Such additional challenges faced by the complementors during a period of generational transition may limit the commercialization success of those innovations with high complement connectedness. Hence, we hypothesize the following:

H4 - The effect of complement connectedness on the innovation's commercialization success will be moderated by platform's generational evolution such that the effect will be less positive when the platform generation is new than when it is mature.

METHOD

The empirical setting for the study is Apple's iPhone ecosystem, and the focal complementor firms are application software (app) developers who participated in the ecosystem from 2008 to 2015 by developing apps for the iPhone within the U.S. market. Apple launched its first generation of iPhone in January 2007, and it developed its own apps for this generation. However, in March 2008, Apple released the first software development kit that allowed external software developers to build apps for the iPhone, and started offering apps from these developers through its App Store in July 2008. Since this shift towards a platform-based strategy, the number of application developers building apps and the number of apps for the iPhone has grown exponentially, and this has been a key enabler of iPhone's success over the past decade. As of June 2015, there were more than 1.5 million apps offered in the App Store, and more than 100 billion copies of apps downloaded by iPhone users.

The setting provides an important and relevant context to study how the commercialization success of complementor's product innovations is shaped by the structure of technological interactions within the ecosystem. The iPhone ecosystem represents one of the largest and most valuable business ecosystems with App Store revenue estimated to be more than $10B in 2016. Hundreds of thousands of app developers participate in this ecosystem by frequently launching new apps. Moreover, apps launched by developers vary in terms of leveraging both the optional components (e.g., camera, GPS, accelerometer) from the iPhone platform, and the other complementary apps (e.g., Google Maps, Dropbox, Facebook) offered by developers in the iPhone ecosystem. Finally, between 2008 and 2015, there were six generational transitions within the iPhone platform when Apple launched new versions of the smartphone operating system and the handset, allowing us to observe the impact of platform's generational evolution on the commercialization success of apps across multiple generations.

Data

The dataset comprises of all the apps that were introduced by developers for the iPhone between July 2008 and March 2013. The primary sources of data are App Annie (www.appannie.com), iTunes (www.apple.com/itunes/), and AppShopper (www.appshopper.com). App Annie and AppShopper are the leading data aggregating and archiving sources for information on apps in the iPhone ecosystem. Since 2008, they have been independently archiving information on the apps launched in the iPhone ecosystem. We first collected information for the apps that were launched until March 2013. Using two different sources helped us to minimize missing data, and we were able to identify 796,876 unique apps. For each of these apps, we collected information on launch date, app description, download price, average consumer rating, content rating, app size, language, in-app purchases and category. We supplemented this with additional information from iTunes on platform components leveraged by the focal app, and all of the version updates up to December 2015.

In the analysis, we only consider those apps whose primary source of revenue is from the App Store through either paid downloads or in-app purchases. We did that for two reasons. First, firms from many industries such as retail and financial services offer iPhone apps as an additional channel to support their existing business. Hence, the app on its own is not their focal product innovation. Second, many firms also offer apps for free and rely on ad-based revenue model. In such cases, apps are the main source of ad-based revenue, but these revenues are not captured by the App Store and, hence, do not allow us to draw inferences with respect to their commercialization success. This reduced the total number of apps to 421,021 apps. In parallel, we gathered information about the Top 500 iPhone apps based on downloads and revenues. Apple provides daily lists of the Top 500 apps based on the number of downloads and the total app revenue. App Annie has archived this daily ranking information from Apple, and we were able to access this information from February 2010 to December 2015. To avoid any left censoring in the data, we excluded 127,703 iPhone apps that were introduced before February 2010. Finally, we induce the extent of complement connectedness from the detailed app description and using a keyword-based approach. This approach made it difficult to include apps offered in other languages, and hence, these apps were excluded from the analysis. We also excluded books, news, and reference apps, whose description typically include portions of the actual content which made the keyword-based approach to identifying complement connectedness less effective. The final dataset comprised of a total of 249,305 apps launched by 20,391 firms. Because of the hypercompetitive nature of this setting, we test our predictions using monthly observations for each of the apps.

Measures

Dependent variable: We measure successful commercialization of an innovation by examining whether the focal app made it to the Top 500 apps list by revenue (e.g., Kapoor and Agarwal, 2017; Davis et al., 2016). The revenue distribution for smartphone apps is heavily skewed. According to Sensor Tower, a leading vendor for App Store marketing and sales tracking software, the top 1 percent of the app developers in the iPhone ecosystem represent approximately 94 percent of total ecosystem-level revenue (SensorTower, 2016). Therefore, having an app in the Top 500 list offers clear evidence of successful commercialization among hundreds of thousands of apps. Such a list is also keenly followed by industry observers and analysts as a reference for successful apps.

Platform connectedness: The iPhone platform comprises of a core mobile computing module that all app developers have to leverage for their apps to function on the iPhone. In addition, app developers can leverage a number of iPhone components such as Bluetooth, camera, GPS, gyroscope, location services, video camera, and Wi-Fi for their apps. The greater is the number of iPhone components that an app is leveraging, the higher will be its platform connectedness. Hence, we measured *platform connectedness* based on the number of non-core components offered by the platform that the focal app leveraged. While about 50 percent of apps leveraged only the core module of the iPhone platform, 30 percent of apps leveraged one optional component, and 20 percent of apps leveraged more than one optional components.

Complement connectedness: In addition to connectedness with the platform, a focal app can also be connected with apps offered by other firms in the ecosystem. For example, many apps in the iPhone ecosystem leverage Google's map app for its navigation functionality via the application programming interfaces (APIs). Similarly, a large number of apps leverage Facebook's apps such as Facebook and Instagram for the social networking functionality. The information on the apps that a focal app leverages is prominently disclosed in the description of the app. We searched the description of all apps for the mentions of these other apps. For example, one of the apps, *ReaddleDocs,* describes its connectedness with other apps such as *MobileMe iDisk, Dropbox, and Google Docs* in its description:

"…readdleDocs is all-in-one document reader for iPhone and iPod touch...readdleDocs allows you to download and upload files from ***MobileMe iDisk, Dropbox, Google Docs****, and other services...."*

Similarly another app, Matg, discusses how it leverages Google Maps:

"….designed for sales, marketing or finance executives, this app allows you to access customers, sales order transactions, accounts receivable statements, item master, and item warehouse information...tight integration with other iPhone features, such as e-mail and ***Google Maps****, will provide you with the ability to communicate effectively with your corporate office about any of your accounts…."*

The greater is the number of other complementary apps that the focal app is leveraging, the higher will be its complement connectedness in the ecosystem. Hence, the variable *complement connectedness* measures the number of other apps that the focal app is connected to in the iPhone ecosystem. While about 13 percent of apps leveraged one complement, about 9 percent of apps leveraged more than one complement. In some cases, apps would increase their complement connectedness as part of their "version update" which includes new features. Hence, in addition to searching through the product description, we also searched through the version update history to identify changes in an app's complement connectedness. As a robustness check, we excluded these apps from the analysis, and found very similar results.

Table 2.1 summarizes the number of apps based on their platform and complement connectedness for all apps in the dataset and for only those apps that made it into the Top 500 list by revenue. Apps that leverage at least one optional component of the iPhone platform are categorized as having high platform connectedness, and low otherwise. Similarly, apps that leverage at least one other complementary app are categorized as having high complement connectedness. Of all the apps in the dataset, 49.3 percent had high platform connectedness whereas of all the Top 500 apps, 64.4 percent had high platform connectedness. This pattern is consistent with the prediction in Hypothesis 1. Similarly, 21.9 percent of apps in the dataset had high complement connectedness whereas of all the top 500 apps, 41.2 percent had high complement connectedness. This pattern is also consistent with the prediction in Hypothesis 2.

Insert Table 2.1 about here

Generational Newness: Between 2008 and 2015, the iPhone platform underwent six episodes of generational transitions. These transitions included both changes in the operating system (iOS) and in the handset. More than 90% of iPhone users have been shown to migrate to the new operating system within the first month whereas the migration to the new handset is much more gradual. From a perspective of an app developer, the changes in iOS are a major consideration as it impacts almost the entire iPhone user base. In order to consider the impact of iPhone platform's generational evolution on the successful commercialization of the focal app, we used the variable *generational newness* which is calculated based on the number of months between the observation month and the month in which the latest generation of the iPhone platform was launched. We multiplied this measure by -1 for ease of interpretation with respect to the hypotheses. Hence, higher values correspond to an early period of a new platform generation.

In order to explore the challenges faced by app developers and users during the early period of a new platform generation, we used Google search data reported in Google Trends (www.google.com/trends). Figure 2.2 shows the graphical plot for normalized monthly trend of U.S. search volume for the search term "iOS app not working" from January 2010 to December 2015. As shown in the figure, there are significant spikes in search volume during the months when the new platform generation is launched, suggesting that iPhone users and app developers faced major challenges with their apps during this period.

Insert Figure 2.2 about here

Control variables: We control for a number of firm-level and app-level effects that can influence the likelihood of successful commercialization for the firm's app. First, we control for firms' experience in the ecosystem using the variable *firm experience,* which is the total number of months that a firm has been participating in the ecosystem. To obtain this measure, we first identified the month in which the firm introduced its first app in the ecosystem (i.e., the month of entry) and then calculated the number of months between the observation month and the month of entry. Second, app developers often try to gain visibility among their potential users by providing free apps. We controlled for this firm-level effect through a dummy variable *top 500 free* 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. Further, an app's successful commercialization is likely to be influenced by the overall demand for its submarket category (e.g., Games, Productivity, Utility, Business). An app in a high-demand submarket category will find it relatively easier to succeed. We account for this possibility using the variable *category demand*, which is the total number of apps from the focal firm's app category in the Top 500 list in a given month. In addition, we also control for any category-level differences by using category fixed effects.

We control for the quality of the app based on consumer ratings received by the focal app. Consumers can rate an app from 1 to 5 stars, with 5 being the highest quality. In the dataset, we were able to observe the cumulative rating offered by the consumer for a given app as of March 2013, but not the changes in the rating over time. We used this time-invariant measure to control for app quality. The variable *app rating* is the cumulative rating received by the focal app as of March 2013. We also control for recent investments made by firms in their focal app by measuring the number of updates to the focal app in the past three months (*3-month updates*) and the total number of updates before the observation month (*Total updates*). Additionally, we controlled for other app-level characteristics like the price for download *(download price)*, recommended age rating for the app (content *rating*), the app's storage space as a proxy for *app complexity,* and whether the app has an in-app purchase option or not (*in-app purchase*). Table 2.2 provides a brief description of the variables used in the analysis.

Insert Table 2.2 about here

Analysis

We tested our hypothesis using continous time event history analysis to estimate the hazard rate of an app achieving successful commercialization. We constructed the data in the long form to account for time-varying covariates. We started analyzing all the apps since their first month of launch on the iPhone platform. For the apps that entered the Top 500 list by revenue, we included information for the months until they first appeared in the Top 500 list. For those apps that did not appear in the Top 500 list until December 2015, we used two different approaches to identify the censoring month. First, many of these apps continue to be available in the App Store without any updates akin to the 'living dead' phenomenon (Bourgeois and Eisenhardt, 1987). Censoring these apps based on the last month of observation (December 2015) might be problematic because the likelihood of them making it to the Top 500 list may be very low beyond a certain month. To account for this possibility, we identify these 'living dead' apps by analysing data on version updates, and we only include monthly observations until 12 months after their last update. As an additional robustness check, we also estimated a model where we only include observations for these apps until six months after their last update. We report this analysis in the robustness checks section after presenting our main results.

We used the Cox proportional hazard 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 about the 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 the proportionality hazard assumption by checking if the slope of the regression equation of scaled Schoenfeld residuals on time is nonzero for the full model as well as for all predictor variables (Grambsch and Thermeau, 1994). The proportional hazard assumption was satisfied for both the full model and all predictor variables. Finally, apps introduced by the same firm often differed with respect to their connectedness within the ecosystem, allowing us to control for unobserved firm-level heterogeneity by treating each firm as a separate stratum (Allison, 1996).

Results

We report the summary statistics and correlations between our covariates in Table 2.3. The results from the Cox model are reported in Table 2.4. The model estimates the hazard of an app achieving successful commercialization as identified by its first inclusion in the Top 500 list by revenue. The reported coefficients can be exponentiated to obtain hazard ratios, which are interpreted as the multiplier of the baseline hazard for the app being included in the Top 500 list when the variables increase by one unit (Allison, 2010). An increase in hazard can also be interpreted as an increase in the likelihood of an app achieving successful commercialization. All standard errors reported were corrected for noninterdependence across multiple observations for the same app by clustering observations for each app. All the models include category-fixed effect and firm-level stratification to control for any unobserved time-invariant differences across categories and firms. Model 1 is a baseline model with only control variables. In Models 2 and 3, we include the variables *platform connectedness* and *complement connectedness* to test Hypotheses 1 and 2, respectively. In Model 4, we include the interaction term between *platform connectedness* and *generational newness* to test Hypothesis 3. Similarly, we include the interaction term between *complement connectedness* and *generational newness* in Model 5 to test Hypothesis 4. Model 7 is the fully specified model with all independent variables and interaction terms.

Insert Tables 2.3 and 2.4 about here

In Hypothesis 1, we predicted that the greater is the innovation's platform connectedness, the higher will be the likelihood of its successful commercialization. We find support for this prediction in both Models 2 and 4. The estimated coefficient for *platform connectedness* is positive and statistically significant ($p < 0.01$). In considering the magnitude of the estimated coefficients in Model 2, we find that a one unit increase in platform connectedness is associated with a 17.4 percent higher likelihood of the focal app making it into the list of Top 500 apps by revenue within the iPhone ecosystem. Similarly, in Hypothesis 2, we predicted that the greater is the innovation's complement connectedness, the higher will be the likelihood of its successful commercialization. We find statistical support for this prediction. The coefficient estimates for the variable *complement connectedness* in Models 3 and 5 are positive and statistically significant ($p < 0.01$). Based on the estimated coefficients from Model 3, an increase in complement connectedness by one unit can increase the focal app's likelihood of making it into the list of Top 500 apps by revenue by 15.1 percent.

In Hypothesis 3, we predicted that the effect of platform connectedness on the innovation's successful commercialization will be weaker during the early period of the platform generation than when platform generation is relatively mature. The results from Model 4 supports the prediction. The estimated coefficient for the interaction term between platform connectedness and generational newness is negative and statistically significant ($p < 0.01$). Hence, the effect of platform connectedness on the app's commercialization success is less positive when the platform generation is new than when it is mature. This suggests that the benefits of platform-level complementarities that accrue to app developers whose apps have high platform connectedness may be buffered by the challenges of managing additional technological interdependencies between their apps and the new generation of iPhone platform.

Finally, in Hypothesis 4, we predicted that the effect of complement connectedness on the successful commercialization of an innovation will be weaker during the early period of the platform generation than when platform generation is relatively mature. We test for the interaction between *complement connectedness* and *generational newness* in Model 5. The estimated coefficient for the interaction term is positive but statistically insignificant, suggesting that the effect of complement connectedness on an app's successful commercialization does not vary with platform's generational evolution.

To further explore this non-finding with respect to Hypothesis 4, we conduct a *post hoc* analysis to understand how the connected complement might differ with respect to its platform connectedness. Our theoretical arguments were premised on the existence of technology bottlenecks and the need for firms to adapt and reconfigure their products during generational transition of the platform (Henderson and Clark, 1990; Kapoor and Agarwal, 2016). However, it is possible that there is some variation in the degree of adaptation required, depending on the level of connectedness between the connected complements and the platform itself. To explore this possibility, we separate the variable *complement connectedness* into two categories depending on the level of platform connectedness of the complement that the focal innovation is connected to.

We identified the complements with high platform connectedness as those that used at least one of the optional components offered by the platform. Apps such as Google Maps, Waze, and YouTube use one or more optional components provided by the iPhone platform, whereas apps like Dropbox and Google Drive use only the mobile computing module of the iPhone platform. We measured *complement connectedness with high platform connectedness* as the number of complements with high platform connectedness that the focal innovation is connected to within the ecosystem. Similarly, we measured *complement connectedness with low platform connectedness* based on the number of complements with low platform connectedness that the focal innovation is connected to within the ecosystem.

In Models 6 and 7, we test for both the direct effect of complement connectedness with high and low platform connectedness respectively, and their interaction effect with *generational newness*. The coefficient for the direct effect of both types of complement connectedness is positive and statistically significant, providing evidence for the argument that complement connectedness increases the likelihood of the focal innovation achieving successful commercialization. Further, the coefficient for the interaction effect of *complement connectedness with low platform connectedness* and *generational newness* is positive and statistically significant. In contrast, the coefficient for the interaction effect of *complement connectedness with high platform connectedness* and *generational newness* is negative and statistically significant ($p < 0.05$). We illustrate this difference in the effect of the two types of complement connectedness through the plots in Figure 2.3. The difference in the effect of complement connectedness depends on the extent of connectedness between the platform and the complement that the focal innovation is connected with. The benefit of complement connectedness is strengthened when Apple introduces the new platform generation and if the complements that the focal app is connected to have *low* platform connectedness whereas it is weakened when Apple introduces the new platform generation and if the connected complements themselves have *high* platform connectedness. These findings clearly highlight the two faces of value creation in ecosystems – the opportunities associated with leveraging complementarities and the challenges associated with managing technological interdependencies.

Insert Figure 2.3 about here

Robustness Checks

We conduct a number of additional checks to establish the robustness of our findings. We report these results in Table 2.5. First, in order to ensure that the results are not the artifact of a large number of observations, we conduct an additional analysis on the randomly drawn subsample based on the weighted exogenous sampling maximum likelihood (WESML) technique suggested by Manski and Lerman (1977). An estimation based on the random exogenous sample was not practical because apps that achieve successful commercialization are rare. There are only 4,213 apps out of 244,034 total apps that achieved successful commercialization during the observation period. From the information point of view, it would be desirable to have a greater fraction of apps that achieved successful commercialization. A choice-based sampling that takes fractions of both successful and unsuccessful apps would not be appropriate. Because this stratification would be done on the dependent variable, the estimates would be subject to selection bias. Hence, the WESML technique is more suited for rare events (Singh, 2005), as it allows for forming a sample with a greater fraction of observations with rare events without any selection bias. Intuitively, the idea is to weigh each sample observation by the number of population elements it represents to make the choice-based sample simulate a random exogenous sample.

In order to construct our sample, we followed the WESML technique laid out by Singh (2005). We constructed the sample by first selecting all the apps that entered the Top 500 list during the observation period and then drawing a random pool of approximately 20 percent of the apps that never entered the top list. This generated a sample of 50,091 apps. We then assigned weights to the each of these apps based on the representation of these apps in the overall dataset. The apps that entered the top list were assigned a weight of '1,' as all these apps from the population were included in the sample. The apps that did not enter the top list were assigned weights as the ratio of total apps in the respective category that were in the sample to that in the entire dataset. The results of the analysis based on this subsample are reported in Model 8 and are qualitatively similar to our main results.

Insert Table 2.5 about here

Alternative specifications

We also conduct additional robustness checks with alternative specifications. First, we test the sensitivity of our results to the use of categorical variables to categorize high or low connectedness (Model 9). The variable takes a value of 1 if the focal app connects with a complement or optional platform components, and 0 otherwise. Moreover, we test the importance of the degree of connectedness, i.e., whether results are driven by the presence of connectedness or whether the degree of connectedness matters. We do so by removing all the apps that did not have any connectedness with the platform or other complement (Model 10). Further, we also test whether our results are sensitive to the window that we have used to specify whether an app is still active in the ecosystem or not. As an additional check, we consider an app to be actively contesting for the top position only if it was updated in the previous six months (Model 11). The results from all of these analyses are consistent with the main results.

Finally, an important issue to consider in our analysis is the possibility that apps self-select into different types of connectedness, which could potentially bias our estimates. We use both coarsened exact matching and instrument variable approach to test the robustness of our results to this potential endogeneity bias.

Coarsened exact matching analysis

Coarsened exact matching approach has been used commonly in economics to address concerns related to selection bias. Recently, scholars in management have started using this approach to address selection bias in their empirical specifications (e.g., Aggarwal and Hsu, 2013; Feldman and Amit, 2014). It is a nonparametric approach to reestablish the conditions of natural experiment by comparing statistical results between a treatment group and a comparable control group, thus, allowing for causal inference. We used this approach to evaluate whether apps with high connectedness with the platform or other complements have higher likelihood of achieving successful commercialization or not. For the purpose of this analysis, we compare apps that have high connectedness with those that have low connectedness. In the case of platform connectedness, apps are considered to have high platform connectedness if they are leveraging at least one optional component provided by the platform, and low otherwise. Similarly, apps that interact with one or more complements in the ecosystem are considered to have high complement connectedness, and low otherwise. We estimate separate models for platform and complement connectedness. The treatment group is defined as the apps that have high connectedness with the platform or other complements. Our control group is drawn from the apps that had low connectedness with the platform or other complement.

The coarsened matching provides an alternative approach by generating counterfactual that closely match with the treatment on the set of observed variables. To implement coarsened exact matching, the logistic regression predicting an app propensity to have platform or complement connectedness is estimated using coarsened values of independent variables, to accurately group innovations that share similar values of these variables. We use cross-sectional data with observations pertaining to the last month to estimate an app's propensity to have platform or complement connectedness. We, then, use the weights calculated by coarsened matching estimator (cem routine in STATA) in the second-stage model that we used in the main analysis. This model estimates the app's likelihood of entering into the top 500 revenue ranking based on its connectedness with platform or complements. The un-coarsened observations are weighted according to the prominence of each stratum into which they fall. Table 2.6 presents the result from the second-stage model. The estimates for second-stage model for platform connectedness and complement connectedness (with high platform connectedness) are statistically significant and consistent with the main model. The coefficient estimate for complement connectedness (with low platform connectedness) is qualitatively similar to the main model but has large standard error.

Insert Table 2.6 about here

Instrument variable analysis

While the coarsened exact matching approach matches the apps with and without connectedness on the basis of observables, it is possible that these apps' connectedness may be due to some unobserved differences. To further check for any potential app-level endogeneity bias, we use instrument variable using ivprobit STATA procedure (Bascle, 2008).

We identify an instrument that is likely to be correlated with an app's likelihood to have platform or complement connectedness, but uncorrelated with the app's commercialization success beyond its effect on the endogenous regressor (Angrist and Pischke, 2008; Bascle, 2008). We use the number of queries posted by developers on an online discussion board about the development challenges associated with the integration of platform components and other complements with their app. The number of queries is reflective of an overall interest within the developer community about the platform components and other complements. Hence, it is likely to be highly correlated with an introduction of platform or complement connectedness in the new apps or existing in the upcoming months. However, it is unlikely that this instrument would be correlated with an app's commercialization success, beyond its effect on the app's connectedness with the platform or complement. Given that our independent variables and queries related to these variables are mutually exclusive, we instrumented each independent variable separately. In this analysis with instrument variable, we focus only on the direct effects as we are not aware of any technique that allows using instrument variable for the interaction term. Further, we believe concerns related to endogenous selection are mainly associated with the direct effects of the connectedness on an app's successful commercialization. Hence, for this analysis we convert the long-panel data into a cross-sectional data by using values of the variables pertaining to the last observation month.

In Models 15, 17 and 19 in Table 2.7, we show the coefficients of the first stage selection model that estimates the effect of the number of queries on the apps' degree of platform and complement connectedness respectively. Models 16, 18 and 20 presents results from the second-stage model. The coefficient for platform connectedness and complement connectedness are positive and statistically significant ($p < 0.01$). The Cragg Donald statistics for three models is greater than 16.28, the recommended threshold provided by Stock and Yogo (2004) to satisfy instrument relevance condition. Overall, these additional analyses help to further establish the robustness of our findings.

Insert Table 2.7 about here

DISCUSSION

A given innovation often does not stand alone. Rather it is connected with other elements in the ecosystem that impacts its value creation. In this study, we draw on this premise in a platform-based ecosystem in which participating complementor firms innovate around a platform to explain the commercial success of its innovation. We depart from the existing conceptualization of these ecosystems as multisided markets in which firms interact with other actors and benefit from network externalities. Instead, we conceptualize them as interconnected technological systems in which the focal innovation interacts with other technology elements to create value. We introduce the notion of connectedness to refer to the extent to which a given innovation interacts with the platform (i.e., platform connectedness) and also with the other complements in the ecosystem (i.e., complement connectedness). On the one hand, higher connectedness may allow the innovation to leverage a broader set of complementarities in the ecosystem. On the other hand, it may subject the innovation to an array of interdependencies that may limits its value creation especially when a generational transition triggered by the platform firm changes the underlying platform architecture.

We explore these arguments on app developers that participated in Apple's iPhone ecosystem between 2008 and 2013 in the U.S. market. We find that higher platform connectedness and higher complement connectedness is associated with a higher likelihood of app's successful commercialization. However, the benefit of platform connectedness is negated during the initial period of the new generation of platform. In contrast, the benefit of complement connectedness with respect to platform's generational evolution is much more nuanced. The benefit is strengthened when Apple introduces the new platform generation and if the complements that the focal app is connected to have *low* platform connectedness whereas it is weakened when Apple introduces the new platform generation and if the connected complements themselves have *high* platform connectedness.

The study contributes to the emerging literatures on ecosystems and platforms, examining both the opportunities and the challenges faced by complementors in creating value from their innovations (e.g., Boudreau, 2010; Ceccagnoli et al., 2012; Kapoor, 2013; Kapoor and Lee, 2013; Altman, 2016; Cennamo, Gu, and Zhu, 2016; Zhu and Liu, 2016; Kapoor and Agarwal, 2017). We show that while participation in platform-based ecosystems enables firms to enhance the value of their innovations by leveraging a broad set of platform components and other complements, such an interconnected architecture of value creation can subject the firm to challenges with respect to managing the technological interdependencies. We also contribute to the literature on platform architecture (e.g., Baldwin and Woodard, 2009; Gawer, 2014). This stream of research provides a detailed account of the modular nature of the platform architecture and emphasizes its role in spurring innovation. We build on this characterization of the platform architecture and elucidate how the modular components of the platform differ with respect to their level of hierarchy within the platform architecture. We illustrate that the platform components can be decomposed into core and optional components, and this difference has important implications for value creation in ecosystems.

Further, we contribute to the research on complementary assets by focusing on complementary technologies that lie outside the firm's value chain. It has long been recognized that complementary assets play an important role in the success of an innovation and in the firms' ability to appropriate value from their innovations (Teece, 1986; Teece 2006). However, the bulk of the attention to this line of inquiry has been on complementary assets that either lie within the boundary of the firms or can be accessed by firms through alternative means such as licensing or strategic alliances (e.g., Dyer and Singh, 1998; Rothaermel, 2001; Arora and Ceccagnoli, 2006). The role of complementary technologies and assets that reside in the external business ecosystem remains relatively underexplored (Adner and Kapoor, 2010; Kapoor and Furr, 2015; Teece, 2006). In this study, we show how complementary technologies that lie outside the firm's value chain can help support the firm's focal innovation. Further, we also show how complementary technologies can be detrimental to a firm's performance when a platform is relatively new.

In practical terms, our study offers some guidance for both platform firms and complementor firms. A platform firm can enhance the overall value potential of an ecosystem by bundling a number of optional components along with the core technological architecture. Complementors can combine these optional components with their focal innovations and create more value for end users. Further, platform firms can also enhance value creation in an ecosystem by attracting participation by the "keystone" complementor firms in their ecosystems. These keystone firms represent a set of complementors who provide specialized technologies or user networks other complementors can leverage. Finally, our results also suggest that platform firms should pay more attention to platform generational transition and its impact on the interfaces by which complements interact with the platform. As these generational transitions can hamper complementor firms, better management of platform interfaces can help platform firms preserve the value of the platform during periods of generational transition.

The findings of this study are subject to a number of limitations that provide an opportunity for future research. First, they are based on a single empirical context, and their validity needs to be established through explorations in other settings. Second, our measure for successful commercialization is based on whether the focal app is ranked within Top 500 apps in terms of revenue in the iPhone ecosystem. Although this measure is consistent with our theory and is widely accepted as a proxy for successful commercialization, it may not represent superior economic performance for firms in general. Finally, the measures for complement and platform connectedness do not account for differences between complements or platform components in terms of their impact on an app's value creation. Despite these and other limitations, the study sheds light on the two faces of value creation for firms innovating in ecosystems -- the opportunities associated with leveraging complementarities and the challenges associated with managing technological interdependencies.

Figure 2.1:Different types of connectedness for an innovation in a platform-based **ecosystem**

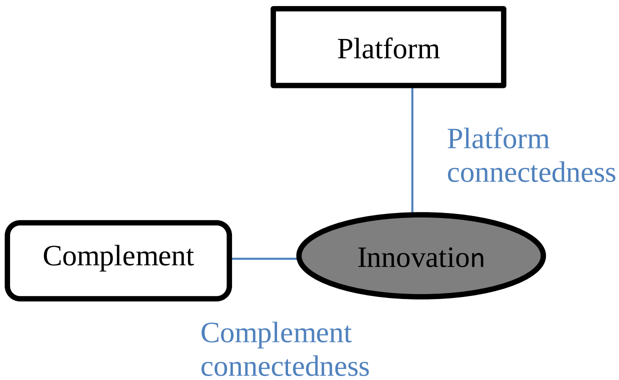


Figure 2.2:Normalized weekly trend of Web search in the U.S. on Google for the term "iOS app not working."

(Data source: Google Trends; http://www.google.com/trends/)

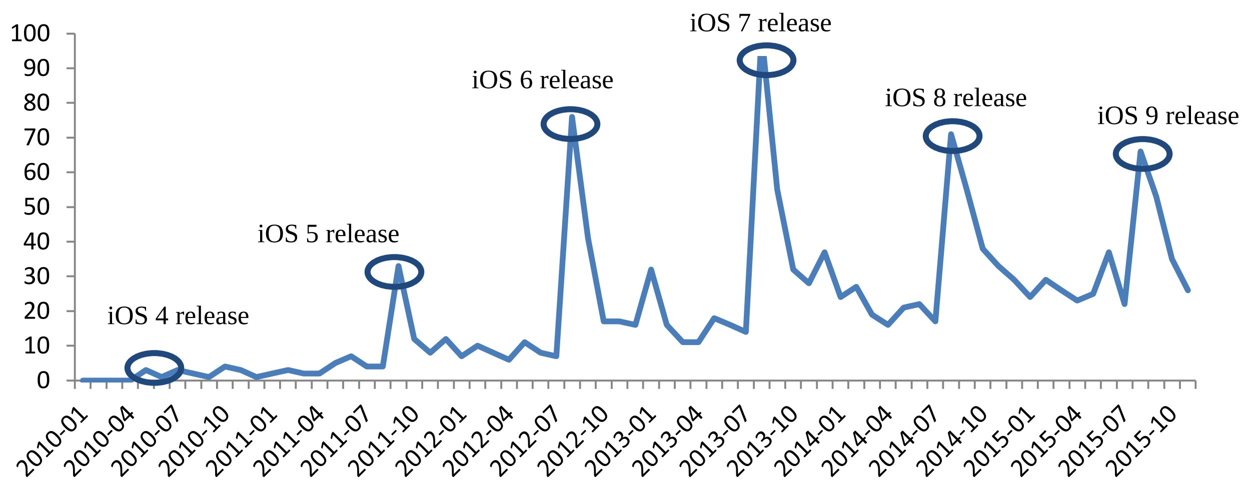
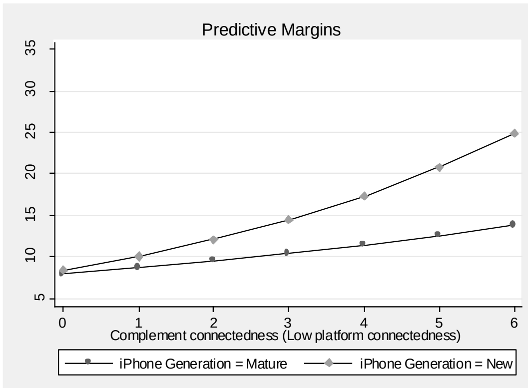


Figure 2.3: Interaction graphs for complement connectedness

<u>Complement connectedness</u>
<u>(Low platform connectedness)</u>



<u>Complement connectedness</u>
<u>(High platform connectedness)</u>

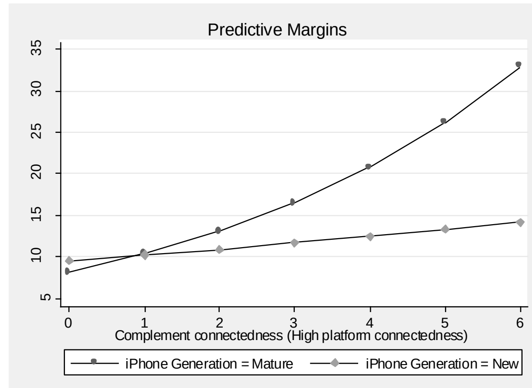


Table 2.1: Apps with platform and complement connectedness

Type of Connectedness		**All Apps**	**% Total apps**	**Top 500 apps**	**% Total Top 500 apps**
Platform connectedness	**Low**	126,311	50.67%	1,654	35.56%
	High	122,994	49.33%	2,997	64.44%
Complement connectedness	**Low**	194,683	78.10%	2,735	58.80%
	High	54,622	21.91%	1,916	41.20%

Table 2.2: Description of variables

Dependent variable	
Successful commercialization	Dummy = 1 for the month in which the app enters the Top 500 list by revenue
Independent variables	
Platform connectedness	Number of optional platform components with which the focal app interacts
Complement connectedness	Number of complements in the ecosystem that the focal app interacts with
Complement connectedness (Low platform connectedness)	Number of connected complements that interact only with the core platform module
Complement connectedness (High platform connectedness)	Number of connected complements that interact with optional platform components
Control variables	
Generational newness	Number of months since the launch of the latest generation of the platform; multiplied by -1 for ease of interpretation
App rating	Cumulative consumer ratings received by the app
App size	The amount of storage space required by the app (in MBs)
App content rating	Recommended age rating based on the app content
3-month updates	Number of times the focal app was updated in the last three months
Total number of updates	Total number of times the focal app was updated since its first launch
In-app purchase	Dummy = 1 for apps that have an in-app purchase option
App price	Price of the focal apps (in U.S. dollars)
Firm experience	Number of months since the focal firm launched its first app
App in Top 500 free	Dummy = 1 if firm has an app in the Top 500 ranking for the free app in a given month
Category demand	Total number of apps for the focal category in the Top 500 ranking based on revenues in a given month

Table 2.3: Descriptive statistics and correlations

No.	Variables	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12
1	Platform connectedness	0.636	0.770	1.000											
2	Complement connectedness	0.393	0.894	-0.003	1.000										
3	Generational newness	-6.901	3.802	0.031	0.007	1.000									
4	App rating	1.463	2.068	0.048	0.129	0.003	1.000								
5	App content rating	139.301	109.943	-0.009	0.024	-0.002	0.039	1.000							
6	App size	47.887	230.691	-0.010	0.010	0.001	0.029	0.039	1.000						
7	In-app purchase	0.308	0.462	0.222	0.068	0.018	0.265	0.055	0.005	1.000					
8	3- months updates	0.534	0.892	0.027	0.068	0.025	0.134	0.025	-0.006	0.077	1.000				
9	Total updates	2.717	2.613	0.025	0.153	0.021	0.257	0.028	-0.016	0.113	0.316	1.000			
10	App price	3.191	19.207	-0.100	-0.029	-0.032	-0.257	-0.091	0.125	-0.117	-0.040	. -0.058	1.000		
11	Firm experience	26.959	16.443	0.165	0.046	0.000	-0.010	0.023	0.047	0.153	-0.107	0.097	0.006	1.000	
12	App in Top 500 free	0.019	0.135	0.018	0.062	-0.001	0.151	0.017	0.036	0.078	0.030	0.012	-0.042	0.061	1.000
13	Category demand	136.111	186.492	0.273	-0.049	0.049	0.172	0.038	0.016	0.289	-0.025	-0.047	-0.124	0.109	0.084

Correlations greater than 0.01 or smaller than -0.01 are significant at $p < 0.05$, N = 3,797,947

Table 2.4: Cox proportional hazard model estimating the likelihood of achieving successful commercialization

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Platform connectedness		0.174***		0.226***			0.217***
		(0.023)		(0.028)			(0.028)
Complement connectedness			0.151***		0.131***		
			(0.024)		(0.030)		
Platform connectedness*Gen. newness				-0.177***			-0.175***
				(0.056)			(0.056)
Complement connect.*Gen. newness					0.070		
					(0.062)		
Complement connect.(Low plat. connect.)						0.100***	0.091***
						(0.035)	(0.035)
Comp. connect.(Low plat. connect.)*Gen. newness						0.182**	0.183**
						(0.076)	(0.076)
Complement connect.(High plat. connect.)						0.264***	0.236**
						(0.093)	(0.094)
Comp. connected (High plat. conn.)*Gen. newness						-0.365**	-0.340**
						(0.172)	(0.172)
Generational newness	0.227***	0.181***	0.203***	0.369***	0.154**	0.150*	0.307***
	(0.064)	(0.064)	(0.064)	(0.089)	(0.078)	(0.078)	(0.099)
App rating	0.831***	0.836***	0.826***	0.835***	0.825***	0.827***	0.834***
	(0.074)	(0.075)	(0.074)	(0.075)	(0.074)	(0.074)	(0.075)
App rating * App rating	-0.069***	-0.070***	-0.069***	-0.070***	-0.069***	-0.069***	-0.071***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
App content rating	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 size	-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)
Has in-app purchase	0.431***	0.384***	0.395***	0.379***	0.397***	0.394***	0.371***
	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.054)	(0.055)
3-month updates	0.251***	0.252***	0.252***	0.252***	0.252***	0.252***	0.248***
	(0.029)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
Total updates	0.131***	0.113***	0.115***	0.113***	0.115***	0.116***	0.114***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
App price	0.189***	0.206***	0.201***	0.205***	0.201***	0.199***	0.205***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Firm experience	-0.046**	-0.046**	-0.052***	-0.044**	-0.052***	-0.052***	-0.046**
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Time effect	0.028	0.028	0.038**	0.027	0.038**	0.038**	0.029
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Top 500 free app	0.832***	0.832***	0.834***	0.831***	0.833***	0.834***	0.830***
	(0.071)	(0.071)	(0.071)	(0.071)	(0.071)	(0.071)	(0.070)
Category demand	0.005**	0.004**	0.005**	0.004**	0.005**	0.005**	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Category demand * Category demand	-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)
Category-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total observation	3,797,947	3,797,947	3,797,947	3,797,947	3,797,947	3,797,947	3,797,947
Total apps	244,084	244,084	244,034	244,084	244,034	244,034	244,034
Total firms	20,174	20,174	20,174	20,174	20,174	20,174	20,174
Total events	4,213	4,213	4,213	4,213	4,213	4,213	4,213
Log likelihood	-7,050.31	-7,028.78	-7,036.16	-7,025.72	-7,035.74	-7,033.68	-7,011.29

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

Table 2.5: Robustness checks (Alternative specification)

	Model 8 WESML	Model 9 Dummy IVs	Model 10 High dep. apps	Model 11 6-mth window
Platform connectedness	0.189***	0.487***	0.157***	0.209***
	(0.047)	(0.091)	(0.032)	(0.028)
Complement connectedness (Low platform connectedness)	0.064**	0.219***	0.085**	0.092***
	(0.025)	(0.066)	(0.037)	(0.034)
Complement connectedness (High platform connectedness)	0.234**	0.239**	0.224**	0.236**
	(0.104)	(0.102)	(0.097)	(0.094)
Platform connectedness*Generational newness	-0.149*	-0.336*	-0.127*	-0.161***
	(0.082)	(0.203)	(0.067)	(0.055)
Comp. connectedness (Low platform connectedness)*Generational newness	0.269**	-0.004	0.181**	0.180**
	(0.131)	(0.151)	(0.082)	(0.075)
Comp. connectedness (High platform connectedness)*Generational newness	-0.504*	-0.324*	-0.254	-0.340**
	(0.288)	(0.190)	(0.170)	(0.173)
Generational newness	0.342**	0.455**	0.191	0.270***
	(0.158)	(0.222)	(0.143)	(0.099)
App rating	1.017***	0.829***	0.821***	0.832***
	(0.102)	(0.088)	(0.089)	(0.076)
App rating * App rating	-0.083***	-0.067***	-0.066***	-0.070***
	(0.013)	(0.011)	(0.011)	(0.010)
App content rating	-0.083***	0.001***	0.001***	0.001***
	(0.013)	(0.000)	(0.000)	(0.000)
App size	-0.000	-0.000	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Has in-app purchase	0.287***	0.281***	0.291***	0.353***
	(0.083)	(0.060)	(0.060)	(0.054)
3-month updates	0.256***	0.217***	0.223***	0.265***
	(0.045)	(0.033)	(0.033)	(0.029)
Total updates	0.180***	0.107***	0.105***	0.087***
	(0.044)	(0.028)	(0.028)	(0.023)
App price	0.182***	0.181***	0.172***	0.198***
	(0.040)	(0.028)	(0.029)	(0.026)
Firm experience	-0.036***	-0.047**	-0.045**	-0.045**
	(0.005)	(0.018)	(0.019)	(0.019)
Time effect	1.017***	0.030	0.030	0.030
	(0.102)	(0.018)	(0.019)	(0.019)
Top 500 free app	0.843***	0.890***	0.861***	0.814***
	(0.106)	(0.078)	(0.077)	(0.070)
Category demand	0.003	0.006**	0.000	0.000
	(0.003)	(0.002)	(0.001)	(0.001)
Category demand* Category demand	-0.000	-0.000**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Total observation	1,053,803	3,797,947	2,267,398	2,925,262
Total apps	50,901	244,034	148,385	244,034
Total firms	6,412	20,174	15,512	20,174
Total events	4,246	4,213	3,416	4,213
Log likelihood	-363.87	-5,307.70	-5,319.49	-6,922.18

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

Table 2.6: Robustness check: Results with Coarsened Exact Matching (CEM)

	Model 12	Model 13	Model 14
Platform connectedness	0.474***		
	(0.139)		
Platform connectedness*Generational newness	-0.540*		
	(0.316)		
Complement connectedness (Low platform connectedness)		0.132	
		(0.169)	
Complement connectedness (Low platform connectedness)* Generational newness		0.182	
		(0.358)	
Complement connectedness(High platform connectedness)			0.189**
			(0.093)
Complement connectedness (High platform connectedness) * Generational newness			-0.352*
Generational newness	0.206	0.226	0.561***
	(0.239)	(0.263)	(0.095)
App rating	0.925***	1.225***	0.846***
	(0.177)	(0.283)	(0.172)
App rating* App rating	-0.054**	-0.102***	-0.055***
	(0.022)	(0.033)	(0.020)
App content rating	0.001	0.001*	0.001*
	(0.001)	(0.001)	(0.000)
App size	0.000	0.000	0.000*
	(0.000)	(0.000)	(0.000)
Has in-app purchase	0.349**	0.496***	0.155*
	(0.139)	(0.152)	(0.085)
3-month updates	0.123	0.323***	-0.176*
	(0.080)	(0.110)	(0.093)
Total updates	0.107	-0.030	0.260***
	(0.067)	(0.092)	(0.085)
App price	0.139*	0.113	0.243***
	(0.078)	(0.080)	(0.046)
Firm experience	-0.112	-0.146**	-0.021***
	(0.092)	(0.072)	(0.002)
Time effect	0.087	0.124*	0.084
	(0.092)	(0.072)	(0.102)
Top 500 free app	0.575***	0.513***	0.472***
	(0.150)	(0.112)	(0.149)
Category demand	0.004	0.010	0.007**
	(0.006)	(0.007)	(0.003)
Category demand * Category demand	-0.000	-0.000**	-0.000***
	(0.000)	(0.000)	(0.000)
Total observation	3,294,869	1,488,883	3,188,760
Total apps	215,983.41	223,089.98	191,100.68
Total events	1,571.63	1,134.00	4,750.97
Log likelihood	-2,216.84	-1,163.06	-15,625.77

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

Table 2.7: Instrument variable analysis along with first stage selection model

	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20
Platform query	17.305***					
	(0.226)					
Platform connectedness		1.047***				
		(0.033)				
Complement query (Low platform connectedness)			4.293***			
			(0.173)			
Complement connectedness (Low platform connectedness)				1.293***		
				(0.005)		
Complement query (High platform connectedness)					6.818***	
					(0.792)	
Complement connectedness (High platform connectedness)						0.149***
						(0.069)
Generational newness	0.024***	0.065**	0.011	0.010	0.036*	0.055*
	(0.007)	(0.032)	(0.007)	(0.013)	(0.020)	(0.042)
App rating	-0.091***	0.454***	0.038***	0.023***	0.154***	0.510***
	(0.004)	(0.021)	(0.001)	(0.005)	(0.010)	(0.028)
App rating * App rating	0.018***	-0.040***	0.004***	-0.016***	-0.013***	-0.034***
	(0.001)	(0.003)	(0.001)	(0.003)	(0.002)	(0.004)
App content rating	-0.000***	0.001***	0.000***	0.000***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
App size	-0.000***	0.000***	0.000***	-0.000*	0.000**	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Has in-app purchase	0.176***	0.166***	0.052***	0.028**	0.034**	0.475***
	(0.005)	(0.026)	(0.005)	(0.011)	(0.013)	(0.024)
3-month updates	0.057***	0.476***	0.048***	0.108***	0.045***	0.632***
	(0.003)	(0.019)	(0.003)	(0.011)	(0.007)	(0.010)
Total updates	0.005***	-0.071***	0.063***	-0.061***	0.023***	-0.031***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
App price	-0.039***	0.253***	-0.005*	0.074***	0.056***	0.287***
	(0.002)	(0.011)	(0.003)	(0.006)	(0.007)	(0.014)
Firm experience	0.003***	-0.033***	0.002***	-0.012***	0.004***	-0.040***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Time effect	0.038***	-0.018***	0.004***	-0.027***	-0.000*	-0.007***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
Top 500 free app	0.019	0.973***	0.307***	-0.075***	0.324***	1.270***
	(0.012)	(0.039)	(0.012)	(0.027)	(0.025)	(0.059)
Category demand	0.005***	-0.012***	-0.002*	-0.004***	-0.004***	-0.007***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
Category demand * Category demand	-0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.169***	-2.812***	0.048***	-0.975***	-2.468***	-3.277***
	(0.013)	(0.102)	(0.013)	(0.054)	(0.043)	(0.066)
Total observation	244,084	244,084	244,084	244,084	244,084	244,084
Cragg-Donald statistic		6296.96		615.52		87.31

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

3. SUSTAINING SUPERIOR PERFORMANCE IN BUSINESS ECOSYSTEMS: EVIDENCE FROM APPLICATION SOFTWARE DEVELOPERS IN THE IOS AND ANDROID SMARTPHONE ECOSYSTEMS

Introduction

There is growing 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). Increasingly, business ecosystems are characterized by a firm that orchestrates the functioning of the ecosystem by providing a platform and setting the rules for other firms to leverage the platform and offer complementary products to the users. Scholars exploring this phenomenon have tended to focus on the strategies and performance of platform firms (e.g., Cusumano et al., 1992; Boudreau, 2010; Gawer and Henderson, 2007; McIntyre and Subramaniam, 2009; 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 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 value creation within the ecosystem.

In this study, we focus on the performance of complementor firms within a platform-based ecosystem. Specifically, we study the extent to which a high performing complementor can sustain its superior performance within the 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 platform-based ecosystems, sustainability of complementors' superior performance has important implications not only for these firms themselves but also for the platform firms whose performance is tied to value creation by their complementors.

To unpack the drivers of sustainability, we offer a novel characterization of complementors' ecosystem-level interdependencies that is rooted in the structural and evolutionary features of the ecosystem. We first consider the structure of the complementor's interdependence within the ecosystem 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 evolutionary features of an ecosystem by taking into account the generational transitions that are initiated by platform firms (e.g., introduction of new generation of operating system), and the experience that complementors gain within an ecosystem over time. Our theoretical arguments are premised on complementors' search processes with respect to innovation and imitation (e.g., Nelson and Winter, 1982, 2002; Gavetti and Levinthal, 2004). We consider how ecosystem-level interdependencies impact these processes, and the resulting performance dynamics among complementors.

The empirical setting for the study is the two dominant smartphone ecosystems in the U.S. - Apple's iOS and Google's Android, and we examine the performance of app developers in these ecosystems from January, 2012 to January, 2014. The setting provides a valuable opportunity to study complementors' performance dynamics in ecosystems with varying levels of complexity and being 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 both ecosystems over time. In addition, we observe three episodes of platform transitions that entail major updates to the smartphone operating system.[2]

We assembled a unique monthly panel dataset of top-performing app developers in the iOS and Android smartphone ecosystems over the two-year period. To gain insights into the challenges of developing apps and competing in these 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. Consistent with our arguments, we find that app developers' ability to sustain superior performance

[2] 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. For Apple, the iOS smartphone ecosystem is effectively the iPhone ecosystem.

is facilitated by the ecosystem complexity and their ecosystem experience but hampered by platform transitions initiated by Apple and Google. Moreover, ecosystem complexity enhances the benefit of ecosystem experience whereas it exacerbates the impact of platform transition.

The study, while limited to a specific empirical context, provides one of the first detailed accounts of the drivers of complementors' performance within a platform-based ecosystem. A key aspect of the study is to offer a novel perspective of complementors' ecosystem-level interdependencies that incorporates both the structural and evolutionary features of the ecosystem, and to show that such a perspective is useful in explaining performance dynamics among complementors within an ecosystem. In so doing, it contributes to the emerging literature stream examining the challenges and opportunities faced by complementors in business ecosystems (e.g., Boudreau, 2010; Ceccagnoli et al., 2012; Kapoor, 2013; Kapoor and Lee, 2013). More broadly, the study offers a new lens on the interactions between firms and their environments. Existing treatments of firms' environments are typically premised on complexity and uncertainty being a general feature of the industry (e.g., Dess and Beard, 1984; Anderson and Tushman, 2001; Davis, Eisenhardt and Bingham, 2009). However, in platform-based ecosystems, environmental complexity and uncertainty for complementors can be shaped by the strategies of platform firms, and as a result, complementors in the same industry can be subject to significantly different environments. Accordingly, there are implications for both platform firms that orchestrate the ecosystem and for complementor firms that leverage the focal platform. As we show in the study that ecosystem complexity can help complementors sustain their superior performance but it can also magnify the challenges that complementors face during periods of platform transition. Our findings also contribute to the literature on technological change which has shed light on how technology transition impacts the performance of firms in the focal industry (Tushman and Anderson, 1986; Henderson and Clark, 1990; Christensen, 1997). We highlight how technological interdependencies between platform firms and complementors in related industries can create a ripple effect for complementors when platform firms introduce a new generation of the platform. Finally, the study is also among the first to offer systematic empirical evidence about the role of complexity on firm performance as theorized within the evolutionary economics perspective of firms (e.g., Levinthal, 1997; Rivkin, 2000; Lenox et al., 2010).

Hypotheses

We focus on the performance of complementors within a platform-based ecosystem. In particular, we take into account that there are performance differences among complementors within an ecosystem, 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). We theorize how complementor's sustainability of superior performance is impacted by ecosystem-level interdependencies.

We first consider the structure of complementor's interdependence in the ecosystem based on the number of unique components that interact with a complementor's product. We refer to this structural feature as ecosystem complexity. The greater the number of unique components that interact with a complementor's product, the greater is the degree of ecosystem complexity faced by the complementor. This uniqueness could be driven by different variants of the components that perform the same function (e.g., distinct versions of a hardware component) or by different components that perform different functions (e.g., a hardware and a software component). Moreover, depending on the architecture of the ecosystem, the same complementor could be subject to varying degrees of complexity across two different ecosystems (e.g., an app developer participating in iOS and in 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).[3] Further, the architecture of the ecosystem can itself change over time depending on the choices of platform and complementor firms. This characterization of ecosystem-level complexity is distinct from existing treatments of industry-level complexity that are rooted in the complexity of firms' internal technological knowledge domains, products and processes (e.g., Ganco, 2013; Fleming and Sorenson, 2001; Lenox et al., 2010; Singh, 1997), or in the concentration of firms' inputs and outputs in the focal industry (e.g., Dess and Beard, 1984; Anderson and Tushman, 2001).

We then consider the impact 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 need to reconfigure their products to leverage the performance improvements accorded by the new generation of the platform. Finally, we consider the impact of complementor's experience in an ecosystem. Given that a complementor's product is closely tied to the ecosystem-specific components, we explore the importance of ecosystem-specific learning as it relates to the sustainability of superior performance.

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

[3] 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.

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). Such a solution comprises of choices that complementors may make regarding their products, tasks, or organization with respect to the ecosystem, and which collectively represent a superior performance configuration. The second process, imitative search, represents firms' attempting to imitate other high performing firms (e.g., Rivkin, 2000). We assume that complementors are continuously searching for superior performance configurations within an ecosystem. The search processes for the new complementors or the existing complementors with inferior performance (follower firms) are likely to be characterized by some combination of innovative and imitative search, while the search processes for the complementors with superior performance (leader firms) are likely to be characterized by innovative search. We first explore the role of ecosystem complexity. We then examine the role of complementors' experience and platform transition and how these factors interact with ecosystem complexity.

Ecosystem Complexity

To explain how ecosystem complexity influences complementors' 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 number of interactions between their products and other components 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 this:

> "We need to test our app on different OEM devices likes Samsung, HTC to make sure our app works on different Android devices.[4] 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."

Hence, an increase in ecosystem complexity translates into an increase in complementor's internal complexity with respect to its decision variables (i.e., the choices that complementors make regarding their products, tasks, and organization). For example, as the number of unique components that the complementor's product interacts with increases, there will be an increase in the number of decision variables with respect to product design. These decision variables may also interact with each other due to technological interdependence (i.e., hardware and software components) or due to performance tradeoffs (i.e., higher value of a design variable that increases performance with respect to one hardware component may decrease the performance with respect to another hardware component).

Under conditions of high ecosystem complexity, the search for superior performance configuration by follower firms will be difficult (e.g., Levinthal, 1997). This is because higher ecosystem complexity increases the number of possible 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.

[4] OEM stands for Original Equipment Manufacturer. In our empirical context, it is used to refer to handset manufacturers. Also, as this quote highlights that app developers do not create different apps for different OEMs within the Android ecosystem. Rather they create the same app and try to ensure that it functions on devices offered by the different OEMs. This is also consistent with our characterization of ecosystem complexity faced by complementors.

Further, such conditions also make it difficult for follower firms to search by incrementally changing their decision variables (Rivkin, 2000).[5]

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; Csaszar and Siggelkow, 2010). 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 ecosystem complexity is high (Rivkin, 2000).

In summary, ecosystem complexity will help complementors sustain their superior performance by making it more difficult for other complementors to search for or to imitate higher performance configurations.[6] Accordingly, we predict:

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

Ecosystem Experience

A complementor's experience within an ecosystem can also play a significant role in its ability to sustain superior performance. Ecosystem experience, which spans the entire period of participation in an ecosystem and not just the period of superior

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[5] It is worth noting that innovative search for superior performance configuration when ecosystem complexity is high will be difficult for all firms. Our focus in this study is to explain the sustainability of superior performance. Hence, our theoretical arguments are premised on some firms achieving superior performance, and we focus on the difficulty of innovative search for follower firms (e.g., Rivkin, 2000).

[6] It is possible that at very high levels of complexity, complementors with superior performance may also find it difficult to innovate and maintain their leadership position. Hence, the difficulties with respect to innovation encountered by both leader and follower firms at very high levels of ecosystem complexity might offset each other. However, imitation by followers will still be difficult at such high levels of complexity. Therefore, in considering the two mechanisms of innovation and imitation, the overall effect at very high levels of ecosystem complexity might depend on the relative impact of these individual mechanisms for the leader and the follower firms. We also note that such an extreme scenario of ecosystem complexity is unlikely to occur in platform-based ecosystems because of the somewhat modular nature of the interfaces between the platform and the complements.

performance, will help confer several types of learning-based advantages on leader firms. Sustaining superior performance requires leader firms to continuously search and identify higher performing configurations. Experience facilitates the development and improvement of routines, making search process underlying leader firms' innovation efforts with respect to other interdependent components 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 in ecosystems is what Rosenberg (1982) referred to as learning-by-using. This type of learning is not a function of the experience in developing and producing the product *per se,* but rather is a function of the experience in the product's utilization by its users in conjunction with the rest of the system. Rosenberg (1982) provided a valuable illustration of learning-by-using by aircraft manufactures and suggested that this type of learning is especially important when the use of the product is influenced by its interaction with other components. The existence of numerous technological interdependencies within a platform-based ecosystem makes it difficult for firms to know in advance how the product will perform during use and, hence, experience that is rooted in the usage of the product by the users plays a vital role in helping firms innovate and improve their products over time. A leader firm, by virtue of having a large user base for a platform, will derive a significant advantage through learning-by-using.

In our interviews, a senior engineer from a leading app developer firm elaborated on the importance of experience as it relates to 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 firms to accumulate knowledge-based assets such as new product development and marketing capabilities. 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.[7] 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.*

Complementor's experiential advantage within an ecosystem may be impacted by the level of ecosystem complexity. Greater ecosystem complexity increases complementor's internal complexity with respect to the choices that complementors make regarding their products, tasks, and organization. This increase in internal complexity can raise the opportunities for learning-by-doing (Balasubramanian and Lieberman (2010)), making it more difficult for followers to catch up with experienced leaders. In addition, the greater the degree of ecosystem complexity that a focal complementor's product is subjected to, the more uncertain will be the interactions

[7] Our focus here is on theorizing with respect to complementors' experience-based advantages for a specific platform-based ecosystem. These advantages stem from learning-by-doing, learning-by-using and time compression diseconomies associated with knowledge-based assets. Experience-based advantages in an ecosystem could also stem from firms' accumulation of other assets such as brand, customer loyalty, as well as firms having a broader portfolio of products over time. We account for these drivers in our empirical analysis, and we also show that complementor's platform-specific experience (e.g., smartphone apps for iOS platform) has a much greater impact on its sustainability than its general experience in the industry (e.g., smartphone apps).

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 knowledge-based assets accumulated by the leader firms are also likely to increase in 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. While extant literature has explored how technology transitions in the focal industry impacts firm performance (Tushman and Anderson, 1986; Henderson and Clark, 1990; Christensen, 1997), we explore how technology transitions initiated by platform firms may impact complementors' performance in the ecosystem. Therefore, we highlight an important evolutionary feature of platform-based ecosystems in which a technological shift orchestrated by the platform firm can have important consequences for the complementors.

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 within the ecosystem (Venkatraman and Lee, 2004; Ansari and Garud, 2009; Adner and Kapoor, 2010). Hence, a new platform generation may represent a case of an architectural change as discussed by Henderson and Clark (1990), where the core design concepts and the associated knowledge are not overturned but there is a change in the nature of interactions between the platform and the complements. This renders the strategic configurations of the high performing complementors 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. App 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 [Operating System] upgrades do a good job of the issue of backward compatibility, but the new OS will depreciate some APIs from the older version.[8] 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."

At the same time, features introduced in the new platform generation can provide opportunities for new complementors to enter the ecosystem and to effectively compete against leader firms. 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 to sustain its superior performance within the ecosystem.*

[8] 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.

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 these firms' ability to adapt — i.e., we explore the interaction between platform transitions and ecosystem complexity. When ecosystem complexity is low, 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 and to move to a high performance configuration in the new platform generation. In contrast, when ecosystem complexity is high, adaptation through local search might not be 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, greater complexity 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, complementors may find it much more difficult to sustain their superior performance in the face of a platform transition when ecosystem complexity is high than when it is low:

> *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

The empirical analysis is carried out 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 represented more than 90% of the U.S. smartphone installed base during this 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 valuable context 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 for its development and distribution by various original equipment manufacturers (OEMs) such as HTC, LG, and Samsung. Hence, an app in the Android ecosystem interacts with multiple 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.

<u>Data</u>

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 apps developed for iOS and Android platforms. 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. 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.[9] Note that both App Annie and appFigures do not generate their own data, but accumulate daily data from Google Play and Apple iTunes App stores over time and offer their users easy-to-use tools for analyzing trends.

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 dataset does not include some e-commerce apps such as those from Amazon and Walmart, that do not generate revenues through paid apps or in-app purchases via Apple iTunes or Google Play App stores. The revenue distribution for smartphone apps is heavily skewed. For example, based on the 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).[10] 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. We use this revenue ranking to characterize firms' superior performance. Ideally, we would have also liked to have information on the actual revenues and profits within an ecosystem for each of the app developers in the sample. However, such data is not made available by app developers. Despite this constraint, rank-based relative performance information

[9] 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.
[10] The report is available at http://www.developereconomics.com/reports/developer-economics-q3-2014/. Last accessed on March 10, 2016.

provides us with an approach to capture the relative performance superiority of app developers in an ecosystem that is consistent with our theory and is also consistent with how industry analysts evaluate performance superiority among 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 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:

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

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 for this relationship 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.[11] 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 also directly contacted some firms to obtain information on their number of employees. 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). We also used the aggregate statistics on installed base, the number of app developers, and the number of apps for both iOS and Android to rule out that the observation period (Jan' 2012 – Jan' 2014) is not idiosyncratic in ways that may impact our inferences. The level of analysis is firm-ecosystem-month, and the final dataset comprises 12,691 observations from 1,516 app developer firms.

<u>Measures</u>

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 the Android ecosystem. These ecosystems represented most of the economic opportunities for smartphone app developers during the observation

[11] 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.

period. Revenues in other smartphone ecosystems such as RIM's Blackberry, Microsoft's Windows Mobile and Nokia's Symbian were relatively negligible. Hence, being ranked in the Top 500 apps by revenue in iOS or Android corresponds to significant economic performance for app developers. 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 in the same month, we treated those cases as a single firm-level observation. A related issue with our measure is that for some firms, sustainability in an ecosystem may be driven by different apps (i.e., App A is in Top 500 list in month t and App B (not App A) is in Top 500 list in month t+1). It is possible that App B may be a close substitute to App A or that App B is a "new" app focusing on a different use. We discuss this issue in the robustness checks section and conduct an additional analysis by including firms which only had a single app in the Top 500 list.

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 respectively.

On average, an app developer 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 technological interdependencies that an app developer is subjected to with other components within a smartphone ecosystem. Therefore, our approach here is consistent with characterizing complexity in terms of the degree of organization. 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 number of operating system and handset combinations that an app developer is subjected to, the greater is the ecosystem complexity faced by the app developer. As Apple controls both the operating system and handset, an app in the iOS ecosystem interacts only with the combination offered by Apple. 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 in the Android ecosystem interacts with handset and operating system combinations from many different OEMs. Our interviews also confirmed that app developers typically do not develop different apps for different OEMs in the Android ecosystem. It is the same app that works across different handset and operating system configurations provided by the OEMs.

Since ecosystem complexity faced by app developers is rooted in the diversity in the operating system and handset combinations offered by OEMs, we use a Simpson index-based diversity measure to operationalize ecosystem complexity (Page, 2010).[12] 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.[13] It 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 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.[14] 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

[12] 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 installed 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 is mathematically equivalent to the popular Herfindahl index used in economics and management literature to measure industry concentration. Herfindahl index is based on the sales of different firms within an industry whereas our measure is based on the installed base of the different OEMs within an ecosystem.

[13] 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 so that the same app works on 6-8 leading smartphones from multiple OEM firms. The Simpson index-based measure helps to account for this concentration effect.

[14] New generations of smartphone operating system were identified based on change in the code name (e.g., change from Ice Cream Sandwich to Jelly Bean in the case of Android, and from iOS 5 to iOS 6), a standard practice in this industry. In addition to launching new generations of operating system, both Apple and Google also offer minor updates which are predominantly "bug fixes" within the existing generation. Therefore, we do not consider these minor updates as platform-level generational transitions.

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 of 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.”[15] Figure 3.1 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.[16]

(Insert Figure 3.1 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 for *firm size* and used this variable to control for scale-related

[15] 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."

[16] We note that the introduction of new generations of smartphone operating system are also typically accompanied by the introduction of new handsets by OEMs. However, the older handsets still account for the majority of users during the transition period. Hence, for both iOS and Android ecosystems, the major driver of app developers’ performance as well as their adaptation requirements during generational transitions stem from the change in the operating system rather than from the launch of the new handsets.

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 markets other than smartphone apps that may confer advantages such as those with respect to brand, customer loyalty, and economies of scope. The variable *other online business* takes a value of 1 if a firm is active in other web- or PC-based businesses like owning a social networking website or developing software for PC. The variable *other offline business* takes a value of 1 if the firm's scope of businesses expanded beyond the internet and PC domain, such as console games.

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. 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 in a given ecosystem as of March, 2014. We also controlled for the *price* of the focal app that is in the Top 500 list (by revenue). For 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 highest rank. Many app developers derive their revenues through in-app purchases, and hence, their revenues include recurring revenues from existing customers. To account for this feature of the business model, we include a variable *In-app purchases,* which takes a value of 1 if the focal app has an in-app purchase option. This would also help us to control for the benefits that firms may derive from customer loyalty or customer switching cost.

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.[17] 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 in the Top 500 list in a given month within the same category as the focal firm's app. 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.

<u>Analysis</u>

We tested our hypotheses using continuous time event history analysis to estimate the hazard rate of app developers exiting the superior performance stratum. This approach is consistent with prior studies which have focused on studying the

[17] 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.

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 an additional robustness check. We did this by including observations for firms that only entered in the iOS or Android ecosystems from January 2012 onwards. We report this analysis in the robustness checks section after presenting our main results.

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 the effect of these variables to vary over 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 3.1. We report the results from the Cox model in Table 3.2. 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, 2000). 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-independence across multiple observations faced by the same firm by clustering observations for each firm. Model 1 is a baseline model. Models 2, 3, and 4, include ecosystem complexity, ecosystem experience, and platform transition to test Hypotheses 1, 2, and 4, respectively. Model 5, includes the interaction term between ecosystem complexity and ecosystem experience to test Hypothesis 3. Model 6, includes the interaction term between ecosystem complexity and platform transition to test Hypothesis 5. Model 7 is the fully specified model with all of the independent variables and the interaction terms.

(Insert Tables 3.1 and 3.2 about here)

The results from the baseline model (Model 1) suggest that the likelihood of app developers sustaining their superior performance increases with their firm size, if they offered in-app purchases, and if they had other web- or PC-based online businesses. Also, app developers who offered apps in both ecosystems and who offered free apps that were ranked among the Top 500 free apps in terms of downloads were likely to sustain their superior performance.

In Hypothesis 1, we predicted that higher ecosystem complexity will be associated with greater likelihood of complementors 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). 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 22%.

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). 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 13%. 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 44% 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. Finally, the coefficient for the interaction term between ecosystem complexity and platform transition is positive and statistically significant in both Models 6 and 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. Figure 3.2 illustrates these interaction effects by plotting the average marginal effects of ecosystem complexity for different values of ecosystem experience and platform transition based on estimates in Model 7, holding all other variables at their mean values. The standard errors for the average marginal effects are estimated using the delta method and are calculated by the margins routine in STATA.

(Insert Figure 3.2 about here)

Robustness checks

We conducted a number of additional checks to establish the robustness of our findings. The robustness checks are summarized in Table 3.3 and the results are reported in Tables 4 and 5 respectively. In Table 3.4, we explore alternative explanations that could drive our main results, and in Table 3.5, we focus on the sensitivity of our results to alternative measures and operationalization.

(Insert Table 3.3 about here)

Alternative Explanations

Firms may be self-selecting into the iOS or Android ecosystems, and this may subject our estimates to a firm-level selection bias. To address this concern, we estimated a model by including data for only those firms that participated in both ecosystems. The coefficient estimates are reported in Model 8 and exhibit 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 = 0.15). Another type of a “selection” issue is that that certain types of firms (unobservable to us) are more likely to achieve superior performance in an ecosystem of a given complexity. If we are not able to characterize the type based on the observables, our inferences with respect to ecosystem complexity might be particularly problematic. To address this concern, we ran an additional check by using the sample of 278 firms that achieved superior performance in both iOS and Android ecosystems, and we included firm-fixed effects in that analysis. The results are reported in Model 9 and are qualitatively similar to our main results. The standard errors for a fixed-effects model with a much smaller sample size are somewhat higher with the interaction terms being marginally insignificant.

(Insert Table 3.4 about here)

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 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. Firms with greater general experience may benefit through superior app development and marketing capabilities as well as having a stronger brand. The results are reported in Model 10. While the coefficient for general experience is negative and statistically significant, the coefficient for ecosystem experience remains statistically significant, and its magnitude is almost twice as that of the coefficient for general experience. Hence, this check helps to reinforce that complementors’ experiential benefit has a strong ecosystem-specific component.[18]

[18] We performed an additional check to ensure that the experience effect is not simply driven by customer loyalty resulting in high app revenues through continued in-app purchases. To do so, we re-ran Model 5 on a

We also explore other possible explanations with respect to different types of firms and their strategies.[19] Firms in our sample include those that are pure app firms which derive all of their revenues from app stores and those firms which also have other online or offline businesses. To check if there are any systematic differences between these firms, we estimated separate models for pure app firms (Model 11) and for firms which also had other businesses (Model 12). The coefficient estimates are qualitatively similar to our main results. The interaction term of ecosystem complexity*experience loses statistical significance possibly because of smaller sample size and the fact that pure app firms are generally younger than the other firms. It is also possible that app developers may differ in terms of their innovations and investments in apps, and the size of their app portfolio. These differences may be correlated with their experience or ecosystem complexity. To rule out these explanations, we collected additional data on the total number of apps and the number of updates to the focal apps for the firms which were active in Jan' 2016. For this sample of firms, we included controls for the total number of updates, and the total number of updates in the previous three months (Model 13), and the total number of apps in a given month (Model 14). Finally, while both iOS and Android were dominant smartphone platforms during the observation period, there is variation in their overall sales growth over time. To ensure that our results are not impacted by the relative differences in sales growth between iOS and Android, we obtained quarterly unit sales data from IDC (the data was not available at monthly intervals), and included it as an additional control in Model 15. The results with these additional control variables continue to support our predictions, and give us greater confidence in our findings.

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sample of 467 firms whose apps in the Top 500 list did not include an in-app purchase option. The experience effects continued to be significant even for a very small sample, giving us additional confidence with respect to our inferences.

[19] We thank the two anonymous reviewers for suggesting these analyses in order to rule out alternative explanations.

Alternative Measures

A 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). 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 and to account for OEM-level screen size variations faced by app developers, 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 high cost of this survey data, we were only able to obtain this information for the period from January, 2012 to May, 2013, which also resulted in the exclusion of observations for an iOS platform transition (i.e., iOS 7).

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. 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. To account for differences in demographics and app usage between the iOS and Android users, we include three control variables. The variable *App download* measures the percentage of users who download 5 or more apps in a given month in the focal platform. The variables *Female user* and *Age* measure the percentage of female users and the percentage of users of age between 18 and 45 years. We report the results in Models 16-18. Model 16 includes the new measure of ecosystem complexity and with controls for user characteristics. Model 17 includes the additional control for *iOS*. The coefficient estimates continue to support our predictions. Model 18 includes the interaction terms. The coefficients for the interaction terms have large standard errors possibly because of multicollinearity with respect to some of the key variables with individual variance inflation (VIF) factors well above the recommended cutoff level of 10 (VIF is 47 for ecosystem complexity, 46 for iOS, and 13 for the ecosystem complexity and experience interaction term), and the fact that there are fewer episodes of platform transitions.

Moreover, our theory and our measures are at the level of the firm in an ecosystem. However, in our empirical design, it is possible that for some firms, sustainability in an ecosystem may be measured across different apps i.e., App A is in top 500 list in month t and App B (not App A) is in top 500 list in month t+1. In our sample, of the 9672 sustainability events for iOS and Android ecosystems (i.e., focal firm has an app in the Top 500 list for two consecutive months), there were only 661 sustainability events where the focal firm had a different app in the Top 500 list in the subsequent month. As an additional robustness check, we only used the sample of firms that had a single app in the Top 500 list in a given ecosystem. The estimates reported in Model 19 continue to support all of the predictions.

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 20), and we also used windows of two and four months (Models 21 and 22). The coefficient estimates for all the three models continue to support our predictions.

(Insert Table 3.5 about here)

Finally, 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 that entered these ecosystems from January 2012 onwards (Model 23). 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. Overall, these additional analyses with alternative measures help to further establish the robustness of our findings.

Discussion

We study the increasingly prominent phenomenon of platform-based ecosystems in which value is created through a network of firms offering complementary products and services around a platform. Value creation in such ecosystems is shaped by platform firms who own the underlying technical architecture and set the rules for complementors' participation. We explore the strategic implications for complementors by considering how ecosystem-level interdependencies affect the extent to which complementors can sustain their value creation in an ecosystem. We offer a novel perspective of complementors' ecosystem-level interdependencies that is rooted in the structural and evolutionary features of the ecosystem. The structural feature is based on the technological interdependence between complementors' products and other components in the ecosystem. We refer to this feature as ecosystem complexity faced by the complementor. We incorporate the evolutionary features by taking into account the technology transitions initiated by platform firms and the experience gained by complementors in an ecosystem over time.

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 faced by app developers impacted the ease with which they could sustain their superior performance within an ecosystem. Consistent with our arguments, we find that higher ecosystem complexity and ecosystem experience helps app developers sustain their superior performance whereas platform transition makes it more difficult. We also find that on the one hand, ecosystem complexity enhances the benefit of ecosystem experience whereas it exacerbates the impact of platform transition

Our study's findings make important contributions to the literature streams in strategy on business ecosystems, platforms, technological change and to the evolutionary economics perspective in general. 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, beyond the platform firms and illustrate how complementors' value appropriation is shaped by the structural and evolutionary features of the ecosystems. Our findings have implications for both platform firms such as Apple and Google that set the rules and own the platform and complementors such as app developers that follow the rules and leverage the platform. We show how the strategies of the platform firms may play a significant role in the complementors' ability to appropriate value over time. While major technological changes within the platform are important for sustaining the progress of the ecosystem over time, these platform transitions can create high uncertainty and disrupt the leadership position of complementors who are significant contributors to value created in the ecosystem. At the same time, platform transitions can present new opportunities for other complementors to create value in the ecosystem. Hence, we shed light on the challenges and the trade-offs that platform firms and complementors face in their quest for value creation and appropriation over time.

By showing how platform firms' strategies can shape the level of complexity and uncertainty faced by complementors, we depart from the existing treatments of firms' environments that are typically premised on complexity and uncertainty being a general feature of the industry (e.g., Dess and Beard, 1984; Anderson and Tushman, 2001; Eisenhardt, 1989). In so doing, we offer a new lens on the interactions between firms and their environments through which complexity and uncertainty faced by complementors is explicitly determined by the strategies of platform firms. This can also result in the same firm being subject to different types of environments in the same industry. Further, literature on technological change has shed light on how technology transitions impacts the performance of firms in the focal industry (e.g., (Tushman and Anderson, 1986; Henderson and Clark, 1990; Christensen, 1997). We contribute to this literature by highlighting how technology transitions initiated by platform firms can impact the performance of complementor firms within an ecosystem. Hence, we highlight that technological interdependencies between platform firms and complementors in related industries can have important consequences for complementors during periods of platform transitions. Relatedly, the evidence in the study also points to the difficulties of coordinating technology transitions at the level of the ecosystem. Even if platform firms intend to create a smooth generational transition for all of their complementors, the system-level interdependencies and technological uncertainties make such coordination difficult.

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 (e.g., Nelson and Winter, 1982, 2002; Levinthal, 1997; Gavetti and Levinthal, 2004). While scholars have drawn on a variety of theoretical approaches to model firms' search processes and their performance outcomes at different levels of complexity, 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 firms with greater ecosystem-specific experience and during periods of platform transitions. Finally, we also offer an empirical contribution to the strategy literature by going beyond the typically used annual datasets to shorter temporal windows of months. We show that finer-grained observational periods can be useful in deciphering performance dynamics in hypercompetitive settings such as the smartphone context.

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 context, and their validity needs to be established across other settings. Relatedly, Apple's closed model and Google's open model played a significant role in determining the extent of ecosystem complexity faced by smartphone app developers. However, theoretically, this correlation does not imply that a closed model will always result in low ecosystem complexity for complementors. The origins of ecosystem complexity might not only be rooted in the choices of the platform firms across different ecosystems but also in the choices of the complementors within the same ecosystem (Agarwal and Kapoor, 2017). Further, while we focus on the short-run impact of platform transitions on complementors, platform transitions can also have a long-run impact on the ecosystem complexity faced by complementors. Second, our measure of superior performance is premised on whether firms' apps are ranked within Top 500 apps in terms of revenue in the two dominant smartphone ecosystems. Although this measure is consistent with our theory and is widely accepted as a proxy for superior performance in these ecosystems, it may not represent superior economic performance for firms in general. Specifically, the measure does not account for the costs of participation in an ecosystem, and is not sensitive to the differences between ecosystems in terms of total revenue. It is possible that a firm may have a high revenue-based rank in an ecosystem with low total revenue (i.e., large share of a small revenue pie), or a firm may incur high cost of participation. Both of these possibilities might result in firms with low performance (revenue/profits) at the level of the industry being categorized as ones with superior performance at the level of the ecosystem. Hence, the applicability of our measure with respect to overall economic performance for the firm is subject to some important boundary conditions. Our finding with respect to the interaction effect between ecosystem experience and ecosystem complexity is less robust than our other findings. This could imply that our theorized mechanism may be subject to some boundary conditions or that our measures are somewhat limited in their ability to tease out this effect. 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 performance of complementor firms in platform-based ecosystems. We propose a novel perspective of complementors' ecosystem-level interdependencies that is rooted in the structural and evolutionary features of the ecosystem, and show that such a perspective is useful in explaining the extent to which complementors can appropriate value within an ecosystem over time. In so doing, the study also sheds light on how the performance of complementors in business ecosystems can be shaped by the rules and the actions of the platform firms that orchestrate the ecosystem.

Figure 3.1: Normalized weekly trend based on Google's search data for the term "app not working" for US-based searches

(Data source: Google Trends; http://www.google.com/trends/: Data last accessed on August 29, 2014)

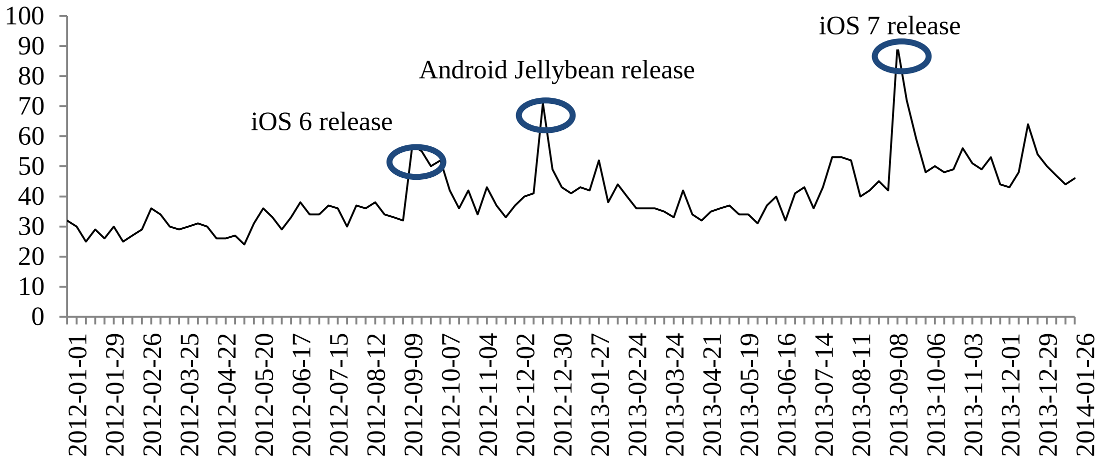

Figure 3.2: Average marginal effects of ecosystem complexity with 95% confidence intervals

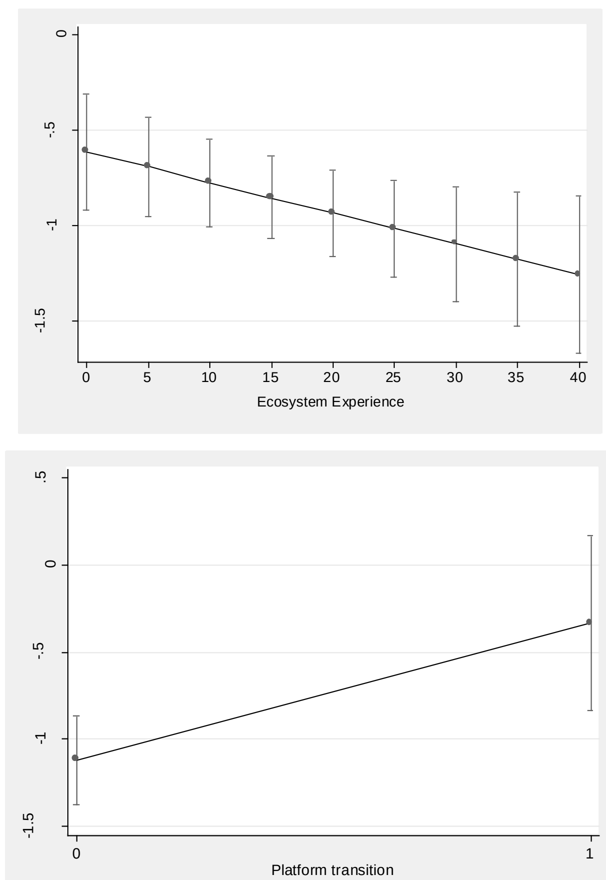

Table 3.1: Descriptive statistics and correlations

No.	Variable	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Ecosystem complexity	-0.66	0.34	1.00													
2	Ecosystem experience	22.91	16.07	-0.55	1.00												
3	Platform transition	0.18	0.38	-0.14	0.13	1.00											
4	New apps	7.84	0.97	-0.14	0.07	0.11	1.00										
5	New firms	6.35	0.77	-0.03	-0.01	0.07	0.95	1.00									
6	Apps in Top 500	199.01	162.78	0.06	-0.08	0.05	0.76	0.71	1.00								
7	Firm size (employees)	6.22	17.92	-0.04	0.17	0.00	-0.06	-0.07	-0.07	1.00							
8	Other online business	0.59	0.49	-0.03	0.10	0.01	-0.04	-0.04	-0.01	0.23	1.00						
9	Other offline business	0.30	0.46	-0.03	0.12	0.01	-0.06	-0.09	-0.07	0.40	0.29	1.00					
10	Dual participation	0.63	0.48	0.12	0.04	0.01	0.12	0.14	0.20	0.15	0.20	0.17	1.00				
11	Firm app rating	4.01	0.49	0.25	-0.29	-0.03	0.17	0.16	0.22	-0.23	-0.14	-0.18	-0.05	1.00			
12	Top 500 free app	0.56	0.50	-0.17	0.16	0.01	0.11	0.12	0.13	0.07	0.03	-0.05	0.08	0.01	1.00		
13	In-app purchases	0.82	0.38	0.03	-0.02	0.03	0.22	0.21	0.29	0.01	-0.02	-0.12	0.08	0.06	0.20	1.00	
14	App price	3.55	30.90	-0.04	0.03	0.00	-0.08	-0.09	-0.10	0.01	0.01	0.04	-0.03	0.01	-0.10	-0.10	1

Correlations greater than 0.01 or smaller than -0.01 are significant at $p < 0.05$, N= 12,691

Table 3.2: Cox proportional hazards estimates for firms exiting the superior performance strata

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Ecosystem complexity		-0.740***			-0.691***	-0.784***	-0.751***
		(0.125)			(0.181)	(0.134)	(0.182)
Ecosystem experience			-0.008***		-0.027***		-0.027***
			(0.002)		(0.008)		(0.008)
Platform transition				0.365***		0.763***	0.839***
				(0.082)		(0.258)	(0.263)
Ecosystem complexity*experience					-0.016*		-0.016*
					(0.008)		(0.009)
Ecosystem complexity*transition						0.661**	0.785**
						(0.317)	(0.325)
New apps	0.074	-0.485**	0.220	0.016	-0.350*	-0.483**	-0.346*
	(0.164)	(0.193)	(0.166)	(0.166)	(0.194)	(0.194)	(0.195)
New firms	-0.182	0.272	-0.295	-0.104	0.206	0.274	0.200
	(0.207)	(0.233)	(0.206)	(0.210)	(0.230)	(0.235)	(0.232)
Apps in Top 500	0.008	0.011	0.008	0.006	0.010	0.010	0.009
	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
$(\text{Apps in Top 500})^2$	-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)	-0.013***	-0.013***	-0.012***	-0.013***	-0.011***	-0.013***	-0.011***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Other online business	-0.217***	-0.224***	-0.216***	-0.217***	-0.226***	-0.223***	-0.226***
	(0.080)	(0.079)	(0.079)	(0.080)	(0.078)	(0.079)	(0.078)
Other offline business	0.125	0.146	0.122	0.127	0.149	0.148	0.152
	(0.096)	(0.094)	(0.096)	(0.096)	(0.094)	(0.094)	(0.094)
Dual participation	-0.481***	-0.436***	-0.472***	-0.474***	-0.410***	-0.436***	-0.410***
	(0.078)	(0.077)	(0.078)	(0.078)	(0.076)	(0.077)	(0.076)
Firm app rating	-0.089	-0.013	-0.135**	-0.081	-0.072	-0.012	-0.070
	(0.068)	(0.068)	(0.067)	(0.067)	(0.066)	(0.068)	(0.066)
Top 500 free app	-0.678***	-0.826***	-0.613***	-0.686***	-0.743***	-0.831***	-0.749***
	(0.101)	(0.107)	(0.103)	(0.101)	(0.107)	(0.107)	(0.107)
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)
In-app purchases	-0.582***	-0.568***	-0.573***	-0.577***	-0.542***	-0.562***	-0.536***
	(0.101)	(0.099)	(0.101)	(0.100)	(0.097)	(0.098)	(0.097)
App price	-0.089	-0.117*	-0.069	-0.090	-0.090	-0.118*	-0.090
	(0.062)	(0.063)	(0.061)	(0.062)	(0.061)	(0.063)	(0.061)
App price*time	0.003	0.004	0.003	0.003	0.004	0.004	0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Category fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total observation	12,691	12,691	12,691	12,691	12,691	12,691	12,691
Total firms	1,516	1,516	1,516	1,516	1,516	1,516	1,516
Total exit events	1,774	1,774	1,774	1,774	1,774	1,774	1,774
Log likelihood	-10,601.36	-10,571.66	-10,592.50	-10,592.08	-10,545.74	-10,545.74	-10,539.44

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

Table 3.3: Summary of robustness checks reported in Tables 4 and 5.

Model	Robustness check	Rationale
8	Included data for only those firms that participated in both ecosystems	Firms may be self-selecting into the iOS or Android smartphone ecosystems
9	Included only those firms that achieved superior performance in both iOS and Android ecosystem with firm-fixed effects	Certain types of firms may be more likely to achieve superior performance in an ecosystem of a given complexity
10	Controlled for firm's general industry experience in smartphone apps	Ecosystem experience may simply be an artifact of general industry experience
11, 12	Ran separate models for pure app firms and firms with other businesses	There might be systematic difference between firms based on their business scope
13	Controlled for total number of updates and updates in the last 3 months for the focal app	Firms' investments in apps might be impacting sustainability
14	Controlled for firm's app portfolio	Firms' app portfolio size might be correlated with their ecosystem experience or ecosystem complexity
15	Controlled for unit handset sales for both iOS and Android	Results may be driven by relative differences in sales growth between iOS and Android
16	Used alternative measure for ecosystem complexity based on the number of unique OEMs and screen size combinations.	Main measure for ecosystem complexity does not account for the diversity of handset configurations within OEMs
16, 17, 18	Used alternative measure for ecosystem complexity and controlled for the focal platform, and user characteristics	Main measure for ecosystem complexity might be capturing unobserved differences with respect to platform firms' strategies or user-characteristics across these platforms
19	Included data for only those firms that had a single app in Top 500 list	Sustainability of superior performance at firm-level may be due to different apps launched by the same firm
20	Used a higher performance threshold based on a firm's app in the Top 250 list by revenue	Results might be sensitive to the choice of Top 500 list to measure superior performance
21, 22	Used two- and four-month windows respectively to measure sustainability	Results might be sensitive to the choice of the three-month window to measure sustainability
23	Included data for only those firms that entered an ecosystem after January 2012	Left truncation

Table 3.4: Robustness checks (Alternative explanations)

	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14	Model 15
Ecosystem complexity	-0.814***	-1.011*	-0.595***	-0.790***	-0.963***	-0.760***	-0.657***	-0.592***
	(0.216)	(0.567)	(0.230)	(0.254)	(0.255)	(0.199)	(0.212)	(0.204)
Ecosystem experience	-0.029***	-0.068*	-0.020*	-0.023*	-0.022*	-0.019**	-0.031***	-0.031***
	(0.010)	(0.036)	(0.010)	(0.012)	(0.012)	(0.009)	(0.009)	(0.009)
Platform transition	0.768**	1.281**	0.769**	0.696*	0.993***	0.726***	0.969***	0.722***
	(0.303)	(0.565)	(0.304)	(0.389)	(0.362)	(0.274)	(0.308)	(0.267)
Ecosystem complexity * Experience	-0.015	-0.047	-0.015	-0.010	-0.011	-0.009	-0.021**	-0.019**
	(0.010)	(0.032)	(0.010)	(0.012)	(0.012)	(0.009)	(0.010)	(0.009)
Ecosystem complexity * Transition	0.705*	1.245	0.711*	0.629	0.946**	0.707**	1.015***	0.627*
	(0.375)	(0.983)	(0.375)	(0.478)	(0.450)	(0.339)	(0.377)	(0.333)
New apps	-0.256	0.179	-0.208	-0.444*	-0.309	-0.489**	-0.313	-0.453**
	(0.257)	(0.808)	(0.255)	(0.270)	(0.295)	(0.205)	(0.220)	(0.217)
New firms	0.013	0.074	-0.015	0.138	0.312	0.447*	0.139	0.046
	(0.301)	(0.916)	(0.298)	(0.335)	(0.341)	(0.246)	(0.264)	(0.301)
Apps in Top 500	0.010	-0.023	0.009	0.009	0.007	0.007	0.007	0.015*
	(0.012)	(0.031)	(0.011)	(0.010)	(0.013)	(0.008)	(0.008)	(0.009)
(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)	(0.000)	(0.000)
Firm size (employee)	-0.011***		-0.011***	-0.067**	-0.010***	-0.012***	-0.011***	-0.010***
	(0.004)		(0.004)	(0.030)	(0.004)	(0.004)	(0.004)	(0.004)
Other online business	-0.201**		-0.196**			-0.220***	-0.158*	-0.228***
	(0.097)		(0.097)			(0.081)	(0.089)	(0.080)
Other offline business	0.155		0.168			0.146	0.130	0.161*
	(0.105)		(0.106)			(0.097)	(0.104)	(0.096)
Dual participation				-0.447***	-0.322***	-0.429***	-0.515***	-0.387***
				(0.115)	(0.100)	(0.080)	(0.087)	(0.078)
Firm app rating	0.004	0.464	0.001	-0.226**	0.111	-0.016	-0.003	-0.028
	(0.086)	(0.326)	(0.086)	(0.094)	(0.091)	(0.068)	(0.077)	(0.068)
Top 500 free app	-0.791***	-0.792*	-0.803***	-0.629***	-0.871***	-0.808***	-0.724***	-0.742***
	(0.125)	(0.425)	(0.125)	(0.155)	(0.148)	(0.116)	(0.130)	(0.118)
Top 500 free app*time	0.002***	0.005*	0.002***	0.001*	0.002***	0.001***	0.001***	0.001***
	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
In-app purchases	-0.573***	-0.321	-0.574***	-0.475***	-0.635***	-0.507***	-0.513***	-0.491***
	(0.133)	(0.507)	(0.133)	(0.145)	(0.132)	(0.104)	(0.118)	(0.099)
App price	-0.205***	0.072	-0.195**	0.025	-0.180**	-0.076	-0.089	-0.080
	(0.077)	(0.272)	(0.077)	(0.096)	(0.078)	(0.066)	(0.078)	(0.072)
App price*time	0.009**	-0.017	0.009**	-0.002	0.007*	0.001	0.004	0.003
	(0.004)	(0.020)	(0.004)	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)
General experience			-0.010**					
			(0.004)					
Update last 3m						0.041***		
						(0.012)		
Total updates						-0.025***		
						(0.005)		
Platform sales growth								5.009*
								(2.936)
Portfolio size							0.002	
							(0.002)	
Category fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effect		Yes						
Total observation	9,999	4,253	9,999	5,228	7,463	11,351	9,510	11,121
Total firms	993	278	993	766	750	1,409	1,095	1,396
Total events	1,236.00	361	1,236	864	910	1,587	1,290	1,568
Log likelihood	-7,117.13	-1,503.29	-7,112.86	-4,346.84	-4,927.98	-9,241.47	-7,281.61	-9,306.81

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

Table 3.5: Robustness checks (Alternative measures)

	Model 16	Model 17	Model 18	Model 19	Model 20	Model 21	Model 22	Model 23
Ecosystem complexity	-0.665***	-1.055*	-1.439*	-0.779***	-0.436**	-0.714***	-0.734***	-0.866***
	(0.223)	(0.565)	(0.769)	(0.234)	(0.207)	(0.178)	(0.186)	(0.298)
Ecosystem experience	-0.017***	-0.016***	-0.022***	-0.024**	-0.032***	-0.027***	-0.025***	-0.058***
	(0.004)	(0.004)	(0.007)	(0.011)	(0.008)	(0.008)	(0.008)	(0.020)
Platform transition	0.302**	0.312**	0.065	1.388***	0.831**	0.644***	0.817***	1.145**
	(0.124)	(0.126)	(0.298)	(0.344)	(0.357)	(0.239)	(0.281)	(0.489)
Ecosystem complexity *Ecosystem experience			-0.008	-0.019*	-0.022***	-0.016*	-0.013	-0.030
			(0.010)	(0.011)	(0.008)	(0.008)	(0.009)	(0.024)
Ecosystem complexity * Platform transition			-0.579	1.341***	0.982**	0.581**	0.705**	1.116*
			(0.642)	(0.425)	(0.416)	(0.295)	(0.344)	(0.578)
New apps	0.194	0.191	0.209	-0.207	-0.357*	-0.410**	-0.383*	0.066
	(0.276)	(0.277)	(0.278)	(0.231)	(0.210)	(0.187)	(0.196)	(0.386)
New firms	-0.205	-0.234	-0.244	0.074	0.293	0.340	0.209	-0.174
	(0.306)	(0.311)	(0.310)	(0.265)	(0.265)	(0.220)	(0.235)	(0.446)
Apps in Top 500	-0.002	-0.002	-0.001	0.014	0.016**	0.008	0.008	0.021
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.015)
$(\text{Apps in Top } 500)^2$	-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)	(0.000)	(0.000)
Firm size (employee)	-0.010**	-0.010**	-0.010**	0.000	-0.006**	-0.013***	-0.011***	-0.025
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.019)
Other online business	-0.271***	-0.270***	-0.274***	-0.226**	-0.078	-0.219***	-0.225***	-0.333***
	(0.095)	(0.095)	(0.096)	(0.092)	(0.086)	(0.076)	(0.079)	(0.116)
Other offline business	0.010	0.010	0.013	0.049	-0.032	0.167*	0.114	0.316**
	(0.116)	(0.116)	(0.116)	(0.121)	(0.100)	(0.093)	(0.098)	(0.157)
Dual participation	-0.405***	-0.407***	-0.408***	-0.316***	-0.217***	-0.382***	-0.435***	-0.199*
	(0.117)	(0.118)	(0.117)	(0.095)	(0.081)	(0.074)	(0.077)	(0.121)
Firm app rating	-0.206**	-0.205**	-0.203**	-0.034	-0.100	-0.067	-0.063	0.075
	(0.093)	(0.093)	(0.093)	(0.079)	(0.074)	(0.065)	(0.068)	(0.110)
Top 500 free app	-0.788***	-0.800***	-0.809***	-0.564***	-0.466***	-0.680***	-0.758***	-0.853***
	(0.126)	(0.128)	(0.129)	(0.147)	(0.144)	(0.107)	(0.108)	(0.211)
Top 500 free app*time	0.002	0.002*	0.002*	0.002***	0.001**	0.001***	0.001***	0.003***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
In-app purchases	-0.578***	-0.577***	-0.578***	-0.484***	-0.377***	-0.513***	-0.519***	-0.451***
	(0.119)	(0.119)	(0.119)	(0.128)	(0.108)	(0.093)	(0.098)	(0.164)
App price	-0.120*	-0.121*	-0.129*	-0.025	-0.038	-0.056	-0.079	-0.015
	(0.067)	(0.067)	(0.069)	(0.071)	(0.046)	(0.058)	(0.062)	(0.096)
App price*time	0.018***	0.018***	0.018***	-0.001	-0.000	0.003	0.003	0.003
	-0.120*	-0.121*	-0.129*	(0.004)	(0.000)	(0.003)	(0.003)	(0.005)
Female Users[a]	1.778	3.260	3.627					
	(3.736)	(4.240)	(4.281)					
User Age[a]	-0.169	1.107	0.312					
	(3.163)	(3.614)	(3.701)					
User App Downloads[a]	-4.301	-3.458	-1.813					
	(4.201)	(4.370)	(4.730)					
iOS		-0.361	-0.864					
		(0.496)	(0.731)					
Category fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Total observation	8,715	8,715	8,715	5,290	6,565	12,691	12,691	3,662
Total firms	1,311	1,311	1,311	1,081	933	1,516	1,516	651
Total events	996	996	996	1,179	1,188	1,996	1,641	611
Log likelihood	-5,926.75	-5,926.49	-5,925.63	-5,975.38	-6,255.50	-11,864.49	-9,755.62	-2,847.90

[a]Variables are calculated based on proportion of total users in the ecosystem. * p<0.1; ** p<0.05; *** p<0.01

4. PARTNERING IN A HAZE: INTERDEPENDENCE MISSPECIFICATION AND FIRM PERFORMANCE IN STRATEGIC ALLIANCES

INTRODUCTION

The strategic alliance literature points to inter-firm task interdependencies as a key link between alliance governance choice and firm performance (Gulati and Singh, 1998; Aggarwal, Siggelkow and Singh, 2011; Reuer and Devarakonda, 2015). Alliances involve the need to coordinate interdependencies across organizational boundaries (Hamel, Doz and Prahalad, 1989; Ring and Van de Ven, 1992), as well as the need to select governance mechanisms for inter-firm decision making (Aggarwal *et al.*, 2011; Reuer and Devarakonda, 2015). The nature of inter-firm interdependence has been shown to influence governance mode choice (Kale and Puranam, 2004; Villalonga and McGahan, 2005) as well as the performance implications of this choice (Sampson, 2004; Mayer and Teece, 2008).

Prescriptive managerial advice stemming from this stream of the extant alliance literature generally makes the implicit assumption that in the course of deciding on a mode of governance, allying firms are “correct” in their representations of inter-firm interdependencies. In practice, however, managers often enter into alliances with an imperfect ex ante understanding of their true patterns of inter-firm interdependence (Haspeslagh and Jemison, 1991; Doz, 1996). This makes selection of a “correct” structure likely to be an unrealistic assumption. Our aim in this paper is thus to better understand the implications of relaxing the assumption that managers correctly understand inter-firm interdependencies when selecting an alliance governance mode. We focus on two forms of such interdependence misspecifications—over-specification and under-specification—analyzing how these incorrect managerial representations of inter-firm task interdependencies influence firm performance in an alliance setting, under varying interdependence and governance mode conditions.

A small set of studies lends credence to the notion that managers do not have a fully correct understanding of their inter-firm task interdependencies when entering into alliances (Doz, 1996; Sosa, Eppinger and Rowles, 2004; Gokpinar, Hopp and Iravani, 2010). Although these studies have made important strides in expanding our understanding of the role of interdependence misspecifications, relatively little large-sample empirical research has addressed this issue (many of these studies are single case-based). One reason for the lack of research on this topic is the difficulty in measuring managers' ex-ante understanding of interdependencies. We consequently have very little understanding of the relative performance implications of different forms of interdependence misspecifications. To remedy this gap we develop a computational model that allows us to simulate managers' understanding of underlying task structures under different scenarios. This approach, we believe, offers a first step in pushing the literature toward a deeper understanding of how interdependence misspecifications influence firm performance in the context of alternate governance mode choices.

A key benefit of employing a computational model is that such models naturally overcome the limitation of not being able to observe counterfactuals, a critical constraint in empirical work. Examining the antecedents of alliance governance choice (e.g., Kogut and Singh, 1988; Hennart and Reddy, 1997; Dyer, Kale and Singh, 2004; Villalonga and McGahan, 2005), for example, very often relies on observing only realized transactions. A computational modeling approach allows us to develop insights by creating counterfactuals and specifying scenarios that are difficult (or impossible) to observe empirically.

We build on a rich body of work that has used computational methods to develop insights into issues in strategy (e.g. Levinthal, 1997). Such an approach enables us to abstract away from industry and firm-level factors such as resource complementarity, trust, and prior experience (Anand and Khanna, 2000; Kale, Dyer and Singh, 2002), and to focus instead on isolating the performance effects of errors associated with task interdependence structure assessment. In particular, we model various task interdependence structures and their associated errors, a goal that would not be possible to accomplish with empirical methods alone.[20]

Our results lead to several sets of insights. First, we find that interdependence misspecifications lead to a loss in firm value, with the relative magnitude of this loss varying by governance mode. Across-mode differences further suggest that normative advice regarding governance mode selection in alliances should be conditional on the relative level of ex-ante managerial certainty regarding the nature of inter-firm interdependence. Second, we find that increases in the actual (correct) level of interdependence reduce the underperformance penalty associated with interdependence misspecifications. Finally, we find that under- and over-specification influence alliance performance through their effect on the extent of exploration and the magnitude of coordination failures experienced by the firms in the alliance. While over-specification increases both exploration and coordination failures, under-specification decreases these two effects. The relative magnitude of the two effects explains the resulting impact on firm performance. When exploration and coordination itself are outcomes of interest in an alliance setting, our insights further point to the possibility of a tradeoff between

[20] Our study complements recent work examining misspecification of interdependencies in a single firm setting (Martignoni, Menon and Siggelkow, 2015). This work differs from ours in important ways, with one key difference being that Martignoni *et al*. (2015) focus on misspecification in a single-firm setting (versus an inter-firm setting like ours in which governance mode issues are paramount).

performance and non-performance outcomes, which may condition alliance governance mode choice.

In the next section we briefly highlight the literature which serves to motivate and frame our research question. In the subsequent sections we detail our computational model and associated analyses, with the aim of more deeply understanding the implications of interdependence misspecifications for firm performance in an alliance setting. We end by discussing the implications of our study for theory and for future research.

MOTIVATING LITERATURE

Alliances are complex inter-organizational relationships with high failure rates (Kale, Dyer and Singh, 2002; Kale and Singh, 2009; Lunnan and Haugland, 2008). A key challenge in an alliance context is governing the joint set of activities of the partnering firms. Recent work on alliance governance has underscored the importance of coordination among partner firms as a critical determinant of relationship success (e.g, Gulati and Singh, 1998; Gulati, Lawrence and Puranam, 2005; Reuer and Arino, 2007). Coordination is often necessary as partners must engage in joint tasks without the benefits of the structures and systems available in traditional hierarchies (Gulati and Singh, 1998). Difficulties arise from decomposing tasks and from ensuring the division of labor outside organizational boundaries, and coordination challenges persist even with perfect alignment of self-interest among the interacting parties (Heath and Staudenmayer, 2000; Kretschmer and Puranam, 2008).

While firms can address coordination challenges through a variety of mechanisms, including the use of detailed contracts that specify tasks, roles and responsibilities (Mayer and Argyres, 2004; Carson, Madhok and Wu, 2006; Reuer and Arino, 2007), contingency plans and responses (Ring and Van de Ven, 1994), and information sharing and feedback (Argyres and Mayer, 2007), explicit governance mechanisms are an over-arching channel through which coordination challenges are often resolved in alliance settings (Gulati and Singh, 1998). Inter-firm interdependencies influence both the nature of the desired alliance governance structure, as well as the consequent performance of the relationship in the context of such a structure (Gulati and Singh, 1998; Mayer and Teece, 2008; Aggarwal *et al*., 2011; Reuer and Devarakonda, 2015; Kim, Zhao and Anand, 2015).

What are the implications of employing particular alliance governance structures when interdependencies are not correctly understood by managers? Though the literature on this question is limited, as the typical assumption is one of perfect knowledge regarding the nature and extent of task interdependencies (which in turn dictates appropriate governance structure choice), several studies have used case examples to illustrate the consequences of incorrect ex ante assessments of such interdependencies (e.g. Doz, 1996; Sosa *et al.*, 2004; Gopkinar *et al.*, 2010). In a study of the R&D alliance between Ciba Geigy and Alza to develop a drug called OROS, for example, Doz (1996) finds that the allying firms started with an incorrect understanding of the nature of interdependencies among their underlying tasks. Their assumption was that the alliance would involve a simple “handover” of the drug from Alza to Ciba Geigy. In reality, however, the alliance required a high level of coordination between the downstream functions of both firms. Over the course of the alliance, as the firms realized the need for tighter coordination, they then ended up over-specifying the level of interdependence, selecting a governance structure that provided greater levels of coordination than actually required. As a consequence of the firms’ interdependence misspecifications (and sub-optimal governance choices), joint development of the drug was slowed, and the alliance failed to meet its intended objectives.

Under-specified representations of task interdependencies can likewise be problematic. Sosa *et al.* (2004; 2007) address the under-specification issue in their study of a large commercial aircraft engine project. They find that a significant number of interdependencies between sub-systems were invisible to system architects. As a consequence, system architects did not set up appropriate structures to deal with underlying interdependencies, with the misalignment in structure and task interdependence resulting in significant cost and program delay.

Despite the fact that over- or under-specification of inter-firm task interdependencies is likely to be common in practice across many types of inter-organizational relationships, there is little systematic evidence in the literature (with the exception of a small set of case-based examples, two of which we mention above) as to how interdependence misspecification might affect the performance of firms, particularly under alternate modes of governing the alliance relationship itself. Our methodological approach in this paper, therefore, is to employ a computational model to investigate the link between misspecified levels of interdependence and alliance performance in a systematic manner. This approach enables us to develop a set of theoretical insights that might then serve as the basis for future empirical research. We turn to the details of our computational model in the next section.

MODEL

Tasks and interdependencies

We draw on the NK approach to modeling firm decision making (Kauffman, 1993, Levinthal, 1997), which conceptualizes firms as consisting of a set of inter-related activities, N, that can represent various organizational decisions such as those related to firm strategy, organizational form, product design, and so forth (Rivkin, 2000).[21] The canonical NK model assumes that these N activities are interrelated so that a change in one activity affects the payoff to the other K activities. Firm performance is based on the unique configuration of these N activities, with the topography ("ruggedness") of the performance landscape determined by the degree of interaction among the firm's activities (Levinthal, 1997).

We build on Aggarwal *et al.* (2011), who extend the canonical NK approach to a two-firm alliance setting. In this model there are two firms, Firm 1 and Firm 2, each of which makes decisions over a set of binary activities denoted by F_1 and F_2. A subset of the activities of each firm is considered to be part of the alliance relationship (the "alliance activities"), denoted by A_i, while the remainder of the activities are outside the scope of the alliance (the "non-alliance activities"), denoted by N_i. Firm 1's activities are thus denoted by $F_1 = \{N_1, A_1\}$ while Firm 2's activities are denoted by $F_2 = \{N_2, A_2\}$. The two-firm system we model consists of a total of 12 activities, each of which is denoted by d_j, with j running from 1 to 12.[22] Figure 4.1 illustrates the allocation of each of the d_j activities to the four activity sets $\{N_1, A_1, A_2, N_2\}$. For Firm 1, for example, the non-alliance activities are represented by $N_1 = \{d_1, d_2, d_3, d_4\}$ and the alliance activities are represented by $A_1 = \{d_5, d_6\}$. Interdependencies among particular activities, which can be either intra-firm or inter-firm, are indicated with an "X".

[INSERT FIGURE 4.1 HERE]

We then consider five different patterns of interdependence, as illustrated in Figure 4.2, each of which contains a different set of interdependencies among the four activity sets described in Figure 4.1. We select these patterns in order to model the

[21] We use the term "activities" interchangeably with "choices" and "tasks" throughout this paper.
[22] This value for N is consistent with prior NK literature (e.g., Rivkin and Siggelkow, 2007; Aggarwal *et al.*, 2011).

characteristics of a broad range of interdependence forms. The patterns not only increase in the overall level of interdependence, but each successive pattern introduces a particular class of interdependence among the activity sets $\{N_1, A_1, A_2, N_2\}$ (e.g., going from Pattern 1 to Pattern 2 introduces interdependencies within the alliance activities) so that we can more easily isolate the implications of interdependencies of different types. While these patterns are certainly not exhaustive, they collectively enable us to conduct a set of analyses that can generate insights into the mechanisms underlying our core research question around the impact of interdependence misspecifications.

Pattern 1, which we refer to as *fully decomposable*, has interactions only within each of the four activity subsets $\{N_1, A_1, A_2, N_2\}$: the activities within the N_1 subset only affect other activities in N_1, and the same holds for activities within $A_1, A_2 \text{ and } N_2$. In Pattern 2, *pure alliance interaction*, we introduce interactions within each of the sets of alliance activities of both the firms (i.e., within A_1 and A_2). In Pattern 3, *firm own-alliance interaction*, we introduce interactions within the firm's own non-alliance and alliance activities so that activities within N_1 interact with activities within $A_{1,}$ and activities within N_2 interact with activities within $A_{2.}$ In Pattern 4, *firm partner-alliance interaction*, the alliance activities of one firm interact with the non-alliance activities of the partner (activities within A_1 interact with activities within N_2, and activities within A_2 interact with those of N_1). And finally, for Pattern 5, *full interdependence*, there is complete interdependence, with all activities interacting with one other.

[INSERT FIGURE 4.2 HERE]

Performance landscapes

Each unique configuration of the N activities in the two-firm system (in which, as discussed above, the full set of N activities is divided into the subsets $\{N_1, A_1, A_2, N_2\}$) has associated with it a particular performance level. To create the performance landscape we follow the standard approach in the NK literature (e.g. Levinthal, 1997; Rivkin 2000): for each of the *N* activities, d_i, in the system, we define a contribution value function C_i. Each C_i takes as parameters the state (either 0 or 1) of d_i, together with the state of the k_i other policies with which d_i interacts (these interactions are defined, as described above, by the interaction matrix associated with the particular interdependence pattern being considered), and is initialized with a value drawn at random from a uniform $U[0,1]$ distribution for each possible combination of the various states of d_i and its k_i interacting policies. The set of N contribution value functions C_i is defined at the outset, and remains unchanged as the simulation progresses.

The overall performance of the entire two-firm system for any given configuration of activities d^* (i.e., the N-dimensional vector of d_i values) is the sum of the N C_i values for that particular configuration i.e. $\sum_{i=1}^{N} C_i$. We can define the performance of Firm 1 for a given d^* as the sum of the contribution values of the activities specific to the firm itself, plus a portion, α, of the alliance activities (we set $\alpha = 0.5$ throughout). The performance of Firm 1, for example is $\sum_{i=1}^{4} C_i(d^*) + \alpha \sum_{i=5}^{6} C_i(d^*)$. To reduce statistical artifacts we follow the commonly employed approach in the NK literature in which the reported performance values are normalized by dividing the raw performance by the performance value at the highest peak in the landscape (see e.g., Rivkin and Siggelkow [2003]).

Interdependence misspecifications

Modeling misspecifications in managerial representations of task interdependencies requires that we model not only the true underlying interaction matrix among the firms, but also that we model the misspecified representation of the interaction matrix that is taken into account by managers as they make decisions. We do so by modeling two matrices, with the true matrix used to determine the actual performance that managers observe as a consequence of their choices, and the misspecified matrix used to determine the choice that managers actually make as they search the landscape.

More formally, we define two interaction matrices. The first interaction matrix, M_0, represents the *true* structure of the underlying pattern of inter-firm task interdependence, and is used to determine the performance landscape as discussed in the prior section. The second interaction matrix, M_1, represents *firms' own representation* of the inter-firm task interdependencies, and can differ from the true matrix M_0. The performance landscape for M_1 is derived from the true performance landscape M_0 to ensure that the (potentially misspecified) performance values are correlated with the true performance values via the processes described later in this section.

Firms search by evaluating alternatives and making choices with respect to their activities based on a set of governance structures which we describe in a subsequent section. In the process of evaluating alternatives and making changes to their activities d_i, the firms take into account performance values as determined by the (misspecified) interdependence matrix, M_1. Once a choice is made in any given period, however, the performance that firms actually experience is defined by performance values stemming from the (true) interdependence matrix, M_0. While searching for high performing configurations, firms compare the performance values of the alternatives based on the M_1 matrix with the observed performance of the current configuration based on the M_0 matrix.

Firms are said to have an under-specified view when the misspecified matrix M_1 has a lower degree of interdependence than the true matrix M_0; and firms are said to have an over-specified view when the misspecified matrix M_1 has a higher degree of interdependence than the true matrix M_0. For the purpose of our analysis we will consider misspecifications that differ by a single pattern difference as defined by the patterns in Figure 4.2. As an example, with a true Pattern 3 interdependence matrix (i.e., where M_0 is based on Pattern 3), *under-specification* is defined as a situation where there is an M_1 based on Pattern 2, while *over-specification* is defined as a situation where there is an M_1 based on Pattern 4.

In the remainder of this section we discuss the processes for calculating the performance values of the landscapes as a function of the under- or over-specification of the M_1 pattern. The performance levels for M_1 (whether under- or over-specified) are derived from the M_0 performance levels. To accomplish this we first define the performance landscape for M_0 via the process described in the previous section; and we then derive the performance landscapes for the under- and over-specified cases using the procedures described next.

Under-specified interdependence matrix $\boldsymbol{M_1}$. What is the procedure we use to construct a performance landscape for an under-specified matrix? The performance values of the under-specified landscape should be correlated with the true landscape in such a way that the under-specified landscape appears to be a slightly "blurry" (or less rugged) version of the true landscape. How do we accomplish this? When the matrix M_1 is under-specified, each decision d_i is affected by $\bar{k}_i$ other decisions, with $\bar{k}_i < k_i$, where k_i is the number of interdependencies associated with d_i in the true matrix M_0. In order to calculate the performance landscape for M_1 we take averages of the contribution values from the true interaction matrix M_0 for each fixed configuration of d_i and its $\bar{k}_i$ interacting choices, an approach consistent with Gavetti and Levinthal (2000).

We can illustrate this process with an example. Assume that in the true matrix M_0 a particular activity d_1 interacts with activities d_2, d_3, and d_4. Also assume that in the misspecified matrix M_1 the activity d_1 is represented by managers as interacting only with activity d_2. The performance landscape M_1 thus requires that we generate contribution values for each unique combination of the d_1 and d_2 activities. For ease of notation, let C_i refer to the contribution value function for activity d_i for the true matrix M_0. Furthermore, let the four arguments of $C_i()$ refer to the states (which can be either 0 or 1) of each of the activities d_1 through d_4. Thus $C_1(0,0,0,0)$ refers to the contribution value assigned to the true (M_0) matrix for activity d_1 where activities d_1 through d_4 are all set to 0. In our example, we would define the contribution values for d_1 in the misspecified matrix M_1 for each of the four possible configurations of the d_1 and d_2 activities as follows:

$d_1 = 0$ and $d_2 = 0$: *Average* $\{C_1(0,0,0,0), C_1(0,0,0,1), C_1(0,0,1,0), C_1(0,0,1,1)\}$

$d_1 = 0$ and $d_2 = 1$: *Average* $\{C_1(0,1,0,0), C_1(0,1,0,1), C_1(0,1,1,0), C_1(0,1,1,1)\}$

$d_1 = 1$ and $d_2 = 0$: *Average* $\{C_1(1,0,0,0), C_1(1,0,0,1), C_1(1,0,1,0), C_1(1,0,1,1)\}$

$d_1 = 1$ and $d_2 = 1$: *Average* $\{C_1(1,1,0,0), C_1(1,1,0,1), C_1(1,1,1,0), C_1(1,1,1,1)\}$

Over-specified interdependence matrix M_1. Having discussed the procedure for constructing an under-specified performance landscape, we turn next to the procedure for constructing the performance values of an over-specified landscape. In this case, rather than being a slightly “blurry” (or less rugged) version of the true landscape (as it was in the under-specified case), the over-specified landscape can be thought of as a more “granular” (or more rugged) version of the true landscape.

How do we accomplish this? When the matrix M_1 is over-specified, each activity d_i is affected by $\bar{\bar{k}}_i$ other activities, with $\bar{\bar{k}}_i > k_i$ (where k_i is the number of interdependencies associated with d_i in the true matrix M_0). This implies that for each unique combination of d_i and the k_i other activities affecting it in the baseline M_0 matrix, there are $2^{\bar{\bar{k}}_i - k_i}$ additional contribution values in the M_1 matrix that must be created to account for the additional M_1 matrix interdependencies. To generate these additional contribution values we follow the following process. First, we generate $2^{\bar{\bar{k}}_i - k_i - 1}$ random numbers ε_j from the uniform distribution $U[0, a]$, where a is $\min(c_i, 1 - c_i)$, and c_i is the particular contribution value for d_i for the specific configuration of d_i and the k_i other policies affecting it (note that c_i is based on the C_i function that defines the landscape for the M_0 matrix). Second, for each random number ε_j we generate two contribution values $c_{ij1} = c_i + \varepsilon_j$ and $c_{ij2} = c_i - \varepsilon_j$. Finally, we randomly assign c_{ij1} and c_{ij2} to the additional $2^{\bar{\bar{k}}_i - k_i}$ activity combinations for which we need the additional contribution values. Constructing the landscape for the over-specified matrix in this way allows us to ensure that the true and misspecified landscapes are correlated with one another in the same way as they are in the under-specified case. More specifically: under-specifying (by one pattern) an over-specified (by one pattern) landscape results in the original (correct) landscape.

We can illustrate the over-specification procedure with an example. Assume that in the true matrix M_0 the activity d_1 interacts with d_2 and d_3, while in the over-specified representation M_1, in addition to these interactions there are two additional interactions, with activities d_4 and d_5. In this case it is necessary to define four additional contribution values for each possible configuration of d_1, d_2 and d_3. In the case where the activity configuration of (d_1, d_2, d_3) is (1,0,0), for example, we need to construct contribution values for activity d_1 where the $(d_1, d_2, d_3, d_4, d_5)$ values take on the following set of four possible configurations: (1,0,0,0,0), (1,0,0,0,1), (1,0,0,1,0), and (1,0,0,1,1). To do this we start with $c_1 = C_1(1,0,0)$. That is, we start with c_1, which is the specific contribution value in the M_0 matrix for the d_1 activity where the configuration of (d_1, d_2, d_3) is (1,0,0). We define $a = \min(c_1, 1 - c_1)$, and then generate two error terms ε_1 and ε_2 from the uniform distribution $U[0, \alpha]$. These two error terms then allow us to generate the four contribution values $c_{11} = c_1 + \varepsilon_1$, $c_{12} = c_1 - \varepsilon_1$, $c_{13} = c_1 + \varepsilon_2$, and $c_{14} = c_1 - \varepsilon_2$, which we then assign at random to the four configurations noted above, (1,0,0,0,0), (1,0,0,0,1), (1,0,0,1,0), and (1,0,0,1,1). E.g., if $C_1^{M_1}(d_1, d_2, d_3, d_4, d_5)$ represents the function that maps the particular configuration of d_1 through d_5 to a particular contribution value for d_1 in the M_1 matrix, then after generating the contribution values through the process described above, the random allocation could generate the following: $C_1^{M_1}(1{,}0{,}0{,}0{,}0) = c_{11}$; $C_1^{M_1}(1{,}0{,}0{,}0{,}1) = c_{13}$; $C_1^{M_1}(1{,}0{,}0{,}1{,}0) = c_{14}$; and $C_1^{M_1}(1{,}0{,}0{,}1{,}1) = c_{12}$.

Governance modes

We turn next to the governance modes that determine how agents in our model search the performance landscape. We draw on Aggarwal *et al.* (2011), considering four governance modes that represent varying points along the spectrum of alliance integration (Kogut and Singh, 1988; Hennart and Reddy, 1997; Dyer *et al.*, 2004; Villalonga and McGahan, 2005). At the opposite ends of the spectrum we have what we refer to as the *modular* and *integrated* modes of governance. As hybrid forms we consider what we refer to as the *self-governing alliance* and *ratification* modes. We describe each of these modes in detail in the remainder of this section.

In the *modular* mode of governance both firms make choices simultaneously within a given period and only consider the profits associated with the particular activities within their scope. We model a 12 activity system, with performance values normalized by the total value of the system at the highest peak of the landscape (performance at the landscape peak is denoted by Π^*). In the *modular* mode Firms 1 and 2 control their respective alliance and non-alliance activities independently, with each firm thus controlling 6 of the 12 activities in the system. In each period Firm 1 evaluates alternatives for activities d_1 through d_6 based on the expected value of the configuration stemming from M_1, comparing these alternatives against the realized performance from the prior period as determined by M_0, and selecting a choice if it increases their expected performance. Firm 2 does the same for its own set of policy choices.

More precisely, in the *modular* mode, Firm 1 evaluates alternatives based on its expected profit, $\sum_{i=1}^{6} C_i^{M_1}\left(\bar{d}_t\right) / \Pi^*$, comparing this against the prior period realized performance, $\sum_{i=1}^{6} C_i^{M_0}\left(\bar{d}_{t-1}\right) / \Pi^*$. Similarly, Firm 2 evaluates its alternatives based on its expected profit $\sum_{i=7}^{12} C_i^{M_1}\left(\bar{d}_t\right) / \Pi^*$, comparing this against $\sum_{i=7}^{12} C_i^{M_0}\left(\bar{d}_{t-1}\right) / \Pi^*$. In this notation $C_i^{M_0}$ and $C_i^{M_1}$ respectively represent the contribution values for activity d_i based on the M_0 and M_1 matrices respectively. Vector $\bar{d}_t$ refers to the configuration of the activities being evaluated in the current period, while vector $\bar{d}_{t-1}$ refers to the existing configuration of activities, as of the end of the prior period. Firm 1 and Firm 2 can change up to two activities in any given period, and agents for each firm evaluate all possible alternatives when making decisions in a given period. For each agent, and for each alternative being considered by each agent, the vector $\bar{d}_t$, which represents the vector being evaluated by the agent, is thus allowed to differ from the prior round's realized configuration $\bar{d}_{t-1}$ by up to two activities. [23]

While the *modular* mode can be conceptualized as a simple case of an arms-length relationship where both firms work independently with full control of their activities, the *integrated* mode lies at the other end of the spectrum. In the *integrated* mode Firms 1 and 2 operate as a single entity that makes decisions with respect to all 12 policy choices. Examples of *integrated* governance structures can be found in long-term equity-based alliances where decision making is fully integrated, and where firms

[23] Prior work has parameterized the number of activities that can be changed in any given period, as well as the number of alternatives considered, referring to these values as "search radius" and "alternatives" (Siggelkow and Rivkin [2005]; Aggarwal *et al.* [2011]). In our study we hold these parameters constant, allowing each agent to have a search radius of 2, and to evaluate all possible alternatives associated with this search radius in any given period. We thus map to what Aggarwal *et al.* (2011) refer to as "Capability Level D". Our results and insights, however, are qualitatively similar and robust to variation in these parameters. For ease of exposition we report all results based on these fixed settings of "search radius" and "alternatives." Results on alternative settings are available upon request.

behave as if they were a single entity (e.g., the alliance between Renault and Nissan, in which there is an integrated governance structure under a single leadership).

In our model of the *integrated* mode, the single agent takes into account the total combined profit of Firms 1 and 2 when evaluating alternatives, comparing this against the profit from the prior round's full configuration. Formally, the quasi-integrated entity evaluates alternatives based on $\sum_{i=1}^{12} C_i^{M_1}(\bar{d}_t) \,/\, \Pi^*$, comparing these against $\sum_{i=1}^{12} C_i^{M_0}(\bar{d}_{t-1}) \,/\, \Pi^*$, where $\bar{d}_t$ is the vector being evaluated, which differs from the prior round's configuration $\bar{d}_{t-1}$ by up to two activities. Though profit is calculated at the level of the system, we can also report profit for each firm; since the firms are symmetric in our analyses, profit for each individual firm is simply ½ of the the profit of the entire system.

In addition to the *modular* and *integrated* governance modes which lie on opposite ends of the governance spectrum, we consider two hybrid modes: *self-governing alliance* and *ratification*, in line with Aggarwal *et al.* (2011). In both cases the alliance function is managed independently by a third agent (e.g., a joint committee formed by both firms to manage the alliance). The agents for Firms 1 and 2 are responsible solely for their respective non-alliance activities (d_1 through d_4 and d_9 through d_{12} respectively), but in the process of evaluating alternatives and making decisions each takes into account their individual total profit, which for each firm is defined as the profit of the firm's non-alliance activities plus a portion, α, of the profit from the alliance activities (we set $\alpha = 0.5$ throughout). The alliance agent considers profit from only the alliance activities (i.e., d_5 through d_8) when evaluating alternatives and making decisions.

More precisely, with the *self-governing alliance* and *ratification* modes, in each period the Firm 1, Firm 2, and Alliance agents each make the following comparisons when evaluating alternatives, with each agent able to make up to two changes to the (four) activities under each of their individual purview (i.e., in each case the N-dimensional vector of binary values $\bar{d}_t$ differs from $\bar{d}_{t-1}$ by at most two activities):

Firm 1 compares: $\sum_{i=1}^{4} C_i^{M_1}(\bar{d}_t) \,/\, \Pi^* + 0.5 * \sum_{i=5}^{8} C_i^{M_1}(\bar{d}_t) \,/\, \Pi^*$

against: $\sum_{i=1}^{4} C_i^{M_0}(\bar{d}_{t-1}) \,/\, \Pi^* + 0.5 * \sum_{i=5}^{8} C_i^{M_0}(\bar{d}_{t-1}) \,/\, \Pi^*$

Firm 2 compares: $\sum_{i=9}^{12} C_i^{M_1}(\bar{d}_t) \,/\, \Pi^* + 0.5 * \sum_{i=5}^{8} C_i^{M_1}(\bar{d}_t) \,/\, \Pi^*$

against: $\sum_{i=9}^{12} C_i^{M_0}(\bar{d}_{t-1}) \,/\, \Pi^* + 0.5 * \sum_{i=5}^{8} C_i^{M_0}(\bar{d}_{t-1}) \,/\, \Pi^*$

Alliance compares: $\sum_{i=5}^{8} C_i^{M_1}(\bar{d}_t) \,/\, \Pi^*$

against: $\sum_{i=5}^{8} C_i^{M_0}(\bar{d}_{t-1}) \,/\, \Pi^*$

Although the way the *self-governing alliance* and *ratification* modes compare alternatives is the same, the two modes differ in the level of independence and degree of oversight over the alliance agent. In the *self-governing alliance* mode, the alliance agent operates independently, without any oversight from the firms. In any given period the alliance agent makes its decisions. Firms 1 and 2 then select their policies simultaneously, taking into account the policy choice made by the alliance agent.

In the *ratification* mode, by contrast, in any given period the Firm 1 and Firm 2 agents decide on their activity set changes, followed by the alliance agent. Firm 1 and Firm 2 then have veto power over the activity changes suggested by the alliance agent. That is, before implementing any activity change, the alliance agent needs to have its proposed change ratified by the agents of the two firms. Ratification requires that *both* firms accept the proposed policy change, with a firm accepting any proposed policy change only if it does not reduce the firm's own profit.

ANALYSIS

We model a 12-policy choice system of two firms, with four activity subsets $\{N_1, A_1, A_2, N_2\}$, sub-divided as depicted in Figure 4.1, and with patterns of interdependence as depicted in Figure 4.2. The model is symmetric for both firms such that the performance results of each are equal when run over a large number of landscapes. We thus focus on analyzing the difference in overall performance of the two-firm alliance system under varying combinations of interdependence pattern and governance structure. We are interested in situations of over- or under-specification, which we define as a single pattern higher or lower, respectively in interdependence (for example, with the patterns in Figure 4.2, over-specification for Pattern 3 would be Pattern 4, while under-specification for Pattern 3 would be Pattern 2). We assume that both firms and the alliance agent (in the case of *self-governing alliance* and *ratification*) have the same misspecified view of the underlying task structure. Each time period in the simulation consists of agents making a set of decisions with respect to their activities (per the mode governing their decisions as described in the previous section). We run the simulation for 200 periods on a particular landscape in order to observe the long-run performance of firms in the system, and then take an average over 10,000 different simulation runs in order to minimize the effects of any statistical artifacts.

Performance implications of over- and under-specification

As a starting point for our analysis we compare long-term performance outcomes, i.e. performance at the end of period 200, for the alliance system in the case of misspecification to the case where all the agents in the system have a correct understanding of their task interdependencies. We refer to the percentage decline in overall performance as the "value-loss" due to the misspecification of task interdependence.

Over-specified case. We begin with the situation where the firm agents (and alliance agent in the case of the *self-governing alliance* and *ratification* modes) have an over-specified view of the underlying task structure. We consider performance for the four different forms of governance under the various interdependence patterns. Table 4.1 compares the performance outcomes of the four governance modes under Patterns 1 through 4 for firms with the over-specified view. We find that the average long-run performance for firms with an over-specified view decreases for all patterns. Pattern 1 has a lower value loss compared to the rest of patterns, due primarily to the difference in the additional number of interdependencies agents consider in the search landscape.[24] Moving on to the rest of the patterns, we find that the overall value loss decreases as we move from Pattern 2 to Pattern 4. For example, for the modular governance mode, the overall value loss is -18.6% for Pattern 2 as compared to -14.8% for Pattern 4. Similarly, for the *self-governing alliance* mode the overall value loss is -15.0% for Pattern 2 whereas it is -4.6% for Pattern 4. Further, for the *ratification* mode the overall value loss is -18.8% for Pattern 2, while it is -8.3% for Pattern 4. For the *integrated* mode the overall value loss is -20.0% for Pattern 2 and -11.3% for Pattern 4.

Our findings on the effects of over-specification are consistent with intuition. The overall loss in value for the firm with an over-specified view is directly linked to the error introduced into the search process as a consequence of the over-specification. For

[24] Pattern 1 differs from other patterns with respect to the total number of interdependencies that the agents consider in their search landscape (an additional 8 interdependencies with an over-specified view). For the other patterns the search landscape has an additional 32 interdependencies.

example, in the case of Pattern 1, while searching for higher performance the firm assumes that the alliance activities of the two firms are interdependent, impacting its performance. In reality, however, the underlying task is fully decomposable, with no interdependence between the alliance activities of the two firms. This misspecification of interdependence leads to an error in the search process, decreasing performance.

Under-specified case. We turn next to examining how under-specification affects the performance of both firms. Table 4.2 shows performance outcomes of the various modes under Patterns 2 through 5 for firms with the under-specified view. We find that under-specification leads to lower performance on average. Similar to the over-specification results we find that Pattern 2 has a lower value loss compared to the other patterns with under-specification, primarily due to the difference in the characteristics of interdependencies that agents consider to be missing in the case of Pattern 2 and the other patterns.[25]

In the under-specified case we also find that the overall value loss decreases as we move from Pattern 3 to Pattern 5. In fact, for Pattern 5, we find that the overall performance increases for the *modular* and *self-governing alliance* modes. For example, in the case of the *modular* governance mode, the overall value loss is -19.1% for Pattern 3 as compared to a 7.8% gain for Pattern 5. Similarly, the overall value loss for Pattern 3 in the case of the *self-governing alliance* is -17.3%, while it is -1.0% for Pattern 5. For other modes the overall value losses for Pattern 2 with the *ratification* and *integrated* modes are -15.6% and -21.6% respectively, while they are -2.5% and -9.5% for Pattern 5 with the *ratification* and *integrated* modes.

[25] Firms consider a total of 8 interdependencies within the alliance agent to be missing when considering the under-specified view of Pattern 2. For the rest of the patterns, firms consider their search landscape to have 32 fewer interdependencies as compared to that of the true landscape.

We can then observe the governance structure that provides the highest performance level when agents have the correct view as compared to when they have a misspecified view. Interestingly, we find that misspecification of task structure often results in a different governance mode providing the optimal level performance. For example, the *integrated* governance mode provides the highest performance for Pattern 4 when firms have the correct view, while the *self-governing alliance* mode provides the highest performance with both under- and over- specified views. On average, we find that the *self-governing alliance* mode provides the highest performance across patterns for both forms of misspecification (Pattern 1 with the over-specified view is an exception where the *modular* governance mode performs better). We turn to the mechanisms driving these results in the next section.

[INSERT TABLES 4.1 AND 4.2 HERE]

Coordination failures and exploration as intermediate explanatory mechanisms

To more deeply understand the reasons for the differences in value loss among the various interdependence pattern-governance mode combinations, we turn next to the mechanisms that may influence firm performance in an alliance setting, building on Aggarwal *et al.*'s (2011) discussion of the role of coordination and exploration in influencing the performance effects of alliance governance. Figure 3 illustrates the over-arching conceptual framework we explore in the remainder of this section: coordination failures and exploration achieved are intermediate measures that link misspecification, governance mode and level of interdependence with firm performance in an alliance setting.

[INSERT FIGURE 3 HERE]

Why do we focus in particular on the dimensions of coordination and exploration? Coordination concerns are pervasive in an alliance context (Litwalk and Hylton, 1962), influencing governance mode decisions (Gulati and Singh, 1998). The ability to effectively coordinate activities among alliance partners, moreover, influences alliance performance (Zollo, Reuer and Singh, 2002; Gulati, Lawrence and Puranam, 2005). In addition to effective coordination, exploration is a key determinant of alliance performance as well (Child, 2001; Grant & Baden-Fuller, 2004; Lavie and Rosenkopf, 2006). We thus aim to understand how interdependence misspecifications, together with governance modes and actual patterns of interdependence, link to firm performance via the mediating effects of coordination and exploration.

Constructing the intermediate measures of coordination and exploration. We construct the measure, *coordination failures*, which we define, in any given period, to be the total number of incidences up to and including the current period in which firms (in total) experience a profit decline as compared to the previous period due to simultaneous decision making by the two firms. Total (Firm 1 + Firm 2) profit can decline both because of simultaneous movement of the agents, as well as because of errors in the search process due to landscape misspecification. We isolate the former by stripping out situations of search-related error.[26] For our analyses in this paper we consider *coordination failures* at period 200, which is the point at which the two-firm system has reached a steady-state level of performance.

[26] Due to differences in the contribution values between the search (M_1) and true (M_0) landscapes, configurations leading to high performance on the search landscape may not lead to high performance on the true landscape. An agent using a misspecified landscape for search may commit to a policy configuration that can lead to a decline in performance on the true landscape. We refer to this decline in performance due to differences in contribution values between the true and search landscapes as "search-related error." We strip out such search-related errors from the measure of *coordination failures* so that the measure reflects only situations where agents simultaneously make a choice that may be correct for each firm individually, but that ends up being performance reducing for the total profits of both firms as a whole.

We also construct the measure *exploration achieved* by calculating the total number of unique contribution values (C_i's) evaluated by the agents in the system over time, normalized by the total number of possible contribution values that exist for the given landscape (Aggarwal *et al*., 2011).[27] The evaluated and total contribution values used as inputs to our *exploration achieved* measure come from the true landscape (M_0), and are based on the agents' search history on the misspecified landscape (M_1). More precisely, for each policy configuration evaluated by the agents on the search landscape (M_1) up to and including the focal period, we take the corresponding configuration on the true landscape (M_0) and identify whether the contribution values for that policy configuration, as derived from the M_0 landscape, have been considered by the agents in the search process up to and including the focal period.[28] We count the total number of such cases where a particular contribution value has been evaluated, and divide this by the total number of distinct contribution values based on $M_{0.}$ As we do with *coordination failures,* we consider *exploration achieved* in the steady-state at period 200.

Implications of over-specification for intermediate measures. How does over-specification affect the intermediate measures of coordination failures and exploration? In the over-specified case the landscape searched by the agents becomes more rugged than that of the true landscape. Additionally, values of adjacent locations on the landscape are less correlated as compared to that of the true landscape. This increases the number of alternatives the agent considers, as well as the duration of the

[27] For instance, the total number of possible contribution values for Pattern 1 is 144, and for Pattern 5 it is 49,152.

[28] Note that any given policy configuration will exist on both landscapes (M_0 and M_1). However, whether or not the corresponding contribution values are "distinct" is a function of the interdependence structure of that landscape (which of course differs between M_0 and M_1). As an example, suppose we take a simple system in where there are only two possible binary policy choices $\{d_{1,}\ d_2\}$. When an agent evaluates the move from the existing policy configuration {0,0} to a new policy configuration {0,1}, the number of distinct contribution values she considers will differ depending on whether the two policy choices are interdependent or not. If they are interdependent, then there would be two unique contribution values, $C_1(0,1)$ and $C_2(0,1)$, which would be taken into account; if they are not interdependent, then only one unique contribution value, $C_2(0,1)$ would need to be considered.

search process before an agent locks itself into a policy configuration. While this increase in the number of alternatives considered leads to a higher degree of exploration achieved, the increase in search time also leads to higher levels of coordination failure. With multiple agents searching the landscape at the same time, the chances of coordination failure increases as policies selected by one agent may not be optimal for the other. The degree of coordination failures between agents thus depends on the duration over which agents search the landscape simultaneously.

We report the results of the effect of over-specification on exploration achieved and coordination failures in the middle two columns of Table 4.3 (falling under the heading "symmetric view"). Similar to Tables 4.1 & 4.2, we compare the performance metric (in this case exploration achieved or coordination failures) for the misspecified case relative to the correctly-specified case at the end of period 200. The table shows that the overall degree of exploration achieved by the agents increases with the over-specified view. Furthermore, the effect of over-specification is more prominent at patterns with a higher degree of interdependence, and with the *modular* and *self-governing alliance* modes. In addition, agents with the over-specified view face a higher level of coordination failure. For example, under Patterns 3 and 4 with the *self-governing alliance* mode, coordination failures increase by 3.5% and 1.6% respectively.

Implications of under-specification for intermediate measures. How does under-specification affect the intermediate measures of coordination failures and exploration? In the under-specified case the search space for the agent is simplified. The agent searches on a landscape with a lower degree of interdependence that is consequently less rugged as compared to the true landscape. Each policy on the search landscape corresponds to a cluster of policies on the actual landscape. This simplification of the search landscape speeds the agent's search processes (e.g., Gavetti and Levinthal, 2000), enabling the agent to relatively quickly identify a peak with respect to its search landscape. Thus, the degree of exploration achieved with the underspecified-view decreases, as Table 4.4 (middle two columns, under the heading "symmetric view") reports. The increase in search speed is particularly helpful in reducing coordination failures: with an increase in search speed agents identify optimal performance configurations with relatively fewer activity changes, reducing the overall number of associated coordination failures.

[INSERT TABLES 4.3 AND 4.4 HERE]

Concordance with conceptual framework. Having discussed the implications of misspecification for coordination and exploration, we now return to Figure 4.3, with the aim of testing the conceptual framework depicted there. To do so we construct a dataset based on our simulation results at period 200 with 320,000 observations: we run 10,000 trials for each combination of misspecification-pattern-governance mode combination; and we then employ seemingly unrelated regression (SUREG) to analyze the results, using the framework depicted in Figure 4.3. We estimate three equations simultaneously: (1) the impact of misspecification on exploration achieved; (2) the impact of misspecification on coordination failures; and (3) the impact of exploration achieved and coordination failures on total performance. Seemingly unrelated regression (SUREG) allows for correlation between the error terms of these equations (Zellner, 1962, 1963), a likely situation given the approach used to construct our dataset.

In our SUREG models the variable, *misspecification*, takes the value of one when the observation is under a misspecified view, and 0 otherwise. We estimate models for over- and under- specification separately. To control for the effects of patterns and governance modes we include dummy variables for these factors. The *modular* *governance mode* is used as the base mode against which to compare the effects of the other modes; and Pattern 2 is used as the base pattern against which to compare the effects of the other patterns.[29]

Estimated standardized coefficients for the two models (over- and under-specified) are reported in Table 4.5. We do not show *p*-values of the estimated coefficients to avoid redundancy, as all the *p*-values are less than 0.001 (with the exception of the effect of misspecification on coordination failures in the case of the over-specified view). As Model 1 shows, the coefficient of misspecification on exploration is positive, suggesting that over-specification of task structure is associated with higher exploration. On average, firms with the over-specified view tend to explore more by 0.10 standard deviation. Similarly, in Model 2, the coefficient of misspecification on coordination failures is negative, suggesting that under-specification is associated with fewer coordination failures. Though we do not find statistically significant effects of over-specification on coordination failures, we do find that under-specification increases coordination failures by 0.19 standard deviations. Furthermore, consistent with earlier research we find that the coefficient of exploration on overall performance is positive, and the coefficient of coordination failures on overall performance is negative, for both Model 1 and Model 2. We find that a standard deviation increase in coordination failures decreases overall performance by -0.21 and -0.37 standard deviations for over- and under-specification respectively. Similarly we find that a standard deviation increase in exploration increases overall performance by 0.38 and 0.45 standard deviations for over- and under-specification respectively.

[INSERT TABLE 4.5 HERE]

[29] Since we do not have any observations for Pattern 1 in the case of the under-specified view, and for Pattern 5 in the case of the over-specified view, we use Pattern 2 as the base pattern, as it is common across both forms of misspecification.

Implications for governance mode choice: asymmetric view

In a final set of analyses we consider the situation in which only one partner has either an under- or over-specified view. The results of the "asymmetric" perspective on coordination and exploration outcomes are shown in the right two columns of Tables 2A and 2B (under the heading "asymmetric view"). The asymmetric view is one in which the focal firm has the correct representation, while the partner has the misspecified view. These results help address the question of what governance mode managers should choose (or rather, negotiate for ex ante), conditional on their assessment of their partners' likely representation of interdependencies.

As Table 4.3 suggests, if managers believe their partner to be over-specified, higher levels of exploration can be obtained by selecting the *modular* governance mode, and coordination failures can be minimized by selecting the *self-governing alliance* mode. If on the other hand managers believe their partner to be under-specified, as Table 4.4 illustrates, they can minimize exploration losses by using the *modular* mode when in a lower interdependence situation (Patterns 2 and 3) and by using the *ratification* mode when in a higher interdependence situation (Patterns 4 and 5). Governance choice thus depends on managers' understanding of their task structure, their partner's level of misspecification, and the ultimate objectives of the alliance (whether this is firm performance itself, achieving high levels of exploration, or avoiding coordination failures).

DISCUSSION

Our aim in this paper was to use a computational model to understand the implications of incorrect managerial representations of inter-firm task interdependencies in the context of alliance relationships, focusing on the effects of under- and over-specification under varying combinations of true inter-firm task interdependence and modes of alliance governance. We derive three sets of results.

First, we find that managerial misspecification of interdependence structures leads to a decline in firm performance, a result consistent with prior case-based work (Doz [1996]; Sosa *et al.* [2007]). Our results suggest a number of interesting nuances. We find that while over- and under-specification of interdependence have similar effects on performance, the degree of value loss due to misspecification varies by governance mode. The decline in performance is on average lower for the *modular* and *self-governing alliance* modes. This difference in the effect of misspecification on various governance modes has important implications. When both firms have a correct understanding of their interdependencies, the *integrated* mode provides better performance at patterns with higher interdependence (Patterns 4 and 5). As we relax the assumption of a correct understanding, however, we find that the *self-governing alliance* mode provides better performance than the *integrated* mode. The degree to which firms have an understanding of their underlying interdependencies is thus important in deciding on the optimal mode of governance.

A second set of results is that the pattern of interdependence has a crucial impact on the level of decline in alliance performance due to misspecification. Interestingly, the decline in performance decreases with an increase in the degree of interdependence in the underlying task structure. As illustrated in Tables 1A and 1B, the value loss for the alliance is lowest with Patterns 4 and 5 for both forms of misspecification. We are able to explain these results using the intermediate measures of coordination and exploration.

Our analysis of these intermediate measures leads to our final set of conclusions, which relates to the possibly competing objectives relating to coordination and exploration. Our study lends insight into the consequences of misspecification for these two objectives, as we find that the two forms of misspecification affect each differently. The overall level of exploration achieved by the alliance increases with an over-specified view; in the case of an under-specified view, however, the overall exploration level decreases (though with a few exceptions for low complexity patterns). Similarly, we find that coordination failures increase when both firms share an over-specified view. Although in the case of the under-specified view coordination failures are limited, they decline at higher levels of interdependence. This presents an interesting trade-off between paying attention to firm performance versus other alliance objectives such as exploration. Firms with an over-specified view of interdependence may achieve higher exploration, yet trade this off with lower performance. Likewise, with higher levels of interdependence firms can take on an under-specified view in order to achieve fewer coordination failures.

From a managerial perspective our results underscore the importance of paying attention to task interdependencies when structuring alliances. Decision makers should, in particular, make attempts to identify the true structure of their inter-firm interdependence. While estimating ex ante the magnitude and direction of misspecification may be difficult, managers may be able to reduce the magnitude of such errors by investing in efforts to identify the true interdependence structures in alliances: e.g., pre-alliance discussions and alliance management capabilities can help reduce the likelihood of any misspecifications. Such investments in understanding the true structure become particularly important because, as our results suggest, firms' task structure representations are significant inputs to the choice of alliance governance mode.

Before concluding we discuss some of the assumptions embedded in our model, and their implications for our results. First, our model assumes that both firms are symmetric with respect to their views on interdependence. However, it may not be uncommon to have an alliance where both partners have different views of their interdependencies. We conducted robustness checks to understand the implications of this assumption. As noted in our discussion of coordination and exploration, we evaluated an 'asymmetric view' scenario in which only one of the partner firms has an incorrect view of their interdependence. The overall performance implications were consistent with our main findings, with the magnitude of value loss decreasing when only one partner has an incorrect understanding.

As a second assumption embedded in our analysis, note that we pre-specify firms' understanding regarding their interdependence structure, and assume that this remains constant for the entire period (i.e., there is no learning by agents about the true nature of their interdependence). It is likely, however, that firms update their understanding based on feedback received over the course of the alliance. While our purpose in the present paper was solely to examine the implications of relaxing the assumption of a correct specification of inter-firm task interdependencies (a gap that the literature has not yet addressed), it would be a natural extension to relax this assumption and to extend our model in order to study how the process of learning about interdependencies over time (and possibly modifying the alliance governance structure accordingly) influences our results.

As a final assumption, note that we use a pre-defined set of patterns of interdependence to represent task structures and firms' understanding of these structures. The current patterns represent discrete points on the continuum of increasing task complexity. These patterns characterize ideal configuration types that are useful for exposition; hybrid patterns may arise in reality, however, and future research might thus examine such patterns. We did run our results using a "random K" scenario to evaluate the implications of increasing levels of interdependence, where these interdependencies were randomly scattered throughout the task matrix. The results on this analysis were broadly consistent with our findings.

Our paper leads to a number of implications for work in the area of alliance governance. While the issue of governance structure choice has been examined both implicitly and explicitly in the alliance literature, with significant progress being made using empirical indicators, ours is the first effort to attempt to understand the implications of relaxing the common assumption that managers operate with a “true” representation of inter-firm interdependencies. Because in practice managers are unlikely to have perfect ex ante representations of their interdependencies, as we discuss up-front with the example from Doz (1996), such an assumption is likely to be unrealistic. Using empirical methods alone, however, is unlikely to allow to us fully address the implications of interdependence misspecifications, as empirical data is unlikely to be structured so as to allow simultaneous and deep observation of managerial representations, interdependencies, and governance structures. As a consequence, computational modeling provides an effective tool with which to examine the implications of managerial errors in interdependence representations in a structured way. The insights we gain from our model can complement future empirical work, and more importantly serve to inform the core theorizing that can guide these future empirical examinations of this topic.

In conclusion, we make an important set of contributions to the literature on alliance governance by highlighting how a partial understanding of task interdependencies can be detrimental for alliance performance. We go beyond prior work to explicitly study the effect of errors on various patterns of interdependence, a task that would be difficult to accomplish using empirical methods alone. In so doing we contribute to the literature on governance choice (e.g. Dyer *et al.,* 2004; Villalonga and McGahan, 2005), shedding new insights into the link between interdependence, governance modes, and firm performance in alliance settings, and offering a promising set of avenues for future research.

Figure 4.1: Interaction matrix example

				Firm 1						Firm 2					
								Alliance							
				N_1				A_1		A_2		N_2			
				d_1	d_2	d_3	d_4	d_5	d_6	d_7	d_8	d_9	d_{10}	d_{11}	d_{12}
Firm 1		N_1	d_1	X	X	X	X								
			d_2	X	X	X	X								
			d_3	X	X	X	X								
			d_4	X	X	X	X								
	Alliance	A_1	d_5					X	X						
			d_6					X	X						
Firm 2		A_2	d_7							X	X				
			d_8							X	X				
		N_2	d_9									X	X	X	X
			d_{10}									X	X	X	X
			d_{11}									X	X	X	X
			d_{12}									X	X	X	X

<u>Note</u>: This example corresponds to "Pattern 1" as described in Figure 4.2

Figure 4.2: Patterns of interdependence

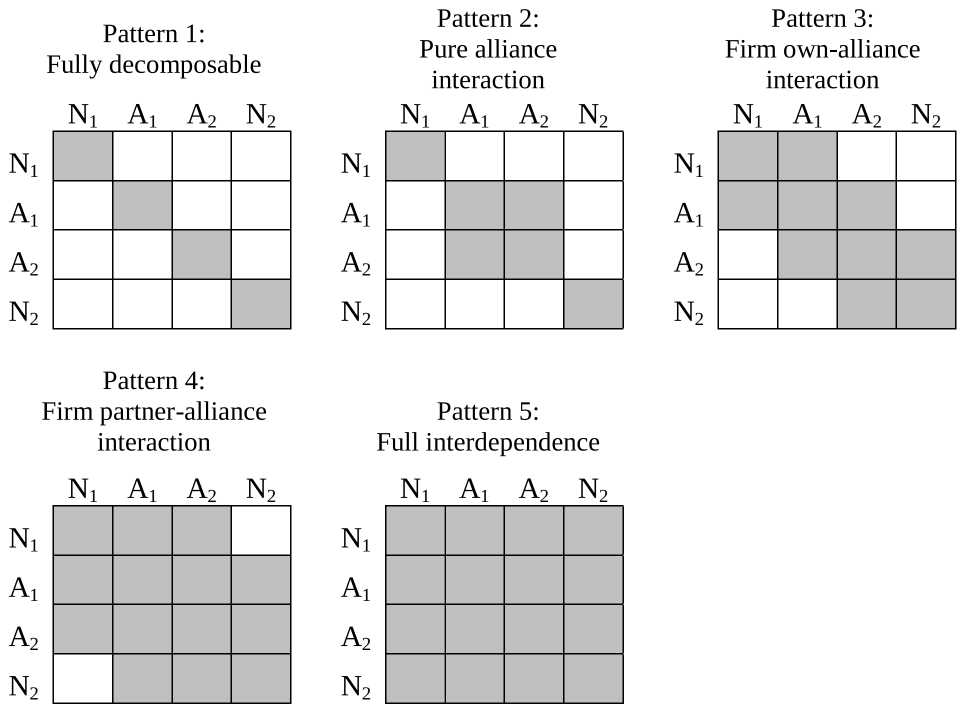

Figure 4.3: Framework for understanding the effect of misspecification

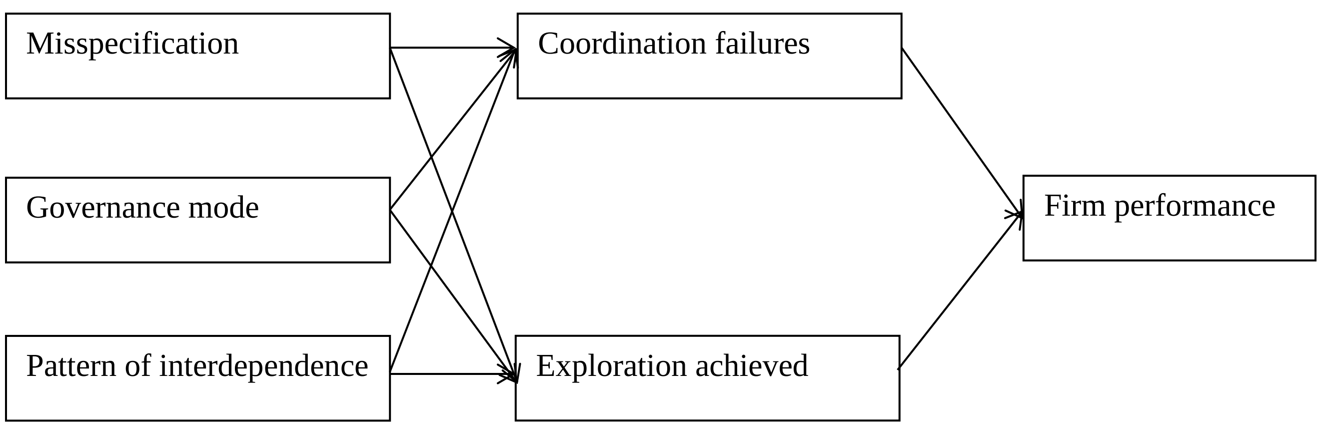

Table 4.1: Value loss, over-specified representation

Underlying pattern	Governance mode	Performance with correct view	Performance with over-specified view	% value loss
Pattern 1	Modular	0.991	**0.949**	-4.1%
	Self-Governing	**0.993**	0.927	-6.8%
	Ratification	**0.993**	0.912	-8.0%
	Integrated	0.989	0.926	-6.4%
Pattern 2	Modular	0.948	0.771	-18.6%
	Self-Governing	**0.989**	**0.842**	-15.0%
	Ratification	**0.989**	0.802	-18.8%
	Integrated	0.986	0.785	-20.0%
Pattern 3	Modular	**0.950**	0.783	-17.0%
	Self-Governing	0.932	**0.793**	-14.9%
	Ratification	0.908	0.765	-15.2%
	Integrated	0.949	0.763	-19.5%
Pattern 4	Modular	0.884	0.747	-14.8%
	Self-Governing	0.884	**0.845**	-4.6%
	Ratification	0.879	0.803	-8.3%
	Integrated	**0.922**	0.816	-11.3%

Table 4.2: Value loss, under-specified representation

Underlying pattern	Governance mode	Performance with correct view	Performance with over-specified view	% value loss
Pattern 2	Modular	0.944	0.921	-2.6%
	Self-Governing	**0.990**	**0.928**	-6.2%
	Ratification	**0.990**	0.918	-7.2%
	Integrated	0.985	0.919	-6.6%
Pattern 3	Modular	**0.950**	**0.773**	-19.1%
	Self-Governing	0.931	**0.773**	-17.3%
	Ratification	0.902	0.770	-15.6%
	Integrated	0.949	0.751	-21.6%
Pattern 4	Modular	0.873	0.745	-15.6%
	Self-Governing	**0.884**	**0.795**	-10.3%
	Ratification	0.877	0.755	-14.7%
	Integrated	0.927	0.749	-19.0%
Pattern 5	Modular	0.747	0.808	7.8%
	Self-Governing	0.828	**0.829**	-1.0%
	Ratification	0.780	0.757	-2.5%
	Integrated	**0.910**	0.823	-9.5%

Note: Values in bold indicate the governance mode providing superior performance for each combination of pattern and managerial representation (either correct or misspecified). For example, in Table 4.1, with the combination of [Pattern 1, Correct View], both the self-governing and ratification modes provide the highest performance.

Table 4.3: Changes in coordination and exploration, over-specified representation

Underlying pattern	Governance mode	Symmetric view		Asymmetric view	
		Exploration	Coordination	Exploration	Coordination
Pattern 1	Modular	0.9%	0.0%	0.7%	0.0%
	Self-Governing	3.4%	0.0%	-0.9%	0.0%
	Ratification	2.3%	0.0%	-0.6%	0.0%
	Integrated	1.6%	0.0%	-	-
Pattern 2	Modular	0.6%	-14.3%	1.6%	-5.6%
	Self-Governing	5.3%	0.0%	0.3%	0.0%
	Ratification	0.5%	0.0%	0.3%	0.0%
	Integrated	1.8%	0.0%	-	-
Pattern 3	Modular	7.7%	0.1%	2.6%	2.4%
	Self-Governing	9.4%	3.5%	0.9%	1.0%
	Ratification	0.2%	6.2%	-0.3%	5.9%
	Integrated	3.7%	0.0%	-	-
Pattern 4	Modular	3.4%	-0.5%	0.7%	2.5%
	Self-Governing	0.5%	1.6%	0.4%	0.9%
	Ratification	0.3%	3.9%	0.0%	4.1%
	Integrated	1.6%	0.0%	-	-

Table 4.4: Changes in coordination and exploration, under-specified representation

Underlying pattern	Governance mode	Symmetric view		Asymmetric view	
		Exploration	Coordination	Exploration	Coordination
Pattern 2	Modular	-1.4%	-11.7%	-0.5%	-10.0%
	Self-Governing	0.6%	0.0%	-1.6%	0.0%
	Ratification	0.1%	0.0%	-1.4%	0.0%
	Integrated	-1.2%	0.0%	-	-
Pattern 3	Modular	2.3%	1.1%	0.1%	1.0%
	Self-Governing	-1.8%	3.4%	-0.8%	0.5%
	Ratification	1.3%	5.1%	0.1%	3.6%
	Integrated	3.0%	0.0%	-	-
Pattern 4	Modular	-2.1%	-11.0%	-1.8%	-8.7%
	Self-Governing	-0.6%	2.4%	-0.5%	0.1%
	Ratification	0.0%	4.6%	-0.1%	0.9%
	Integrated	1.1%	0.0%	-	-
Pattern 5	Modular	-2.6%	-24.3%	-1.7%	-17.6%
	Self-Governing	-1.3%	-1.1%	-0.9%	-1.8%
	Ratification	-0.6%	-13.9%	-0.4%	-12.1%
	Integrated	0.0%	0.0%	-	-

Table 4.5: Effect of misspecification on exploration, coordination failure and total profits

Dependent variable	Independent variable (all dummy variables except for constant)	Model 1 (Over-specification)	Model 2 (Under-specification)
Exploration	Misspecification	0.098	-0.009
	Self-governing	-0.147	-0.221
	Ratification	-0.234	-0.250
	Integrated	1.055	0.787
	Pattern 1	0.293	
	Pattern 3	-1.053	-1.328
	Pattern 4	-1.629	-1.958
	Pattern 5		-1.988
	Constant	0.379	1.244
	R^2	0.874	0.818
Coord. failures	Misspecification	0.003	-0.193
	Self-governing	-0.694	-0.801
	Ratification	-0.600	-0.561
	Integrated	-0.768	-0.916
	Pattern 1	-0.278	
	Pattern 3	-0.077	-0.081
	Pattern 4	0.282	0.117
	Pattern 5		0.478
	Constant	0.532	0.537
	R^2	0.132	0.179
Performance	Exploration	0.383	0.459
	Coordination failures	-0.212	-0.375
	Misspecification	-1.116	-0.830
	Self-governing	0.116	0.012
	Ratification	-0.005	-0.127
	Integrated	-0.423	-0.445
	Constant	0.636	0.555
	R^2	0.413	0.390
	Observations	320,000	320,000

Note: All independent variables are dummy variables, except for *exploration*, *coordination failures*, and the constant. The *misspecification* dummy variable refers to the over-specified view for Model 1 and to the under-specified view for Model 2.

5. DISCUSSION

This final section concludes by summarizing the core results from three essays and discussing their contribution to theory and practice. Together, the three essays had the broad objective of systematically examining the structure of interdependencies that underlie the success of a firm's innovative efforts, particularly in the context of platform-based ecosystems. The dissertation starts with the premise that firms are situated in a complex web of interdependencies that often lies outside their boundaries. It then builds on this premise to offer novel characterizations of these interdependence structures based on the interaction between a firm's products and other elements of the ecosystem and to explore how these characterizations help explain firms' performance dynamics.

The first essay takes a granular view of the interdependence structure and starts with examining the interdependencies that lie at the level of a firm's innovation. It conceptualizes a platform-based ecosystem as an interconnected technological system in which a firm's innovation interacts with the platform and other complements to create value. It introduces the notion of 'connectedness' to describe an innovation's interdependence with other elements in the ecosystem. It explicitly distinguishes between an innovation's connectedness with the platform and other complements. In so doing, it examines how these two types of connectedness help firms leverage complementarities from the ecosystem, as well as create challenges that may limit an innovation's value creation. In the context of the Apple iPhone ecosystem, I find that the higher connectedness with the platform and complements increases the likelihood of successful commercialization. However, the benefit of platform connectedness is negated during the initial periods of the new generation of the platform. The effect of complement connectedness during the initial periods of the new generation of the platform is more nuanced and varies with the extent to which the connected complement is interdependent on the platform itself.

The second essay zooms out to the interdependencies that lie at the level of an ecosystem and are primarily driven by the structural properties of the ecosystem. Specifically, it examines how the ecosystem-level interdependencies, characterized by the number of components that interact with a firm's product, shape the extent to which complementors can sustain their value creation. The empirical context is Apple's iOS and Google's Android ecosystems, which provides a nice opportunity to study complementors' dynamics in ecosystems with varying levels of interdependence. Overall, I find that greater ecosystem complexity helps firms sustain their value creation. Further, the firms' ability to sustain superior performance is facilitated by their experience within the ecosystem, but hampered by transitions initiated by platform firms.

While the first two essays are focused on the structure of interdependencies in explaining firm performance, the third chapter takes a more behavioral perspective and addresses the implications of a partial understanding of these interdependence structures by decision makers. I use a computational model to understand the implications of over- and underrepresentation of interfirm task interdependencies in the context of the alliance relationships. The results suggest that both types of misrepresentation of task structure are, on average, detrimental to alliance performance. However, the degree of value loss varies by governance mode. The decline in performance is lower for the modular and self-governing alliance modes. Interestingly, I also find that the decline in performance decreases with an increase in the degree of interdependence in the underlying task structure.

Collectively, these essays make several theoretical and empirical contributions to the strategy and innovation literatures. First, this dissertation contributes to the emerging strategy literature on platforms and ecosystems by providing a detailed account of interdependencies that exist within an ecosystem (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). In this dissertation, I look at the other side of the phenomenon, beyond the platform firms, and illustrate how the performance of complementor firms is shaped by the structure of interdependencies faced by them within the ecosystem. I show that complementor firms can enhance the value of their innovations by leveraging a broad set of complementary technologies provided by platform and other complementor firms, but they must consider the platform-level generational transitions that may offset the benefits. This finding provides practical implications to both the platform firms and the complementor firms. From the platform firm's perspective, a platform firm can increase opportunities for value creation for the complementor firms by integrating additional components along with the core module of the platform. From the complementor firms' perspective, they can increase the utility of their innovation for the users by connecting it with additional platform components and other complements available in the ecosystem. Further, I also show that the sustainability of a complementor firm's performance is driven by the number of components that its product interacts with within the ecosystem. This finding highlights how platform firms' strategies with respect to the design of the platform architecture and governance of the ecosystem can shape complementor firms' performance.

Further, this dissertation also contributes to the literature on technological change, which is typically premised on how technological transitions impact the performance of firms in the focal industry (e.g., Tushman and Anderson, 1986; Henderson and Clark, 1990; Christensen, 1997). In this dissertation, I show how technology transitions initiated by platform firms can impact the performance of complementor firms within an ecosystem. It highlights that technological interdependencies between platform firms and complementors in related industries can have important consequences for complementors during periods of platform transitions. Relatedly, the evidence in the study also points to the difficulties of coordinating technology transitions at the level of the ecosystem. Even if platform firms intend to create a smooth generational transition for all of their complementors, the system-level interdependencies and technological uncertainties make such coordination difficult.

This dissertation also makes an important set of contributions to the literature on alliance governance by highlighting how a partial understanding of task interdependencies can be detrimental to alliance performance. It goes beyond prior work to explicitly study the effect of errors on various patterns of interdependence—a task that would be difficult to accomplish using empirical methods alone. In so doing, it contributes to the literature on governance choice (e.g., Dyer *et al.,* 2004; Villalonga and McGahan, 2005), shedding new insights into the link between interdependence, governance modes, and firm performance in alliance settings and offering a promising set of avenues for future research.

Finally, I also briefly note several avenues for future research given the theoretical and empirical results of the essays in this dissertation. While this dissertation is a first attempt to shed light on the microstructures of interdependencies that exist in a platform-based ecosystem, it has not accounted for the vast heterogeneity that exists with respect to the interdependent elements. For example, in the case of an iPhone ecosystem, an app interacts with different actors present in the ecosystem, such as handset providers and wireless providers. These actors differ from one another in many aspects, such as their added value in the ecosystem and their bargaining power. In future work, I hope to further characterize the structure of interdependencies introduced in this dissertation by explicitly taking into account these differences. Finally, while I show the role of the structure of interdependencies in value creation, it would be important to understand how these interdependencies arise and evolve over time. In future work, I also hope to explicitly consider firm-level factors to understand how they drive the benefits and challenges posed by the interdependence structures that firms are subjected to in an ecosystem.

BIBLIOGRAPHY

Abadie, A., & Imbens, G. W. 2006. Large sample properties of matching estimators for average treatment effects. *econometrica*, *74*(1), 235-267.

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., & Kapoor, R. 2016. Innovation ecosystems and the pace of substitution: Re-examining technology S-curves. *Strategic Management Journal*, *37*, 625-648

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

Aggarwal, V.A., Siggelkow, N.,& Singh, H. 2011. Governing collaborative activity: interdependence and the impact of coordination and exploration. *Strategic Management Journal* **32**(7): 705-730.

Aggarwal, V. A., & Hsu, D. H. 2013. Entrepreneurial exits and innovation. *Management Science*, *60*(4), 867-887.

Altman, J. E. Dependency Challenges, Response Strategies, and Complementor Maturity: Joining a Multi-Sided Platform Ecosystem, Working paper.

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.

Allison, P. D. 2010. *Survival analysis using SAS: a practical guide*. Sas Institute.Allison, P. D. (1996). Fixed-effects partial likelihood for repeated events. *Sociological Methods & Research*, *25*(2), 207-222.

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)

Anand, B.N.,& Khanna, T. 2000. Do firms learn to create value? The case of alliances. *Strategic Management Journal* **21**(3): 295-315.

Anderson, P, & Tushman, M.L. 2001. Organizational environments and industry exit: The effects of uncertainty, munificence and complexity. *Industrial and Corporate Change*, **10**(3): 675-711.

Angrist, J. D., & Pischke, J. S. 2008. *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

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

Armstrong, M. 2006. Competition in two-sided markets. *The RAND Journal of Economics*, *37*(3), 668-691.

Arora, A., & Ceccagnoli, M. 2006. Patent protection, complementary assets, and firms' incentives for technology licensing. *Management Science*, *52*(2), 293-308.

Argyres, N., Mayer,& K.J. 2007. Contract design as a firm capability: An integration of learning and transaction cost perspectives. *Academy of Management Review* **32**(4), 1060-1077.

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., & Woodard, C. J. 2008. The architecture of platforms: A unified view

Baldwin, C. Y., & Clark, K. B. 2000. *Design rules: The power of modularity* (Vol. 1). MIT press

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

Bascle, G. 2008. Controlling for endogeneity with instrumental variables in strategic management research. *Strategic organization*, *6*(3), 285-327.

Biossfeld, H. P., & Rohwer, G. 1995. Techniques of Event History Modeling. *New Approaches to Causal Analysis. Mahwah und*.

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

Boudreau, K. J. 2012. Let a thousand flowers bloom? An early look at large numbers of software app developers and patterns of innovation. *Organization Science*, *23*(5), 1409-1427.

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

Bourgeois, L. J., & Eisenhardt, K. M. 1987. Strategic decision processes in Silicon Valley: The anatomy of a" Living Dead". *California Management Review*, *30*(1), 143-159.

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.

Carroll, G. R., & Hannan, M. T. 2000. *The demography of corporations and industries*. Princeton University Press.

Carson, S.J., Madhok, A., & Wu, T. 2006. Uncertainty, opportunism, and governance: The effects of volatility and ambiguity on formal and relational contracting. *Academy of Management Journal* **49**(5): 1058-1077.

Cennamo, C., Yuan G. & Feng Z. 2016. Value co-creation and competition in the creative industry: The case of the US video game market. Working paper.

Ceccagnoli, M., Forman, C., Huang, P. & Wu, D.J. 2012. Cocreation of value in a platform ecosystem: the case of enterprise software. *MIS Quarterly, 36*(1): 263-290

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

Child, J. 2001. Learning through strategic alliances. *Handbook of organizational learning and knowledge.* Oxford University Press: Oxford, UK.

Christensen, C.M. *The innovator's dillemma*. Harvard Business School Press: Cambridge, MA.

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*, 269-276.

Csaszar, F.A., & Siggelkow, S. 2010. How much to copy? Determinants of effective imitation breadth." *Organization Science* **21**(3), 661-676.

Cusumano, M.A., Mylonadis, Y. and Rosenbloom, R.S. 1992. Strategic maneuvering and mass-market dynamics: The triumph of VHS over Beta. *Business History Review*, ***66***(01): 51-94

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

Davis, J. P., Eisenhardt, K. M., & Bingham, C. B. 2009. Optimal structure, market dynamism, and the strategy of simple rules. *Administrative Science Quarterly*, *54*(3), 413-452.

Davis, J. P., Yin, P. & Chhabra, Y. 2016. Experimentation Strategies and Entrepreneurial Innovation: Parallel and Sequential Innovation in the iPhone App Ecosystem. Working Paper

Dess, G.G. & Beard, D.W. 1984. Dimensions of organizational task environments. *Administrative Science Quarterly*, **29**(1): 52-73.

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

Doz, Y.L. 1996. The evolution of cooperation in strategic alliances: initial conditions or learning processes? *Strategic Management Journal* **17**(S1): 55-83.

Dyer, J.H., Kale, P.,& Singh, H. 2004. When to ally and when to acquire. *Harvard Business Review* **82**(7-8): 108-115.

Dyer, J. H., & Singh, H. 1998. The relational view: Cooperative strategy and sources of interorganizational competitive advantage. *Academy of management review*, *23*(4), 660-679.

Eisenmann, T., Parker, G., & Van Alstyne, M. W. 2006. Strategies for two-sided markets. *Harvard business review*, *84*(10), 92.

Ethiraj, S. K. 2007. Allocation of inventive effort in complex product systems. *Strategic Management Journal*, *28*(6), 563-584.

Evans, D. S. 2003. Some empirical aspects of multi-sided platform industries. *Review of Network Economics*, *2*(3).

Evans, D. S., Hagiu, A., & Schmalensee, R. 2008. *Invisible engines: how software platforms drive innovation and transform industries*. MIT press.

Feldman, E. R., Amit, R. R., & Villalonga, B. 2014. Corporate divestitures and family control. *Strategic Management Journal*.

Fleming, L., & Sorenson, O. 2001. Technology as a complex adaptive system: evidence from patent data. *Research policy,* **30(**7): 1019-1039.

Ganco, M.2013. Cutting the Gordian knot: The effect of knowledge complexity on employee mobility and entrepreneurship. *Strategic Management Journal,* **34 (**6): 666-686.

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

Gavetti, G.,& Levinthal, D. 2000. Looking forward and looking backward: Cognitive and experiential search. *Administrative Science Quarterly* **45**(1): 113-137.

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. 2014. Bridging differing perspectives on technological platforms: Toward an integrative framework. *Research Policy*, *43*(7), 1239-1249.

Gawer, A., & Cusumano, M. A. 2002. *Platform leadership: How Intel, Microsoft, and Cisco drive industry innovation* (pp. 29-30). Boston: Harvard Business School Press.

Gawer, A., & Henderson, R. 2007. Platform owner entry and innovation in complementary markets: Evidence from Intel. *Journal of Economics & Management Strategy*, *16*(1), 1-34.

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.

Gokpinar, B., Hopp, W.J., & Iravani, S.M. 2010. The impact of misalignment of organizational structure and product architecture on quality in complex product development. *Management Science* **56**(3): 468-484.

Grambsch, P. M., & Therneau, T. M. 1994. Proportional hazards tests and diagnostics based on weighted residuals. *Biometrika*, 515-526.

Grant, R.M., & Baden-Fuller C. 2004. A knowledge accessing theory of strategic alliances. *Journal of Management Studies* **41**(1): 61-84.

Gulati, R., & Lawrence, P.R., & Puranam, P. 2005. Adaptation in vertical relationships: beyond incentive conflict. *Strategic Management Journal* **26**(5): 415-440.

Gulati, R., & Singh, H. 1998. The architecture of cooperation: Managing coordination costs and appropriation concerns in strategic alliances. *Administrative Science Quarterly* **43**(4): 781-814.

Hamel, G., Doz, Y.L., & Prahalad, C.K. 1989. Collaborate with your competitors and win. *Harvard Business Review* **67**(1): 133-139.

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

Haspeslagh, P.C.,& Jemison, D.B. 1991. *Managing acquisitions: Creating value through corporate renewal*. Free Press: New York

Heath, C., & Staudenmayer, N. 2000. Coordination neglect: How lay theories of organizing complicate coordination in organizations. *Research in Organizational Behavior* **22:** 153-191.

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

Hennart, J.F., & Reddy, S. 1997. The choice between mergers/acquisitions and joint ventures: The case of Japanese investors in the United States. *Strategic Management Journal* **18**(1): 1-12.

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

Hughes, T. P. 1983. Networks of Power: Electric supply systems in the US, England and Germany, 1880-1930. *Baltimore: Johns Hopkins University*.

Iansiti, M., & Levien, R. 2004. Strategy as ecology. *Harvard business review*, *82*(3), 68-81.

Kale, P., Dyer, J.H., & Singh, H. 2002. Alliance capability, stock market response, and long-term alliance success: the role of the alliance function. *Strategic Management Journal* **23**(8): 747-767.

Kale, P., & Puranam, P. 2004. Choosing equity stakes in technology sourcing relationships: An integrative framework. *California Management Review* **46**(3): 77- 99.

Kale, P., & Singh, H. 2009. Managing strategic alliances: What do we know now, and where do we go from here. *Academy of Management Perspectives* **23**(3): 45-62.

Kapoor, R. 2013. Collaborating with Complementors: What Do Firms Do. *Advances in strategic management*, 30, 3-25.

Kapoor, R. & Agarwal, S.2017. **S**ustaining Superior Performance in Business Ecosystems:Evidence from Application Software Developers in the iOS and Android Smartphone Ecosystems. *Organization Science*.

Kapoor, R., & Furr, N. R. 2015. Complementarities and competition: Unpacking the drivers of entrants' technology choices in the solar photovoltaic industry. *Strategic Management Journal*, *36*(3), 416-436.

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.

Karim, S. 2012. Exploring structural embeddedness of product market activities and resources within business units. *Strategic Organization*, *10*(4), 333-365.

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.

Katz, M. L., & Shapiro, C. (1986). Technology adoption in the presence of network externalities. *Journal of political economy*, *94*(4), 822-841.

Kauffman, S. 1993. *The origins of order: Self-organization and selection in evolution.* Oxford University Press: New York.

Kelly, E. (2015). Introduction: business ecosystems come of age. *Business Ecosystems Come of Age*, Deloitte University Press, pp. 3-15.

Kim, S.,Zhao, J.,& Anand, J. 2015. Knowledge Complexity and the Performance of Inter-unit Knowledge Transfer Structures. Working paper.

Kogut, B., & Singh, H. 1988. The effect of national culture on the choice of entry mode. *Journal of International Business Studies* **19**(3): 411-432.

Kretschmer, T., & Puranam, P. 2008. Integration through incentives within differentiated organizations. *Organization Science* **19**(6), 860-875.

Lavie, D.,& Rosenkopf, L. 2006. Balancing exploration and exploitation in alliance formation. *Academy of Management Journal* **49**(4): 797-818.

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. 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.

Litwalk, E.,& Hylton, L.F. 1962. Interorganizational analysis: A hypothesis on coordinating agencies. *Administrative Science Quarterly* **6**: 395-420.

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

Lunnan, R., & Haugland, S.A. 2008. Predicting and measuring alliance performance: a multidimensional analysis. *Strategic Management Journal* **29**(5): 545–556

Manski, C. F., & Lerman, S. R. (1977). The estimation of choice probabilities from choice based samples. *Econometrica: Journal of the Econometric Society*, 1977-1988.

Martignoni, D., Menon, A.,& Siggelkow, N. 2015. Consequences of misspecified mental models: Contrasting effects and the role of cognitive fit. *Strategic Management Journal*, forthcoming.

Mayer, K.J.,& Argyres, N.S. 2004. Learning to contract: Evidence from the personal computer industry. *Organization Science* **15**(4), 394-410.

Mayer, K.J., & Teece, D.J. 2008. Unpacking strategic alliances: The structure and purpose of alliance versus supplier relationships. *Journal of Economic Behavior and Organization* **66**(1): 106-127.

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.

Reuer, J.J.,& Arino, A. 2007. Strategic alliance contracts: Dimensions and determinants of contractual complexity. *Strategic Management Journal* **28**(3), 313.

Reuer, J.J., & Devarakonda, S. 2015. Mechanisms of hybrid governance: Administrative committees in non-equity alliances. *Academy of Management Journal*, forthcoming.

Ring, P.S.,& Van de Ven, A.H. 1994. Developmental processes of cooperative interorganizational relationships. *Academy of management review* **19**(1), 90-118.

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.

Rivkin, J.,& Siggelkow, N. 2003. Balancing search and stability: Interdependencies among elements of organizational design. *Management Science* **49**(3): 290-311.

Rivkin, J., & Siggelkow, N. 2007. Patterned interactions in complex systems: Implications for exploration. *Management Science* ***53***(7), 1068-1085.

Rochet, J. C., & Tirole, J. 2003. Platform competition in two-sided markets. *Journal of the european economic association*, *1*(4), 990-1029.

Rochet, J. C., & Tirole, J. 2006. Two-sided markets: a progress report. *The RAND journal of economics*, *37*(3), 645-667.

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

Rothaermel, F. T. 2001. Incumbent's advantage through exploiting complementary assets via interfirm cooperation. *Strategic Management Journal*, *22*(6-7), 687-699.

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

Sampson, R. 2004. The cost of misaligned governance in R&D alliances. *Journal of Law, Economics, and Organization* **20** (2): 484-526.

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*(2), 387-398.

SensorTower. 2016. https://sensortower.com/blog/app-store-one-percent?platform=hootsuite. (last accessed on July 30, 2016)

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

Singh, J. 2005. Collaborative networks as determinants of knowledge diffusion patterns. *Management science*, *51*(5), 756-770.

Singh, K. 1997. The impact of technological complexity and interfirm cooperation on business survival. *Academy of Management Journal,* **40**(2): 339-367.

Sosa, M.E., Eppinger, S.D.,& Rowles, C.M. 2004. The misalignment of product architecture and organization structure in complex product development. *Management Science* **50** (12): 1674-1689.

Sosa, M.E., Eppinger, S.D.,& Rowles, C.M. 2007. Are your engineers talking to one another when they should? *Harvard Business Review* **85** (11): 133-142.

Stock, J. H., & Yogo, M. 2002. Testing for weak instruments in linear IV regression. Working Paper. Department of Economics, Harvard University, Cambridge, MA.

Teece, D. J. 2006. Reflections on “profiting from innovation”. *Research Policy*, *35*(8), 1131-1146.

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

Teece, D. J. 1986. Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research policy*, *15*(6), 285-305.

Tushman, M. L., & Anderson, A. 1986. Technological discontinuities and organizational environments. *Administrative Science Quarterly,* **31**(3): 439-465.

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.

Villalonga, B.,& McGahan, A.M. 2005. The choice among acquisitions, alliances, and divestitures. *Strategic Management Journal* **26**(13): 1183-1208.

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.

Zellner, A.1962. An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias. *Journal of the American Statistical Association.* **57**: 348-368.

Zellner, A. 1963. Estimator for Seemingly Unrelated Regressions: Some Exact Finite Sample Results. *Journal of the Americal Statistical Association* **58**: 977-992.

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

Zhu, F., & Qihong L. 2016. Competing with Complementors: An Empirical Look at Amazon.com. Harvard Business School Technology & Operations Mgt. Unit Working Paper.

Zollo, M., Reuer, J.J.,& Singh, H. 2002. Interorganizational routines and performance in strategic alliances. *Organization Science* **13**(6): 701-713.

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