1-1-2019

Essays on Business Value Creation in Digital Platform Ecosystems

He Li

ESSAYS ON BUSINESS VALUE CREATION IN DIGITAL PLATFORM ECOSYSTEMS

by

He Li

A Dissertation

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Doctor of Philosophy

Major: Business Administration

The University of Memphis

August 2019

ACKNOWLEDGEMENTS

First and foremost, I am deeply grateful to my dissertation co-chairs, Dr. William J. Kettinger and Dr. Chen Zhang, for their guidance, support, patience, and encouragement. I cannot envision going through this process without their mentorship, help, and expertise. Working with them on several projects has made this exciting journey more enjoyable. They provided me tremendous suggestions in improving my research, teaching, service, and life quality. I look forward to continuing our academic relationship and friendship in the future.

I am also grateful to my dissertation committee members, Dr. David Kemme and Dr. Ali Adeli, for their insightful comments and suggestions, especially the methodological aspects of my dissertation. The methodology part of the third essay is greatly benefited from Dr. David Kemme's Econometrics III class and his constructive feedback on earlier versions.

I also thank for all other BIT faculty members, who have provided me with valuable feedback about my dissertation. I appreciate the help from BIT department secretary Christy Smith for her administrative support and copy editing of my two research papers. My colleagues, fellow Ph.D. students, and friends are also well deserved to be acknowledged, with whom I have shared many happy moments. A special thank goes to Sungjin Yoo, who has been an incredible friend and colleague throughout the process.

Last but not least, I must express my deepest gratitude for the unlimited support and unconditional love of my parents and grandparents. My father Zhonghai Li and my mother Lihua Cui have sacrificed so much to support my pursuit of a doctoral degree, and without whom I would not have been able to achieve my dream. They have been by my side through all exciting and exhausting moments. I hope our family will be fulfilled with happiness and love forever.

ABSTRACT

Li, He. Ph.D. The University of Memphis. August 2019. Essays on Business Value Creation in Digital Platform Ecosystems. Co-Major Professors: William J. Kettinger, Ph.D. and Chen Zhang, Ph.D.

Digital platforms and the surrounding ecosystems have garnered great interest from researchers and practitioners. Notwithstanding this attention, it remains unclear how and when digital platforms create business value for platform owners and complementors. This three-essay dissertation focuses on understanding business value creation in digital platform ecosystems.

The first essay reviews and synthesizes literature across disciplines and offers an integrative framework of digital platform business value. Advised by the findings from the review, the second and third essays focus on the value creation for platform complementors.

The second essay examines how IT startups entering a platform ecosystem at different times can strategically design their products (i.e., product diversification across platform architectural layers and product differentiation) to gain competitive advantages. Longitudinal evidence from the Hadoop ecosystem demonstrates that product diversification has an inverted U-shaped relationship with complementors' success, and such an effect is more salient for earlier entrants than later entrants. Earlier entrants should develop products that are similar to other ecosystem competitors to reduce uncertainty whereas later entrants are advised to explore market niche and differentiate their products.

The third essay investigates how platform complementors' strategies and products co-evolve over time in the co-created ecosystem network environment. Our longitudinal analysis of the Hadoop ecosystem indicates that complementors' technological architecture coverage and alliance exploration strategies increase their product evolution rate. In turn, complementors with faster product evolution are more likely to explore new partners but less likely to cover a wider

range of the focal platform's technological layers in subsequent periods. Network density, co-created by all platform complementors, weakens the effects of complementors' strategies on their product evolution but amplifies the effects of past product evolutions on strategies.

This three-essay dissertation uncovers various understudied competitive strategies in the digital platform context and enriches our understanding of business value creation in digital platform ecosystems.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

INTRODUCTION

Information systems (IS) scholars are increasingly interested in understanding the performance implications of digital platforms. IS strategy literature has recognized that organizations can use digital platforms to achieve competitive advantage by enabling IT agility, reconfiguring IS resources, and enhancing dynamic capabilities (e.g., El Sawy, Malhotra, Park, & Pavlou, 2010; Sambamurthy, Bharadwaj, & Grover, 2003). Organizations can initiate digital platforms to undertake digital transformation, foster digital innovation, and facilitate scale and scope economics by involving third-party contributions (Tiwana, Konsynski, & Bush, 2010). However, companies may also find that control issues arise due to the diversity of third-party contributors, expansion of organizational boundaries across levels of the ecosystem, and the increased complexity of managing agency relationships (Wareham, Fox, & Giner, 2014). The socio-technical nature of digital platforms can make it challenging to manage the ecosystem and create business value (Eaton, Elaluf-Calderwood, Sørensen, & Yoo, 2015).

Digital platform ecosystems provide entrepreneurial opportunities whereby entrepreneurs can reduce investment in hard-to-duplicate resources, gain access to a larger install base of potential consumers, and enhance social legitimacy by participating in a major digital platform ecosystem (Ceccagnoli, Forman, Huang, & Wu, 2012). However, joining in a digital platform ecosystem often requires the exposure of “ideas” and intellectual property, which will increase the risk of being imitated by platform owners or other competitors (Gans & Stern, 2003).

Therefore, digital platforms expose paradoxes at multiple levels challenging platform owners and complementors. We are prompted to address a crucial research question: *How do digital platforms create business value for platform owners and complementors*? This dissertation contains three essays answering this broad research question.

Essay 1 focuses on one type of digital platforms—i.e., software platforms—and provides a systematic review of this literature. Synthesizing the literature, we develop three themes of software platform business value research, summarize three key characteristics of software platforms (i.e., multi-sided market, openness, and digital artifact), and identify major theoretical perspectives adopted in the literature. Building upon the literature summary, we conceptualize platform capabilities and complementary capabilities for platform owners and complementors. Specifically, the construct of platform capabilities is reflected by three dimensions: intermediarity, evolvability, and stability. The dimensions of complementary capabilities include creativity, interconnectivity, and appropriability. Based on our informed opinions, we develop an integrative framework of software platform business value. We offer theoretical propositions that explain (1) how software platforms affect platform owners' and complementors' performance by enhancing their capabilities; and (2) the co-evolution among platform owners, complementors, and the ecosystem environment. We conclude with the suggested guidelines for future research.

Advised by the findings from the systematic review, the second and third essays focus on the value creation for platform complementors. As a starting point, Essay 2 examines how IT startups entering a platform ecosystem at different times can strategically design their products (i.e., product diversification across platform architectural layers and product differentiation) to gain competitive advantages. Our longitudinal analysis of the Hadoop ecosystem validates the theorized inverted U-shaped relationship between complementors' product diversification and entrepreneurial success, and demonstrates that such effect is stronger for earlier entrants than later entrants. Product differentiation increases later entrants' success but reduces the success of earlier entrants. These findings have implications for understanding competitive dynamics, product design, and entry timing. Platform complementors are advised to strategize product design at different times of entry.

Essay 3 goes beyond complementors' strategies at the entry point and investigates the evolutionary intra-platform competition among complementors. We investigate their dynamics over time by examining the mutual influence between complementors' strategies and product evolution as well as the moderating role of the network environment. Our longitudinal analysis of the Hadoop software ecosystem indicates that complementors' technological architecture coverage and alliance exploration strategies positively affect their product evolution rate. In turn, product evolution rates influence subsequent strategies. Specifically, complementors with faster product evolution are more likely to explore new partners but less likely to cover a wider range of the focal platform's technological layers in subsequent periods. Network density, co-created by all platform complementors, weakens the effects of complementors' strategies on their product evolution but amplifies the effects of past product evolutions on strategies. Our research theoretically contributes to the understanding of intra-platform competition over time by delineating the coevolution of complementors' strategies, product evolution, and co-created network environments. Our results recognize the circulative nature of digital platform co-evolution and practically suggest implications for improved complementor survival in a dynamic software platform ecosystem.

Overall, this three-essay dissertation is expected to enrich our understanding of business value creation in digital platform ecosystems. Our software platform business value framework (in Essay 1) provides a theoretical foundation for future research. The second and third essay complements prior digital platform research by investigating complementors' various competitive strategies such as product diversification, product differentiation, entry timing, technological architectural coverage, and alliance strategy from a strategic management perspective. Our results also offer practical insights on how digital platform ecosystems create business value and how complementors should develop and adapt their various strategies to achieve and sustain superior performance.

ESSAY 1. BUSINESS VALUE OF SOFTWARE PLATFORMS: A REVIEW AND INTEGRATIVE FRAMEWORK

INTRODUCTION

A software platform is defined as "the extensible codebase of a software-based system that provides core functionality shared by modules that interoperate with it and the interfaces through which they interoperate" (Tiwana et al., 2010, *p*. 675). Organizations that provide the extensible codebase are recognized as platform owners, and therefore often make the decisions concerning standards and governance rules. The add-on software subsystems interconnecting to the platform are known as modules or third-party applications (abbreviated as *apps* hereafter), and their providers are platform complementors. The collection of the focal platform, add-on apps, platform owners, and complementors forms the software platform ecosystem (Eaton et al., 2015). Table 1 summarizes different types of software platforms that are commonly examined in the prior literature.

By initiating a platform business model, software providers can foster open innovation and facilitate scale and scope economics by involving third-party contributions (Tiwana et al., 2010). However, companies may also find that control issues arise due to the diversity of third-party developers, expansion of organizational boundaries across levels of the ecosystem, and the increased complexity of managing agency relationships (Wareham et al., 2014). The socio-technical nature of software platforms can make it challenging to manage the ecosystem and create business value (Eaton et al., 2015; Gawer, 2014). In addition, software platforms provide entrepreneurial opportunities whereby complementors can reduce investment in hard-to-duplicate resources, gain access to a larger installed base of potential consumers, and enhance social legitimacy by participating in a major software platform (Ceccagnoli et al., 2012).

However, joining in a software platform often requires the exposure of ideas and intellectual property, which will increase the risk of being imitated by platform owners or other competitors (Gans & Stern, 2003). Therefore, software platforms expose paradoxes at multiple levels challenging platform owners and complementors. We are prompted to address a crucial research question: *How do software platforms create business value for software platform owners and complementors*?

Table 1

Examples of Software Platforms

Category	Example	Platform Owner	Platform Complementors
Mobile Platforms	iOS; Android; Blackberry	Providers of the mobile platform	Mobile app developers
Video Game	Nintendo Wii; PS3; Xbox 360	Game consoles or provider of the platform	Game developers or the providers of titles
Handheld Computer Devices	Palm; Psion; Newton; Microsoft Mobile; PenRight; Magic Cap	Providers of operating systems and hardware of handheld computers that open for complementary components	Independent hardware developers that provide complementary innovations related to board-level electronics designs, industrial design, and enhanced integration
Enterprise Software	SAP	Providers of the enterprise software such as SAP	Independent software vendors who make their products compatible with or extend the platform functions
Operating Systems	Microsoft; Linux	Providers of the operation systems	Add-on application providers
Browser	Firefox; Chrome; Internet Explorer	Providers of the browser	Developers of the add-on extensions

Advised by prior IT business value research (e.g., Devaraj & Kohli, 2003; Kohli & Grover, 2008; Melville, Kraemer, & Gurbaxani, 2004), we focus on the performance implications of software platforms. Accordingly, we define *software platform business value* as the platform owners' and complementors' performance impacts and as comprising the operational and financial impacts, innovation impacts, and environmental fitness impacts. Although emerging research is beginning to investigate pieces of the software platform business value puzzle, knowledge remains unsystematic and underdeveloped.

This review aims to supplement the cumulative knowledge in the IS discipline by synthesizing what we know about software platform business value and suggesting what could be done to enrich the knowledge accumulation and creation process. Specifically, this review has three main objectives: (1) to conceptualize platform capabilities and complementary capabilities; (2) to theorize an integrative framework of software platform business value and develop related propositions, and (3) to categorize existing research and suggest a future research agenda. We hope that our literature synthesis, theory building, and suggested future research agenda facilitates the cumulative tradition in IS research.

LITERATURE REVIEW AND RESEARCH METHODOLOGY

The intention of this review is to focus on a stream of research and develop a new theory around the phenomenon of value in software platforms. Thus, this is a *broad theorizing review* in Leidner's (2018) categorization of *Theory and Review* research. The deliverable of this review is a *"phenomenon" theory*, which is a broad theory of an emergent area (i.e., business value of software platforms) within an established area (i.e., platforms or specifically software platforms). Review and synthesis of existing literature directly informs our new theory development. Hence, we specify the role of theory in our review as: synthesized existing theoretical perspectives from an existing body of software platforms research, and which are used as foundations for the development of our new theory of software platform business value. We start our review by collecting, coding, and synthesizing literature about software platforms.

Since the focus of our review is business value creation, we limit our initial sample of empirical research examining the platform owners' and complementors' performance and strategies as well as complementors' participation and continued participation decisions. Given the vast amount of literature and our research focus, we only choose empirical articles that are grounded in the context of software platforms. In addition, to broaden our understanding of the phenomenon, we have identified key conceptual frameworks, research commentary, editorial comments, issues and opinions, and review and theory manuscripts related to all types of platforms and/or platform ecosystems.

The literature on software platforms is interdisciplinary. Following the methodology suggested by Webster & Watson (2002), we perform a literature search spanning IS, industrial organization (IO) economics, strategic management, operations management, and marketing. Several approaches were used to search and select appropriate studies. First, we conducted a search in selected top tier journals[1] using the keywords such as "platform", "platform ecosystem", and "software ecosystem". We then looked through the references of key articles to identify any overlooked articles. We also performed a search using the same keywords in the first step on multiple databases, such as Google Scholar, INFORMS, Science Direct (Elsevier), Taylor & Francis Online, SpringerLink, and Business Source Premier, to collect other related articles published on other journals. In total, we have selected 79 articles from 29 different journals (see Appendix 1 for the detailed distribution).

[1] Samples of journals included are Basket of Eight IS journals, *Academy of Management Journal*, *Academy of Management Review*, *Strategic Management Journal*, *Administrative Science Quarterly*, *Management Science*, *Organization Science*, *Journal of Marketing Research*, *Journal of Marketing*, *American Economic Review*, and *International Journal of Industrial Organization*.

We follow the prior seminal work of theory and review research (e.g., Leidner & Kayworth, 2006; Webster & Watson, 2002) to analyze the collected articles. For each empirical paper in our set, we initially created a summary of its method, platform context, levels of analysis, dependent variable, independent variables, theory or theoretical perspectives, and key findings (shown in Appendix 2). Conceptual articles were reviewed to summarize the following information: research focus, method, level of analysis, theoretical perspectives, and deliverables (see Appendix 3). These two appendices serve as the basis for our subsequent analysis to categorize literature, perceive gaps, conceptualize key constructs, and derivation of the integrative framework.

Thematic Summary of Current Literature

The thematic analysis approach categorizes content systematically and identifies the interrelations among different themes (Lane, Koka, & Pathak, 2006; Leidner & Kayworth, 2006; Roberts, Galluch, Dinger, & Grover, 2012). We follow the procedure of literature categorization widely used in prior literature (e.g., Roberts et al., 2012). Based on the article summaries (i.e., Appendix 2 and 3) and considering our review focus of business value creation, the authors grouped the papers into different themes. The categorization was presented to a seminal workshop with participants who have a research background and practical experience with software platforms. Adjustments were made using feedback from the seminal discussions and following further discussions between the authors. The process resulted in three major themes of software platforms research. We discuss each theme below.

Theme 1: Inter-Platform Competition and Platform Strategies. A stream of software platforms literature explores inter-platform competition and platform strategies. Recognizing the importance of two-sided network effects (Parker & van Alstyne, 2005), these studies investigate the many ways in which platform owners can maximize their performance. Well examined platform strategies include, but are not limited to: revenue model, pricing, tying, information asymmetry, envelopment, differentiation, and platform quality investments. Furthermore, going beyond the aforementioned aspects, some studies focused on understanding the structure of two-sided network effects. Extant analytical and empirical research examined the scope of indirect network effects (Corts & Lederman, 2009), the performance implications of indirect network effects (Clements & Ohashi, 2005; Zhu & Iansiti, 2012), and the asymmetry between two-sided network effects (Song, Xue, Rai, & Zhang, 2017) in a software platform ecosystem. Often, these studies adopted the IO economics perspective and demonstrated winner-take-all (WTA) strategies.

Inter-platform competition studies from the strategic management perspective found that WTA may not always work (Cennamo & Santalo, 2013) and platform firms are likely to be trapped in a prisoner's dilemma when pursuing purely aggressive network effect strategies (Mantovani & Ruiz-Aliseda, 2016). Literature from the strategic perspective demonstrated that platform owners need to assess strategically the competitive environment they live in and undertake corresponding platform strategies (Cennamo & Santalo, 2013). Literature also suggest diverse ways for platform owners to attract complementors including monetary, reputational, and signaling motivations (Boudreau & Jeppesen, 2015).

Theme 2: Intra-Platform Competition and Entrepreneurship. A second stream of research explores the competition among complementors within a platform ecosystem. Given that most complementors are small startups, this stream of literature studied entrepreneurship-related topics. Prior intra-platform competition literature examines potential complementors' participation and continuance in a software platform ecosystem (Huang, Ceccagnoli, Forman, &

Wu, 2013; Kim, Kim, & Lee, 2016; Song, Baker, Wang, Choi, & Bhattacherjee, 2018; Ye & Kankanhalli, 2018) and the benefits of participating in the ecosystem (Ceccagnoli et al., 2012). On average, joining in a major platform ecosystem is associated with increased sales and the likelihood of initial public offering (Ceccagnoli et al., 2012). Taking into consideration the paradox of disclosure, complementors' appropriability mechanisms (such as IPRs and downstream assets) will increase their motivation for (Huang et al., 2013) and benefits from (Ceccagnoli et al., 2012) joining an ecosystem.

Further research in this stream has acknowledged and leveraged the fact that platform ecosystems are hyper-turbulent. Accordingly, prior studies have suggested several competitive strategies for complementors, including the architectural design of complementary products (Tiwana, 2015a, 2015b), product portfolio management (Lee & Raghu, 2014), exploiting ecosystem experience (Kapoor & Agarwal, 2017), multihoming (Cennamo, Ozalp, & Kretschmer, 2018), inter-organizational networking (Venkatraman & Lee, 2004), search and redemption of new capabilities (Selander, Henfridsson, & Svahn, 2013), in-app pricing and advertising strategies (Ghose & Han, 2014), and employing the two-way logic of profession and market synthesis (Qiu, Gopal, & Hann, 2017), etc. In addition, extant literature has examined several ways platform owners' strategies can influence an ecosystem environment and complementors' innovation and performance including: improving platform governance structure (Tiwana, 2015a, 2015b), offering innovation incentives, adding producers (Boudreau, 2012), reducing ecosystem complexity, and encouraging platform generation transitions (Kapoor & Agarwal, 2017).

Theme 3: Platform Ecosystem Governance and Evolution. Literature in this area concentrates on the tension between evolvability and stability by examining the impacts of platform governance on the ecosystem's evolution. Prior studies proposed ecosystem-wide governance rules (Nielsen & Aanestad, 2006; Wareham et al., 2014) and dyadic governance tension (Huber, Kude, & Dibbern, 2017) to sustain value creation in software platform ecosystems. The premise is that adequate control should be retained to ensure the quality of complementary products while simultaneously keeping the focal platform open enough to foster unfettered innovation. Contrary to practicing governance rules in platform ecosystems, some studies conceptualized boundary resources as the collection of software components along with a set of governance rules. These studies investigated the importance of boundary resources in managing evolvability-stability tension as well as the evolution of boundary resources in a software platform ecosystem (Eaton et al., 2015; Ghazawneh & Henfridsson, 2013).

Among the multiple dimensions of platform governance, researchers in this stream are especially interested in the role of platform openness. They believed that through platform openness design, the "opened" parts of a software platform can encourage complementors' innovation activities, while the less "opened" components can sustain the quality of the contribution. Researchers have investigated different approaches of opening a software platform from the platform owners' perspectives, including granting access and giving up control of core technological resources to third-party complementors (Boudreau, 2010). Research examines the influences of platform openness on platform owners' market potential (Ondrus, Gannamaneni, & Lyytinen, 2015) and innovation outcomes (Parker, Van Alstyne, & Jiang, 2017). From the complementors' perspectives, extant studies conceptualized complementors' perceived openness (Benlian, Hilkert, & Hess, 2015) and examined the impacts of openness on complementors' innovation and performance (Parker & Van Alstyne, 2017).

Summary of the Research to Date. Based upon our literature summary, we outline the key findings of prior studies in each theme as shown in Table 2. The large number and variety of studies dealing with aspects of platform owners' and complementors' performance demonstrates the strong interest in understanding how software platforms create business value for platform owners and complementors. The studies reviewed provide a rich foundation of different value creation mechanisms for platform owners and complementors.

Table 2

Summaries of Key Findings in Prior Software Platform Research

Theme 1: Inter-Platform Competition and Platform Strategies
• Platform owners can maximize their profits by adjusting their strategies concerning revenue models, business models, pricing, tying, information asymmetry, multi-sidedness, horizontal and vertical (i.e., quality) differentiation, envelopment, backward compatibility, platform-level integration or cooperation, search diversion, first-party content, promotions, customer orientation, usage limit, restricting choice, advertising, commitment, and heterogeneous contracts with complementors. • Platform owners can utilize diverse strategies to reshape and monetize the two-sided network effects and switching costs. However, platform owners also need to strategically assess the competitive environment they live in and undertake corresponding differentiated platform strategies. • Platform owners can employ diverse strategies to attract complementors, including monetary, reputational, and signaling motivations. • With the increase intensity of platform competition, platform owners should strategically develop IS capabilities (such as IS infrastructure, resources, and skills).
Theme 2: Intra-Platform Competition and Entrepreneurship
• Software platforms provide entrepreneurial opportunities. It is beneficial (i.e., the increase of sales and likelihood of IPO) for complementors to join in a major software platform ecosystem. • In the hyper-competitive platform ecosystems, complementors should make strategic decisions (such as product architectural design, appropriation strategies, product portfolio management, and two-way logics of profession and market synthesis) to better survive in evolutionary competition. • The platform or ecosystem structure and rules affect the performance of complementors in software platform ecosystems.

Table 2 (Continued).

Theme 3: Platform Governance and Ecosystem Evolution
• Although software platforms have great potentials to co-create value through ecosystems, platform owners should seriously consider the governance costs. • Platform owners should design appropriate governance rules (such as input control, coordination, decision right allocation, granting access, and platform openness) to better balance the evolvability-stability tension in software platform ecosystems. • Software platform ecosystems, in essence, are socio-technical ecosystems. The evolution of software platforms components (especially the boundary resources) is enabled by the cascading actions of rejections and accommodations of inter-connected heterogeneous actors and artifacts.

Limitations and Areas for Extension

Despite the insightful findings in the current literature, there are limitations and areas for extension in software platform research. We outline these key points as follows:

Lack of Generic Theories. A preponderance of past software platform studies employ theoretical lenses from other disciplines such as IO economics, strategic management, and sociology. This approach has value given the lack of generic theories specific to the context of software platforms. Although analyzing the phenomenon of software platforms based on existing theoretical frameworks adds practical guidelines, the lack of generic theories in a software platforms context weakens its rigor as a mature IS research stream.

Level of Analysis. Software platform scholars can investigate business value of software platforms at multiple levels of analysis: platform owners, complementors, boundary resources, and the ecosystem. To date, extant studies tend to focus on a single level. The co-evolutionary dynamics among different levels of players and stakeholders are not well theorized and empirically investigated.

Variance vs. Process Models. Software platform research has developed several types of research models including analytical, variance, and process models. Since different kinds of models provide unique insights for the understanding of software platforms, all of them are valuable (Sabherwal & Robey, 1995). Insights derived from individual research models often complement each other. However, the use of different research models is not evenly distributed; a strong preference is given to analytical and variance models in current software platforms research. There is a clear lack of process-based theories to explain the software platforms phenomena. In addition, most prior research adopts a single research methodology, possibly limiting the comprehensiveness and uniqueness of insights generated by the study.

Alignment with Organizational Business Strategy. Current software platform research treats software platforms or their ecosystems as a unique context of the study. Business processes of platform owners and complementors are often inadequately considered in existing software platform research; however, software platforms are often part of an organization's software business strategy for fostering open innovation or building competitive advantages. For complementors, participating in a software platform ecosystem requires them to adjust their business processes to match the governance model of the focal software platform. Furthermore, most software platforms studies do not account for the business processes embedded in the operation of platforms.

Given these key findings and current research limitations, we try to address some of these research gaps. We believe that the software platform business value research stream is mature enough to synthesize the various value creation mechanisms from both platform owners' and complementors perspectives. Our integrated software platform business value framework is a multi-level model grounded in the platform-specific context, taking the perspective of organizational strategies and synthesizing previous analytical, process, and variance models to date. Consistent with most IS strategy and IT business value studies (e.g., Kohli & Grover, 2008; Mithas, Ramasubbu, & Sambamurthy, 2011; Nan & Tanriverdi, 2017; Sambamurthy et al., 2003), our theoretical framework intends to formalize the nomological network from software platforms to organizational capabilities (i.e., platform capabilities and complementary capabilities) and performance. We posit platform and complementary capabilities based on a synthesis of the specific characteristics of software platforms and key theoretical perspectives.

Key Characteristics of Software Platforms

Multi-Sidedness. Software platforms, by encouraging third-party complementors' participation in their software ecosystems, form the multi-sided market where the focal software platform serves as a mediator between application providers and end users (Gawer, 2014; Hagiu & Wright, 2015). In software platform ecosystems, users can interact directly with third-party application providers through focal software platforms. For instance, the iOS and Android platforms provide a marketplace where users can access mobile applications developed by third-party developers.

The multi-sidedness of software platforms delivers two fundamental features that require new strategies in software platform ecosystems (Hagiu & Wright, 2015). First, a multi-sided market enables direct interactions among multiple sides of the software platform. Second, each side of the platform is affiliated with the focal platform. Thus, the multi-sidedness of software platforms not only expands organizational boundaries, but also triggers the emergence of two-sided network effects. Hence, the benefit to complementors (i.e., complementors and end users) depends on the number of complementors on the same side (i.e., direct network effects) as well as the other side (i.e., indirect network effects) (Parker & van Alstyne, 2005; Zhu & Iansiti, 2012).

Openness. One goal of software platforms is to foster innovation and achieve scale economics through openness. Researchers in technology development and commercialization widely acknowledge that an innovator may “open” its technology by involving third-party complementors in its business processes (Shapiro & Varian, 1998). Openness is broadly defined as the extent to which the use, development, and commercialization of a technology is unrestricted (Boudreau, 2010). In a software platform ecosystem, platform owners provide a set of software components that serve as standard interfaces as well as governance rules. Third-party complementors can develop add-on applications by interacting and extending the software components through standard interfaces (such as Application Programming Interfaces [API] and Software Development Kits [SDK]) while simultaneously conforming to governance rules predefined by the platform owner (Tiwana et al., 2010). Platform owners often have multiple software components, and they can strategically decide how many software components can be opened on their software platform (Boudreau, 2010). In addition, focal software platforms can give up some control over the software components. Software platforms differ in how much openness is embedded in their technical and non-technical designs. For instance, in the mobile app market, iOS is the proprietary platform with Apple owning the platform. On the contrary, Android, the competing software platform in that industry, chooses an open business model whereby app developers enjoy a free-of-charge licensing policy (Lee, Lee, & Hwang, 2015). Both granting access and giving control over boundary resources demonstrate the open characteristics of software platforms (Benlian et al., 2015; Boudreau, 2010).

Digital Artifacts. The main difference between a software platform and a traditional multi-sided market is the existence of digital artifacts. Digital artifacts cause software platforms to play an important role in organizational agility achievement, digital business strategy, and digital transformation (Bharadwaj, El Sawy, Pavlou, & Venkatraman, 2013; Sambamurthy et al., 2003). The digital artifacts embedded in software platforms are increasingly editable, interactive, reprogrammable, and distributable (Kallinikos, Aaltonen, & Marton, 2013). Software platforms allow software components with layered modular architecture where software (and/or physical) resources are broken down into loosely coupled components interconnected through pre-defined standard interfaces and assembled from a set of heterogeneous hierarchical layers (Yoo, Henfridsson, & Lyytinen, 2010). For instance, in software platforms such as iOS, Firefox, SAP, and Hadoop, platform owners provide a set of software components through standard interfaces (i.e., APIs and SDKs) that can be extended by third-party applications (Tiwana et al., 2010). In an Internet of Things (IoT) platform, sensors often are embedded in physical things such as watches (Agarwal & Tiwana, 2015). Networks serve as the intermediary layer connecting the applications and the sensors on the physical products. Through the layered architecture, physical products have the attributes of digital artifacts, triggering digital innovation in the layered modular architecture (Yoo et al., 2010). Digital artifacts differ in scale and scope from earlier software technologies that were primarily confined within the boundaries of a single organization (Eaton et al., 2015; Ghazawneh & Henfridsson, 2013; Lyytinen & King, 2002). Therefore, managing software platform ecosystems, wherein digital artifacts exist, is fundamentally different than creating value through previously used software technologies (Woodard, Ramasubbu, Tschang, & Sambamurthy, 2013).

Theoretical Perspectives Used in Software Platform Business Value Research

Previous platform related Theory and Review papers (e.g., Gawer, 2014; Lusch & Nambisan, 2015; McIntyre & Srinivasan, 2017; Thomas, Autio, & Gann, 2015; Tiwana et al., 2010) as well as empirical studies have synthesized and adopted three main categories of theoretical perspectives. We briefly describe each perspective and use them as the foundation of our conceptualizations of platform and complementary capabilities and of theory building.

Competition Perspective. Software platform scholars have used the theoretical lens of IO economics and strategic management to investigate how organizations strategically improve their performance in a competitive environment. This stream of studies often positions software platforms and their ecosystems within industrial competition. IO economics and strategic management theories share the same competition perspective.

IO economics researchers focus on *two-sided network effects* and believe that complementors' interactions are impacted by network effects and facilitated by intermediaries (Parker & van Alstyne, 2005). Software platform ecosystems can be regarded as an interconnected system of players, among them platform complementors, end users, and platform owners. Platform complementors' behaviors and associated outcomes are influenced by network effects (Eisenmann, Parker, & Van Alstyne, 2011; Hagiu & Wright, 2015). Two-sided network effects arise when the level of benefit for complementors varies according to the number of complementors on the same side—i.e., direct network effects—as well as the other side—i.e., indirect network effects (Parker & van Alstyne, 2005; Zhu & Iansiti, 2012). A software platform's installed base (number of active users) determines the choices of complementors and end users. The mutual influences of the multiple sides of a software platform suggest the possibility of WTA outcomes (Eisenmann, Parker, & Van Alstyne, 2006; Katz & Shapiro, 1994), especially when the demand for product differentiation is low and multi-homing costs are high for platform complementors (Hagiu, 2009). Due to elevated two-sided effects and WTA outcomes, platform owners should implement strategies for aggressively attracting platform complementors, such as new pricing strategies, subsidies, and marketing (Boudreau & Jeppesen, 2015).

However, WTA-oriented strategies derived from the IO economics perspective are sometimes flawed (Boudreau & Jeppesen, 2015; Cennamo & Santalo, 2013). First, the key underlying assumption about two-sided network effects is that platform users strongly prefer platforms with a large number of complementors, and in turn, complementors are incentivized by the large number of users (Boudreau & Jeppesen, 2015). Such an assumption might be challenged if complementors' motivations for participating in a software platform ecosystem are non-monetary. Therefore, it is crucial to consider the heterogeneity of complementors' behaviors from a strategic point of view. Platform owners can initiate various complementor engagement strategies (e.g., knowledge seeding strategy) (Huang et al. 2018) and/or provide social incentives for complementors with learning, intrinsic, and own-use motivations (Aral & Van Alstyne, 2011; Boudreau & Jeppesen, 2015). Second, two-sided network effects and WTA strategies are often assumed to be exogenous in an industry by IO economics researchers (McIntyre & Srinivasan, 2017). However, platform firms pursuing aggressive network effect strategies are also likely to fall into a prisoner's dilemma, wherein they create more value through a larger amount of investments but fail to capture greater value because the value created relative to industry competitors did not change (Mantovani & Ruiz-Aliseda, 2016).

To this end, strategic management researchers have focused on the utilization of platform ecosystems with two-sided network effects for achieving competitive advantage. They study strategic decisions that are relative to a platform's competitors, such as entry timing (Eisenmann, 2006) and a platform's relative quality (Anderson, Parker, & Tan, 2014; Zhu & Iansiti, 2012). Moreover, scholars have investigated organizational performance indicators that are relative to other competitors in the dynamic environment (Cennamo & Santalo, 2013; Venkatraman & Lee, 2004). However, comparable to the IO economics perspective, a strategic management perspective alone has not solved the optimization problem (McIntyre & Srinivasan, 2017). Significant uncertainty about the strategies for platform owners and complementors remains.

Because neither of the above approaches has proven to be sufficient on their own, there seems to be a mutual dependency between IO economics and strategic management perspectives. Strategic management literature builds on the core idea of IO economics and expands the theoretical analysis to a competitive and dynamic environment (McIntyre & Srinivasan, 2017). Both IO economics and strategic management researchers emphasize the importance of competition in software platform business value research. Overall, this general stream of literature rests on the premise of two-sided network effects of software platforms and models the competition in a dynamic environment at different levels.

Generative and Sociological Perspective. Sociology scholars view a software platform ecosystem as a network of complementors or software components with social relations (Uzzi, 1997). Thus, the economics and social activities of platform owners and complementors are embedded in social networks of software platform ecosystems. Research on software platform business value from a sociology perspective has highlighted the power of *interactions* at two distinct levels: (1) technical connections among different components (in the digital artifacts), and (2) social relationships among various platform participants such as platform owners and complementors.

Researchers have examined the impacts of digital artifacts under the theoretical lens of modularity and generativity. This area of literature centers on the special layered modular architecture of software platforms that offers *generativity*, allowing the software platforms to create, generate, or produce new outcomes (such as products, services, structure, business processes, and behaviors) without any specific input from the platform owners (Tilson, Lyytinen, & Sørensen, 2010; Yoo et al., 2010). In a modular architectural design, software components are separated into different modules based on their specific functionalities and can be loosely coupled through standard interfaces (Tiwana et al., 2010). The modularity of a system enables the future evolution or extension of software components by providing the capability to connect to new add-on applications through standard interfaces. In addition, modularity makes it possible to achieve digital innovation by recombining different software components. Thus, modularity of digital artifacts of software platforms can effectively reduce complexity and increase flexibility (Simon, 1996). Furthermore, layered architecture forms a continuum by adding generativity to traditional modular architecture (Yoo et al., 2010). Modular architecture has boundary conditions specific to the product itself. Designing modular software components to have different layers makes it possible to transform components from product specific to product agnostic, and to assemble them from a set of heterogeneous layers (Clark, 1985). Therefore, generativity can be achieved in a layered modular architecture through loose couplings across layers of software components whereby generative innovations can be incubated independently at any layer, leading to cascading effects on other layers (Adomavicius, Bockstedt, Gupta, & Kauffman, 2008; Boland, Lyytinen, & Yoo, 2007; Parker et al., 2017). A layered modular architecture can enhance the products' functionalities and software capabilities by recombining components within or across different layers (Yoo et al., 2010). Extant studies in this stream have investigated how platform owners and complementors strategically design their digital artifacts to improve performance (Eaton et al., 2015; Ghazawneh & Henfridsson, 2013; Tiwana, 2015a, 2015b; Tiwana et al., 2010).

Furthermore, scholars have investigated the performance impacts of platform complementors' social embeddedness. As conceptualized by Uzzi (1997, *p*. 35), "embeddedness is a logic of exchange that promotes economics of time, integrative agreements, Pareto improvements in allocative efficiency, and complex adaptation." Upon participating in software platform ecosystems, complementors often form strategic *inter-organizational relationships*, creating the network structure of software platform ecosystems. From a complementor's perspective, strategic inter-organizational relationships confer information, knowledge, and resources critical to the performance of complementors (Venkatraman & Lee, 2004). These relationships also have significant influence on the development of products, services, and processes in software platform ecosystems. For software platform owners, the inter-organizational relationships of complementors affect the flow of information, knowledge, resources, and behaviors by shaping the software platform ecosystem's network structure. Based on social network theory, prior literature has investigated the social structure of a software platform ecosystem as well as the impacts of a platform complementor's network embeddedness (Avgerou & Li, 2013; Basole, 2009; Venkatraman & Lee, 2004).

Control Perspective. Unlike their counterparts from competition and sociology perspectives, scholars using the *control* perspective believe that software platform ecosystems create value by effectively solving the tension between evolvability and stability (Tiwana et al., 2010). Software platform ecosystems' business values are enhanced when they evolve to fit with the dynamic environment and simultaneously sustain the quality and growth of the ecosystem

(Demsetz, 1997; Wareham et al., 2014). The openness characteristic of software platforms increases the heterogeneity of consumer preferences, the fragmentation of technologies, and the uncertainty of platform ecosystems' evolutionary trajectories (Wareham et al., 2014). Thus, this stream of literature emphasizes the merits of standardization in effectively managing a large complementor ecosystem (Parker & van Alstyne, 2005; Wareham et al., 2014). The common theme of this literature stream is that software platform ecosystems create business value when platform owners retain sufficient control to ensure successful integration between the focal platform and diverse complementors, while relinquishing enough control to foster open innovation by complementors (Tiwana et al., 2010). Researchers have investigated two main determinants in predicting the business value of software platforms: platform governance and coordination.

Platform *governance* has been conceptualized as the design of effective ecosystem-wide mechanisms (Gulati, Puranam, & Tushman, 2012). Ecosystem-wide governance mechanisms include rules that clarify when and how complementors may access the platform's boundary resources to supply their complementary applications that serve as the guidelines for value co-creation in the software platform ecosystem (Huber et al., 2017; Tiwana et al., 2010; Wareham et al., 2014). Ecosystem-wide governance rules and value include decision rights allocation, control mechanisms, and openness[2] (Tiwana et al., 2010). Overall, these dimensions of platform governance rules and value demonstrate the extent to which a platform owner can make decisions about the focal platform. By leveraging different levels of control over various boundary resources, the more "opened" components become adaptable and foster innovation through the mechanism of generativity, while the less "opened" components encourage the

[2] For a more detailed discussion of different dimensions of platform governance, please refer to Tiwana et al. (2010) and Wareham et al. (2014).

formation and reuse of standardized processes (Tiwana et al., 2010; Wareham et al., 2014). Extant studies have used this theoretical lens to investigate the effective design of platform ecosystem governance policies (Wareham et al., 2014), the evolution of platform governance rules (Huber et al., 2017), impacts of input control and decision right allocation on complementors' performance (Tiwana, 2015a, 2015b), and the influences of platform openness (Benlian et al., 2015; Wessel, Thies, & Benlian, 2017).

The second predictor of the business value of software platform ecosystems is coordination. *Coordination* issues arise at multiple levels, including with platform owners, complementors, and in their dyadic relationships. Coordination costs refer to the efforts required to manage dependencies (Malone & Crowston, 1994); however, coordination challenges can persist even in the absence of agency conflicts (Gulati, Lawrence, & Puranam, 2005). Considering the layered modular architecture of software components (Yoo et al., 2010), the diversity of complementary applications (Tiwana et al., 2010), and the multi-sidedness of a platform market (Hagiu & Wright, 2015), platform owners must manage strategically the interdependencies among software components, the interconnections to their diverse complementors, and the relationships between complementors and end users. Coordination issues also are critical for platform complementors, as software components in a platform ecosystem evolve as the environment changes. Consequently, platform complementors should develop strategies to manage the interdependencies among the focal platform's boundary resources (Tiwana, 2015b). Prior studies with this theoretical perspective examined the determinants of coordination costs, the effects of coordination on organizational performance, and the influences of a platform's coordination on the evolution of the ecosystem (e.g., Tiwana, 2015b; Parker & Van Alstyne, 2017).

CONCEPTUALIZING PLATFORM AND COMPLEMENTARY CAPABILITIES

We conceptualize platform capabilities and complementary capabilities by synthesizing factors examined in the extant literature (see Appendix 4 for abstracting the dimensions of platform and complementary capabilities), and simultaneously capturing the specific attributes of software platforms and different underlying theoretical mechanisms.

Platform Owners: Conceptualizing Platform Capabilities

We define *platform capabilities* as a software platform's ability to mediate simultaneously and effectively between complementors and end users, evolve to serve new purposes and emerging possibilities, and sustain the quality of complementary applications. As summarized in Table 3, our theory development delineates three distinct dimensions of platform capabilities: (1) intermediarity, (2) evolvability, and (3) stability. Given that the platform capabilities construct exists at the same level (i.e., platform level) as its dimensions (i.e., intermediarity, evolvability, and stability) and is conceptualized as different combinations of its dimensional characteristics (i.e., multi-sidedness, digital artifacts, and openness), it is theorized as a multi-dimensional construct (i.e., a profile model) (Law, Wong, & Mobley, 1998).

Intermediarity. As a multi-sided market, a software platform ecosystem can execute two-sided network effects, which trigger the growth of a software platform through the ecosystem of complementors and end users. Although software platform studies more commonly theorize the given characteristic of multi-sidedness, it is necessary to recognize that many platform organizations can make informed decisions concerning how near or far they are from a multi-sided platform-based business model (Hagiu & Wright, 2015). Such multi-sidedness of a software platform design has strategic implications. A higher level of multi-sidedness can facilitate information transparency, reduce search costs, and foster the growth of software platform ecosystems through two-sided network effects (Granados, Gupta, & Kauffman, 2010;

Table 3

Conceptualizing Platform Capabilities

Concept	Definition	Platform Characteristic	Value Creation Mechanism
Platform Capabilities	The ability to mediate simultaneously and effectively between complementors and end users, evolve to serve new purposes and emerging possibilities, and sustain the quality of complementary applications.	Three characteristics of software platforms (see below)	Theoretical mechanisms corresponding to the platform characteristics and based on perspectives taken in the previous literature (see below)
Constructs			
Intermediarity	The capacity to efficiently match the heterogeneous needs of end users to the diverse complementors through its digital artifact.	Multi-Sidedness	*Two-sided Network Effects*: the benefit of complementors depends on the user base at the same side (i.e., direct network effects) and the other side (i.e., indirect network effects).
Evolvability	The capacity to efficiently change to serve new purposes and emerging possibilities.	Digital artifact	*Generativity*: the ability to create, generate, or produce new outcomes (such as applications, structure, process, and behaviors) without any specific input from the platform owners.
Stability	The capacity to sustain the quality of complementary applications as well as the ecosystem evolution.	Openness	*Hierarchical Quality Controls*: make the more "opened" components adaptive and foster innovation, while the less "opened" components can encourage the formation and reuse of standardized processes.

Greenwood & Wattal, 2017; Parker & van Alstyne, 2005). Meanwhile, the increased multi-sidedness of software platforms makes it more difficult for platform owners to control the platform ecosystems (Hagiu & Wright, 2015). Therefore, we conceptualize a software platform's intermediarity as the first dimension of platform capabilities.

Intermediarity refers to a software platform's capacity to match efficiently the heterogeneous needs of end users to diverse complementors through its digital artifact. Intermediarity reflects the extent to which a software platform is close to a multi-sided economic model (Hagiu & Wright, 2015). Although some studies have used the degree of cross-side or indirect network effects between complementors and consumers to define intermediarity (Armstrong, 2006; Kim, Prince, & Qiu, 2014; Song et al., 2017), the most fundamental determinants of intermediarity are the extent to which the software platform enables direct interactions between different sides and the degree of each side's affiliation to the focal software platform (Hagiu & Wright, 2015). In the context of software platforms, intermediarity is only feasible when a platform owner strategically charges fees to match complementors and end users in the platform market (Baye & Morgan, 2001). However, platform intermediaries also have a "catch-22 dilemma[3]" of having to simultaneously satisfy the different needs of complementors and end users, forcing platform owners to design their information transparency strategies carefully and comprehensively (Granados et al., 2010). Prior studies demonstrated that greater transparency in product and price information attracts more users (Lynch & Ariely, 2000). Also, product offers made through recommendation systems could increase users' utilities (Montgomery, Hosanagar, Krishnan, & Clay, 2004). As a consequence, the increase of users'

[3] Soh et al. (2006, *p*. 706) defined the "catch-22 dilemma" in the context of electronic marketplaces as the scenario in which information transparency works differently for buyers and suppliers in an electronic marketplace. Taking the example of price transparency, high price transparency will discourage sellers' interests, while low price transparency cannot effectively attract buyers. Such "catch-22 dilemmas" widely exist in digital platforms, and platform owners should devise appropriate transparency strategies beyond merely product prices (Granados et al., 2010).

utilities and complementors' accessible installed base through intermediarity can trigger two-sided network effects in the software platform ecosystem (Parker & van Alstyne, 2005).

Evolvability. When adapted for business environments, the sociological concepts of natural selection theory and the Red Queen competition theory demonstrate that a software platform must evolve to keep up with its rivals and thrive in a dynamic environment (Agarwal & Tiwana, 2015; Barnett, 2008). Additionally, one important dimension of platform strategies is the purposeful cultivation of a software platform ecosystem's ability to create, generate, or produce new outcomes (such as applications, structure, business processes, and behaviors) without any specific input from the platform owners (Tilson et al., 2010; Yoo et al., 2010). Therefore, we recognize evolvability as an important dimension of platform capabilities.

Evolvability of a software platform ecosystem is defined as its capacity to change efficiently to serve new purposes and emerging possibilities (Agarwal & Tiwana, 2015). A higher level of evolvability increases a software platform's capacity to grow alongside evolving technologies, to survive in a dynamic industrial and macro environment, and to keep pace with varied and changing consumer preferences (Tiwana et al., 2010).

Since evolvability includes digital artifacts and their embedded social behaviors (Avital & Te'eni, 2009), platform owners can enhance their platform evolvability through both technical and non-technical approaches. First, from a technical perspective evolvability often means embedded irreversibly in the software platform design. Platform owners should be mindful of designing their platform architecture to accommodate future enhancements (Baldwin & Woodard, 2009). An ideal platform architectural design supports diverse demands in the present while allowing for necessary changes over time (Tiwana et al., 2010). A software platform can be made evolvable through layered modular architectural design, wherein software components are segmented into loosely coupled components interconnected through pre-defined standard interfaces and comprising a set of heterogeneous and hierarchical layers (Yoo et al., 2010). In a layered modular architectural design, innovative software components can be triggered through the recombination of existing components in the platform ecosystem. In addition, platform complementors can develop strategic add-on applications based on various software components across layers. Motivated by the desire to survive in the hyper-competitive platform ecosystem environment, platform complementors can innovate their applications by recombining the heterogeneous software components to serve new purposes (Tiwana, 2015a).

From a non-technical perspective, evolvability can be achieved through an ecosystem of autonomous complementors (Wareham et al., 2014). According to two-sided network effects, the number and diversity of add-on applications provided by complementors in a software platform ecosystem can attract more complementors as well as more consumers to participate in the ecosystem (Song et al., 2017). Thus, to increase the evolvability of a software platform ecosystem, platform owners can provide incentives for complementors participating in the ecosystem (Boudreau & Jeppesen, 2015). Platform owners should develop social incentives such as learning, intrinsic, and own-use motivations (Aral & Van Alstyne, 2011; Boudreau & Jeppesen, 2015) to supplement the monetary incentives enjoyed by complementors who seek business opportunities in the ecosystem (Parker et al., 2017; Tiwana, 2015a).

Stability. Although generative mechanisms and evolvability improve a software platform's prospects for long-term growth and survival in an extremely volatile environment, there are uncertainties and risks. First, uncontrolled creative third-party applications sometimes may negatively affect the evolution of the ecosystem (Wareham et al., 2014). Second, low-quality add-on applications may result in the negative user experiences and reviews, harming the economic sustainability and the social reputation of the ecosystem (Boudreau, 2012). Increasing heterogeneity of consumer preferences, fragmentation of software technologies, and uncertainty of ecosystems' evolutionary trajectories are present in software platform ecosystems (Wareham et al., 2014). Hence, platform owners should design control mechanisms to appropriately bound complementors' behaviors without destroying the desired level of evolvability. This concept is known as evolvability-stability tension (Tilson et al., 2010; Wareham et al., 2014). Therefore, we conceptualize stability as another crucial dimension of platform capabilities.

Stability refers to the platform owners' capacity to sustain the quality of complementary applications and ecosystem evolution. Platform ecosystem stability requires complementary applications to align their actions and outputs in a direction leading to quality control and simultaneously to encourage contributions to the ecosystem's growth (Wareham et al., 2014). Hierarchical quality controls over various software components and ecosystem players are necessary to make the more "opened" components adaptive and foster innovation through generativity mechanisms. On the contrary, the less "opened" components encourage the formation and reuse of standardized processes (Tiwana et al., 2010; Wareham et al., 2014).

Platform owners can enhance their stability through formal governance policies and informal coordination strategies. First, platform owners must design governance mechanisms such as decision rights allocation, control, granting access, and appropriability to balance the tradeoff between evolvability and stability (Boudreau, 2010; Tiwana et al., 2010). How decision-making authority is divided between platform owners and complementors affects the stability of the ecosystem. Decision right allocation determines what complementary applications should do, how they should do it, and who controls the standard interfaces (Tiwana, 2009). As a control strategy, platform owners can preset the criteria, methods, and procedures by which complementors' add-on applications are evaluated, rewarded, and penalized (Kirsch, 1997). Platform owners also should strategically select the ecosystem's openness by determining the extent to which complementors can use, develop, and commercialize the software components without restrictions (Boudreau, 2010). A more open ecosystem may enjoy the benefits of diverse input, ideas, and knowledge from a broader pool of complementors (Benlian et al., 2015; Boudreau, 2010; Ondrus et al., 2015). Meanwhile, opening a platform ecosystem simultaneously may reduce all parties' incentives to participate in the ecosystem due to the reduction of property rights (Benlian et al., 2015; Boudreau, 2010; Katz & Shapiro, 1994).

With respect to informal coordination strategies, the heterogeneous complementors in software platform ecosystems increase agency costs (Foros, Kind, & Shaffer, 2017); therefore, platform owners must coordinate ecosystems with diverse and evolving complementors, users, and software components to solve the evolvability-stability tension (Tiwana, 2015b). Given that the focal platform's software components often are designed in a layered modular architecture (Yoo et al., 2010), platform owners should manage the inter-dependencies among these modular components at multiple layers. In addition, diverse complementors provide various add-on applications through standardized interfaces (Tiwana et al., 2010), requiring platform owners to manage effectively their interconnections with diverse complementors. Because of the multiple sides of a platform ecosystem, platform owners should develop strategic policies to coordinate different parts of the ecosystem and trigger desired two-sided network effects (Song et al., 2017). Meanwhile, complementors should develop specific strategies to manage interdependencies among the focal platform's software components and standard interfaces since the focal platform's software components evolve with the change of the environment (Tiwana, 2015b).

Table 4

Conceptualizing Complementary Capabilities

Concept	Definition	Platform Characteristic	Value Creation Mechanism
Complementary Capabilities	The ability to create valuable and novel complementary applications that are protected from imitation or reproduction and that can be interconnected to the platform artifact and other complementors in an effective way.	Three characteristics of software platforms (see below)	Theoretical mechanisms corresponding to the platform characteristics and based on perspectives taken in the previous literature (see below)
Constructs			
Creativity	The creation of a valuable and novel complementary idea, business model, product, service, procedure, or process by individual or entrepreneurs in a platform ecosystem.	Multi-Sidedness	*Complementor and User Diversity*: diverse complementors and end users with heterogeneous preferences and behaviors simultaneously exist and interact with each other in a platform ecosystem.
Interconnectivity	The state or quality of being connected to the focal software platform's artifact or other complementors in the ecosystem, or to the potential to connect in an easy and effective way.	Digital artifact	*Boundary Resources*: the layered modular architectural software components serve as interfaces and can be extended by complementors.
Appropriability	The ability to capture profits generated by its complementary applications without being imitable or reproducible.	Openness	*Paradox of Disclosure*: platforms provide complementors' hard-to-duplicate assets and install base of users; but the disclosure of ideas will increase the risk of being imitated by platform owners or other competitors.

Platform Complementors: Conceptualizing Complementary Capabilities

Similar to the development of platform capabilities, we theorize *complementary capabilities* as a multi-dimensional construct, (or, more specifically, a profile model) (Law et al. 1998) and define it as a software platform complementor's ability to create valuable and novel complementary applications that are protected from imitation or reproduction and that can be interconnected to the platform artifact and other complementors in an effective way. As summarized in Table 4, we identified three distinct dimensions of complementary capabilities: (1) creativity, (2) interconnectivity, and (3) appropriability.

Creativity. A software platform ecosystem is a complex environment where diverse complementors and end users simultaneously exist and interact with each other (Eaton et al., 2015). End users have varied preferences toward the complementary applications on a platform ecosystem (Parker et al., 2017; Tiwana, 2015a). To satisfy end users' diverse and changing preferences, complementors constantly should innovate their offerings to stand out from other competitors and survive in the ecosystem (Tiwana, 2015a). In addition, software components in a platform ecosystem are resources shared by interested third-party contributors (Boudreau, 2010). Thus, due to end users' complex preferences and the similarity of software components provided by competing businesses, the ability of complementors' to separate themselves clearly from potential competitors is critical. Therefore, adapting our understandings from organizational strategy literature, we consider complementary creativity the first dimension of complementary capabilities in the context of software platform ecosystems. (Woodman, Sawyer, & Griffin, 1993) conceptualized organizational creativity as "the creation of a valuable, useful new product, service, idea, procedure, or process by individuals working together in a complex social system." Based on their definition (Woodman et al., 1993), we describe *complementary creativity* as the creation of a valuable and novel complementary idea, business model, product, service, procedure, or process in a software platform ecosystem.

Creativity is critical to the digital innovation and growth of complementors in an ecosystem (Goncalo, Chatman, Duguid, & Kennedy, 2015). However, eliciting creativity is difficult since it often challenges the status quo and is often controversial (Amabile, Barsade, Mueller, & Staw, 2005). Complementary creativity raises the tension between value and novelty, in which both divergent (i.e., necessary in the creativity process) and convergent (i.e., important in the post-creativity evaluation process) thinking exists (Chua, Roth, & Lemoine, 2015; Goncalo et al., 2015). Creators must adopt a divergent approach to produce novel ideas and technologies, and doing so requires creators to think differently, view things from an alternative perspective, and find inspiration from other domains (Amabile et al., 2005). However, at the end of the creativity life cycle, the final product ultimately will be evaluated based on rational criteria (such as profitability and efficiency), political correctness, and accessibility (Goncalo et al., 2015) all setting the boundary conditions and placing limits on the divergent process (Wang, Lee, Meng, & Butler, 2016).

Complementors should propose strategies to balance the tradeoff between value and novelty when designing their applications, processes, and business models (Amabile et al., 2005; Goncalo et al., 2015; Wang et al., 2016). Complementors should also assess the environments at the platform ecosystem, industry, and macro levels as the external environments sets the boundary conditions that enhance or constrain complementary creativity (Wang et al., 2016; Woodman et al., 1993).

Interconnectivity. Given the layered modular architecture of software platforms, complementors purposely can design their complementary products to be architecturally modularized (i.e., loosely coupled software components) and connected to the focal platform through standardized interfaces and to other complementors (Tiwana, 2015a). Also, since organizations (especially entrepreneurships) often face barriers caused by limited resources (i.e. limitations in technical skills, human resources, information resources, and necessary knowledge), inter-organizational relationships are necessary to absorb such constraints. Therefore, we conceptualize interconnectivity as another dimension of complementary capabilities. *Interconnectivity* is defined as a complementor's state or quality of being connected to the focal software platform's artifact or other complementors in the ecosystem, or to the potential to connect in an easy and effective way.

In the context of software platform ecosystems, there are three different levels of interconnectivity. First, complementors should design applications that will interact with the focal software platform's software components through standard interfaces (Eaton et al., 2015; Tiwana, 2015a). Developing add-on applications based on a larger number of varied software components at different layers can achieve the economics of scope and enhance complementors' dynamic and improvisational capabilities (Bharadwaj et al., 2013; El Sawy et al., 2010; Karimi & Walter, 2015; Pavlou & El Sawy, 2010). Meanwhile, more variety in interconnected software components increases the coordination costs for complementors (Tiwana, 2015b). Second, complementors should design architectural connectedness (i.e., modularity) within their own products' architecture (Tiwana, 2015a, 2015b). The microarchitecture of complementary products plays an important role in determining their evolvability in a competitive environment because a modularized complementary product can reduce the complementor's coordination costs (Tiwana, 2015b) and is more likely to evolve more quickly and keep pace in a dynamic environment (Tiwana, 2015a). Third, complementors can confer information, knowledge, and resources through interorganizational relationships with other complementors in the ecosystem or outside players (Khanna, Gulati, & Nohria, 1998; Mowery, Oxley, & Silverman, 1996; van Angeren, Alves, & Jansen, 2016; Venkatraman & Lee, 2004). Based on their strategic orientation, internal resources, and external environment, complementors should build alliances to absorb constraints (Casciaro & Piskorski, 2005). According to inter-organizational relationship literature from the strategic management field (Casciaro & Piskorski, 2005; Hillman, Withers, & Collins, 2009; Hoffmann, 2007), complementors should employ a tactical approach to forming inter-organizational relationships (i.e., partnership, merger, or acquisition) as they determine their own position in the inter-organizational network and those of target organizations.

Appropriability. Entrepreneurs often face a pivotal challenge when they attempt to commercialize their innovative ideas or technologies. They must choose between producing a standalone product or service to directly compete with incumbents, or collaborating with incumbents (Gans & Stern, 2003). By joining in a major software platform ecosystem, complementors can reduce investments on hard-to-duplicate complementary assets, access a larger installed base of users, conform to a set of quality certifications, and enhance social legitimacy (Ceccagnoli et al., 2012).

However, the paradox of disclosure may occur since the disclosure of ideas will increase the risk of being imitated by platform owners or other complementors and competitors (Gans & Stern, 2003). Participation in a software platform ecosystem often is achieved through an inter-organizational relationship with the focal platform (Huang et al., 2013). Such inter-organizational collaboration frequently causes some degree of unintended knowledge transfer (Khanna et al., 1998; Mowery et al., 1996). Although unprotected knowledge can be profitably used by partners (Bresser, 1988), prior literature demonstrates the risk when platform owners enter a complementors' market segmentation by offering similar products once exposed to an idea (Foerderer, Kude, Mithas, & Heinzl, 2018; Gawer & Henderson, 2007). Hence, in order to enhance the value creation, complementors should handle the disclosure strategically.

We conceptualize appropriability as another dimension of complementary capabilities. *Appropriability* is defined as a complementor's ability to capture profits generated by its complementary applications without being imitable or reproducible (Teece, 1986). Appropriability enhances complementors' ability to deter potential new entrants and gain sustainable competitive advantages (Rothaermel & Hill, 2005). Complementors with greater appropriability can deter imitation or use their appropriability mechanisms to prevent entry once imitation happens (Gans, Hsu, & Stern, 2002).

Research in the area of innovation identified four frequently practiced types of appropriability mechanisms[4]: intellectual property rights (IPRs), secrecy, lead time, and investment in complementary assets (James, Leiblein, & Lu, 2013). First, IPRs such as patents and copyrights are common in exercising appropriability in high-tech industry and software platform contexts (Arora & Ceccagnoli, 2006; Ceccagnoli et al., 2012). Second, secrecy uses internal procedures and policies to restrict the information flow both within and across organizations (Liebeskind, 1997). Secrecy of information regarding technological advantages not disclosed during the patent application process can be further maintained (James et al., 2013). Third, complementors may gain lead time advantages by commercializing a specific technology or providing complementary products before their competitors. Lead time strategy can bring learning curve advantages, enhance the adsorptive capacity to innovate faster than rivals, and better recognize, identify, and create technological opportunities (Ethiraj & Zhu, 2008;

[4] For a detailed discussion of each dimension of appropriability mechanisms and the institutional, industrial, organizational, and technological determinants, please refer to James et al. (2013).

Lieberman & Montgomery, 1988). Fourth, complementors can invest in complementary assets such as trademarks (which are often conceptualized as downstream capabilities, marketing capabilities, or product differentiation) to produce, market, and distribute their complementary applications (Arora & Ceccagnoli, 2006; Ceccagnoli et al., 2012; Gans et al., 2002; Teece, 1986). Specialized skills that are hard to transfer to other applications often are embedded in trademarks (Teece, 1986). Empirical studies have found that different appropriability mechanisms such as IPRs and trademarks have significant influences on complementors' decisions to join in a software platform ecosystem (Huang et al., 2013) and the business value of participating in a major platform ecosystem (Ceccagnoli et al., 2012).

INTEGRATIVE MODEL OF SOFTWARE PLATFORM BUSINESS VALUE

Having synthesized the main theoretical perspectives; and conceptualized platform capabilities and complementary capabilities, we now develop an integrative theory of software platform business value (as shown in Figure 1) based on our informed opinions. Two groups of propositions are derived: (1) how platform capabilities and complementary capabilities affect performance of platform owners and complementors, respectively, and (2) the co-evolution among platform owners, complementors, and ecosystem environment.

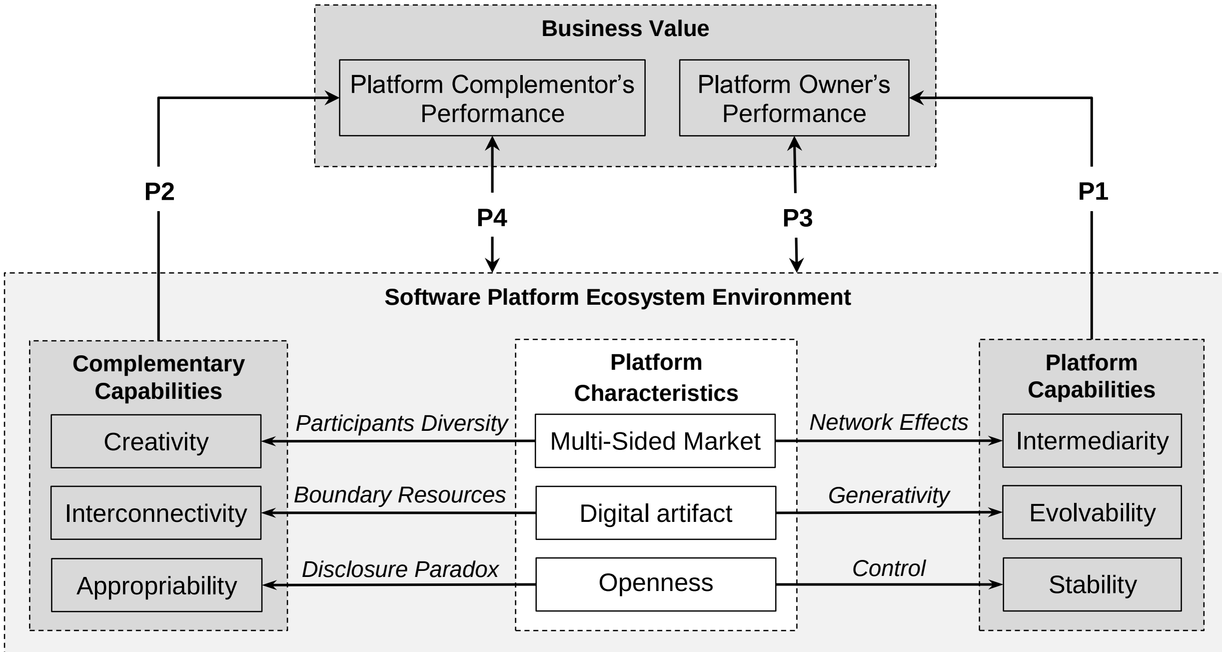


Figure 1. Software Platforms Business Value Model

Capability-Building and Value Creation

Each dimension of our conceptualization of platform capabilities has theoretical implications for platform owners' performance. First, with a higher level of intermediarity, complementors' end users are more likely to interact directly with each other (Hagiu & Wright, 2015). As a consequence, information transparency is increased while search costs are reduced, suggesting an enhanced level of market efficiency (Granados et al., 2010; Greenwood & Wattal, 2017). Additionally, an increased level of intermediarity can better strengthen the degree of indirect network effects (Armstrong, 2006; Kim et al., 2014; Song et al., 2017), fostering the growth of the software platform ecosystem. Second, a more evolvable software platform has a higher level of flexibility and the agility to update its core technologies, product and service offerings, and its ecosystem structure in response to a dynamic industrial and macro environment, consumers' changing preferences, and evolving technologies (Tiwana et al., 2010). The evolvability of a software platform also can motivate and attract diverse and high-quality complementors. Both digital artifact design and changing social behaviors of ecosystem players can trigger the generativity of a software platform ecosystem (Yoo et al., 2010). Thus, a more evolvable software platform can adapt better in the environment and is more likely to achieve better performance in evolutionary competition (Agarwal & Tiwana, 2015; Tiwana et al., 2010). Third, a higher level of stability can sustain the quality of complementary applications and guarantee the fitness of the ecosystem's evolution (Boudreau, 2010). Through effective platform governance, complementary applications simultaneously subsume their actions and outputs to create some form of quality-control rules and encourage contributions to the ecosystem growth (Wareham et al., 2014). In addition, stability requires a better coordination policy, which ultimately will reduce agency costs for platform owners. Hence, the stability of a software platform can boost platform owners' performance by increasing quality and reducing agency costs. Therefore, a higher level of platform capability is associated with increased market efficiency by facilitating two-sided network effects, the growth of the ecosystem through generativity, and the sustainability of ecosystem quality.

Proposition 1. *Platform capabilities—including intermediarity, evolvability, and stability—create business value for software platform owners by conferring two-sided network effects, generativity, and effective governance and coordination mechanisms.*

The three dimensions of complementary capabilities theoretically affect the performance of platform complementors. First, a creative complementor can produce innovative products to target unserved market segments in a software platform ecosystem (Goncalo et al., 2015). Another benefit of creating unique complementary products is that doing so allows a complementor to differentiate itself from other complementors in a hyper-competitive platform ecosystem (Chua et al., 2015; Goncalo et al., 2015). Creativity thus enhances a complementor's market capabilities through the formation of valuable and novel complementary ideas, business models, products, services, processes, and procedures (Amabile et al., 2005; Goncalo et al., 2015; Wang et al., 2016). Our second complementary capability, the internal interconnectivity of a complementor's product architecture, can reduce coordination costs (Tiwana, 2015b) and allow quicker evolution to serve new purposes (Tiwana, 2015a). A complementor's interconnectivity with the software components of the focal platform positively influences the acceleration of scope economics and the enhancement of dynamic and improvisational capabilities (Bharadwaj et al., 2013; El Sawy et al., 2010; Karimi & Walter, 2015; Pavlou & El Sawy, 2010). Increased interconnectivity with other complementors or players outside the ecosystem can confer information, knowledge, and resources (Khanna et al., 1998; Mowery et al., 1996; Venkatraman & Lee, 2004). Consequently, greater interconnectivity improves the performance of complementors by increasing the availability and absorption of slack resources. Third, the paradox of disclosure in software platform ecosystems suggests complementors with a higher level of appropriability can capture profits generated by their complementary products without being reproduced and imitated (Arora & Ceccagnoli, 2006; Ceccagnoli et al., 2012; Gans et al., 2002; Teece, 1986). To sum up, complementary capabilities positively affect the performance of complementors by capturing unique market opportunities, accessing and absorbing slack resources, and appropriating their outcomes.

Proposition 2. *Complementary capabilities—including creativity, interconnectivity, and appropriability—create business value for software platform complementors by satisfying end users' heterogeneous preferences, interconnecting the software platform's boundary resources and other complementors, and securing their opened outputs.*

Co-Evolutionary Adaptation

Platform owners can design their architecture and governance strategies deliberately to manage the development and evolution of their ecosystems. A software platform's architectural design significantly affects its ability to attract complementors' participation (Tiwana et al., 2010). Complementors are more likely to join a software platform ecosystem that has more compatible components and requires less effort to use. Moreover, the governance rules of a software platform ecosystem directly affect the motivation, innovation, competitiveness, and performance of complementors (Boudreau, 2010; Huber et al., 2017; Parker & Van Alstyne, 2017; Tiwana, 2015a). Furthermore, platform owners' other deliberate strategies such as innovation incentives, adding producers (Boudreau, 2012), ecosystem complexity, and platform generation transitions (Kapoor & Agarwal, 2017) significantly influence complementors' innovation and performance. Therefore, platform owners' strategies directly affect complementors' motivations, behaviors, and performance in the ecosystem; these effects trigger changes within the ecosystem environment. In line with recent advancement in IS strategy theories (Nan & Tanriverdi, 2017), there are two-way impacts between platform owners' deliberate strategies and the ecosystem environment. Changes in the software platform ecosystem environment provoke internal changes in the dynamics of platform owners' organizations, and these factors must be considered when decisions are made. Extant studies have found that complementors, as the key components of a software platform ecosystem, can invert platform owners' decisions (Parker & Van Alstyne, 2017). In addition, the impacts of platform capabilities on platform owners' performance depend on ecosystem structure and evolution. The ecosystem with better fitness can enhance platform owners' ability to capture value. Therefore, a co-evolutionary relationship exists between software platform owners' deliberate strategies and the dynamics of software platform ecosystems.

Proposition 3. *Software platform owners' digital artifacts and governance strategies shift the evolution of software platform ecosystems' environments. In turn, the ecosystems' environment provides the boundary conditions for the business value creation of platform owners.*

In a software platform ecosystem, complementors co-create business value with platform owners (Ceccagnoli et al., 2012). The enhanced performance of complementors in a software platform ecosystem bolsters the reputation of the ecosystem, attracts more complementors, and offers more high-quality products that satisfy users' heterogeneous preferences (Parker & van Alstyne, 2005). Also, a software platform ecosystem should be treated as a complex socio-technical environment where complementors' behaviors significantly affect the trajectory of ecosystem evolution (Eaton et al., 2015). Complementors undertake strategic actions such as inter-organizational relationships and multi-homing behaviors to achieve better performances in an unstable environment (Tanriverdi & Lee, 2008). Therefore, complementors' actions and outputs in a software platform ecosystem significantly influence the ecosystem environment (Parker et al., 2017). In turn, complementary applications directly connect to the focal software platform's components. Complementors' behaviors and outputs are controlled by the regulatory rules set by the platform owner. Furthermore, the ecosystem environment defines the competitors, resources, consumer base, and boundaries of complementors in a software platform ecosystem (Kapoor & Agarwal, 2017). Thus, complementors' value creation in a software platform ecosystem is constrained by the ecosystem environment, so there is a co-evolutionary relationship between complementors' deliberate strategies and the ecosystem environment.

Proposition 4. *Software platform complementors' complementary actions and outputs shift the evolution of software platform ecosystems' environment. In turn, the ecosystems' environment provides the boundary conditions for the business value creation of platform complementors.*

FUTURE RESEARCH GUIDELINES

Based upon our literature review and the integrated Software Platforms Business Value Framework and propositions, we develop some future research guidelines and propose a research agenda. We first discuss some guidelines that correspond to address the current research limitations identified in earlier as follows:

Developing Generic Theories

We recommend software platform scholars consider employing grounded theory to develop more generic theories of software platforms. A grounded theory approach allows researchers to use existing related concepts as a base from which to develop inductive theories while still being open to newly emerging or unexpected concepts (Glaser & Strauss, 1967). By doing so, researchers will not overlook potentially important concepts (informed by existing theories). Also, some important new concepts can be incorporated in the theory development process (Burton-Jones & Volkoff, 2017). Further, the contextualization approach could play a critical role in developing generic theories that are specific to a software platforms context. Context can be theorized as the salience of situational characteristics, the situational strength, a cross-level effect, a configuration or bundle of stimuli, a more precise meaning, or a constant (Johns, 2006). Researchers should distinguish between omnibus context and discrete context in the contextualization process for software platform ecosystems. Omnibus context specifies the who, what, when, where, and why of the theory, whereas discrete context demonstrates the specific situational factors that influence the behaviors directly or moderate the relationships between constructs (Johns, 2006). Furthermore, researchers can utilize the advantages of both grounded theory and contextualization approaches by employing a grounded theory model to develop a context-specific theory of software platforms (Burton-Jones & Volkoff, 2017).

Level of Analysis

Considering the multi-level nature of software platform ecosystems, future research should pay more attention to the development and empirical testing of multi-level theories. A multi-level theory or perspective can provide an alternative representation for investigating phenomena by simultaneously examining multiple levels of attributes (Zhang & Gable, 2017). Theoretical lenses such as event systems theory (Morgeson, Mitchell, & Liu, 2015) and complexity theories (Nan & Tanriverdi, 2017) can provide guidelines for multi-level theory development in the context of software platform ecosystems. Future studies can also investigate the co-evolution among different players within or across software platform ecosystems. Several theoretical lenses including path dependency, path creation, and path constitution theories (Singh, Mathiassen, & Mishra, 2015) and methodologies such as sequential mining (Sabherwal & Robey, 1993; van de Ven, 1992) and fsQCA (El Sawy et al., 2010) can be applied to theorize and empirically test the co-evolution phenomena. Furthermore, there are some unique levels of analysis specific to the software platform ecosystems context beyond traditional levels of analysis based on key players. For instance, the boundary resources phenomenon has been recognized as one such unique level of analysis (Eaton et al., 2015; Ghazawneh & Henfridsson, 2013). It links the theoretical lenses of control and sociological perspectives. In addition, boundary resources typically involve multiple actors, such as platform owners and complementors. Future research can develop generic theories to better understand these levels.

Variance vs. Process Models in Theory Development

We call for more research developing process-based models to understand interrelationships and sequences of events in the platform ecosystems context. In addition, we recommend that software platform researchers employ mixed-method approaches to enhance the comprehensiveness, uniqueness, and robustness of theory development and empirical tests, since different research models provide unique insights. For instance, researchers can employ archival data analysis or qualitative case analysis to demonstrate the usefulness of analytical models and further validate the assumptions of the models. If a software platform's research is based primarily on archival data analysis, researchers may run a post-hoc qualitative analysis to uncover additional insights on the phenomenon. For process-model researchers, more quantitative evidence could be used to strengthen theory development. Furthermore, with the recent advances in data analysis techniques and methodologies (such as sequence mining and fsQCA), future research can combine variance and process models to generate unique and valuable insights.

Aligning Organizational Business Strategy

We recommend that more software platform research take a business process-based view while investigating the organizational performance of software platforms. A business process-based view of software platforms would require researchers to conceptualize software platforms as business process integrators (Markus & Loebbecke, 2013). The theory development should be based on a thorough understanding of the contextualized factors associated with the organizational business processes. In addition, future research can be done to better understand how software platforms may develop as a part or extension of organizational business processes. The unit of analysis would be the connection between software platforms and organizational business processes. Furthermore, informed by prior IS strategy research about IS alignment, software platform researchers may investigate the implications of alignment among software platforms, organizational software business strategy, business process, IS and business infrastructure, and IS and organizational resources.

Based on the key findings in prior studies and advised by our integrated framework, we outline possible future research questions in each identified research theme as shown in Table 5. While we do not claim our assessment complete, we hope that our literature summary and proposed future research agenda motivates IS researchers' in software platforms and offer a starting point for future related studies.

Table 5

Future Research Agenda

Theme 1: Inter-Platform Competition and Platform Strategies
• How can platform owners strategically design the platform infrastructure that can enable future planned evolvability? • How do platform owners' employ strategies of managing boundary resources (i.e., API strategies)? • How can platform owners strategically manage the complex network structure of the software platform ecosystems to ensure success? • Are platform firms' inter-organizational network strategies different from traditional pipeline-based firms? If so, what are the implications for both pipeline firms and platform businesses? • How can platform owners strategically decide on the extent to which they seek compatibility with other platform-based and pipeline-based organizations? • How can potential platform-based entrepreneurs effectively find the market opportunities to undertake disruptive innovation through software platforms? • How can established companies design software platforms to foster innovation? • How can established companies strategically align their business processes with software platforms? • What macro-environmental factors predict the success of launching software platforms?

Table 5 (Continued)

Theme 2: Intra-Platform Competition and Entrepreneurship
• How can entrepreneurs strategically design their complementary applications in conformance to the focal platform architecture? • What should be the criteria and entry strategies for potential complementors to select and join a particular software platform? • How can platform complementors strategically manage their relationship with other platform complementors and/or players outside the ecosystem? • How can platform complementors strategically design their evolutionary trajectories within the platform ecosystem and adjust them to better fit with the intra-platform competitive environment? • What roles do top management teams' insights/ knowledge play in the success of platform complementors' entrepreneurship? • How do platform complementors strategically response/ deter the (potential) entry of platform owners or other competitors?
Theme 3: Platform Governance and Ecosystem Evolution
• What should be platform owners' rules to better govern platform ecosystems at different levels (such as platform, ecosystem, dyadic levels)? • How to effectively theorize and empirically address the complex dynamics in software platform ecosystems? • What are the platform strategies to better manage the longitudinal evolution of software platforms? • How do the boundary resources, different stakeholders (such as platform owners, complementors, alliance partners, and outside players), and the ecosystem's external and internal environments co-evolve over time? • What are the spatial and temporal processes through which a specific event happens at a particular level (such as complementors, alliance, and ecosystem) and how do these affect the evolutionary trajectory of software platforms?

CONCLUSION

This research undertook a *broad theorizing review* of literature about software platforms with a primary objective of *theorizing* and a research focus of *description* (Leidner, 2018). Our main perspective in the literature review is software platform business value, which is motivated by a core and sustained theme of IS research on IT business value. Researchers across different disciplines such as IS, economics, strategic management, and marketing are increasingly interested in the phenomenon of software platforms. Although diverse scholarly areas contribute to our cumulative knowledge of software platforms, the conversations tend to be isolated and, to the best of our knowledge, there is no integrative theoretical framework that synthesizes how software platforms create business value. Therefore, this research aims to develop a *phenomenon theory* to explain how software platforms create business value for platform owners and complementors (Leidner, 2018).

We begin by summarizing and categorizing extant software platform business value studies, as well as discussing key findings and limitations in each theme. Synthesizing the literature, we summarize the specific characteristics of software platforms and the existing theoretical perspectives. By linking the different dimensions of software platform characteristics to the main theoretical perspectives, we conceptualize platform capabilities for platform owners and complementary capabilities for platform complementors. Recognizing the multi-level nature of software platforms, we built an integrative theoretical framework explaining how software platforms' different characteristics create business value by enhancing platform capabilities and complementary capabilities. Based on our review and synthesis of software platform literature, we discuss opportunities for future research. We hope that our thematic analysis and theory building efforts provide a stimulus for future research on business value of software platforms.

ESSAY 2. WHAT YOU DO AND WHEN YOU DO IT: PRODUCT STRATEGIES, ENTRY TIMING, AND ENTREPRENEURIAL SUCCESS IN A PLATFORM ECOSYSTEM

INTRODUCTION

> *With the growing demand of business analytics and artificial intelligence of big data, Hadoop's various open source projects with different layers of functionalities (e.g., data storage, data processing, data access, data management, hardware, cloud, and development tool) have created great business opportunities for software companies. Over time, there is an increasing number of Hadoop-based companies offering diverse products, taking different competitive strategies, and witnessing different outcomes. Two success stories include: Quest Software, an early entrant in the Hadoop ecosystem, launched its first products in June 2010 and focused on the database, data access, and cloud functionalities. These architectural product layers were also commonly covered by other entrants at the time such as Amazon Web Services, Cloudera, Canonical, and Zettaset. Quest Software was acquired by Dell in 2012 for 2.4 billion US dollars. Voltage Security, which was acquired by HP in 2015, entered the Hadoop ecosystem later in 2013. Voltage Security specialized in the security layer, which features fewer competitors as compared to other architectural product layers.*

Information Technology (IT) companies are increasingly joining platform ecosystems to overcome resource obstacles and enhance institutional legitimacy. Platform ecosystems provide IT entrepreneurs (i.e., known as complementors) with essential technologies, a ready customer installed base, and an ability to achieve quicker market reputation and gain innovation opportunities (Boudreau, 2010). However, the competition among complementors within a platform ecosystem is intense due to platforms' unique characteristics such as low entry barriers, shared resources, fluid ecosystem boundaries, and risks of being imitated (Huang et al., 2013). Given such platform tensions and as evidenced in the above Hadoop cases, platform complementors need to *design the "right" products at the "right" time*.

Digital platform ecosystems organize their technological resources into layered modularity architectures (Yoo et al., 2010). Complementors strategically decide how to offer products across these layers. Taking the Hadoop ecosystem as an example, firms such as Hortonworks and Cloudera offer products across most Hadoop layers, while companies such as

Voltage Security and Joyent take a more “specialized” strategy by focusing on a smaller number of layers. This product diversification strategy signifies complementors’ dependencies on the focal platform, diversity of market segments, groups of customers with various preferences, and utilization of platform resources (Eaton et al., 2015; Lee & Raghu, 2014; Tiwana, 2015a). However, the impact of complementors’ product diversification across platform layers is neither theorized nor empirically examined. In this research we contextualize *within-platform product diversification* as the extent to which a platform complementor’s product covers a range of the heterogeneous technological layers of the focal platform.

In addition, a platform ecosystem is a hyper-competitive environment, in which complementors compete with each other over the customer base and platform resources (Tiwana et al., 2010). Thus, it is crucial for complementors to decide how much their product design should deviate from that of other complementors. However, prior literature tends to regard a complementor’s product strategy as more of an insularly, rather than competitor relative, decision—how the complementor’s product design relative to other complementors’ product offerings affects its performance is under-studied. Therefore, we examine the performance implication of complementors’ *product differentiation*, which is defined as the extent to which the complementor’s product is dissimilar from other complementors’ products in the platform ecosystem.

Furthermore, platform ecosystems are rapidly evolving over time (Eaton et al., 2015). Complementors entering the platform ecosystem at different times face different environmental uncertainty, resources and capabilities endowment, and changing customer demands (Fosfuri, Lanzolla, & Suarez, 2013; Rietveld & Eggers, 2018). Prior strategy literature has called for future research examining the coupling of entry timing with technology markets such as platform ecosystems where platform owners and early entrants have less control over the key technological resources (Fosfuri et al., 2013). Since firms entering the market at different times deploy different resources and skills (Robinson, Fornell, & Sullivan, 1992), it is more compelling to examine the timing for complementors to develop resources and capabilities to adapt the platform resources to specific uses (Fosfuri et al., 2013). Hence, this research further investigates how earlier and later entrants can develop different product strategies to better assimilate platform resources and improve performance.

In sum, this research examines the impacts of platform complementors' within-platform product diversification and product differentiation strategies as well as the moderating effects of entry timing on their performance. Our research is conducted in the context of the Hadoop ecosystem, which is one of the leading platforms for big data and analytics (Tambe, 2014). We choose to focus on startups because most complementors in platform ecosystems are startups (Ceccagnoli et al., 2012; Huang et al., 2013) playing an important role in shaping the development of these ecosystems (Ceccagnoli et al., 2012). Furthermore, compared with public firms, the success of startups relies more heavily on the development of the focal platform and its ecosystem. We use the likelihood of being acquired as the critical measure of startup success (or performance) for several reasons. Acquisition by an established company has been proved to be an important liquidity event (Campbell, 2013) and a successful exit event for entrepreneurial firms (Hallen, Katila, & Rosenberger, 2014). Being acquired has been identified as a commercialization strategy for entrepreneurs to sell their businesses to an established company and earn returns (Gans & Stern, 2003). Being acquired also secures the entrepreneurial funding to continue the technology or idea development for the young startup (Andersson & Xiao, 2016).

Our longitudinal empirical analysis demonstrates that complementors' within-platform product diversification has an inverted U-shaped relationship with their likelihood of success. Such a curvilinear effect of product diversification is greater for complementors that enter the platform ecosystem earlier than those with later entry timing. Product differentiation and entry timing jointly affect complementors' success such that product differentiation is negatively associated with earlier entrants' likelihood of success but positively influences the success of later entrants. Together these findings offer theoretical understanding of and practical insights into platform complementors' product strategies, entry timing, and their interactions.

LITERATURE REVIEW AND THEORETICAL BACKGROUND

Platform Complementors' Competitive Strategies

Platform researchers initially emphasized how platform owners can technically and strategically create a platform, attract and govern the ecosystem of users and complementors, dominate a market, and evolve over time (see McIntyre & Srinivasan, 2017 for a review). Recognizing the hyper-turbulence and dynamism of platform ecosystems and the importance of complementors for the value co-creation within the ecosystem, recent research increasingly examined complementors' competitive strategies and performance. First, based on the perspective of innovation appropriation, research found that IT startups participating in a platform ecosystem, on average, have better performance such as increased sales and likelihood of IPO (Ceccagnoli et al., 2012). Complementors with stronger appropriability mechanisms (e.g., patents and trademarks) will obtain higher returns and are more motivated to join a platform ecosystem (Ceccagnoli et al., 2012; Huang et al., 2013). In addition, prior research has taken the architectural view and examined the impacts of complementors' product architectural design on their performance. For example, platform complementors that design their products with a higher level of modularity—i.e., loosely decoupling and interface standardization—are more likely to evolve their products at a faster rate (Tiwana, 2015a) and reduce coordination costs (Tiwana, 2015b).

Furthermore, prior platform studies have adopted the strategic management perspective and examined how complementors' product portfolio affects their performance. For example, emphasizing the presence of network externalities in the platform context, Tanriverdi & Lee (2008) found that simultaneous implementation of related diversification across platforms and related diversification across software product market segments improves complementors' sales growth and market share. Research also examined factors that influence complementors' strategies and performance, such as platform owner's entry (Foerderer et al., 2018; Wen & Zhu, 2019), structural and evolutionary features of the platform ecosystem (Kapoor & Agarwal, 2017), multi-homing (Cennamo et al., 2018), and preference heterogeneity between earlier and later platform adopters (Rietveld & Eggers, 2018).

This research extends this stream of literature by investigating how strategic product designs relative to the platform's architectural layers (i.e., within-platform product diversification) and relative to other complementors competing in the ecosystem (i.e., product differentiation) affect the performance of complementors entering the ecosystem at different times. The simultaneous examination of within-platform product diversification, product differentiation, and entry timing not only yields strategic implications for platform complementors, but also is among the first in the intra-platform competitive dynamics literature.

Product Diversification

Within-platform product diversification refers to the extent to which a complementor's products cover a wide range of the heterogeneous technological layers of the focal platform. A higher level of product diversification indicates that the platform complementor's products are more likely to have a higher degree of architectural diversity and are more dependent on the platform architectural evolution. The construct of within-platform product diversification integrates the core idea of platform modules' micro-architectural design from a technical perspective (Tiwana, 2015a) as well as product attributes such as scope, proliferation, variety, niche width, and diversity from a strategic perspective (Lee & Raghu, 2014; Tanriverdi & Lee, 2008). Specifically, it measures complementors' strategic product design on the scope of architectural components that are interacting with the focal platform architecture.

Strategy literature has identified both advantages and drawbacks of product diversification. Product diversification benefits firms due to the economics of scope through synergies of operating and management (Tanriverdi & Lee, 2008), demand synergies by enabling consumers' needs of 'one-stop shopping' (Giarratana & Fosfuri, 2007), capabilities of exploiting organizational assets such as technology (Li & Greenwood, 2004), organizational learning effects (Stern & Henderson, 2004), and abilities of forming entry barriers by saturating product niches (Lancaster, 1990). In addition, the digital innovation view suggests that product diversification across different categories facilitates the recombination of heterogeneous components in generating innovative products (Yoo et al., 2010). However, higher product diversification may increase coordination costs (Jones & Hill, 1988), difficulties of control (Barroso & Giarratana, 2013), and other costs related to cognitive management abilities (Simon, 1991). Product diversification may also cause cannibalization from the demand perspective (Hui, 2004). Furthermore, from the niche width theoretical perspective (Freeman & Hannan, 1983), firms with greater product diversification need to allocate their capacities across different types of activities, reducing their abilities to build identity.

Prior research has made considerable efforts on empirically examining how exactly product diversification influences firm performance. However, there is still no consistent answer: some research has found a positive relationship (Bayus & Agarwal, 2007; Tanriverdi & Lee, 2008) while others show a negative or null impact (Li & Greenwood, 2004; Stern & Henderson, 2004). Recent studies took aim to solve this puzzle. First, some research employs the curvilinear approach and suggests considering different product strategies that firms simultaneously pursue. For example, Barroso & Giarratana (2013) examined both across-niche product proliferation (i.e., intra-industry diversification or breadth) and within-niche product proliferation (i.e., product versioning or depth) on firm performance. They found that across-niche product proliferation has a U-shaped impact on firm performance but the effect of within-niche product proliferation is inverted U-shaped. In addition, prior literature has explored contingency factors that may moderate the impact of firms' product diversification on firm performance. These moderators include but are not limited to top management team, board of directors, employees, suppliers, industry environment, and sociopolitical environment (see Su & Tsang, 2015 for a review).

Informed by these studies, we theorize the curvilinear relationship between complementors' within-platform product diversification and performance. In addition, considering the dynamism of platform ecosystems, we simultaneously examine the impacts of within-platform product diversification and product differentiation on complementors' performance, as well as how these relationships are moderated by their entry timing.

Product Differentiation

Dickson *et al.* (1987, *p*. 4) define product differentiation as the extent to which a product differs from its competition on any physical (e.g., reliability, safety, size, and color) or nonphysical (such as image and status) characteristics. In the IT sector, two firms using identical technological components would generate indistinguishable variations of the product (Fosfuri, 2006). Thus, from the technology management perspective, product differentiation is mainly caused by differences in the underlying technologies. In addition, in the volatile and dynamic IT industry, new product development could be more critical than branding and price competition (Wadhwa & Kotha, 2006).

Marketing, industrial organization, and strategy theorists have examined firms' positioning choices in the product space and the subsequent impacts that various positioning configurations have on firm performance (Colombo, 2013). A large body of literature has employed the analytical modeling approach with various extensions of Hotelling (1929) and vertical differentiation (Gabszewicz & Thisse, 1979; Shaked & Sutton, 1982) models based on assumptions such as firm rationality, oligopolistic market structure, and normal distribution of consumers. Past literature also empirically examined the outcome of pursuing higher product differentiation. For example, firms with stronger emphasis on product differentiation are more likely to pioneer new categories of products (Danneels, 2002), possess stronger capabilities of transforming resources and skills into product innovations (Branzei & Vertinsky, 2006), protect their own not-easily-substitutable market niches (Fosfuri, 2006), and successfully commercialize product innovations (Levie, 1995). In addition, product differentiation strategies interact with other firm-level strategies and environmental factors in determining firm performance. For instance, Boone, Wezel, & van Witteloostuijn (2013) found that product positioning at entry and industry-level product differentiation jointly affect entrepreneurs' survival, such that entrepreneurs are better to enter through similar products if the industry-level product homogeneity is low, and vice versa.

In the platform context, prior research has adopted the analytical modeling approach to examine how product differentiation at the platform level influences market structure, pricing strategies, performance, and social welfare (Anderson et al., 2014; Cennamo & Santalo, 2013). Different from these studies, this research empirically measures how a platform complementor's product differentiates from other complementors' products in the ecosystem and examines its impacts on the complementor's likelihood of success.

Entry Timing

The timing of entering a new market is a strategic decision affecting the adoption and diffusion of products, firm survival, and performance (Bayus & Agarwal, 2007; Fosfuri et al., 2013; Klingebiel & Joseph, 2016). Entry timing literature has compared the benefits and drawbacks of earlier and later entrants (Bayus & Agarwal, 2007).

Classic entry timing literature has proposed several mechanisms in favor of the early mover's advantages (Golder & Tellis, 1993; Kerin, Varadarajan, & Peterson, 1992). Consumers have heightened familiarity with the early entrants' products and less likely to try late entrants' products to avoid uncertainty and switching costs (Schmalensee, 1982). In addition, early entrants have advantages of choosing optimal positions in the product space. Such early mover advantages are more salient when consumers have stronger preferences on product attributes rather than product quality (Bohlmann, Golder, & Mitra, 2002). From producers' perspective, early entrants' large market share and sales base increase their resources and strengthen their capabilities of utilizing process innovations and reducing costs (Lieberman & Montgomery, 1988).

In contrast, recent research has started to explore the contingent situations where late entry is more compelling (Ethiraj & Zhu, 2008; Lieberman & Montgomery, 1988; Suarez &

Lanzolla, 2007). First, several studies found that fast-changing technologies make it more difficult for early entrants to sustain competitive advantages (Zhu & Iansiti, 2012). In such a situation, early entrants are more likely to be tied to older technologies and therefore have disadvantages in the market (Fosfuri et al., 2013). Second, late entrants often face lower market uncertainties. When the external environment is characterized by hyper-turbulence and dynamism such as fast-paced technological and market evolution, first mover advantages will be reduced (Suarez & Lanzolla, 2007). Third, at the later stage of a market, market uncertainty will decrease because of improved market information. Early entrants' product information can be used by late entrants to develop superior imitative products (Ethiraj & Zhu, 2008).

Therefore, firms face a tradeoff between establishing first mover advantages or joining the game later to decrease uncertainty (Dowell & Swaminathan, 2006). Strategy literature examined the optimal timing to enter a new market (Kalish & Lilien, 1986) as well as the impacts of entry timing on firm innovation (Klingebiel & Joseph, 2016), development of dominant product design (Suarez, Grodal, & Gotsopoulos, 2015), survivability (Bayus & Agarwal, 2007; Dowell & Swaminathan, 2006; Papyrina, 2007), and financial performance (Isobe, Makino, & Montgomery, 2000). A recent compelling stream of research explores how early and late entrants follow different strategies to improve competitive advantages. For example, different from early entrants' strategies, late entrants' development of complementary assets such as copying followers' strategies and commercialization capabilities (Teece, 1986) becomes more critical. Also, early and late entrants may adopt different business models to achieve better performance (Markides & Sosa, 2013). One well-known example is the success of Facebook through its closed and within-university networks business model (Fosfuri et al., 2013).

In the context of platform ecosystems, prior literature has investigated the optimal launch timing of platforms (Bhargava, Kim, & Sun, 2013) and late entrants' optimal strategies to succeed (Zhu & Iansiti, 2012) from the platform owner's perspective. However, little research has examined the issue of entry timing from platform complementors' perspectives. Strategy literature acknowledged that new research opportunities will emerge from "the coupling of entry-timing research with the literature on markets for technology" (Fosfuri et al., 2013, *p*. 306). Hence, how platform complementors at different time of entry adopt different product strategies to maximize the orchestration of platform resources becomes crucial. Therefore, in this research we examine how platform complementors' product strategies (i.e., product diversification and product differentiation) affect their likelihood of success differently for early versus late entrants.

HYPOTHESES DEVELOPMENT

Effects of Within-Platform Product Diversification

We theorize the effects of within-platform product diversification on platform complementors' success for the following reasons. First, greater product diversification facilitates scope economies, which indicate that the firm's simultaneous manufacturing of different product layers is more cost-effective. A platform complementor's diversification across more technological layers will synthesize the development, operation, and management of products, therefore decreasing its layer expansion costs due to the initial investment in human capital and the implicit knowledge acquired from prior projects (Cottrell & Nault, 2004). Second, a higher level of product diversification enables synergies from the demand side by offering customers the option of 'one-stop shopping' (Giarratana & Fosfuri, 2007). Consumption economies demonstrate that customers are more likely to purchase multiple products from the same vendor or a single product supporting various functions (Cottrell & Nault, 2004) because the same vendor's product offering ensures compatibility and reduces learning efforts. Third, from the technology management perspective, complementors with greater product diversification have more opportunities of experimenting with the recombination of heterogeneous layers of technological components to generate innovative products (Yoo et al., 2010). Product innovation capabilities are more salient for platform complementors because of the hyper-turbulent environment of platform ecosystems and the interdependencies between complementors and platform architecture (Foerderer et al., 2018). Complementors with stronger innovation capabilities can better cope with the fast-changing platform architecture, consumer preferences, and the ecosystem environment (Tiwana, 2015a).

However, the coordination cost and difficulty of control inherent in the within-platform product diversification strategy could limit its success (Tiwana, 2015b). In the platform ecosystem context, there are three major types of coordination cost. First, considering the heterogeneity of technological components in different layers, platform complementors should make efforts in coordinating their internal components' dependencies (Tiwana, 2015a). Second, platform architecture and resources are fast evolving as a consequence of the platform owner's strategic moves and the diverse third-party products with different evolutionary trajectories (Tiwana et al., 2010). Complementors must maintain their products' compatibility with the focal platform's architecture and standards (Tiwana, 2015a). Third, most technological components are supported by, and co-evolve with, the third-party developers who directly contribute the source code (Eaton et al., 2015). Thus, platform complementors may also need to coordinate with these third-party developers in the open source ecosystem of the selected components in different layers. These coordination efforts required for platform complementors not only directly increase their costs (Tiwana, 2015b) but also lead to difficulty of control (Barroso & Giarratana, 2013). Besides, similar to other contexts, greater product diversification is associated with the risks of reduced cognitive management abilities (Simon, 1991), demand cannibalization (Hui, 2004), and challenges of developing and maintaining a coherent identity (Barroso & Giarratana, 2013).

These contrasting mechanisms inform a threshold level for the negative (or positive) relationship between within-platform product diversification and complementors' likelihood of success. In other words, the relationship may be curvilinear (i.e., inverted U-shaped). When diversifying into too many technological layers, platform complementors face greater coordination costs, difficulty of control, cognitive management costs, and risks of identity development and customer cannibalization. However, focusing on too few layers may limit the potential customer base, capabilities of experimenting with generative innovations, and the economies of scope. Thus, before reaching the critical threshold, the platform complementor's product diversification can increase its market performance by growing the customer base, leveraging knowledge acquired from prior experience, and improving their social legitimacy. However, once surpassing a threshold, the costs in the aforementioned areas associated with product diversification will outweigh the benefits. Therefore, we hypothesize that

Hypothesis 1 (H1). *Platform complementors' within-platform diversification has a curvilinear (inverted U-shape) relationship with their likelihood of success.*

Effects of Product Differentiation

From the consumer's perspective, marketing literature demonstrates that product differentiation helps firms build distinctive brand and satisfy consumers' unique preferences. Distinguishing a firm's product from peers' products on both relevant and irrelevant attributes will improve its performance by informating customers in resisting competitive attacks (Carpenter, Glazer, & Nakamoto, 1994). Specifically, differentiated products will be more favorably evaluated since the information conveyed to customers is novel (Carpenter et al., 1994). In terms of inter-brand comparisons, product differentiation makes the brand more distinctive in customers' minds because it is different, salient, and perceptually dominant (Carpenter & Nakamoto, 1989).

Past strategy literature regards product differentiation as important in pushing existing differentiated technologies towards achieving incremental innovations (Berry, 2018). To better satisfy consumers' fast-changing tastes, complementors keep enhancing their existing product technical designs towards the frontier of technological innovation. Complementors differentiating their products from other complementors' products gain unique insights, knowledge, and resources. Such generic differences embedded in products and services are more likely to produce innovative products that are fundamentally different from other complementors in the ecosystem. By focusing on differentiated niches of the platform market and continuing to innovate the products and technologies, firms with greater product differentiation will have stronger capabilities and more opportunities of building their unique identities and becoming innovators.

Furthermore, sociology theorists view market competition as a process of comparative selection in which attributes interact with the embedding environment to determine firm performance and market efficiency (Metcalfe, 1998). Product differentiation can be seen as creating market niches, and therefore reducing competitive selection pressure (Kaniovski, 2005). In the platform ecosystem, differentiated complementors would be motivated to develop complementary rather than competing resources and capabilities. In this way, complementors that differentiate their products will focus on a different subset of the platform's install base relative to their ecosystem competitors. Therefore, we hypothesize that

Hypothesis 2 (H2). *Platform complementors with higher level of product differentiation are more likely to succeed.*

Moderating Effects of Entry Timing

We theorize that product diversification has a stronger influence on early entrants than late entrants. At the early stage of the platform ecosystem, platform resources are often not well defined (Tiwana et al., 2010). The platform owner typically has not accumulated sufficient knowledge and experience in developing and commercializing the ecosystem. Early entrants interacting with less mature APIs and SDKs face greater technological and market uncertainty. On the contrary, when the ecosystem evolves to a later stage, the platform owner has more experience and capabilities of managing the ecosystem and the platform architecture is more stable. Late entrants therefore have less technological and market uncertainty (Suarez et al., 2015). Hence, early entrants should more strategically decide on their positioning in the technological layers to mitigate the uncertainty.

Furthermore, early entrants are more likely to gain access to more technological, informational, and reputational resources from the platform owner (Klingebiel & Joseph, 2016). They are also more likely to participate in the co-creation of dominant product designs, which would further enhance their ability to leverage the focal platform's resources (Fosfuri et al., 2013). In the early stage of the platform ecosystem, complementors can better utilize their "superior" product diversification design to occupy a leadership position in the platform ecosystem. Positioning in the "right" range of the focal platform's technological layers will enhance their capabilities of dominating the market and evolvability with the platform ecosystem. In contrast, it may be more difficult for late entrants to be actively involved in shaping the dominant product design, acquire better network position, and compete with existing complementors for resources (Dowell & Swaminathan, 2006). The strategic diversification across layers of platform resources thus becomes less salient in obtaining better market performance. Therefore, we hypothesize that

Hypothesis 3 (H3). *In a platform ecosystem, the impact of product diversification on complementors' likelihood of success is stronger for earlier entrants than later entrants.*

We next examine how product differentiation affects platform complementors' likelihood of success differently for earlier versus later entrants. First, platforms in the early stage are characterized by a high level of uncertainty (Landsman & Stremersch, 2011). The requirements and properties of technological components of the platform architecture are less-defined and less-understood (Argyres & Bigelow, 2010), increasing uncertainties and risks in technical investments and product-specific engineering efforts. Hence, by converging to the product design of other ecosystem competitors, early entrants can learn the "best practices" of others and therefore reduce the uncertainties in product development. On the contrary, firms entering the ecosystem later when the uncertainty is reduced face less risk in their efforts and investments. However, by then earlier entrants have raised entry barriers for later entrants via trademarks, patents, spatial saturation, and exclusive contracts (Ethiraj & Zhu, 2008). In such an environment, later entrants can offer products that are differentiated from earlier entrants' products to survive in more specific and uncovered market niches.

In addition, at the early stage of the platform ecosystem, complementors can offer similar products to facilitate the development of ecosystem standards and accumulate ecosystem-wide information and knowledge, which is crucial to firms in the high-tech industry with strong network externalities. Besides, convergence to other complementors' product design increases the complementor's legitimation by promoting its recognition in the broader stakeholder community (Boone et al., 2013). However, at the later stage of the platform ecosystem, these positive externalities spillover to earlier entrants and the ecosystem standards emerge. The product market competition also becomes more intensive because similar complementors depend on the same pool of platform resources (Boone et al., 2013). Later entrants therefore are better able to differentiate their products to explore new market niches and reduce the intensity of market competition (Kaniovski, 2005).

Furthermore, in the traditional proprietary market, prior technology management literature has demonstrated that late entrants are less likely to survive if early entrants have stronger control of key complementary technological resources (Teece, 1986). However, by granting access of their technological assets to third-party developers, platforms open a technology market that reduces the criticality of technology as a source of competitive advantage. Regardless of their entry timing, complementors can freely access the platform resources through standard interfaces. Thus, later entrants can develop complementary resources and tailor their products to specific needs of their target customers (Fosfuri et al., 2013). Although early entrants have advantages of size, choosing optimal positions, and dominating the market (Bohlmann et al., 2002; Klepper, 1996), late entrants' product attributes that differentiate them from earlier entrants are better recognized and remembered by consumers (Zhang & Markman, 1998), indicating the importance of differentiating product offering for late entrants to succeed in a platform ecosystem. Therefore, we hypothesize that

Hypothesis 4 (H4). *In a platform ecosystem, the impact of product differentiation on complementors' likelihood of success is stronger for later entrants than earlier entrants.*

Figure 2 depicts the research model.

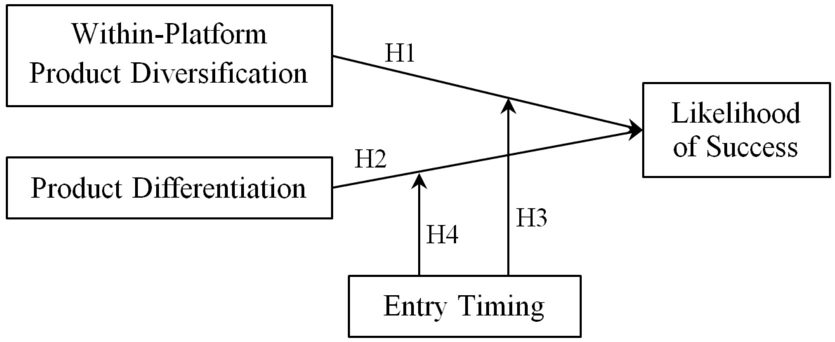


Figure 2. The Conceptual Model (Essay 2)

RESEARCH METHODOLOGY

Research Context

We selected the Hadoop ecosystem[1] as our research context. Hadoop is one of the dominant platforms for big data and analytics (Tambe, 2014) and is an architectural framework that consists of numerous open source projects with different layers of functionalities. Hence, from a technical perspective, Hadoop provides an excellent context to quantify complementors' interconnection with platform architecture and examine the impacts of the platform's layered modular architecture. Since Hadoop is an open source platform, its self-organizing attribute makes the competition among platform complementors dynamic. Furthermore, the Hadoop platform shares the common characteristics of openness and layered modular architecture with other software platforms such as SAP, Cisco, IBM, and J2EE, providing us with the opportunity to generalize our results to other platform contexts. In addition, observing the entrepreneurial potential of Hadoop platform, a large number of startups either emerge from, or participate in, the ecosystem. These Hadoop complementors enter the ecosystem, adopt diverse product

[1] As shown in the Hadoop official site, Hadoop is "*a framework that allows for the distributed processing of large data sets across clusters of computers using simple programming models. It is designed to scale up from single servers to thousands of machines, each offering local computation and storage. Rather than rely on hardware to deliver high-availability, the library itself is designed to detect and handle failures at the application layer, so delivering a highly-available service on top of a cluster of computers, each of which may be prone to failures.*" More details can be accessed at http://hadoop.apache.org/.

strategies and evolve such strategies over time, demonstrating varying levels of success as shown in the mini-case presented at the beginning of the article. Therefore, the dominant position of Hadoop ecosystem in big data and analytics as well as the turbulence and variation in the ecosystem make it a suitable context to examine entrepreneurial success in platform ecosystems.

Data

We conducted a full-text search of the Lexis-Nexis database to form the list of firms that participate in the Hadoop ecosystem. The keywords "Hadoop" and the names of Hadoop-related projects such as "ZooKeeper" and "HBase" were employed to identify Hadoop platform complementors. To the best of our knowledge, this identification approach produces the most comprehensive list of firms that participate in Hadoop ecosystem since there is no existing secondary data source to store and maintain the related information. After a comprehensive content analysis of all the searched texts, 71 startup firms are identified as complementors of the Hadoop ecosystem by the end of the first quarter in 2016.

Then, we collected each identified firm's press releases about its business description, product description, acquisition events, and other strategic alliances from its official website. To complement the announcements retrieved from the firm's website, we conducted a text search on Lexis-Nexis database, major newswire such as PR Newswire and BusinessWire, and Google by using the keywords of firm name and "Hadoop". Firms' patents and trademarks data were gathered from the United States Patent and Trademark Office (USPTO) database. Other controls such as firm age, firm size, and funding were collected from Crunchbase (Kacperczyk & Marx, 2016) and verified by the information gathered from LinkedIn (Ge, Huang, & Png, 2016; Tambe, 2014).

Measurement

Dependent Variable. As discussed in the Introduction section, we use the likelihood of being acquired by an established firm to measure entrepreneurial success. The unit of analysis in this study is firm-quarter, with the acquisition variable equal to 1 if a firm was acquired in that quarter and 0 otherwise. The post-acquisition observations were deleted from the sample because the firms are no longer exposed to the hazard of being acquired (Ceccagnoli et al., 2012; Huang et al., 2013). In total, 18 out of the 71 firms have successfully exited (i.e., being acquired) during the observation window (i.e., from 2009 to 2016). To utilize the survival analysis, we define the dependent variable *Duration* as the number of quarters between a firm's entry into the ecosystem and its acquisition by another firm. In addition, to distinguish whether the firm was acquired at the end of the observation window, we add a censor variable *ACQ* which takes the value of 1 if the firm has been acquired and 0 otherwise.

Within-Platform Product Diversification. Based on our conceptualization, *ProductDiversification* is a time-variant count variable indicating the number of heterogeneous technological layers that a firm offers in its products. We first categorized Hadoop platform's technological components into eight categories[2]. Broadly, there are four main categories: hardware, software distribution, cloud, and development tool. The software distribution category is further divided into five distinct groups including data storage (i.e., Hadoop Distributed File Systems and HBase), data processing (i.e., MapReduce and YARN), data access (such as Hive, Pig, Mahout, and Sqoop), data management (including Oozie, Flume, and ZooKeeper), and security (e.g., Sentry, Knox Gateway, and Ranger). Hardware layer offers hardware and appliances, and cloud provides the cloud computing platforms. Development tools are specifically offered to developers and can be either for a particular layer (such as database

[2] A detail list of projects in Hadoop ecosystem can be accessed on https://hadoopecosystemtable.github.io/.

development tool) or a configuration of multiple layers (e.g., development tool for Hortonworks Distribution Platform). Such categorization schema is developed based on a thorough analysis and synthesis of expert opinions, media articles, and academic publications. Two authors of this paper have jointly developed the schema after intensive discussions and research meetings and an industry expert has evaluated the coding schema. The two authors and the domain expert performed content analysis on each firm's product description, major product update release, and related new articles to code the technological layers that a firm covers. We took an iterative approach until the disagreement between the coders is resolved.

Product Differentiation. Consistent with prior literature (e.g., Hoberg & Phillips, 2016), we performed text mining on the product description of Hadoop ecosystem complementors to measure product differentiation. Although we focus on startups in this research, we evaluated the similarity of the text in all Hadoop complementors' product descriptions. We collected startups' business descriptions in each quarter (Hoberg & Phillips, 2016). Since public firms have much broader product lines and are less likely to cover their Hadoop-related products in their business descriptions in the 10-K report, we used the description of Hadoop-related products in their product release announcements. Appendix 5 and Appendix 6 present the examples of startups' business descriptions and public firms' Hadoop-related product descriptions respectively. We use the standard natural language processing approach to remove stop words and stem words to their root forms. We also omit numbers describing time periods, market demand, partners, geographical words such as state and city names, as well as company names. Next, we build document vectors using keywords for each firm's product description in each period, and adopt Term Frequency times Inverse Document Frequency (TF-IDF) as the weight for each keyword. TF-IDF can effectively capture the relative importance of keywords in each document by simultaneously using within-document and cross-document keyword frequencies (Tata & Patel, 2007). Appendix 7 shows the top 30 TF-IDF weighted keywords in selected periods. Using the vector document with weighted keywords, we computed the firm-by-firm similarity using cosine similarity scores. We use each complementor's average of similarity scores relative to all other complementors in each quarter to measure its broad product similarity (Hoberg & Phillips, 2016), which ranges from 0 to 1, where 0 indicates that the complementor's product is not similar to any other complementor in the ecosystem and 1 refers to the case when the complementor's product is completely the same as other complementors. Thus, the variable *ProductDifferentiation* is computed as the difference between 1 and the average similarity score of a complementor. Mathematically, the variable is computed as:

$$ProductDifferentiation_{it} = 1 - \frac{\sum_{j=1}^{N} \frac{W_{it} \cdot W_{jt}}{|\overrightarrow{W_{it}}| \times |\overrightarrow{W_{jt}}|}}{N}$$

where W_{it} and W_{jt} represent the TF-IDF weighted document vector of complementor *i* and *j* at time *t*; *N* refers to the total number of ecosystem competitors (i.e., *N*+1 is the total number of complementors in the ecosystem at time *t*); $\frac{W_{it} \cdot W_{jt}}{|\overrightarrow{W_{it}}| \times |\overrightarrow{W_{jt}}|}$ is the cosine similarity score between complementor *i* and *j* at time *t*.

Entry Timing. By tracking the specific date of each complementor's first Hadoop-related product release, we computed variable *EntryTiming* representing the number of quarters between the firm's entry date and the date of the first ecosystem entrant (i.e., 03/16/2009) (Dowell & Swaminathan, 2006). The measurement captures the relative order of entry, in which smaller values indicate earlier entry.

Control Variables. We control for possible confounding factors related to firm characteristics, innovation capabilities, and strategic alliances that may affect firms' likelihood of success. Extant studies prove that the size and age of firms would affect their capabilities to dominant partners, market power, and survival, etc. (Gans & Stern, 2003; Lin, Yang, & Demirkan, 2007; Raz & Gloor, 2007). Compared with smaller firms, larger firms have more resources and experiences to update their products and succeed. However, they are not as flexible as smaller firms, because smaller firms can recombine their resources at a faster rate. Similarity, firms' resources, capabilities, and opportunities are also expected to be associated with their age. Therefore, both firm age and firm size are controlled. We calculated *FirmSize* as a firm's number of employees. We transformed the estimated range of the number of employees listed on Crunchbase and LinkedIn into an ordinal variable. The number of 1 to 7 represents the range of 1-50, 51-100, 101-250, 251-500, 501-1000, 1001-5000, and 5001-10000, respectively. *FirmAge* is computed by the number of quarters between a firm's founding and the end of each observed time period. Furthermore, prior studies have acknowledged that the availability of funding is critical for the survival and performance of startups (Ceccagnoli et al., 2012; Hsu, 2006; Stuart, Hoang, & Hybels, 1999). We therefore compute a variable *Funding* to denote the total amount of funding received from corporate investment, venture capital investment, and private investment for each firm in a thousand US dollars unit. Prior platform literature also demonstrated the significant impacts of complementors' multi-homing behaviors (Cennamo et al., 2018), we thus control for whether a complementor only offers Hadoop-related products. The variable *HadoopFirm* is a dummy variable, which takes the value of 1 if it only provides Hadoop-related products and 0 otherwise.

A growing body of literature has proven the importance of innovation capabilities in firms' evolutionary trajectory as well as operational and financial performance (Ceccagnoli et al., 2012). In line with prior related studies (e.g., Ceccagnoli et al., 2012; Huang et al., 2013), we use firms' patents and trademarks to measure their innovation capabilities. To mitigate the potential bias caused by the significant time lag between patent filling and granting, a patent is counted from its filling quarter. Given that most firms in our sample do not have any patents, we create a variable *Patent* to denote whether a firm has a Hadoop-related patent(s), which takes the value of 1 if the firm has and 0 otherwise. In addition, we use the variable *Trademark* to measure the cumulative number of trademarks that a firm has. Only the trademarks that listed as "Live" status are counted in each period.

Partnership is a common practice for firms to enhance each partner's capabilities and bring additional information and resources (Hoffmann, 2007). Thus, a firm with more partners may acquire more internal and external resources to succeed. Furthermore, platform complementors may absorb their constraints by acquiring another firm. Through acquisition, the acquirer's resources on intellectual properties, human capital, and potential customer base will be improved. These resources often increase platform complementors' likelihood of success. Therefore, we control for platform complementors' partnership and acquisition behaviors in the platform ecosystem. The variable *Partner* is computed to represent a complementor's total number of strategic alliances related to the Hadoop ecosystem. *Acquisition* is a dummy variable[3] demonstrating whether a complementor has acquired another firm in the observed period, which takes the value of 1 if it has and 0 otherwise.

Firms sequentially enter the Hadoop ecosystem. Earlier and later entrants have different external environment and extent of ecosystem competition. In addition, the size and competitive strategies of existing ecosystem complementors significantly influence the opportunities, resources, and entry barriers of new entrants. Furthermore, the number of complementors in a

[3] We coded *Acquisition* as a dummy variable instead of count because only 12.4% of the (firm-quarter) observations have at least one acquisition. If we use the count variable to measure it, the distribution will be highly skewed.

platform ecosystem correlates to the popularity and maturity of the ecosystem. We therefore control for the size of the platform ecosystem. We use the variable *EcosystemSize* to measure the total number of firms that offer Hadoop-related products at each period.

Table 6 presents the summary of descriptive statistics and correlations of all variables.

Table 6

Descriptive Statistics and Correlations

Variable	Mean	SD	1	2	3	4	5
1. ACQ_{it}	0.02	0.15					
2. $ProductDiversification_{it}$	2.42	1.68	0.002				
3. $ProductDifferentiation_{it}$	0.79	0.06	0.029	-0.559			
4. $EntryTiming_{i}$	12.72	6.10	0.009	-0.445	0.357		
5. $HadoopFirm_{it}$	0.50	0.50	-0.034	0.306	-0.295	-0.233	
6. $Partner_{it}$	0.41	0.60	0.043	0.509	-0.330	-0.265	0.157
7. $Acquisition_{it}$	0.13	0.33	0.068	0.238	-0.115	-0.094	-0.208
8. $FirmAge_{it}$	2.95	0.86	0.055	-0.038	0.111	0.033	-0.481
9. $FirmSize_{it}$	2.78	1.71	-0.021	0.265	-0.137	-0.189	-0.309
10. $Patent_{it}$	0.19	0.40	0.054	0.124	0.021	0.064	-0.118
11. $Trademark_{it}$	0.75	0.81	-0.001	0.183	-0.097	-0.175	-0.276
12. $Funding_{it}$	2.37	1.85	-0.048	0.465	-0.324	-0.286	0.136
13. $EcosystemSize_{t}$	4.17	0.64	0.073	-0.040	0.163	0.529	-0.147

Notes. Number of observations: 788; Number of firms: 71.

Table 6 (Continued)

Variable	6	7	8	9	10	11	12
7. $Acquisition_{it}$	0.200						
8. $FirmAge_{it}$	-0.048	0.194					
9. $FirmSize_{it}$	0.315	0.415	0.311				
10. $Patent_{it}$	0.068	0.282	0.196	0.218			
11. $Trademark_{it}$	0.162	0.534	0.239	0.580	0.253		
12. $Funding_{it}$	0.325	0.161	-0.066	0.316	0.192	0.269	
13. $EcosystemSize_{t}$	-0.104	0.072	0.241	-0.098	0.204	0.080	0.047

Notes. Number of observations: 788; Number of firms: 71.

Empirical Approach

Survival analysis (also referred to as duration, hazard, or event history model) considers the time to an event and censors the event at the same time. Survival analysis not only relaxes the normality assumption of linear regression but also can effectively address the incomplete observation of survival times when censoring happens (Hosmer, Lemeshow, & May, 2008). Therefore, survival analysis is an appropriate method to use in our research context. This estimation technique has witnessed its popularity in strategy research (Bayus & Agarwal, 2007; Huang et al., 2013). We employ the Cox (1972) semi-parametric model, which does not assume the baseline hazard function form, to identify the factors affecting the hazard rate that a firm will be acquired. In the benchmark specification, the conditional instantaneous hazard rate of firm *i* in time *t*+1, with $h_0(y)$ representing the unspecified baseline hazard rate is given as:

$$h(t+1 \mid X_{it}) = h_0(t) \cdot e^{\beta_1 X_1(t) + \beta_2 X_2(t) + \cdots + \beta_n X_n(t)}$$

where $h(t+1 \mid X_{it})$ represents a firm's hazard function at time $t+1$, with n time varying covariates $X_1(t)$, $X_2(t)$, …, $X_n(t)$; β_1, β_2, …, β_n are regression coefficients, and $h_0(y)$ refers to a non-negative and unspecified baseline hazard function.

RESULTS

Results of Hypothesis Testing

We hierarchically add independent variables and interaction terms into the baseline model. As shown in Table 7, all values of variance inflation factor (VIF) are well below the threshold of 10, indicating that multi-collinearity is not a major concern. We centered all independent variables by subtracting the mean and dividing by the standard deviation.

Table 8 reports the results of hypothesis testing. Column (c) in Table 8 shows that product diversification has an inverted U-shape impact on complementors' success (*ProductDiversification*: $\beta = 2.673$, $p = 0.002$; *ProductDiversification*^{2}: $\beta = -2.813$, $p = 0.003$), indicating that before reaching the threshold of critical number of technological layers, complementors are more likely to succeed if they package a wider range of the focal platform's technological layers. Once reaching the diversification threshold, firms are less likely to succeed when their within-platform product diversification increases. Therefore, H1 is supported. Independent of the models, we find that the threshold level at which increased within-platform product diversification reduces complementors' likelihood of success is around 0.5 standard deviation from the sample mean—i.e., roughly three or four Hadoop technological layers out of the total eight available layers.

Table 7

Results of Variance Inflation Factor

Variable	Model a	Model b
$ProductDiversification_{it}$	4.40	4.17
$ProductDiversification_{it}^2$	4.83	2.98
$ProductDifferentiation_{it}$	1.71	1.71
$ProductDiversification_{it} \times EntryTiming_i$	4.21	
$ProductDiversification_{it}^2 \times EntryTiming_i$	9.04	
$ProductDifferentiation_{it} \times EntryTiming_i$		1.26
$EntryTiming_i$	4.60	2.21
$HadoopFirm_{it}$	1.77	1.73
$Partner_{it}$	1.55	1.56
$Acquisition_{it}$	1.56	1.56
$FirmAge_{it}$	1.47	1.45
$FirmSize_{it}$	2.04	2.08
$Patent_{it}$	1.25	1.24
$Trademark_{it}$	1.98	1.98
$Funding_{it}$	1.70	1.63
$EcosystemSize_t$	2.01	1.93
Mean VIF	2.94	1.96

Consistent with H3, the moderating effect of entry timing on the relationship between product diversification and complementors' likelihood of success is negative and significant (*ProductDiversification* × *EntryTiming*: β = -1.249, p = 0.018; *ProductDiversification*^{2} × *EntryTiming*: β = 1.834, p = 0.003). As shown in Figure 3(a), early entrants' product diversification has a stronger (i.e., steeper or higher slope) inverted U-shaped impact on their success, but the impact of product diversification on late entrants' success is weaker.

Table 8

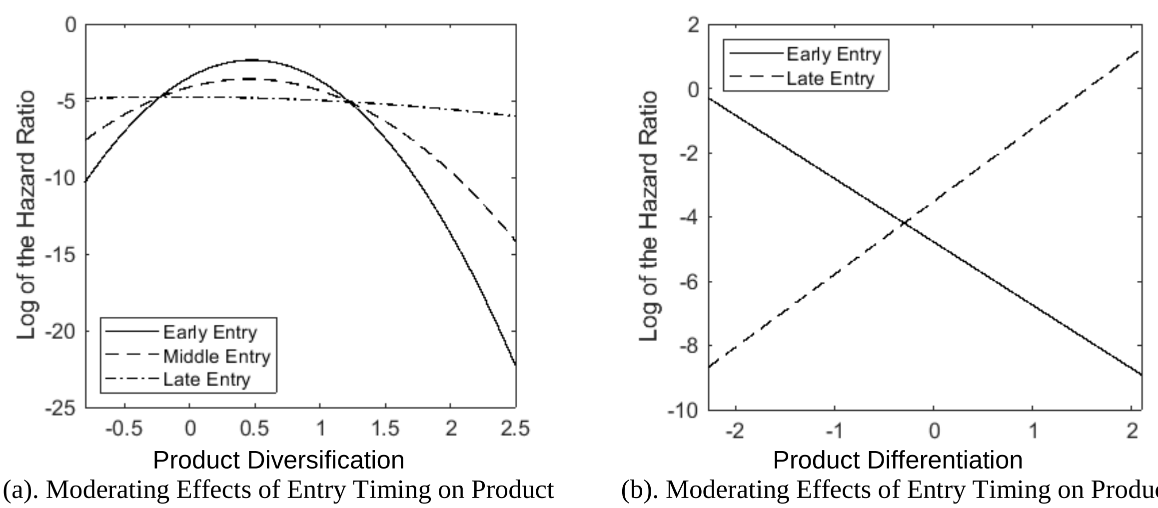
Results of Hypothesis Testing (Essay 2)

Variable	Model (a)	Model (b)	Model (c)	Model (d)
$ProductDiversification_{it}$		1.879*** (0.589)	2.673*** (0.867)	2.057** (0.844)
$ProductDiversification_{it}^2$		-1.942*** (0.635)	-2.813*** (0.932)	-2.354*** (0.698)
$ProductDifferentiation_{it}$		0.520 (0.378)	0.821* (0.422)	0.449 (0.383)
$ProductDiversification_{it} \times EntryTiming_i$			-1.249** (0.527)	
$ProductDiversification_{it}^2 \times EntryTiming_i$			1.834*** (0.611)	
$ProductDifferentiation_{it} \times EntryTiming_i$				1.189*** (0.311)
$EntryTiming_i$		0.641 (0.698)	-0.127 (0.791)	0.395 (0.806)
$HadoopFirm_{it}$	-0.779 (0.684)	-1.350* (0.718)	-1.370** (0.648)	-1.675** (0.701)
$Partner_{it}$	-0.912 (0.657)	-1.153 (0.718)	-1.186 (0.867)	-1.333 (0.869)
$Acquisition_{it}$	1.596*** (0.495)	1.361** (0.625)	1.508* (0.772)	1.421** (0.715)
$FirmAge_{it}$	-0.230 (0.306)	-0.357 (0.315)	-0.329 (0.276)	-0.230 (0.255)
$FirmSize_{it}$	-0.184 (0.222)	-0.374 (0.259)	-0.317 (0.247)	-0.429* (0.241)

Table 8 (Continued)

Variable	Model (a)	Model (b)	Model (c)	Model (d)
Patent$_{it}$	1.196* (0.635)	1.983** (0.841)	2.209** (0.881)	2.269*** (0.841)
Trademark$_{it}$	-0.652 (0.480)	-1.026** (0.488)	-1.209** (0.580)	-1.078** (0.525)
Funding$_{it}$	-0.241 (0.153)	-0.274 (0.210)	-0.350* (0.199)	-0.402** (0.194)
EcosystemSize$_t$	0.222 (0.862)	-0.656 (0.989)	-0.347 (1.081)	-0.223 (1.410)
Wald χ^2	20.97**	27.19**	44.27***	51.19***

Note: Number of observations: 717; Number of firms: 71; Number of acquired firms: 18; Robust standard errors clustered by firm are in parentheses; *p < 0.1, **p < 0.05, ***p < 0.01.



(a). Moderating Effects of Entry Timing on Product Diversification

(b). Moderating Effects of Entry Timing on Product Differentiation

Figure 3. Moderating Effects of Entry Timing

As shown in column (d) in Table 8, the hypothesized positive influence of complementors' product differentiation on their likelihood of success is insignificant ($\beta = 0.449$, $p = 0.241$). H2 therefore is not supported. One possible reason is that complementors' product differentiation should be aligned with the environmental dynamics of the platform ecosystem. As discussed in the literature review, firms' product differentiation has both benefits and drawbacks for their performance especially in a turbulent and dynamic environment. The insignificance of *ProductDifferentiation* also confirms the rationality of examining how product differentiation strategy affects earlier versus later entrants differently. In support of H4, the results show that the joint effect of product differentiation and entry timing on complementors' likelihood of success is significant ($\beta = 1.189$, $p = 0.000$). As depicted in Figure 3(b), early entrants' product differentiation is negatively associated with their likelihood of success, while the increase of product differentiation will improve late entrants' likelihood of success.

Robustness Checks

We conducted a series of robustness checks by using alternative samples, econometrics model specifications, and measures. First, we used a sub-sample of complementors that have less than 1,000 employees and are less than seven and a half years old; and a sub-sample of complementors that have less than 500 employees and were founded less than 20 quarters ago, following prior literature (Ceccagnoli et al., 2012; Puranam, Singh, & Zollo, 2006). In addition, although we can use the likelihood of issuing an IPO to measure the entrepreneurial success (e.g., Ceccagnoli et al., 2012; Cockburn & MacGarvie, 2009; Hallen et al., 2014; Petkova, Wadhwa, Yao, & Jain, 2014), only two firms in the Hadoop ecosystem went IPO during our observation window. To further rule out the potential bias caused by the possible different mechanisms of issuing an IPO and being acquired, we removed the two IPO firms from the sample.

To control for potential unobserved heterogeneity, we ran alternative model specification by utilizing the strength of the panel data structure. The estimation of nonlinear models such as the Cox proportional model using firm-level fixed effects is likely to be inconsistent and biased because of the incidental parameters problem (Huang et al., 2013). We addressed this potential issue through the discrete choice of whether a complementor is acquired at a certain period, rather than using the hazard rate. To identify the error term structure, we performed the Hausman specification test. Results in all models show that there is no significant difference between the fixed effects and random effects estimators, indicating that a random effects model will be preferred because of its high efficiency. We therefore fit the panel data random effects Probit and Logit models. Furthermore, we performed additional survival analysis to ensure the robustness of our results regarding the distributional assumptions of the Cox hazard model. Although the Cox model assumes the hazard rate function to be a continuous-time, the survival times in some cases are observed less precisely and within the interval of a quarter or month which the acquisition event happened. In this scenario, the discrete-time hazard model will be more appropriate. Consistent with prior studies (e.g., Bayus & Agarwal, 2007; Huang et al., 2013) with similar data structure—i.e., the event is less precisely coded and only can occur once—we estimated a binary response model with a complementary log-log link function.

Although the text mining-based approach of measuring firms' product differentiation is regarded as a novel approach and recently widely used in strategy research (e.g., Hoberg & Phillips, 2016), firms' product descriptions might be self-selected in terms of words choices and linguistic styles, causing potential noises in the measurement. We thus used an alternative approach based on our content analysis of Hadoop firms' technological layers to measure product differentiation. Consistent with prior literature (e.g., Hoberg & Phillips, 2016), we firstly calculate the firm-by-firm similarity by the configurations of firms' technological layers for every pair of firms in our sample in each quarter. Given that each complementor's configuration of technological layers is a finite set, we employ the Jaccard index to measure the similarity between two firms' product. Then, we aggregate the firm-by-firm similarity scores and use each complementor's average of similarity scores with all other complementors at each quarter to indicate how much the firm's product is similar to other complementors in the ecosystem. The average similarity score ranges from 0 to 1, where 0 indicates that the complementor's product layers is not similar to any other complementors in the ecosystem and 1 refers to the case when the complementor's product is completely same with other complementors. Thus, the variable *ProductDifferentiation* is computed as the difference between 1 and the average similarity scores of a complementor. Mathematically, the variable is computed as:

$$ProductDifferentiation_{it} = 1 - \frac{\sum_{j=1}^{N} \frac{|P_{it} \cap P_{jt}|}{|P_{it}| + |P_{jt}| - |P_{it} \cap P_{jt}|}}{N}$$

where P_{it} and P_{jt} represent the technological layer set of complementor *i* and *j* at time *t*; *N* refers to the total number of ecosystem competitors (i.e., *N*+1 is the total number of complementors in the ecosystem at time *t*); $\frac{|P_{it} \cap P_{jt}|}{|P_{it}| + |P_{jt}| - |P_{it} \cap P_{jt}|}$ is the Jaccard similarity score between complementor *i* and *j* at time *t*.

We replicate the analyses used in our main hypothesis testing and robustness checks. The results as depicted in Table 9 and Table 10 demonstrate that the interested relationships are all consistent in terms of using alternative samples, model identifications, and the measurement of product differentiation.

Table 9

Results Using Alternative Samples and Model Identifications

Variables	Employee<1000 & Age<30Q		Employee<500 & Age<20Q		Drop IPO Firms		RE Probit Model		RE Logit Model		Complementary log-log	
$ProductDiversification_{it}$	3.478 [1.255] (0.006)	2.671 [1.133] (0.018)	3.477 [1.257] (0.006)	2.671 [1.134] (0.018)	2.672 [0.867] (0.002)	2.056 [0.844] (0.015)	1.220 [0.334] (0.000)	0.899 [0.341] (0.008)	2.582 [0.767] (0.001)	1.922 [0.780] (0.014)	2.985 [0.962] (0.002)	1.989 [0.737] (0.007)
$ProductDiversification_{it}^2$	-3.219 [1.184] (0.007)	-2.970 [0.844] (0.000)	-3.217 [1.187] (0.007)	-2.970 [0.845] (0.000)	-2.812 [0.933] (0.003)	-2.353 [0.698] (0.001)	-1.384 [0.405] (0.001)	-1.193 [0.264] (0.000)	-2.843 [0.880] (0.001)	-2.391 [0.551] (0.000)	-3.156 [0.972] (0.001)	-2.354 [0.620] (0.000)
$ProductDifferentiation_{it}$	0.877 [0.610] (0.151)	0.289 [0.544] (0.595)	0.876 [0.610] (0.151)	0.289 [0.544] (0.596)	0.821 [0.423] (0.052)	0.449 [0.383] (0.241)	0.360 [0.156] (0.021)	0.153 [0.165] (0.354)	0.804 [0.383] (0.036)	0.341 [0.375] (0.362)	0.881 [0.403] (0.029)	0.348 [0.420] (0.408)
$ProductDiversification_{it}$ × $EntryTiming_i$	-1.239 [0.591] (0.036)		-1.239 [0.592] (0.036)		-1.249 [0.527] (0.018)		-0.532 [0.226] (0.019)		-1.080 [0.509] (0.034)		-1.683 [0.596] (0.003)	
$ProductDiversification_{it}^2$ × $EntryTiming_i$	1.724 [0.791] (0.029)		1.724 [0.792] (0.029)		1.834 [0.611] (0.003)		0.920 [0.307] (0.003)		1.888 [0.714] (0.008)		2.470 [0.785] (0.002)	
$ProductDifferentiation_{it}$ × $EntryTiming_i$		1.336 [0.468] (0.004)		1.336 [0.468] (0.004)		1.188 [0.311] (0.000)		0.675 [0.147] (0.000)		1.357 [0.307] (0.000)		1.565 [0.421] (0.000)
$EntryTiming_i$	-1.415 [0.933] (0.129)	-1.175 [0.787] (0.135)	-1.415 [0.933] (0.129)	-1.174 [0.787] (0.136)	-0.127 [0.791] (0.872)	0.395 [0.806] (0.624)	-0.870 [0.299] (0.004)	-0.713 [0.268] (0.008)	-1.756 [0.701] (0.012)	-1.374 [0.557] (0.014)	-2.065 [0.880] (0.019)	-1.437 [0.876] (0.101)

Table 9 (Continued)

Variables	Employee<1000 & Age<30Q		Employee<500 & Age<20Q		Drop IPO Firms		RE Probit Model		RE Logit Model		Complementary log-log	
HadoopFirm$_{it}$	-2.126 [0.845] (0.012)	-2.464 [0.925] (0.008)	-2.125 [0.847] (0.012)	-2.464 [0.926] (0.008)	-1.370 [0.648] (0.035)	-1.674 [0.702] (0.017)	-0.668 [0.295] (0.024)	-0.811 [0.324] (0.012)	-1.302 [0.619] (0.035)	-1.565 [0.645] (0.015)	-1.463 [0.751] (0.051)	-1.748 [0.783] (0.025)
Partner$_{it}$	-0.910 [1.188] (0.443)	-1.109 [1.251] (0.375)	-0.910 [1.188] (0.444)	-1.109 [1.252] (0.376)	-1.186 [0.868] (0.172)	-1.333 [0.869] (0.125)	-0.760 [0.386] (0.049)	-0.814 [0.412] (0.048)	-1.526 [0.904] (0.091)	-1.669 [0.956] (0.081)	-1.717 [0.900] (0.057)	-1.803 [0.900] (0.045)
Acquisition$_{it}$	2.209 [2.069] (0.286)	2.142 [1.819] (0.239)	2.207 [2.074] (0.287)	2.142 [1.821] (0.240)	1.507 [0.773] (0.051)	1.420 [0.716] (0.047)	1.274 [0.446] (0.004)	1.270 [0.441] (0.004)	2.540 [0.966] (0.009)	2.468 [0.971] (0.011)	2.309 [1.063] (0.030)	2.172 [1.035] (0.036)
FirmAge$_{it}$	-0.534 [0.311] (0.086)	-0.438 [0.294] (0.136)	-0.534 [0.311] (0.087)	-0.438 [0.294] (0.136)	-0.329 [0.276] (0.234)	-0.230 [0.255] (0.367)	-0.142 [0.120] (0.240)	-0.091 [0.119] (0.444)	-0.320 [0.277] (0.248)	-0.219 [0.264] (0.407)	-0.308 [0.297] (0.300)	-0.228 [0.308] (0.458)
FirmSize$_{it}$	-1.142 [0.668] (0.088)	-1.166 [0.520] (0.025)	-1.141 [0.670] (0.089)	-1.166 [0.521] (0.025)	-0.317 [0.247] (0.199)	-0.429 [0.241] (0.076)	-0.239 [0.117] (0.041)	-0.309 [0.123] (0.012)	-0.471 [0.272] (0.083)	-0.601 [0.277] (0.030)	-0.416 [0.301] (0.167)	-0.658 [0.298] (0.027)
Patent$_{it}$	2.927 [1.159] (0.012)	2.976 [1.197] (0.013)	2.927 [1.161] (0.012)	2.976 [1.198] (0.013)	2.208 [0.882] (0.012)	2.269 [0.842] (0.007)	1.021 [0.333] (0.002)	1.112 [0.354] (0.002)	2.138 [0.749] (0.004)	2.297 [0.786] (0.003)	2.190 [0.939] (0.020)	2.591 [0.962] (0.007)
Trademark$_{it}$	-3.144 [2.221] (0.157)	-3.004 [2.101] (0.153)	-3.143 [2.223] (0.157)	-3.004 [2.103] (0.153)	-1.209 [0.581] (0.037)	-1.078 [0.525] (0.040)	-0.506 [0.219] (0.021)	-0.482 [0.225] (0.032)	-1.124 [0.520] (0.031)	-1.035 [0.512] (0.043)	-1.198 [0.590] (0.043)	-0.938 [0.494] (0.058)

Table 9 (Continued)

Funding$_{it}$	-0.228 [0.361] (0.528)	-0.358 [0.375] (0.339)	-0.228 [0.361] (0.528)	-0.358 [0.375] (0.339)	-0.350 [0.199] (0.078)	-0.402 [0.194] (0.038)	-0.168 [0.082] (0.040)	-0.233 [0.091] (0.011)	-0.374 [0.183] (0.041)	-0.490 [0.196] (0.012)	-0.405 [0.229] (0.077)	-0.537 [0.244] (0.028)
EcosystemSize$_t$	2.824 [1.862] (0.129)	4.329 [2.329] (0.063)	2.824 [1.863] (0.130)	4.329 [2.331] (0.063)	-0.346 [1.081] (0.749)	-0.223 [1.410] (0.874)	1.156 [0.475] (0.015)	1.455 [0.557] (0.009)	2.558 [1.420] (0.072)	3.090 [1.608] (0.045)	3.018 [2.087] (0.148)	-0.537 [0.244] (0.028)
Wald χ^2	64.15 (0.000)	70.20 (0.000)	63.91 (0.000)	70.01 (0.000)	44.14 (0.000)	51.05 (0.000)	22.47 (0.096)	22.12 (0.076)	23.56 (0.073)	23.51 (0.053)	149.21 (0.000)	98.36 (0.000)
Total Firms	61	61	56	56	69	69	71	71	71	71	71	71
Succeed Firms	14	14	14	14	18	18	18	18	18	18	18	18
Observations	645	645	567	567	699	699	717	717	717	717	717	717

Notes. Robust standard errors clustered by firm are in brackets; *p*-values are in parentheses

Table 10

Results Using Alternative Measurement of Product Differentiation

Variables	Full Sample		Employees<1000 & Age<30Q		Employees<500 & Age<20Q		Drop IPO Firms		RE Probit Model		RE Logit Model		Complementary log-log	
$ProductDiversification_{it}$	2.223 [0.877] (0.011)	1.539 [0.843] (0.068)	2.901 [1.121] (0.010)	2.123 [1.022] (0.038)	2.900 [1.123] (0.010)	2.122 [1.023] (0.038)	2.222 [0.877] (0.011)	1.539 [0.843] (0.068)	1.126 [0.356] (0.002)	0.720 [0.363] (0.048)	2.405 [0.804] (0.003)	1.570 [0.777] (0.043)	2.590 [0.910] (0.004)	1.406 [0.756] (0.063)
$ProductDiversification_{it}^2$	-2.516 [0.847] (0.003)	-1.946 [0.742] (0.009)	-2.686 [0.857] (0.002)	-2.474 [0.628] (0.000)	-2.684 [0.859] (0.002)	-2.474 [0.630] (0.000)	-2.515 [0.848] (0.003)	-1.945 [0.742] (0.009)	-1.327 [0.395] (0.001)	-1.064 [0.388] (0.006)	-2.687 [0.816] (0.001)	-2.169 [0.650] (0.001)	-2.897 [0.894] (0.001)	-2.052 [0.843] (0.015)
$ProductDifferentiation_{it}$	0.544 [0.474] (0.252)	0.159 [0.503] (0.752)	0.521 [0.787] (0.508)	0.018 [0.779] (0.982)	0.521 [0.787] (0.508)	0.018 [0.779] (0.982)	0.544 [0.474] (0.252)	0.159 [0.503] (0.752)	0.298 [0.171] (0.081)	0.049 [0.228] (0.831)	0.684 [0.409] (0.094)	0.198 [0.451] (0.661)	0.695 [0.451] (0.123)	0.004 [0.477] (0.994)
$ProductDiversification_{it} \times EntryTiming_i$	-1.105 [0.524] (0.035)		-1.050 [0.505] (0.037)		-1.050 [0.505] (0.038)		-1.105 [0.524] (0.035)		-0.510 [0.229] (0.026)		-1.025 [0.525] (0.051)		-1.551 [0.601] (0.010)	
$ProductDiversification_{it}^2 \times EntryTiming_i$	1.641 [0.556] (0.003)		1.418 [0.623] (0.023)		1.417 [0.623] (0.023)		1.641 [0.556] (0.003)		0.890 [0.297] (0.003)		1.773 [0.664] (0.008)		2.310 [0.766] (0.003)	
$ProductDifferentiation_{it} \times EntryTiming_i$		0.996 [0.395] (0.012)		1.097 [0.423] (0.009)		1.097 [0.423] (0.009)		0.995 [0.394] (0.012)		0.578 [0.231] (0.012)		1.126 [0.404] (0.005)		1.581 [0.486] (0.001)
$EntryTiming_i$	-0.020 [0.804] (0.980)	0.502 [0.784] (0.522)	-1.417 [0.866] (0.102)	-0.980 [0.714] (0.170)	-1.416 [0.866] (0.102)	-0.980 [0.714] (0.170)	-0.020 [0.804] (0.980)	0.502 [0.784] (0.522)	-0.903 [0.293] (0.002)	-0.625 [0.292] (0.032)	-1.824 [0.703] (0.010)	-1.216 [0.571] (0.033)	-1.900 [0.874] (0.030)	-1.436 [0.777] (0.065)
$HadoopFirm_{it}$	-1.454 [0.632] (0.021)	-1.451 [0.679] (0.033)	-2.124 [0.779] (0.006)	-2.155 [0.811] (0.008)	-2.123 [0.781] (0.007)	-2.155 [0.812] (0.008)	-1.454 [0.633] (0.022)	-1.450 [0.679] (0.033)	-0.710 [0.278] (0.011)	-0.717 [0.370] (0.053)	-1.426 [0.572] (0.013)	-1.355 [0.622] (0.029)	-1.469 [0.688] (0.033)	-1.541 [0.636] (0.015)

Table 10 (Continued)

Variables	Full Sample		Employees<1000 & Age<30Q		Employees<500 & Age<20Q		Drop IPO Firms		RE Probit Model		RE Logit Model		Complementary log-log	
$Partner_{it}$	-1.206 [0.901] (0.181)	-1.312 [0.881] (0.136)	-0.811 [1.226] (0.508)	-0.997 [1.192] (0.403)	-0.811 [1.226] (0.508)	-0.997 [1.193] (0.403)	-1.204 [0.902] (0.182)	-1.311 [0.881] (0.137)	-0.803 [0.408] (0.049)	-0.864 [0.413] (0.037)	-1.654 [0.961] (0.085)	-1.779 [0.984] (0.070)	-1.770 [0.942] (0.060)	-1.900 [0.930] (0.041)
$Acquisition_{it}$	1.203 [0.695] (0.083)	1.218 [0.675] (0.071)	1.417 [1.648] (0.390)	1.927 [1.703] (0.258)	1.414 [1.654] (0.393)	1.926 [1.706] (0.259)	1.201 [0.696] (0.085)	1.217 [0.676] (0.072)	1.132 [0.404] (0.005)	1.227 [0.581] (0.035)	2.183 [0.864] (0.011)	2.378 [0.909] (0.009)	1.908 [0.972] (0.050)	1.996 [0.963] (0.038)
$FirmAge_{it}$	-0.385 [0.298] (0.196)	-0.307 [0.278] (0.271)	-0.632 [0.297] (0.034)	-0.468 [0.293] (0.111)	-0.632 [0.298] (0.034)	-0.468 [0.293] (0.111)	-0.385 [0.298] (0.196)	-0.307 [0.278] (0.271)	-0.171 [0.121] (0.158)	-0.124 [0.146] (0.397)	-0.388 [0.281] (0.167)	-0.285 [0.231] (0.217)	-0.372 [0.298] (0.212)	-0.322 [0.244] (0.187)
$FirmSize_{it}$	-0.263 [0.251] (0.293)	-0.388 [0.248] (0.117)	-1.023 [0.604] (0.090)	-1.181 [0.555] (0.033)	-1.022 [0.606] (0.092)	-1.181 [0.556] (0.034)	-0.263 [0.251] (0.294)	-0.388 [0.248] (0.118)	-0.201 [0.116] (0.083)	-0.277 [0.150] (0.065)	-0.401 [0.274] (0.143)	-0.552 [0.272] (0.042)	-0.338 [0.314] (0.281)	-0.569 [0.291] (0.050)
$Patent_{it}$	2.200 [0.872] (0.012)	2.349 [0.725] (0.001)	2.771 [1.061] (0.009)	2.885 [1.051] (0.006)	2.770 [1.063] (0.009)	2.884 [1.052] (0.006)	2.199 [0.873] (0.012)	2.348 [0.725] (0.001)	1.028 [0.345] (0.003)	1.233 [0.410] (0.003)	2.152 [0.781] (0.006)	2.435 [0.722] (0.001)	2.296 [0.975] (0.019)	2.896 [0.938] (0.002)
$Trademark_{it}$	-1.079 [0.560] (0.054)	-0.872 [0.543] (0.109)	-3.054 [2.076] (0.141)	-2.990 [1.988] (0.133)	-3.052 [2.077] (0.142)	-2.990 [1.990] (0.133)	-1.078 [0.561] (0.055)	-0.871 [0.543] (0.109)	-0.464 [0.212] (0.029)	-0.434 [0.278] (0.119)	-0.997 [0.498] (0.045)	-0.839 [0.511] (0.100)	-1.026 [0.546] (0.060)	-0.770 [0.517] (0.136)
$Funding_{it}$	-0.376 [0.205] (0.067)	-0.389 [0.189] (0.039)	-0.242 [0.424] (0.568)	-0.258 [0.442] (0.560)	-0.242 [0.424] (0.569)	-0.258 [0.442] (0.560)	-0.376 [0.205] (0.067)	-0.389 [0.189] (0.039)	-0.169 [0.080] (0.034)	-0.214 [0.109] (0.050)	-0.384 [0.183] (0.036)	-0.444 [0.177] (0.012)	-0.452 [0.230] (0.049)	-0.566 [0.235] (0.016)
$EcosystemSize_{t}$	-0.566 [1.260] (0.653)	-0.385 [1.322] (0.771)	3.216 [1.971] (0.103)	3.840 [2.464] (0.119)	3.216 [1.971] (0.103)	3.840 [2.465] (0.119)	-0.566 [1.260] (0.654)	-0.385 [1.322] (0.771)	1.224 [0.561] (0.020)	1.348 [0.548] (0.014)	2.714 [1.707] (0.112)	2.766 [1.382] (0.045)	2.610 [2.251] (0.246)	3.178 [1.784] (0.075)

Table 10 (Continued)

Variables	Full Sample		Employees<1000 & Age<30Q		Employees<500 & Age<20Q		Drop IPO Firms		RE Probit Model		RE Logit Model		Complementary log-log	
Wald χ^2	51.61 (0.000)	52.51 (0.000)	60.93 (0.000)	43.89 (0.000)	60.66 (0.000)	43.72 (0.000)	51.34 (0.000)	52.29 (0.000)	22.45 (0.097)	22.52 (0.069)	23.82 (0.068)	24.04 (0.045)	136.61 (0.000)	99.29 (0.000)
Total Firms	71	71	61	61	56	56	69	69	71	71	71	71	71	71
Succeed Firms	18	18	14	14	14	14	18	18	18	18	18	18	18	18
Observations	717	717	645	645	567	567	699	699	717	717	717	717	717	717

Notes. Robust standard errors clustered by firm are in brackets; *p*-values are in parentheses.

DISCUSSIONS AND CONCLUSION

This study examines complementors' product strategies (i.e., within-platform product diversification and product differentiation) as well as the moderating effects of entry timing on their likelihood of success in a platform ecosystem. By conducting a longitudinal analysis of the Hadoop ecosystem, we found that complementors' diversification across the focal platform's architectural layers has an inverted U-shaped impact on their success. Such a curvilinear influence of product diversification is stronger for earlier entrants than later entrants. In addition, increased product differentiation relative to their competitors is positively associated with later entrants' success but negatively influences the success of earlier entrants.

Theoretical Implications

This research offers theoretical implications for multiple streams of research. First, our theoretical development complements prior intra-platform competition literature by examining the role of complementors' product strategies, entry timing, and their interactions. Platforms provide technological resources and business opportunities for IT entrepreneurs. However, how complementors strategically utilize the open resources in their product strategies becomes more critical in hyper-turbulent platform ecosystems (Eaton et al., 2015). In addition, the use of platform resources increases complementors' dependencies on the focal platform. Complementors should not only manage their internal product designs but also need to co-evolve with the platform ecosystem and ensure compatibility with the dynamic platform architecture (Tiwana, 2015a). Although prior platform studies started to explore some aspects of complementors' product strategies such as architectural modularity (Tiwana, 2015a, 2015b) and product update (Foerderer et al., 2018), this research offers unique insights about complementors' product strategies relative to the platform's layered architectural resources and to other complementors in the ecosystem. In doing so, our examination of complementors' within-platform product diversification and product differentiation better captures the unique attributes of platform ecosystems—i.e., the interconnectivity between complementors and focal platform as well as the hyper-competitive nature of platform ecosystems.

In addition, previous platform studies examining complementors' product strategies implicitly assume that complementors' product design and strategies have a uniform impact on all complementors who may enter the ecosystem at different points in time. How complementors' product strategies influence their performance differently as the platform ecosystem evolves is under-studied. Recent platform literature calls for future research to incorporate the time dimension in platform theory building (Tiwana et al., 2010). This research responds to such a call by examining the moderating effect of entry timing. Drawing on prior entry timing studies in strategy research, we posit that the platform ecosystem has different resources availability, environmental dynamism, consumer preferences, and competition structure as it evolves over time. Complementors follow a sequential order to enter the ecosystem, and different entry timing may be associated with different business opportunities for resource and capability development, market structures, and relative power of other competitors in the ecosystem. Therefore, a more compelling explanation of complementors' success is that complementors entering at different times can adopt different competitive product strategies to achieve success. Our results indeed demonstrate that early entrants are better off by offering products similar to other ecosystem complementors' products but should be more careful about diversification across the focal platform's technological resources layers. In contrast, product diversification does not matter too much for late entrants but product differentiation does.

Furthermore, this study offers implications for product strategies and entry timing literature. First, the puzzle concerning the relationship between product diversification and firm performance is well documented in strategy literature (Barroso & Giarratana, 2013). This research builds on this stream of literature and further demonstrates several useful ways to address the inconsistencies, including the curvilinear approach, the simultaneous consideration of firms' various aspects of product strategies (i.e., internal diversification and external differentiation comparing to other competitors) as well as the examination of contingency factors such as entry timing. Our results demonstrate that the relationship between within-platform product diversification and complementors' success is curvilinear. Second, utilizing text mining on firms' product descriptions and content analysis, we develop robust measure of firms' product differentiation and offer empirical evidence of how complementors' product differentiation affects their success in a platform ecosystem. Third, this research responds to the call for research on coupling entry timing literature with the technology market research (Fosfuri et al., 2013). We also confirm that instead of examining entry timing alone, simultaneous examinations of when (i.e., entry timing) and how (i.e., product strategies) the firm enters the ecosystem have the potential to offer more holistic theoretical insights.

Managerial Implications

Our results have important managerial implications for platform complementors about how to design products at different times of entry. First, to strategically exploit the focal platform's technological resources and customer base, complementors in general should cover a threshold level of the platform's technological layers. For example, in our empirical context of the Hadoop ecosystem, complementors are advised to develop products based on three or four technological layers out of the eight available layers in total. With the threshold level of product diversification across the platform architectural components, complementors can balance the benefits—such as scope economics, demand synergy, and generative innovation capabilities—

and the drawbacks of costs on coordination, control, and cognitive management, etc. In addition, given the simultaneously existence of high uncertainty and business opportunities in the early-stage platform ecosystem, early complementors should pay more attention to such product diversification strategies. However, for late entrants, product diversification across platform architecture becomes less important because of the maturity of the platform ecosystem, the low environmental uncertainty, and less opportunities of developing dominant product design and taking central positions.

What plays a more important role for late entrants is the level of product differentiation. Given the characteristics of later-stage platform ecosystem environments, late entrants are advised to differentiate their positioning in the platform layers. In other words, late entrants still can have superior performance if they strategically find new market niches and design products that use different configurations of the focal platform's technological layers. In contrast, earlier entrants are suggested to converge to the norm of how other complementors position their products in the layers of the focal platform architecture. By offering products that use a similar set of the focal platform's technological layers, earlier entrants can collaboratively reduce market uncertainty and develop the dominant design. Overall, our results provide practical insights into the product diversification and product differentiation strategies for complementors that enter into a platform ecosystem at different times.

Limitations and Future Research

Although this study provides insights for both academia and practitioners, we discuss some limitations that offer directions for future research. Future studies could combine archival data analysis with other methodologies such as survey and qualitative approach to overcome the limitation of data availability. Furthermore, although exit through acquisition is faster and more flexible for newer entrepreneurs than IPO (Hallen et al., 2014; Petkova et al., 2014), some entrepreneurs may aim at becoming an ecosystem leader and exit through issuing an IPO. Future research can use the likelihood of issuing an IPO as the dependent variable and use more mature platform ecosystems where more IPO events happened as the study context. Studies would also be valuable in suggesting different strategies for platform complementors that aim to exit through IPO versus acquisition. Some other unique dependent variables in the platform ecosystem context such as within- and across-ecosystem product innovation, evolutionary trajectories, and alliance formation could be of interest. Finally, future research can further investigate other important aspects of complementors' product strategies, such as product architectural design (e.g., technical components configurations, loose coupling, and interface conformance) and product portfolio attributes (e.g., volume, complexity, and integration).

ESSAY 3. CIRCUMNAVIGATING OVER TIME: COEVOLUTION OF COMPLEMENTORS' STRATEGIES AND PRODUCTS IN A DIGITAL PLATFORM ECOSYSTEM

INTRODUCTION

When competing in digital platform ecosystems it might be easy for managers to confine their strategic decision-making parameters to the here and now—one-time, linear, cause and effect relationships between strategies and performance outcomes. However, digital platforms are tightly woven and networked supra-organizations with the potential of complementors' strategic actions reverberating throughout the network affecting outcomes and in turn these outcomes influencing future strategic actions. Meanwhile a firm's positioning in the ecosystem can moderate the effects of these circuitous impacts. Understanding this complex competition within digital platform ecosystems such as the Android app ecosystem, the SAP software ecosystem, and the Hadoop ecosystem has emerged as a critical strategic issue for software companies (Ceccagnoli et al., 2012; Tiwana et al., 2010).

A digital platform refers to a collection of technologies with dedicated functionalities that act as a base upon which other applications, processes, and technologies are developed; existing and new players may leverage and extend this base (Tiwana et al., 2010). The add-on applications, processes, and technologies that interact with the focal platform are regarded as the platform's modules. A digital platform ecosystem includes the platform, its modules, the platform owner(s), and the complementors (i.e., module providers) delivering products and services. Digital platform ecosystems are rapidly evolving (Tiwana et al., 2010; Wareham et al., 2014). This is due to such factors as frequent adjustment of platform owner's strategies, updates to the platform architecture and complementors' products, low entry barriers in the ecosystem, and intense competitions and innovation efforts by complementors.

From a complex ecosystem perspective (Tanriverdi, Rai, & Venkatraman, 2010), it is crucial to understand such dependent variables as product evolution, derivative mutation, durability, and survival that supplement classical notions of performance with the temporal aspects (Tiwana et al., 2010). As Tiwana et al. (2010, *p*. 682) point out, “the temporal distinctions can be a useful starting point for bringing the time dimension into theory development, using either the platform’s ecosystem or the module as the unit of analysis.” Extending prior platform literature (e.g., Foerderer et al., 2018; Tiwana et al., 2010; Tiwana, 2015a), we examine one of such long-term evolutionary variables, product evolution, that we define as the rate at which a platform complementor releases updates of its existing products with new features and/or launches new platform-related products. In addition, the complex and dynamic nature of platform ecosystem triggers the faster adaptation of complementors’ competitive strategies and the coevolution of their strategies and evolutionary outcome. While most prior platform studies have focused on the direct impacts of complementors’ strategies, we examine the *mutual* influence between the complementor’s strategies and product evolution in the ecosystem, namely how the complementor’s strategies impact product evolution and how product evolution shapes subsequent strategies.

Complementors’ strategic decisions that drive the dynamic evolution of the platform ecosystem are: the technical product design and its updates (Tiwana et al., 2010; Foerderer et al., 2018) and the formation of inter-firm relationships to pool resources, develop new products and services, reduce risk, and so on (Basole, 2009; van Angeren et al., 2016). A good product strategy helps firms in an ecosystem leverage network effects, attract more end users, and survive in a hyper-competitive and dynamic environment (Sorenson, 2000). However, an important aspect of the complementor’s product strategy, namely its strategy concerning the coverage of layers of a platform's layered modular architecture, has not been examined in existing research. In addition, while prior literature has shown the prevalence and fast-evolving nature of inter-firm relationships among complementors in a platform ecosystem (Basole & Karla, 2011; van Angeren et al., 2016), the consequences of such inter-firm strategies in the digital platform context are not yet well understood. Consequently, our research focuses on complementors' product architecture design decisions relative to the platform's layered modular architecture as well as decisions regarding inter-firm alliances. We define a platform complementor's *technological architecture coverage* as the extent to which the complementor's product covers the heterogeneous layers of the focal platform architecture. In terms of alliance-related decisions, we focus on the extent of exploration in the complementor's alliance portfolio.

Furthermore, platform complementors' strategies coevolve with the environment (El Sawy et al., 2010). Having identified environmental dynamics as a core element of the platform evolution research framework, Tiwana et al. (2010) call for research on how ecosystem's environments influence the evolution of the ecosystem and how the environment may interact with endogenous platform attributes. To address this call, we examine how network density, a key environmental characteristic of the ecosystem, impacts the interplay between the complementor's strategies (i.e., technological architecture coverage and alliance exploration) and its product evolution.

We study the coevolution of complementors' strategies, product evolution, and ecosystem environment in the Hadoop ecosystem, which is based on the Hadoop open source software platform for reliable, scalable, and distributed computing (Mone, 2013). Hadoop is one of the most widely adopted platforms for big data analytics (Tambe, 2014). Many Hadoop complementors such as Hortonworks, Cloudera, and MapR Technologies have achieved success in a short time while others such as Hadoop Nation and Malhar have gone out of business. The Hadoop platform's open nature reduces barriers to entry, increases environmental turbulence, and speeds up coevolution between complementors and the ecosystem environment (de Reuver, Sørensen, & Basole, 2018), creating an excellent laboratory for investigating evolutionary intra-platform competition. We analyze a quarterly dataset of 112 firms that participated in the Hadoop ecosystem from the second quarter of 2009 to the first quarter of 2016.

Our empirical estimation of a panel vector autoregression (PVAR) model demonstrates that when platform complementors increase their architectural layers and more freely explore alliance formation, product evolution rates improve in the subsequent period. In turn, complementors who evolve their products at a faster rate are less likely to offer a wider range of architectural layers but more likely to explore new alliance partners in the subsequent period. Our results also confirm the moderating effects of network density on the mutual influences of complementors' strategies (i.e., technological architecture coverage and alliance exploration) and product evolution. Specifically, the effects of complementors' strategies on their product evolution will be weaker in a denser network while network density amplifies the impact of complementors' product evolution on their future strategies.

Our research theoretically contributes to an understanding of intra-platform competition and platform ecosystem evolution by delineating the mutual influence between platform complementors' strategies and their product evolution as well as the moderating role of the co-created network environment. Our findings also provide practical implications regarding how platform complementors need to circumspectly manage their product and inter-firm strategies over time by recognizing the coevolution between strategies and evolution.

LITERATURE REVIEW AND THEORETICAL BACKGROUND

Complementor Strategies in a Digital Platform Ecosystem

Many studies have focused on complementors in digital platform ecosystems (see Appendix 8 for a summary of representative studies). Such research has explored the determinants of complementors' decision to join (Huang et al., 2013) and leave a platform ecosystem (Tiwana, 2015b), benefits of participating in a software platform ecosystem (Ceccagnoli et al., 2012), reactions to the platform owner's entry (Foerderer et al., 2018), their entrepreneurial activities (Qiu et al., 2017), and determinants of their performance and product evolution (Kapoor & Agarwal, 2017; Lee & Raghu, 2014; Tiwana, 2015a). Studies have found that the complementor's product evolution and performance may be influenced by its ecosystem-specific experience (Kapoor & Agarwal, 2017), product characteristics such as product modularization (Tiwana, 2015a), product portfolio management (Lee & Raghu, 2014), and product diversification (Tanriverdi & Lee, 2008), as well as platform-related factors such as generational transitions initiated by the platform owner (Kapoor & Agarwal, 2017) and platform owner's input control (Tiwana, 2015a).

While a good product strategy helps firms leverage network effects, attract more users, and survive in a hyper-competitive and dynamic environment (Sorenson, 2000), in the existing digital platform research, few researchers have tackled the complementor's product strategy regarding the platform's layered modular architecture. In addition, prior digital platform research has confirmed that complementors "actively collaborate and co-create through interfirm relationships" in commercial platform ecosystems such as Microsoft Office365 and Google Chrome (van Angeren et al., 2016, *p*. 19) and form a complex inter-firm network that evolves over time (Basole, 2009). However, the formulation and consequences of such inter-firm strategies over time in the digital platform context has yet to be fully understood. Thus, we focus on complementors' strategies for technological architecture coverage (as an important type of product strategy) and inter-firm relationships in the digital platform ecosystem.

Complementors' Technological Architecture Coverage as a Strategy. A platform's technological architecture, the arrangement of interlinking different subsystems and components (Kruchten, Obbink, & Stafford, 2006), not only represents technical decisions but also has strategic consequences within platform evolution (Agarwal & Tiwana, 2015). Many digital platforms, by their nature, have layered modular architecture, allowing their complementors to produce generative innovations by recombining heterogeneous components (Yoo et al., 2010). For instance, in the Hadoop ecosystem commercial firms develop their solutions by packaging layers of Hadoop's technological components ranging from data storage, data processing, data access, data management, and security to development tools. Android, a commonly used mobile application platform, has its major components—power management, Linux kernel, hardware abstraction layer (HAL), native C/C++ libraries, Android runtime, Java API framework, and system apps—in a layered structure[1]. Therefore, considering layered modular architecture of digital platforms (Yoo et al., 2010) and prior strategy and marketing literature about firms' product strategies including product scope, diversification, and variety (Cottrell & Nault, 2004; Sorescu, Chandy, & Prabhu, 2003; Su & Tsang, 2015; Tanriverdi & Lee, 2008), we define a platform complementor's *technological architecture coverage* as the extent to which the complementor's product covers the heterogeneous layers of the focal platform architecture. Technological architecture coverage captures the vertical depth of the complementor's products in terms of the focal platform's architectural components; it also reflects the extent to which the complementor's product design is interconnected with the focal platform's boundary resources.

[1] For more details about the Android platform architecture, please refer to https://developer.android.com/guide/platform/.

Prior marketing literature has examined product scope as an important aspect of product strategies. Product scope is defined as the degree of depth and breadth a firm's product portfolio has within an industry (Sorescu et al., 2003). Firms have a greater vertical scope when they produce more of their inputs in the supply chain and a broader horizontal scope when they sell more product lines. Various performance implications of firms' product scope have been examined widely. For example, firms with wider product scope obtain higher value from radical innovations (Sorescu et al., 2003) and amplify the effects of salesperson solution involvement on their sales (Panagopoulos, Rapp, & Ogilvie, 2017).

Similarly, strategy research has investigated product diversification, the extent to which firms operate in more than one product market or industry, including both "related diversification" within the same industry group and "unrelated diversification" across industry groups (Palepu, 1985). Given the debate over the direct effects of product diversification on firms' financial performance, prior strategy literature has examined the contingent factors that moderate the effects of product diversification from the perspectives of a firm's primary stakeholders—i.e., the top management team, board of directors, employees, suppliers, customers, and shareholders—and secondary stakeholders—i.e., various non-governmental and non-profit organizations (e.g., see: Su & Tsang, 2015 for a review of these contingent factors). Prior strategy literature also has conceptualized product variety, the extent to which a firm integrates different application categories in its products and offers them in a product family or a platform (Cottrell & Nault, 2004). Due to economy of scope, product variety improves firm performance such as operational efficiency (Brahm, Tarzijan, & Singer, 2017) and survivability (Cottrell & Nault, 2004). However, product variety may increase sourcing complexity, coordination costs, and routine execution costs, thus negatively influencing firm performance (Brahm et al., 2017; Zhou & Wan, 2017).

In sum, strategy and marketing research acknowledges that a resource-based view and transaction costs economics are important in explaining a firm's strategic product decisions—e.g., diversification, scope, or variety (Su & Tsang, 2015; Wernerfelt, 2005; Zhou & Wan, 2017). Specifically, a firm's resources and capabilities positively affect its related diversification (Diestre & Rajagopalan, 2011; Wernerfelt, 2005) while economics of scope and economics of integration predict its unrelated diversification (Jones & Hill, 1988). However, internal coordination costs as well as complexity of the external social-political and socio-technical environment caused by product diversification inhibit diversification (Brahm et al., 2017; Su & Tsang, 2015). Firms must continually strategically select and adjust their level of product scope/diversification/variety based on internal and external environments.

Considering the existence of network externality in platform ecosystems, Tanriverdi & Lee (2008) have found that complementors' related diversification across operating system platforms and related diversification across software product-markets complement each other in improving firm performance (e.g., sales and market share). Tiwana (2015a; 2015b) focuses on the extent to which a complementor's product is loosely coupled with the platform and interacts with the platform through standardized interfaces. Such product modularization increases complementors' product evolution capabilities (Tiwana, 2015a) and reduces their coordination costs (Tiwana, 2015b). Recognizing the importance of the economy of scope, Lee & Raghu (2014) have investigated the positive effects of platform complementors' product variety (i.e., the number of apps) and product diversification across categories (i.e., the number of categories) on their superior performance (i.e., on the Top charts in terms of product sales). Unlike the aforementioned studies of product strategies in platform ecosystems, we focus on complementors' product coverage decisions across layers of the focal platform's modular architecture in order to capture a critical characteristic of digital platforms—layered modular architecture.

Complementors' Inter-Firm Relationship Strategies. Prior platform research has emphasized the relationships among firms in the ecosystem. For example, van Angeren et al. (2016) examine relationships among app development firms in commercial platform ecosystems including Google Apps, Google Chrome, Microsoft Office365, and Internet Explorer ecosystems. By analyzing cross-sectional inter-firm network data, the study reveals that complementors in platform ecosystems actively engage in inter-firm relationships. The prevalence of such relationships and the continuously evolving structure of the inter-firm network are also found in mobile apps platform ecosystems (Basole & Karla, 2011).

Alliance strategy refers to the goal-oriented development and configuration of a portfolio of inter-firm relationships that aims to create or maintain competitive advantages (Hoffmann, 2007). Alliance formation is especially prevalent in domains featuring industry standards and network effects (Rosenkopf & Padula, 2008). Prior strategy literature has acknowledged the tradeoff between exploitation and exploration in firms' alliance formation[2] (Lin, Peng, Yang, & Sun, 2009; Lin et al., 2007; Raisch, Birkinshaw, Probst, & Tushman, 2009). Forming exploratory alliances can enhance the firm's capabilities to discover new opportunities, adapt to

[2] As summarized by Lavie & Rosenkopf (2006), there are three main dimensions to distinguish exploitive and exploratory alliances: *functional* (i.e., the content or value chain functions of alliances), *attribute-based* (i.e., the inter-temporal variance in organizational characteristics), and *structural* (i.e., the network position of alliance partners). In this study, we concentrate on the structural dimensions of firms' alliance strategies. In digital platform ecosystems the variance of firms' alliance strategies in terms of functional dimensions are relatively low and change marginally over time. Also, the complementors of a digital platform ecosystem have many similar attributes, as they share the same focal platform's opened technological components. Hence, the attribute-based dimensions do not exhibit satisfactory variance among firms to provide an ideal research perspective. Compared with the other two dimensions, the structural dimension perspective incorporates external social capital factors that are directly associated with firm performance (Baum et al., 2000). In addition, in a platform ecosystem a firm's position in the network is relative to others and changes over time; the structural dimensions of strategic alliances directly capture the dynamics of the inter-firm network (Lin et al., 2007).

environmental changes, and develop new competitive advantages (Lin et al., 2007; March, 1991). Alternatively, exploitative alliances can help the firm strengthen existing capabilities, enhance efficiency, maintain stability, and join current competencies across organizational boundaries (Rothaermel & Deeds, 2004).

Prior strategy literature has identified effects of exploration versus exploitation in different contexts (Aggarwal, Siggelkow, & Singh, 2011; Lin, Peng, et al., 2009). For example, in the biotechnology industry, firms' alliance exploitation positively affects R&D project performance while exploration has a negative influence on R&D project performance (Hoang & Rothaermel, 2010). Explorative strategies positively affect upstream performance but negatively influence downstream performance whereas exploitative strategies benefit downstream but harm upstream performance (Nielsena & Gudergan, 2012). Moreover, firms who strategically balance alliance exploration and exploitation across different organizational activities or modes tend to achieve better performance. For instance, forming R&D alliances while exploiting existing partners or engaging in marketing and production alliances while exploring new partners improves firms' market value and profits (Lavie, Kang, & Rosenkopf, 2011).

Furthermore, past research has examined factors influencing alliance formation decisions in terms of exploration and exploitation. These factors may include the firm's internal resources (Park, Chen, & Gallagher, 2002), absorptive capacity (Lavie & Rosenkopf, 2006), organizational inertia (Lavie & Rosenkopf, 2006), external market demand (Park et al., 2002), and method of financing (Galloway, Miller, Sahaym, & Arthurs, 2017). For example, firms with fewer resources are more likely to form exploitative alliances than explorative alliances when there is a positive trend in market demand (Park et al., 2002). In addition, corporate venture-backed firms are more likely to form explorative alliances; whereas, firms backed by venture capitalists prefer exploitative alliances (Galloway et al., 2017). Furthermore, firms' alliance formation exhibits path dependencies that reinforce exploration or exploitation with respect to the value chain function of alliance partners, the attributes of partners, and partners' network positions (Lavie & Rosenkopf, 2006).

Mutual Influence between Complementor Strategies and Product Evolution in a Dynamic Digital Platform Ecosystem

Digital platform ecosystems are dynamic and evolve over time (Tiwana et al., 2010, Wareham et al., 2014), as evidenced by and rooted to the following aspects. First, platform owners often initiate generational transitions by updating the platform's architectural design to compete over time (Kapoor & Agarwal, 2017, Tiwanan et al., 2010). The archiectural change of the platform shifts the nature of the platform's interactions with its complementors and modifies the fitness landscape of the complementors (Kapoor & Agarwal, 2017). A well-known example is that some music apps stopped working when Apple introduced its iOS 6. To avoid this problem, complementors need to update their products frequently to ensure compatibility with the updated platform architecture. For example, the SDK of the iOS ecosystem has gone through a complex process of tuning where the platform and third-party developers have accommodated and resisted the change of SDKs over time (Eaton et al., 2015). Overall, a digital platform ecosystem often is considered a socio-technical ecosystem consisting of diverse actors who develop their own technical artifacts and meanwhile interact with each other in shaping the technical resources of the focal platform (Eaton et al., 2015).

Second, digital platforms provide a marketplace with low entry barriers, as evidenced by the millions of third-party apps in Android and iOS that increase market competition and require app developers to evolve to survive (Tiwana, 2015a). Such low entry barriers not only provide opportunities for new entrants (Ceccagnoli et al., 2012) but also increase complementors' mortality rates (Tiwana, 2015b). For example, around 41 percent of apps on the Android platform and more than 60 percent of apps in iOS and Windows were dead by 2013, according to StarDust[3], a mobile testing service provider. Furthermore, Kapoor & Agarwal (2017) have found that app developers in the iOS and Android ecosystem sustained their superior performance for only six months on average during the two-year period from January 2012 to January 2014. More importantly, once exiting the top performance list in a given platform ecosystem, the app developer was unlikely to regain its superior performance.

Third, in a dynamic digital platform ecosystem, complementors actively respond to competitors' threats by enhancing their innovation output, leading to supply-side competitive dynamics or "Red Queen" effect (Foerderer et al., 2018). When all complementors strive for superior performance by engaging in innovation (e.g., product evolution), they end up racing to achieve their goals as quickly as possible (Agarwal & Tiwana, 2015). At times Intel has deliberately stimulated complementors' innovative activities by launching similar products and thereby raising the threat level to competitors (Gawer & Henderson, 2007). Similar results concerning the positive effect of platform owner's entry on complementors' engagement in innovation are found in the Android platform ecosystem (Foerderer et al., 2018).

Fourth, the openness characteristic of some platforms also makes it easier for competitors to copy, reverse engineer, and exploit the openly available technical resources (Boudreau, 2010). Platform complementors or external competitors may strategically exploit the open platform's resources and create a new platform that directly competes with the focal platform while maintaining interoperability (Karhu, Gustafsson, & Lyytinen, 2018). For example, the Android platform has experienced several forking instances such as the Amazon Fire OS platform, the

[3] https://venturebeat.com/2013/08/26/700k-of-the-1-2m-apps-available-for-iphone-android-and-windows-are-zombies/.

Nokia X platform, and the Xiaomi MIUI platform. In the Hadoop ecosystem, several commercial vendors such as Hortonworks, Cloudera, and MapR Technologies have packaged Hadoop open source projects to develop their own distributions of the platform. Platform owners may also envelop their platforms in a market to enter another platform market and offer a multi-platform bundle (Eisenmann et al., 2011). Apple's iPhone platform, for example, has enveloped to several different platforms in other markets such as Amazon's Kindle and Nintendo's Gameboy. The forking and envelopment of platforms further complicates competition among complementors, increases ecosystem turbulence, and fosters ecosystem evolution over time.

Hence, from the complex ecosystem perspective (Tanriverdi et al., 2010), it is important to examine the temporal dynamics of *mutual influence* between the complementor's strategies and its product evolution. However, prior platform studies have focused primarily on the influence of the complementor's strategies on its performance. Therefore, to address this gap, we work to reveal how the platform complementor's strategies impact its product evolution and how its product evolution, in turn, help shape subsequent strategies.

We focus on the complementor's product evolution based on prior platform research (Agarwal & Tiwana, 2015; Foerderer et al., 2018; Tiwana, 2015a) and natural selection theory (Darwin, 1895; Simon, 2002). Theoretically, a subsystem that adapts faster increases its odds of survival by enhancing its fitness with its environment (Simon, 2002). Due to diverse and uncertain users' needs associated with emerging technologies (Cottrell & Nault, 2004), firms often need to infer and discover such needs through experimentation with their products and services. During the trial-and-error process, firms receive feedback information from various sources. Therefore, firms with faster product evolution typically are better able to incorporate the new information into their subsequent product development and enhancement efforts (Tiwana, 2015a). In addition, changes made by a firm in its product may cater not only to the unmet needs of existing users but also trigger new needs for potential users or even cause a shift in users' demands. Furthermore, the digital platform gradually evolves when new features and bug fixes are added (Tiwana et al., 2010). Such technical updates to the platform itself may compel the complementor to update its own complementary products to meet the platform standard. In addition, digital platform ecosystems often have low entry barriers (Ceccagnoli et al., 2012; Tiwana et al., 2010). Platform complementors often are threatened by new entrants with innovative niche products. By keeping their core products at the technological frontier and attracting new users, complementors can accumulate their technical know-how, increase the barriers for new entrants, and enjoy a greater market share (Giarratana & Fosfuri, 2007). Empirically, the positive link between product evolution and market performance has also been validated in prior research (Tiwana, 2015a).

Network Density and Mutual Influence between Complementor Strategies and Product Evolution in a Dynamic Digital Platform Ecosystem

Firms do not make key decisions in a vacuum. Instead, a firm must consider the context in which it interacts with other firms (Echols & Tsai, 2005). Extensive research has identified the importance of social networks in determining firms' actions and the effectiveness of these actions (Coleman, 1990; Granovetter, 1985). Furthermore, prior digital platform literature has acknowledged that the endogenous choices of the entities in the platform ecosystem coevolve with the ecosystem environment, influencing the evolution of the ecosystem (Tiwana et al., 2010). Hence, it is important to examine the coevolution of participating firms' endogenous choices and the environmental dynamics in the ecosystem at both the ecosystem level and the module level (Tiwana et al., 2010). Nonetheless, the mutual influence between strategies and evolution, which are embedded in the dynamic network of the ecosystem, has not received much attention in existing digital platform research. We do not yet understand the ecosystem environment's role in shaping the interplay between complementors' strategies and product evolution.

One network characteristic that marketing and strategy research has found to have both a direct (Swaminathan & Moorman, 2009) and a moderating impact (Thomaz & Swaminathan, 2015) on firm performance is network density. Network density refers to the degree of inter-connectedness among actors in a network (Coleman, 1988) or the number of actual connections as a proportion of possible connections in the network (Swaminathan & Moorman, 2009). It influences the overall speed of information delivery, trustworthiness between actors, and the depth of resources flow (Schilling & Phelps, 2007). In a dense network, information and resources are delivered quickly, reliably, and accurately since there are more direct relationships among partners (Schilling & Phelps, 2007). The delivered information not only decreases uncertainty about the environment but also enhances the firm's understanding of technological trends, customer demands, and disruptive forces in the environment (Chi, Ravichandran, & Andrevski, 2010). From a cognitive perspective, dense networks foster cooperation, shared understanding, and trust among network members (Inkpen & Tsang, 2005; Reagans & McEvily, 2003). Given that firms' opportunistic behaviors would be discouraged in a dense network, alliance partners are more likely to share implicit knowledge and resources (Chi et al., 2010; Hansen, Mors, & Løvås, 2005; Reagans & McEvily, 2003).

Prior strategy literature has also conceptualized network density as an environmental indicator and found its moderating role in the effectiveness of firm strategies. For example, since high network density facilitates information sharing and improves firms' abilities to acquire external information and resources, network density amplifies the effect of inter-firm ties on firm performance such as innovation outcome (Soh, 2010) and R&D capability (Mahmood, Zhu, & Zajac, 2011). A dense network also promotes trust and reciprocity among members in the network, amplifying the positive effect and mitigating the potential negative influence of network diversity on firms' exploratory innovation (Phelps, 2010). Furthermore, network density moderates the impact on the firm's idiosyncratic risk after an alliance announcement (Thomaz & Swaminathan, 2015).

Therefore, in this research, we examine how network density, as a network characteristic co-created by platform complementors, influences the mutual impact between complementors' strategies and product evolution in the platform ecosystem.

RESEARCH MODEL AND HYPOTHESES

Evolutionary theories provide a fundamental lens for understanding competition among platform complementors (Tiwana, 2015a; Tiwana et al., 2010). "Traditional" evolutionary theories argue that the competitive survival of entities in an ecosystem is based on natural selection. Entities that are better suited to the ecosystem environment are more likely to survive in evolutionary competition (Darwin, 1895), and variations are viewed as a random chance or blind emergence (Van de Ven & Poole, 1995). The purposive behaviors and cognitions specific to humans in social ecosystems are not significantly considered under traditional evolutionary theories, which are primarily modeled after biological ecosystems.

Compared with many biological ecosystems, complementors in a digital platform ecosystem have two distinct features: (1) strategic human agency and (2) dynamic ecosystem boundaries. First, platform complementors are subject to strategic human agency. Seeking survival in hyper-competitive environments, complementors develop complex strategies to modify the natural selection process (El Sawy et al., 2010). Given that complementors depend upon the platform owner, their first strategic choice is how to develop their product architecture independently and make it relevant to the focal platform. For example, based on modular systems theory, Tiwana (2015a) theorized that a module's technical architecture modularization—the extent to which a platform module interacts through standardized interfaces and is loosely coupled with the focal digital platform—affects its adaptive capabilities in the environment. In addition, platform complementors face strategic decisions about inter-firm relationships with other complementors because platform ecosystems "involve heterogeneous actors who struggle with their own technology artifacts, while at the same time, engaging with each other in shaping the boundary resources" (Eaton et al., 2015, *p*. 221). Second, complementors' behaviors such as pursuing a technical architecture and establishing inter-firm relationships can change platform structure (Parker et al., 2017), meanwhile, platform structural factors (e.g., ecosystem complexity, governance policy, and platform transition) influence complementors' performance in ecosystems (Kapoor & Agarwal, 2017; Tiwana, 2015a, 2015b).

Therefore, to understand evolutionary intra-platform competition, it is crucial to theorize a framework that simultaneously considers the roles of complementors' strategies (relative to platform's layered modular architecture and relative to other complementors) and unintentional ecosystem environmental restructuring as well as the two-way impacts between strategies and the environment co-created (Nan & Tanriverdi, 2017). Figure 4 presents our research model.

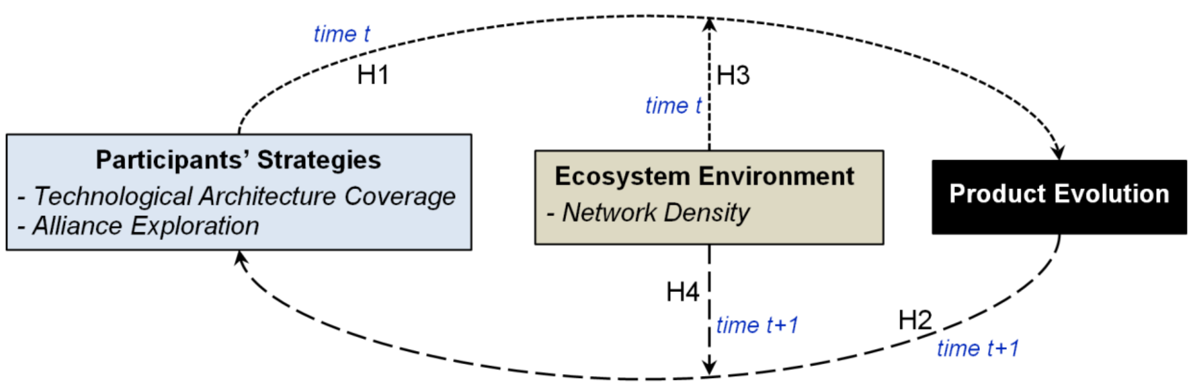


Figure 4. The Research Model (Essay 3)

According to generative views (Yoo et al., 2010), systems or subsystems with more diversity are expected to evolve faster to achieve a better fit with their environment because they need less time to recombine and have more time for experimentation with new products. In a platform ecosystem, if a complementor covers a wider range of platform components, it can acquire more experience and tacit knowledge in the product development process. Furthermore, complementors with a wider scope of products typically have more opportunities and are better able to update or recombine their existing offerings when customer preferences change. Also, once the focal platform updates the design or specifications of its technological components, complementors are expected to update their products to maintain compatibility with the platform and to comply with the governance policy. Complementors with more diverse product scope, therefore, enjoy a higher probability of adapting their products to the focal digital platform. Furthermore, in hyper-competitive digital platform ecosystems, complementors act aggressively to innovate (Cottrell & Nault, 2004) and strive to stay ahead of the competition by updating their products quickly. According to evolutionary theories and the generative view, if complementors have a more diverse set of products based on the focal platform's components, they are more likely to undergo innovative experimentation. Therefore, we hypothesize that

Hypothesis 1A (H1A). *In a digital platform ecosystem, complementors whose products cover a more diverse set of the focal platform's technological components will experience product evolution at a faster rate in the subsequent period than other complementors.*

Although both exploration and exploitation in alliance formation have distinct advantages and constraints, we argue that, in digital platform ecosystems, alliance exploration may be more critical for complementors' product evolution than alliance exploitation. First, in the fast-changing platform ecosystem environment, platform architecture, strategies of platform owner and complementors, and market demands evolve constantly (Tiwana, 2015a, 2015b). If ecosystem complementors keep exploring new connections with a diverse set of firms, they can gain access to more information about the changes related to the platform, complementors, and customers (Chi et al., 2010; Goerzen & Beamish, 2005). Second, firms' resources and capabilities become short-term in a turbulent environment. If firms strategically explore new connections in their network, their access to and acquisition of information and resources are more efficient because the uncertainty of partners' information accuracy and the costs of developing and maintaining the relationships can be reduced.

By acquiring valuable information and resources from partners, a firm has more opportunities and capabilities to update its products. Advantages accrue from innovating, recombining products/services in response to changes in consumer preferences, and keeping up with the evolution of both the focal platform and other firms in the ecosystem (Tiwana et al., 2010). Therefore, we hypothesize that

Hypothesis 1B (H1B). *In a digital platform ecosystem, complementors focusing on explorative formation of alliances with new partners will likely update their products at a faster rate in the subsequent period than others focusing on exploitative formation of alliances with existing partners.*

Furthermore, participating firms' product evolution likely will influence their strategic product-related decisions. Externally, through more frequent updates to their existing products and development of new innovative products, they are better able to garner a market response, feel the pulse of customers, and sense changes in customer demands. Consequently, they can identify new market opportunities more easily. Internally, they can gain more experience in product research and development, allowing them to become more efficient and effective in managing product development process. Through faster product evolution, these firms also can develop in-depth technical design knowledge about the focal platform and its components, increasing their efficiencies in coordinating a wider range of technological components and reducing the uncertainty in expanding their existing technological components. In addition, the hyper-turbulent nature of digital platform ecosystems fosters Red Queen competition where a firm evolves "progressively faster just to keep up with its cohort of rivals" (Agarwal & Tiwana, 2015, *p*. 473). Firms with faster product evolution are more likely to understand this context and engage in progressively competitive actions. In summary, complementor firms who evolve their products at a faster rate are more likely to achieve a good fit with the focal platform's technological resources, sense market opportunities brought by changing customer demands and technologies, and engage in more effective product development efforts. Hence, they tend to be better positioned to offer a more diverse set of platform components. We thus hypothesize that

Hypothesis 2A (H2A). *In a digital platform ecosystem, complementors with faster product evolution are more likely to have products covering a more diverse set of the focal platform's technological components in the subsequent period.*

We next study how complementor firms' product evolution may affect their subsequent adjustment of alliance strategies. Firms with higher product evolution rates have access to more timely and accurate information about the market, customers, competitors, and the overall platform ecosystem environment. Such information helps firms better identify new partners, evaluate their prospects, and mitigate the risks associated with forming new alliances. Therefore, they are better equipped to increase exploration in their alliance portfolio (Lavie & Rosenkopf, 2006) to spread risk and reduce uncertainty in the dynamic platform ecosystem. In addition, while updating their existing products or developing new products, these firms are subject to internal resource constraints and may need to seek technical expertise and resources that new partners can offer. To enhance their capacity for innovative product evolution, they may adjust their alliance strategies to broaden their access to network resources from various partners (Ahuja, 2000; Lavie, 2006). What's more, by exploring new alliance partners, the focal firm can obtain a cost-efficient and time-sensitive mode of learning (Kumar & Nti, 1998), resulting in better assimilation of new partners' knowledge and improvement in its innovativeness in the market. Hence, we hypothesize that

Hypothesis 2B (H2B). *In a digital platform ecosystem, complementors with faster product evolution are more likely to form explorative alliances in the subsequent period.*

By interacting with each other, firms in the platform ecosystem co-create and shape the interorganizational network. Next, we discuss how network density—a key network characteristic capturing the extent to which entities in a network are inter-connected (Chi et al., 2010; Wasserman & Faust, 1994)—influences the interplay between complementors' strategies and product evolution in the platform ecosystem.

In a dense network, information diffuses rapidly because there are more direct relationships among firms (Schilling & Phelps, 2007). Timely information enhances a firm's understanding of the market competition, customer needs, and disruptive technology trends (Chi et al., 2010), thereby reducing uncertainty about the platform environment. From a relational perspective, it is easier to foster cooperation, develop shared understanding, and build trust among firms in a denser network (Inkpen & Tsang, 2005; Reagans & McEvily, 2003), leading to more sharing of knowledge and other resources among firms (Chi et al., 2010; Hansen et al., 2005; Reagans & McEvily, 2003).

A denser network provides complementors with a wider range of in-depth information and resources, allowing innovation and product improvements. Thus, complementors may depend less on their product and inter-firm strategies during the product evolution process. Although a firm focuses on a smaller set of the focal platform's technological components, it may combine its knowledge with the technical information obtained in the dense network to facilitate innovation. Thus, the strategic impact of product design on the firm's product evolution may be reduced by the density of the network where the firm is embedded. In addition, in a denser network firms may find it easier to reach other firms, reducing the number of partners needed for new opportunities, external information, and resources. Hence, the effectiveness of product and inter-firm strategies on complementors' product evolution will be less salient when the inter-firm network is denser. Therefore, we hypothesize that

Hypothesis 3 (H3). *In a digital platform ecosystem, the impacts of technological architecture coverage (H3A) and forming explorative alliances (H3B) on complementors' product evolution rates will be weakened in a dense network.*

In a dense network ties between firms foster cooperation and trust. Complementors embedded in a dense platform ecosystem network may be more willing to reveal private information and share knowledge than those in a sparse network (Kale, Singh, & Perlmutter, 2000). As a result, dense platform complementors can access more detailed and accurate information from the network (Dyer & Nobeoka, 2000). Overall, they are more likely to take advantage of information from trusted network partners and gain more knowledge that complements the specific knowledge they gained through product evolution. Thus, firms in a denser platform ecosystem network are better able to sense new market opportunities and changes in the platform environment.

Complementors tend to have greater ability to absorb and leverage information received from the network because alternative perspectives are shared more easily and rapidly among firms in dense networks. This facilitates the complementor's experimentation and problem solving efforts and increases its absorptive capacity (Phelps, 2010). Strategy adjustments (i.e., expanding technological architecture layers and exploring new partners) based on past product evolution performance will be amplified in a dense network. In dense networks, trust, cooperation, and shared understanding among complementors (Inkpen & Tsang, 2005; Reagans & McEvily, 2003) reduce uncertainty and risks associated with expanding into new platform architecture layers and exploring new partners.

In summary, in a dense network firms with faster product evolution not only gain a better understanding of the market and the ecosystem environment but also more effectively leverage such knowledge to expand their products' technological coverage and degree of exploration in their alliance portfolio. Therefore, we hypothesize that

Hypothesis 4 (H4). *In a digital platform ecosystem, the impacts of product evolution rates on firms' technological architecture coverage (H4A) and alliance exploration (H4B) will be amplified in a dense network.*

METHODOLOGY

Research Context

We use the Hadoop ecosystem to validate our research model for several reasons. First, the Hadoop ecosystem is economically significant. At the platform level, Hadoop is one of the most widely adopted technologies for big data analytics (Tambe, 2014). At the complementor level, the Hadoop ecosystem provides business opportunities for both incumbents and new enterprise data management entrants. Some well-established firms such as Cisco, IBM, Dell, HP, and Google have expanded their products and/or services into the Hadoop space. Depending on their expertise, these established firms develop commercial software distributions, provide appliances, deploy cloud platforms, or offer consultation services around the Hadoop components. The fast growth of the Hadoop ecosystem also has promoted the birth and rapid development of many startups including Cloudera, Hortonworks, and MapR Technologies, etc.

Second, in the highly competitive Hadoop ecosystem some firms such as Hortonworks and Cloudera have grown substantially in a short time while others such as Hadoop Nation and Malhar, Inc. have failed. In addition, as an architectural framework-based digital platform, Hadoop provides a number of heterogeneous technological components (i.e., in the forms of various open source projects) for different functionalities, ranging from data storage (such as HDFS and HBase) to data processing (i.e., MapReduce and YARN), data access (e.g., Pig, Mahout, and Hive), data management (e.g., ZooKeeper and Oozie), and security (e.g., Helix and Brooklyn). Correspondingly, Hadoop ecosystem complementors are diverse. Firms like Cloudera and Hortonworks provide software solutions while HP offers hardware appliances and Google Cloud Platform and Amazon Web Services develop cloud platforms. Firms such as DataStax may focus on a single layer of Hadoop architecture (e.g., DataStax); meanwhile Hortonworks, Cloudera, and MapR Technologies work with multiple layers. Overall, the Hadoop ecosystem is well-suited to a study of evolutionary intra-platform competition because of its rapid evolution, turbulence, and diverse complementors.

Third, prior intra-platform studies (shown in Appendix 8) have focused on firm-owned platforms such as iOS, Android, Firefox, SAP, and Sony. However, many open platforms such as Hadoop, J2EE, and Linux currently are creating business value. By definition, open platforms do not restrict participation and use of platform resources (Parker & Van Alstyne, 2017), enhancing complementors' interactions. As a result, it "is likely to continue as new kinds of technologies and new patterns of organizational and human behavior co-evolve" (de Reuver et al., 2018). The low entry barriers and the dynamism of open platforms amplify the impact of the ecosystem's environment on complementors; whose behaviors then influence the environment.

Finally, our research model and results are still generalizable to other platform contexts. First, complementors in a firm-owned platform ecosystem also undertake various strategies such as architectural design (Tiwana, 2015a, 2015b), portfolio management (Lee & Raghu, 2014), product update (Foerderer et al., 2018), and multi-homing (Selander et al., 2013) to achieve better performance. In addition, extant literature on intra-platform competition has examined the impacts of platform or ecosystem level factors such as input control (Tiwana, 2015a), platform owner's entry (Foerderer et al., 2018), ecosystem complexity, and platform transitions (Kapoor & Agarwal, 2017) on platform complementors. These results demonstrate that in other platform contexts—for instance, iOS and Firefox—the ecosystem environment impacts complementors' product evolution (or performance) and the effectiveness of their strategies.

Data

The Lexis-Nexis database was the starting point for forming our sample. To find firms offering products and/or services within the Hadoop ecosystem, we searched the keywords "Hadoop," "HBase," "Apache Pig," and "ZooKeeper" among others to retrieve news articles. A content analysis of 1,161 news and articles identified 165 firms as participating in Hadoop's ecosystem by the end of 2016's first quarter. We deleted from the sample firms that did not offer software or appliance products. To fit the dynamic empirical model, we also removed firms with fewer than three consecutive observations. The final dataset includes 112 commercial firms who participated in Hadoop ecosystem from the third quarter of 2009 to the first quarter of 2016.

Data concerning alliances was collected primarily from press releases found on each firm’s website. Because some firms do not publicize partnership agreements on their websites, we also searched Lexis-Nexis using firm names and alliance-related words such as “alliance,” “partner,” “partnership,” and “compatibility.” We also searched for news and announcements on major newswire services such as BusinessWire and PR Newswire. Furthermore, we conducted a general Google search for each firm’s Hadoop-related alliances. After obtaining each firm’s list of alliances, we further filtered the alliances data by keeping only the alliances related to the Hadoop ecosystem. To the best of our knowledge, this formalized approach produced a comprehensive list of inter-firm alliances in the Hadoop ecosystem given that no existing secondary data sources maintain inter-firm alliance information (Chellappa & Saraf, 2010).

To construct the inter-firm networks, we create inter-firm relationships matrices for each quarter. Following prior strategic alliance research, we use the moving-window approach to construct the inter-firm network. Since most organizational alliances do not report partnership termination data, the moving-window approach can reduce the potential bias of the underreported alliance termination data. In addition, the lagged effects of network structure and alliance strategy can be captured by the moving-window approach. Considering the hyper-competitive and fast-changing nature of digital platform ecosystems (Benlian et al., 2015; Ceccagnoli et al., 2012; Huang et al., 2013; Tiwana, 2015a, 2015b), we choose the three-year moving window to test the theoretical model (Chi et al., 2010; Dovev Lavie, 2007). Therefore, inter-firm alliances formed during the previous three years are included in each matrix. For instance, the matrix for the first quarter of 2015 contains the alliances formed between 04/01/2013 and 03/31/2015. The visualizations of three years of strategic alliance networks are presented in Figure 5.

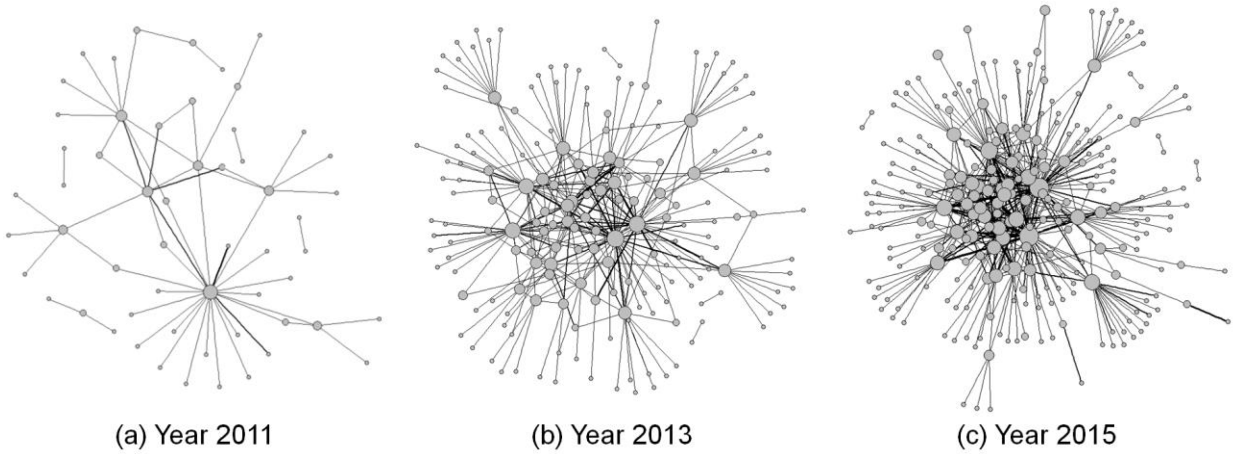


Figure 5. The Evolution of Strategic Alliances Network in the Hadoop Ecosystem

To measure product evolution rates, we collected each firm's product update information by using the same method as the collection of alliances data. Furthermore, we collected additional data for control variables. Firms' patents and trademarks data was collected from the United States Patent and Trademark Office (USPTO).

Measures

Product Evolution. We compute the variable *ProductEvolution* at the firm level as the change in the number of updates of existing products with new features and/or launches of new products from the previous quarter. We focus on firms' releases of existing products with new features and launches of new products because they not only are observable through firms' press releases but also represent the milestone updates of firms' products (Foerderer et al., 2018). In addition, comparing with the absolute number of new product releases, the relative change in the number of such releases can better capture whether a firm evolves its products at a faster or slower rate relative to the previous period.

Technological Architecture Coverage. We conducted content analysis on the product releases of all firms during the observed period to identify the technological layers covered in Hadoop-related products. To ensure the comprehensiveness of firms' product releases, one author of this paper formed the initial sample, and another supplemented the dataset. The initial pool includes 745 Hadoop-related product releases. Although two authors' compilation enhances the completeness, there may be some releases irrelevant to Hadoop. Three coders (i.e., one domain expert and two authors of this paper) examined independently whether each release is related to Hadoop. The three coders agreed on the coding of all product releases in our sample and identified 222 product releases that are irrelevant. This first-stage coding yields 523 unique product releases that can be used to identify firms' product architectural layers.

Next, all three coders examined product releases and used a tentative coding schema derived from the functionalities of Hadoop platform's technological components to identify the technological layers covered by each firm's products. The coders next independently coded the first 50 product releases using the schema. Because the coders could not agree on the coding of some releases, the coding criterion was revised during a follow-up group discussion. After revising the coding schema a second time, all coders agreed on the coding of the first 50 product releases. Our final coding criterion categorizes firms' products into eight different layers, ranging from hardware and software (i.e., data storage, data process, data access, data management, and security) to the cloud computing platform and development tools shown in Figure 6.

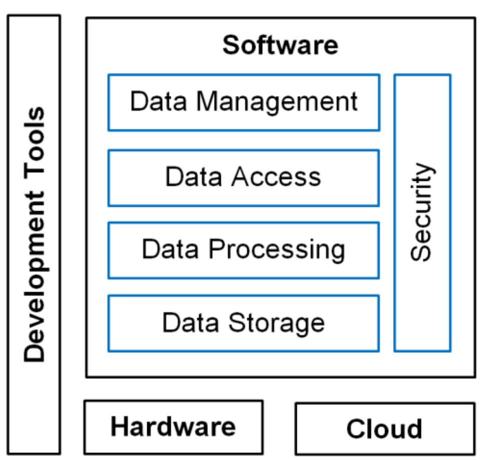


Figure 6. Technological Architecture of the Hadoop Platform

Table 11

Coding Criterion for Hadoop Product Layers

Layers	Description	Exemplar Hadoop Projects
Data Storage	Data storage is where the data is stored using distributed file systems. Specifically, the Hadoop Distributed File Systems (HDFS) storages large files on a cluster of commodity hardware. NoSQL databases store unstructured data in Hadoop in different formats, which may include columnar, document, key-value, and graph databases as well as stream data model.	HDFS; HBase; Cassandra; Accumulo; Kudu; MongoDB; Rethink DB; RocksDB; Neo4J; ArangoDB; EventStore
Data Processing	Data processing is where the scheduling, resource management, and cluster management to be calculated takes place. Specifically, it refers to the framework for applications that process data stored in HDFS.	MapReduce; YARN
Data Access	Data Access is the layer to analyze and query the processed data, implement structured queries and machine learning algorithms, and govern data such as meta-data exchange, data formats, data streaming, and data injection.	Hive; Pig; Mahout; Avro; Solr; Sqoop; Parquet; Kafka; Storm; Atlas; Flume; Chukwa
Data Management	The Data Management layers provides the coordination services for distributed applications, maintain configuration information (naming, providing distributed synchronization, and providing group services), simplify Hadoop clusters by developing software for provisioning, managing, deploying, and monitoring Hadoop clusters, and schedule workflow to manage Apache Hadoop jobs.	Oozie; ZooKeeper; Ambari
Security	The security layer focuses on the security of Hadoop-related workflows. It enhances the security of data and information.	Sentry; Knox Gateway; Ranger
Development Tools	This layer offers development tool for developers. Development tools can be either a single layer (e.g., database development tool) or a combination of several layers (e.g., development tool for Cloudera Distribution of Hadoop)	Spring XD; Jumbune

Table 11 (Continued)

Layers	Description	Exemplar Hadoop Projects
Hardware	Hardware is the layer that provides hardware and appliance.	
Cloud	The cloud layer provides the cloud computing platforms that support the cloud infrastructure as a service (IaaS) and platform as a service (PaaS).	

Table 11 presents the criteria for coding firms' technological layers. When the three coders independently had coded all product releases (n = 523) and resolved coding discrepancies, they agreed on the final coding. We use the number of Hadoop technological layers that have been covered by the focal firm to measure the variable *Architecture*. Table 12 summarizes the distribution of firms' product architectural layers.

Table 12

Distribution of Complementors' Product Technological Architecture

Year	Data Storage	Data Processing	Data Access	Data Management	Security	Hardware	Cloud	Development Tool
2009	1	2	1	1	0	0	1	0
2010	3	2	7	1	1	0	6	1
2011	13	9	19	7	1	1	6	7
2012	23	14	31	13	6	8	11	15
2013	31	20	46	19	15	12	28	24
2014	35	27	59	26	22	19	36	29
2015	32	28	67	29	29	21	37	31

Alliance Exploration. Due to the longitudinal nature of this study, we recorded the time of each strategic alliance formation, for which we also checked whether each pair of partners had a previous connection. A three-year moving window approach is applied to identify new and existing partners. Then, following prior related literature (e.g., Beckman, Haunschild, & Phillips, 2004; Lavie & Rosenkopf, 2006; Lin, Peng, et al., 2009; Lin et al., 2007; March, 1991), the exploration index of firm *i* at time *t* is computed as:

$$AllianceExploration_{it} = \frac{NewPartners_{it}}{AllPartners_{it}}$$

where $NewPartners_{it}$ and $AllPartners_{it}$ represent the total number of new partners and all partners of firm *i* during the three-year period until time *t* respectively.

Network Density. Network density was computed as the fraction of actual ties divided by the total number of possible ties in the network (Lin, Yang, & Arya, 2009; Rothaermel & Hess, 2007; Vasudeva, Spencer, & Teegen, 2013). The variable *NetworkDensity* was calculated for each time period. The value of network density ranges from 0 to 1 with larger values demonstrating greater density.

Control Variables. We also control for the factors associated with firm characteristics that may affect the evolution strategies formulation of firms in platform ecosystems.

In digital platform ecosystems, different kinds of firms both cooperate and compete. The launching of a digital platform creates new business opportunities. Thus, existing firms may move into the ecosystem alongside startups. Different types of firms are expected to have heterogeneous competitive strategies and evolutionary results due to their varied capabilities and opportunities to evolve in the ecosystem. Therefore, we used a dummy variable, *FirmType*, to represent whether the firm is a public or startup, which takes the value of 1 if it is a public firm and 0 otherwise.

Higher network centrality demonstrates that the firm is able to access more technical resources (Vanhaverbeke, Duysters, & Noorderhaven, 2002; Vasudeva et al., 2013) and various aspects of information and knowledge (Chi et al., 2010; Schilling, 2015) ranging from product development to commercialization and capitalization of products. Following previous organizational strategic alliances research (Lin, Yang, et al., 2009; Ravindran, Susarla, Mani, & Gurbaxani, 2015; Rosenkopf & Padula, 2008; Yang, Lin, & Lin, 2010), we use Bonacich's (1987) eigenvector centrality to measure a firm's network position in the platform ecosystem. Inter-firm alliances demonstrate symmetric ties because alliances indicate firms' positions relative to each other in the network (Ahuja, & Mitchell, 2009). Bonacich's (1987) eigenvector measure captures this characteristic of inter-firm alliances since firms linked to a larger number of other firms have higher Bonacich's (1987) eigenvector centrality scores and are in turn connected to many other firms (Lin, Yang, et al., 2009; Rosenkopf & Padula, 2008). In other words, Bonacich's eigenvector measure considers both directly connected members and indirectly connected members (Ibarra & Andrews, 1993); so, it considers the entire network when computing the centrality of each firm (Ravindran et al., 2015).

Firms' heterogeneous research and development (R&D) capabilities also are controlled. In the hyper-competitive digital platform market, a firm's R&D capability is critical for its evolution in the turbulent environment (Li, Shang, & Slaughter, 2010). Following extant related studies (Bardhan, Krishnan, & Lin, 2013; Jaffe, 1986), we use firms' patents to measure their R&D capability. Similar to the approach of collecting trademarks data, we counted the number of each firm's patents for one year before it entered the ecosystem. Given that 54.32 percent of firms in the Hadoop ecosystem have no patents during the time period, we develop a discrete variable *Patent* to denote whether or not a firm has a patent, which takes the value of 1 if the firm has and 0 otherwise.

Trademarks have been used by many marketing studies to measure the marketing, advertising, and branding issues of new products (Arora & Nandkumar, 2011; Ceccagnoli et al., 2012; Fosfuri & Giarratana, 2009; Huang et al., 2013). From an economic perspective, trademarks represent the mechanism by which firms describe product differentiation (Gao & Hitt, 2012). We collected trademarks data from the USPTO database. Only the trademarks denoted as "live" during each time period are counted. To identify Hadoop-related trademarks for companies that provide products and services beyond the Hadoop platform, we used the following approaches. First, we collected each firm's trademarks starting from one year before the date of its first Hadoop-related product launch or inter-organizational relationship. Second, by analyzing the trademarks of Hadoop only firms, we observed that almost all identified trademarks are filed under the codes "IC 009," "IC 041," and "IC 042." As a result, we removed trademarks not filed under one of these three codes. Third, we performed a keyword search in the Description of Goods and Services of each identified trademark. We purged any trademarks not matching either a firm's product names or their associated Hadoop layers.[4] [5] Finally, we performed a search on the Lexis-Nexis database, major newswires, and Google using keywords

[4] We used keywords related to the product layers that the firm offered in the matching process. If a firm covers the Hardware and Storage layer, "storage" or "hardware" was used. If a firm covers the Cloud Computing layer, "cloud" or "elastic" was used. If a firm covers layers of Data Process, Access, and Management, "big data," "analytics," or "computing" were used. Finally, we used "security" to identify the trademarks of firms covering the Security layer. In addition, we used keywords embedded in the name and description of products related to Hadoop. For instance, HDInsight is Microsoft's product that supporting the Hadoop ecosystem, so we used "HD" or "Insight" to match Microsoft trademarks. It is worth noting that with this keyword match approach, we included all identified trademarks regardless of time periods, since a firm may expand its existing product line to the Hadoop ecosystem at any time.

[5] An author who is familiar with the Hadoop-related firms and products performed a content analysis on the description of Goods and Services to identify whether or not the trademarks collected from the search results are

of company names, “Hadoop”, and “trademark”. The variable *Trademark*, therefore, measures a firm’s number of trademarks in a given period.

Based on the resource-based view and the social network perspective, if firms have many connections with diverse partners, they are supposed to access effectively more in-depth heterogeneous information, knowledge, and resources from alliance partners (Hoffmann, 2007). These informational, reputational, and resources benefits generated from an optimal alliance portfolio range from market to technology to consumers (Chellappa & Saraf, 2010; Vasudeva et al., 2013). Therefore, we control for the diversity of the firm’s alliance portfolio, which is denoted as *AllianceDiversity*. Based on the technological architecture of Hadoop ecosystem as shown in Figure 6, we categorize each firm. Note that a firm may or may not be classified under a single category. In line with previous research (Jacquemin & Berry, 1979), we use entropy to measure the diversity of firms’ alliance portfolio. Furthermore, in our sample, 213 (out of 1352) observations have no inter-firm alliance formation, yielding a rate of 15.75%. We thus created a binary variable *AllianceDummy* to denote whether a firm has strategic alliances during the three-year periods until the observed quarter.

Table 13 summarizes the measures of all variables and their descriptive statistics. Table 14 presents the pairwise correlations of all variables.

Hadoop-related. If the content coder could not clearly identify that a certain trademark is related to Hadoop, more descriptive information obtained from a Google search of the trademark was used to make the judgement.

Table 13

Variable Definition and Descriptive Statistics

Variable	Definition	Mean	SD	Range
ProductEvolution	Total number of updates of existing products and launch of new products – total number of updates of existing products and launch of new products at last period	-0.08	0.81	[-3, 4]
Architecture	Total number of technological layers	2.54	1.70	[1, 7]
AllianceExploration	Total number of new partners divided by the total number of partners during the three-year periods	0.72	0.36	[0, 1]
NetworkDensity	10 × (the fraction of actual ties divided by the total number of possible pairs of ties in the network)	0.26	0.26	[0.16, 3.33]
Centrality	Bonacich's (1987) eigenvector centrality score	0.16	0.21	[0, 1]
AllianceDummy	Whether a firm has strategic alliances during the 3-year periods until the time period.	0.16	0.37	[0, 1]
FirmType	Whether the firm is a public or startup, which takes the value of 1 if it is a public firm and 0 otherwise.	0.37	0.18	[0, 1]
AllianceDiversity	The entropy of all partners' technological layers	1.22	0.64	[0, 2.14]
Patent	Whether a firm has a patent or not, which take value of 1 if the firm has and 0 otherwise.	0.46	0.50	[0, 1]
Trademark	Log (1 + total number of trademarks that are "live" and related to Hadoop in a given period)	0.85	0.77	[0, 3.04]

Table 14

Correlations

Variable	1	2	3	4	5	6	7	8	9
1. *ProductEvolution*									
2. *Architecture*	0.053								
3. *AllianceExploration*	0.039	0.202							
4. *NetworkDensity*	-0.058	-0.006	-0.075						
5. *Centrality*	0.047	0.500	0.157	0.137					
6. *AllianceDummy*	-0.062	-0.282	-0.871	0.127	-0.351				
7. *FirmType*	0.001	0.036	0.019	-0.062	0.065	-0.135			
8. *AllianceDiversity*	0.049	0.380	0.621	-0.188	0.513	-0.739	0.164		
9. *Patent*	0.003	0.134	0.088	-0.109	0.075	-0.169	0.610	0.160	
10. *Trademark*	0.035	0.220	0.220	-0.043	0.359	-0.303	0.240	0.368	0.292

Notes. The number of observations for *ProductEvolution* is 1240 and for all other variables is 1352; Number of firms: 112; Numbers greater than 0.06 or less than -0.06 are significant at $p < 0.05$.

Empirical Approach and Model Identification

We utilized a panel vector autogression (PVAR) model, which has the strengths of both VAR and a panel data structure. VAR model assumes that each dependent variable is a function of its own lagged values and the lagged values of all other dependent variables. It does not require priori information by assuming the endogeneity of the main variables. Therefore, the VAR model is particularly suitable for testing the bidirectional relationships between a system of endogenous variables without imposing restrictions (Adomavicius, Bockstedt, & Gupta, 2012). It ensures the robustness of estimations to concerns of endogeneity, auto-correlation, and reverse causality (Granger & Newbold, 1986). In addition, the panel data structure enables us to control for firm-level unobserved heterogeneity (Love & Zicchino, 2006). Given that the within-group fixed effects estimator might be biased in dynamic models (Arellano, 2003), the generalized method of moments (GMM) is often used in PVAR model. GMM uses the lagged values of both dependent variables and their differences as instruments in the estimation (Hansen, 1982). Furthermore, we used the robust standard errors, clustered by firm, to determine the significance level of predictors. We specify our PVAR model as follows:

$$\boldsymbol{y}_{i,t} = \sum_{s=1}^{p} \boldsymbol{\Phi}_s \boldsymbol{y}_{i,t-s} + \boldsymbol{\beta Controls_{i,t-s}} + \boldsymbol{\nu}_{i,t}$$

where $\boldsymbol{y}_{i,t} = \begin{pmatrix} ProductEvolution_{i,t} \\ Architecture_{i,t} \\ AllianceExoloration_{i,t} \\ NetworkDensity_{i,t} \end{pmatrix}$ is a four-element column vector for firm *i* at time *t*.

$\boldsymbol{\Phi}'_s$ represent the matrices of endogenous variables' slope coefficients. *p* indicates the number of lagged time periods. $\boldsymbol{Controls_{i,t-s}}$ denotes the vector of all control variables. $\boldsymbol{\upsilon_{i,t}}$ is the matrix of error terms that are uncorrelated when a sufficient lag *p* is used.

We transformed the variables using the forward orthogonal deviation (FOD, also known as Helmert transformation) to eliminate firm-level fixed effects (Manuel Arellano & Bover, 1995). FOD transformation removes the mean of future observations available in each panel and therefore avoids the correlations between firm-level fixed effects and lagged regressors (Love & Zicchino, 2006). PVAR model estimation requires the stationary of endogenous variables. We reported the unit roots of the companion matrix (Abrigo & Love, 2015) in Figure 7. The results show that the eigenvalues of all endogenous variables lie inside the unit circle, indicating that our PVAR estimation satisfies the stationary condition.

To use the standard GMM estimator, we should specify the length of lags. We estimated the first- to third-order panel VAR models using the first five lags of endogenous variables as instruments. We used the selection criteria proposed by Andrews & Lu (2001) to specify the proper length of lags. The results as shown in Table 15 indicate that the first lag model has the smallest values on MBIC, MAIC, and MQIC. In addition, Hansen J statistics in the first-order model is insignificant at the 5% level. We thus cannot reject the null hypothesis that the over-identification restrictions are valid. Therefore, we fitted a first-order panel VAR model with the first five lags of endogenous variables as instruments using the standard GMM estimation.

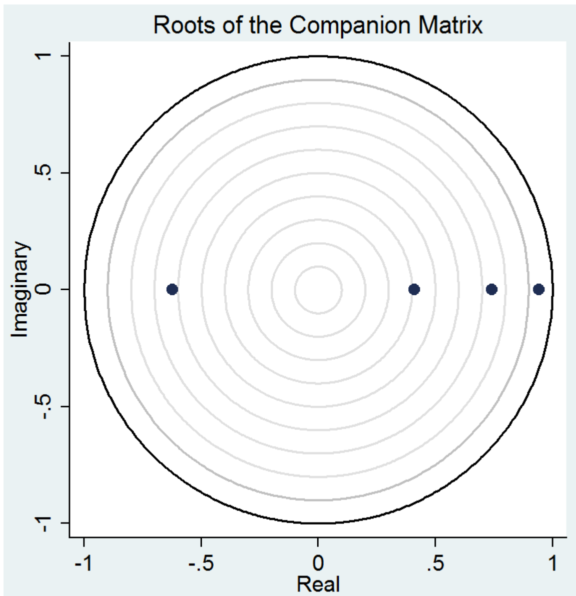


Figure 7. Results of the Unit Root Test

Table 15

Model Selection Criteria

Lag	CD	Hansen J	J p-value	MBIC	MAIC	MQIC
1	1.00	54.26	0.25	-266.60	-41.74	-128.12
2	1.00	46.99	0.04	-166.92	-17.01	-74.60
3	1.00	11.15	0.80	-95.80	-20.85	-49.64

Notes. First five lags of endogenous variables were used as instruments.

RESULTS

Results of Hypothesis Testing

Table 16 presents the estimation results of all equations for the hypothesis testing purpose. We first explore the direct causal relationships among complementors' product architecture, alliance exploration, and product evolution in Eq(1). The results demonstrate that the impact of $Architecture_{i,t-1}$ on $ProductEvolution_{it}$ is positive and statistically significant (β = 0.525, $p < 0.05$), indicating that firms whose products cover more layers of the focal platform's technological components will update their platform-specific products at a faster rate. H1A therefore is supported. Consistent with H1B, we find that $AllianceExploration_{i,t-1}$ positively and significantly affects firms' $ProductEvolution_{it}$ (β = 9.024, $p < 0.01$), demonstrating that firms with a higher tendency to form explorative alliances with new partners are more likely to update their platform-specific products at a faster rate. The second and third columns of the Eq(1) as shown in Table 16 illustrate how firms adjust their product-related and alliance-related decisions based on their past performance. The results show that $ProductEvolution_{i,t-1}$ negatively and significantly influences $Architecture_{it}$ (β = -0.023, $p < 0.05$), indicating that firms who evolve their products at a faster rate are less likely to cover a wide range of the focal platform's architectural layers. H2A, therefore, is not supported. A possible explanation might be that when platform complementors update their products at a faster rate, it may be unnecessary for them to further expand their technological coverage in order to experiment with and recombine innovative solutions. In fact, with enough evolvability, their expansion in technical coverage may increase the costs and efforts in managing product complexity, maintaining product compatibility, facilitating coordination, and mitigating market uncertainties. In support of H2B, the effect of $ProductEvolution_{i,t-1}$ on $AllianceExploration_{it}$ is positive and significant (β = 0.006,

$p < 0.1$), demonstrating that firms with a faster product evolution rate are more likely to form strategic alliances with new partners in the subsequent period.

In Eq(2) and Eq(3), we tested the moderating effect of the network density on complementors' strategies by adding the interaction terms into Eq(1). We specified interaction terms as endogenous variables in the estimation[6]. The results in Eq(2) demonstrate that $Architecture_{i,t-1}$ and $NetworkDensity_{i,t-1}$ jointly influence $ProductEvolution_{it}$ ($\beta = -0.674$, $p < 0.01$) such that the effects of technological architecture coverage on firms' product evolution are weaker when the inter-firm network of the platform ecosystem is dense. Thus, H3A is statistically supported. In support of H3B and as demonstrated in Eq(3), $AllianceExploration_{i,t-1}$ and $NetworkDensity_{i,t-1}$ jointly influence $ProductEvolution_{it}$ ($\beta = -1.971$, $p < 0.01$), indicating that the formation of explorative alliances with new partners will have a weaker effect on firms' product evolution rate when the density of the platform ecosystem's inter-firm network is high.

[6] We also run the models with exogenous interaction terms and obtain the consistent results. The results of these models are not reported due to space limitations but are available upon request.

Table 16

Results of Hypothesis Testing (Essay 3)

	Eq(1)			Eq(2)	Eq(3)	Eq(4)	
	Product Evolution$_{it}$	*Architecture$_{it}$*	*Alliance Exploration$_{it}$*	*Product Evolution$_{it}$*	*Product Evolution$_{it}$*	*Architecture$_{it}$*	*Alliance Exploration$_{it}$*
ProductEvolution$_{i,t-1}$	-0.574*** (0.045)	**-0.023**** **(0.011)**	**0.006*** **(0.004)**	-0.535*** (0.033)	-0.552*** (0.037)	0.010 (0.012)	-0.003 (0.005)
Architecture$_{i,t-1}$	**0.525**** **(0.242)**	0.930*** (0.062)	-0.033 (0.021)	0.522*** (0.165)	0.145 (0.171)	0.892*** (0.054)	-0.025 (0.019)
AllianceExploration$_{i,t-1}$	**9.024***** **(2.861)**	-0.087 (0.608)	0.350 (0.264)	5.555*** (1.622)	7.312*** (2.037)	0.029 (0.500)	0.186 (0.224)
NetworkDensity$_{i,t-1}$	1.376*** (0.320)	-0.182*** (0.057)	-0.120*** (0.035)	2.568*** (0.466)	1.967*** (0.236)	-0.325*** (0.045)	-0.072** (0.033)
NetworkDensity$_{i,t-1}$ × *Architecture$_{i,t-1}$*				**-0.674***** **(0.144)**			
NetworkDensity$_{i,t-1}$ × *AllianceExploration$_{i,t-1}$*					**-1.971***** **(0.365)**		
NetworkDensity$_{i,t-1}$ × *ProductEvolution$_{i,t-1}$*						**-0.128***** **(0.021)**	**0.039***** **(0.011)**
Centrality$_{i,t-1}$	15.957*** (4.599)	-0.570 (0.961)	-1.032** (0.467)	9.267*** (2.279)	14.008*** (2.612)	-0.718 (0.526)	-1.157*** (0.288)

Table 16 (Continued)

	Eq(1)			Eq(2)	Eq(3)	Eq(4)	
	Product Evolution$_{it}$	*Architecture*$_{it}$	*Alliance Exploration*$_{it}$	*Product Evolution*$_{it}$	*Product Evolution*$_{it}$	*Architecture*$_{it}$	*Alliance Exploration*$_{it}$
AllianceDummy$_{i,t-1}$	8.992*** (3.013)	-0.153 (0.650)	-0.395 (0.281)	5.333*** (1.724)	6.362*** (2.122)	0.050 (0.528)	-0.574** (0.249)
FirmType$_{i,t-1}$	3.745 (3.555)	0.460 (0.885)	-0.455 (0.292)	2.357 (2.046)	2.353 (2.044)	0.607 (0.579)	-0.358* (0.207)
AllianceDiversity$_{i,t-1}$	-0.235 (0.463)	0.009 (0.111)	0.039 (0.046)	-0.078 (0.302)	-0.411 (0.355)	0.032 (0.074)	0.052 (0.037)
Patent$_{i,t-1}$	1.803** (0.811)	-0.159 (0.217)	-0.048 (0.064)	0.223 (0.510)	1.388** (0.602)	-0.171 (0.147)	-0.064 (0.058)
Trademark$_{i,t-1}$	0.675 (0.637)	-0.110 (0.168)	-0.068 (0.060)	0.321 (0.425)	0.767 (0.494)	-0.028 (0.138)	-0.116** (0.058)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes. Number of observations: 1016; Number of firms: 112; Robust standard errors, clustered by firm, are in parentheses; Significance Level: *p < 0.1, **p < 0.05, ***p < 0.01. The estimation results of full models are available upon request.

Eq(4) examines how network density moderates the effects of complementors' product evolution. The results demonstrate that the coefficient on the interaction term between *NetworkDensity*$_{i,t-1}$ and *ProductEvolution*$_{i,t-1}$ is statistically significant (β = -0.128, p < 0.01). Since both the direct effect of product evolution and the interaction term are negative, the negative effects of product evolution on firms' technological architecture coverage will be stronger if the ecosystem network is dense. Therefore, although the direct effect of product evolution on technological architecture coverage is reversed compared to our original hypothesis (i.e., H2A), the hypothesized positive moderating effect of network density on the relationship between product evolution and technological architecture coverage is significant. Hence, H4A is supported. In addition, the relationship between *ProductEvolution*$_{i,t-1}$ and *AllianceExploration*$_{i,t}$ will be strengthened by *NetworkDensity*$_{i,t-1}$ (β = 0.039, p < 0.01), demonstrating that if the ecosystem network is dense, complementors that update their products at a faster rate are more likely to form explorative alliances with new partners. Hence, H4B is supported.

Long-Term Effects

We used impulse response functions (IRFs) to examine the long-term effects of the dynamics among complementors' strategies, product evolution, and ecosystem network environment. IRFs can describe how future values of a dependent variable change with one unit increase of a predictor variable (Enders, 2008) and whether a shock to one predictor will cause a permanent or transitory influence on the dependent variable. Further, if the effect is transitory, IRFs also can demonstrate how long the effect will be dissipated (Chen, De, & Hu, 2015).

Given that our PVAR model satisfies the stationary condition, we can compute the simple IRFs by rewriting the model as an infinite vector moving-average (VMA). However, there is no causal interpretation in the simple IRFs because a shock on one variable also may be correlated with shocks in other variables. In addition, the structural PVAR estimation results cannot be directly used to compute IRFs since it is impossible to recover all information about parameters, variance of error terms, and covariance among error terms. To avoid this potential problem, we first transformed the VMA parameters into the orthogonalized IRFs. In addition, we used the Cholesky decomposition (Sims, 1980) to impose a recursive structure on the PVAR. Table 17 presents the forecast-error variance decomposition.

Table 17

Forecast-Error Variance Decomposition

Response Variable	Step	Impulse Variable			
		ProductEvolution	*Architecture*	*AllianceExploration*	*NetworkDensity*
Product Evolution	1	1	0	0	0
	2	0.6094546	0.0064176	0.3823399	0.0017879
	3	0.6225988	0.0061821	0.3688522	0.002367
	4	0.6147941	0.00635	0.3766183	0.0022375
	5	0.6150746	0.0063206	0.376112	0.0024929
	6	0.6146116	0.0063519	0.3765502	0.0024862
	7	0.6145008	0.0063414	0.3765935	0.0025643
	8	0.6144638	0.0063541	0.3766107	0.0025714
	9	0.6144287	0.0063513	0.3766259	0.0025941
	10	0.6144211	0.0063582	0.3766219	0.0025986

Table 17 (Continued)

Response Variable	Step	Impulse Variable			
		ProductEvolution	*Architecture*	*AllianceExploration*	*NetworkDensity*
Architecture	1	0.0794558	0.9149789	0.0055653	0
	2	0.0619741	0.9337445	0.0036336	0.0006479
	3	0.0672518	0.9260029	0.0047676	0.0019778
	4	0.0655568	0.9262486	0.004993	0.0032015
	5	0.0670488	0.9221595	0.0063547	0.0044371
	6	0.0668569	0.9206318	0.0070038	0.0055076
	7	0.0673926	0.9183053	0.0078253	0.0064768
	8	0.067445	0.9168982	0.0083458	0.007311
	9	0.0676818	0.9154181	0.0088577	0.0080423
	10	0.0677626	0.9143317	0.0092345	0.0086713
Alliance Exploration	1	0.064093	0	0.9359071	0
	2	0.0598393	0.004531	0.9331789	0.0024508
	3	0.0626077	0.0102986	0.922399	0.0046946
	4	0.0622683	0.0170265	0.9142205	0.0064846
	5	0.0627852	0.0227642	0.9070684	0.0073823
	6	0.0626279	0.0279721	0.9015509	0.0078491
	7	0.0627577	0.032309	0.8969147	0.0080186
	8	0.0627063	0.0360922	0.8931319	0.0080696
	9	0.0627567	0.0392973	0.8898833	0.0080627
	10	0.0627496	0.0420852	0.8871242	0.0080411

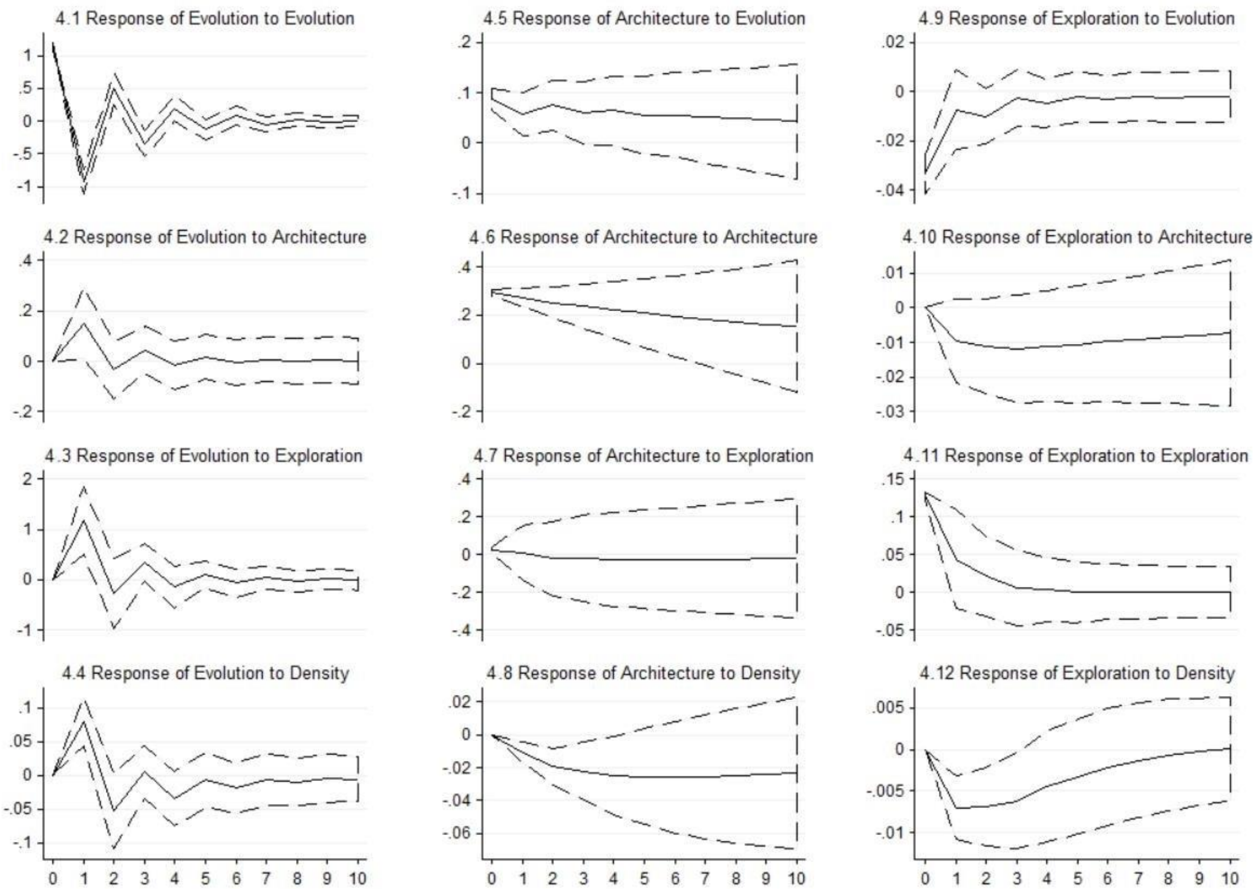
Given that the decomposition forces the PVAR system to be potentially asymmetric, the ordering of the variables may affect the accuracy of the forecast. To order the variables, we performed the Granger causality test and presented the results in Table 18. Accordingly, we specified the ordering of *ProductEvolution*, *AllianceExploration*, *Architecture*, and *NetworkDensity* with the sequence of "causality priority".

Table 18

PVAR-Granger Causality Wald Test

Excluded Variable	Equation			
	ProductEvolution	*Architecture*	*AllianceExploration*	*NetworkDensity*
ProductEvolution	--	4.969**	2.860*	2.127
Architecture	4.717**	--	2.588	0.863
AllianceExploration	9.944***	0.021	--	0.527
NetworkDensity	18.474***	10.337***	11.439***	--
All	20.535***	15.009***	16.842***	7.441*

Figure 8 presents the IRFs along with the 95% confidence intervals. To calculate the confidence intervals, we used Monte Carlo simulations to generate 200 random draws based on the estimated model. Specifically, Figures 8-4.2 to 8-4.4 display the response of firms' product evolution to their strategies and network density. The results demonstrate that the effects of both strategies (i.e., product architecture and alliance exploration) and network density on firms' product evolution are short-term, in which the effects are statistically significant only at period one. Figure 8-4.5 indicates that one-unit shock to firms' product evolution will cause 0.087 increase in their product architecture at period one and this effect continues till the fourth quarter (with a long-run cumulative effect of 0.342 increase at period four). However, the effect of firms' product evolution on their alliance exploration tendency (see Figure 8-4.9) is short-term and only statistically significant at period one.



Note: X-axis represents the forecast horizon in quarters; Y-axis refers to the predicted response of the dependent variable to one-unit shock in the corresponding independent variable; The dashed lines denote the 95% confidence intervals, which are computed using Monte Carlo simulations with 200 repetitions based on the estimated PVAR model.

Figure 8. Impulse Response Functions

Furthermore, Figure 8-4.8 and 8-4.12 show that network density has a longitudinal effect on firms' strategies in product architecture and alliance exploration. Specifically, as shown in Figure 8-4.8, one-unit shock to the density of the inter-firm network is associated with 0.011 decrease in firms' product architecture at period one and this effect will continue until the third quarter (with a cumulative effect of 0.052 decrease at period three). Figure 8-4.12 indicates that one-unit shock to network density is associated with 0.007 decrease in firms' alliance exploration tendency at period one and this effect lasts till the third quarter (with a cumulative effect of 0.020 decrease at period three).

In conclusion, the IRFs analysis demonstrates that the mutual influence between complementors' strategies and product evolution is short-term in nature. However, the platform ecosystem network, which is co-created by all complementors' strategies, has shown its long-term effect on their formulation of future strategies.

DISCUSSION AND CONCLUSIONS

Drawing on the lens of evolutionary theories and focusing on intra-platform competition, we study the mutual influence between platform complementors' strategies and their product evolution as well as the moderating effects of the co-created network environment. By conducting a longitudinal analysis of the Hadoop ecosystem, we find that platform complementors' architectural layer coverage and exploration tendency in their inter-firm relationship formation contribute to greater product evolution in the subsequent period. In turn, after evolving their products at a faster rate, complementors are less likely to offer a wider range of architectural layers in their product design but are more likely to explore new alliance partners. Furthermore, network density, as an important indicator of platform ecosystem's network structure co-created by all complementors, weakens the impacts of complementors' strategies on product evolution but amplifies the effects of product evolution on the adjustment of future strategies. Overall, our results demonstrate the coevolution of platform complementors' architectural and inter-firm strategies, product evolution, and the co-created ecosystem's network environment over time.

Theoretical Implications

To the best of our knowledge, we are the first to theorize and empirically test the mutual influence between platform complementors' strategies and their product evolution and the moderating role of the network environment in the digital platform ecosystem. Such coevolution of complementors' strategies, ecosystem environment, and evolution is particularly important to understand in complex and hyper-turbulent environments (e.g., digital platform ecosystems). In such environments, complementors take strategic actions alone or in collaboration with others in order to achieve better performance. When all firms simultaneously undertake deliberate actions, they co-create and unintentionally shift the structure of the platform environment, creating boundary conditions for their survival and success in the ecosystem. Firms' evolution or performance, therefore, is the joint effect of their strategies and the co-created environment. Considering the highly dynamic nature of digital platform ecosystems, firms should evolve their strategies constantly by assessing their prior product evolution (or performance) as well as the ecosystem environment they are embedded in to achieve superior performance.

By focusing on the coevolution of complementors' strategies, ecosystem environment, and product evolution, we develop a multi-level theoretical model that simultaneously considers both platform complementors and the platform ecosystem structure. Research that examines phenomenon at a single level may be "incomplete and disjointed" (Zhang & Gable, 2017). A multi-level perspective can account for factors at multiple levels simultaneously, leading to a "more comprehensive approach to theory building" (Zhang & Gable, 2017, *p*. 203). Our theoretical development not only delineates the mutual influence between complementors' strategies and product evolution at the lower level (i.e., platform complementor level) but also theorizes how the higher-level platform ecosystem structure co-created by complementors' strategies moderates the mutual strategy-evolution links at the lower level (i.e., top-down effects). Furthermore, our theoretical model is *contextualized* in that it increases our understanding of where the contextual structures originate (i.e., the aggregation of complementors' inter-firm strategies form the unique structure of ecosystem networks) as well as how context-specific elements influence lower-level phenomenon (i.e., the moderating effects of network environments on the mutual influences between complementors' strategies and product evolution) (Johns, 2006). Our theoretical development of platform complementors' coevolution of strategies, evolution, and ecosystem environment responds to calls for the development of contextualized theories in both strategy (e.g., Johns, 2006) and IS fields (Burton-Jones & Volkoff, 2017).

By leveraging the strength and unique insights provided by our multi-level and contextualized theory building, our research contributes to our understanding of evolutionary intra-platform competition. Our work extends this research stream by incorporating the temporal dimension and specifically considering the dynamic evolution of platform ecosystems (e.g., Tiwana et al., 2010, Wareham et al., 2014) from the complementor's perspective. We find not only the impacts of complementors' strategies on their outcomes as most prior studies did but also demonstrate that complementors' future strategies are influenced by their past product evolution rate. Furthermore, prior platform literature recognized that endogenous choices of platform complementors coevolve with the ecosystem environment, shaping the evolutionary dynamics in the ecosystem (Tiwana et al., 2010). Although past research has investigated the impacts of platform strategies such as generational transitions and input control on complementors' performance (e.g., Kapoor & Agarwal, 2017; Tiwana, 2015a), we add further insights about the role of emergent ecosystem network environment in shaping the mutual influences between complementors' strategies and product evolution.

Our focus on complementors' product-related and interfirm-related strategies (i.e., technological architecture coverage and alliance exploration) complements prior digital platform research. Our conceptualization and examination of platform complementors' technological architecture coverage captures the unique characteristic of digital platform—layered modular architecture. Furthermore, we move beyond the descriptive demonstration of the prevalence of inter-firm relationships among platform complementors (e.g., Basole & Karla, 2011; van Angeren et al., 2016) by exploring the strategic implications of such inter-firm relationships.

Practical Implications

Drawing from our theoretical model and empirical results, we offer guidelines to digital platform complementors engaged in evolutionary intra-platform competition. The main takeaway from this research is the coevolution of platform complementors' strategies (i.e., product technological architecture coverage and alliance exploration), product evolution, and ecosystem network environment. Specifically, in dynamic and complex platform ecosystems, complementors' strategies and product evolution mutually affect each other over time. More importantly, such mutual influences are short-term—i.e., the effects of complementors' strategies on their product evolution and vice versa last for only a short period (i.e., one quarter in our Hadoop context). Also, complementors coevolve with the ecosystem environment such that the platform ecosystem structure moderates the mutual influences between their strategies and product evolution. Therefore, in order to survive in the platform ecosystem, complementors are advised to reformulate their strategies constantly based on prior product evolution and the ecosystem environment they co-created.

First, complementors should pay attention to at least two types of competitive strategies: product architectural design and inter-firm relationships. Complementors' product architecture should consider not only their internal modularity and product portfolio as suggested by prior platform literature, but also should make strategic decision concerning the layers of the focal platform's architecture. Both academic literature and business practices demonstrate the specific architecture of platforms—layered modular architecture. Deciding how many heterogeneous layers they will focus on is one strategic decision complementors should make. To enable the future evolvability of their products, firms would do well to package more heterogeneous layers of the focal platform's technological components thereby facilitating recombination among different layers in generating innovative outcomes. In addition, platform complementors actively engage in inter-firm relationships to absorb external resources and knowledge. Given the tradeoffs between exploring new partners and exploiting existing partners, platform complementors should decide strategically with whom they want to be interconnected. Our empirical analysis of the Hadoop ecosystem demonstrates that on average, complementors with an explorative formation of alliances with new partners can seek new opportunities and, therefore, will evolve their products at a faster rate in the subsequent period. Thus, in turbulent environments such as platform ecosystems, firms are advised to actively explore new partners to adapt to the fast-changing environment.

Second, our results inform complementors how to adjust their product and inter-firm strategies dynamically based on past performance. Specifically, if complementors evolve their products at a faster rate, they likely will need new partners to support new features and acquire new information and resources. At the same time, they should be cautious in expanding their product scope to cover more technological layers of the focal platform, perhaps due to increasing coordination costs and technical complexity.

Third, the results concerning the moderating effects of ecosystem network structure provide additional guidelines. Specifically, in a dense network where there is a high proportion of realized inter-firm connections, complementors' strategies for expanding product technological coverage and exploring new alliance partners will have weaker influences on their product evolution. Thus, when the exchange of information and resources in the ecosystem network is faster and stronger relationships form among complementors as indicated by a higher level of network density, complementors may benefit from this "superior" ecosystem environment and should consider investing less on implementing strategies.

Our study offers insights to platform owners on growing and sustaining their ecosystems. Platform owners may want to keep monitoring the ecosystem network and proactively promote interconnectivity among complementors. Complementors gain resources not only from the focal platform but also from their partners as well as the ecosystem's network environment. By promoting a dense network or a network structure that facilitates information and resource flows, complementors can increase their innovation capabilities and improve their evolutionary outcomes, ultimately enhancing the platform value and the platform owner's performance.

Limitations and Future Research

Although our study contributes to both theory and practice, we recognize that there are some limitations that might be overcome by future research. First, like prior empirical studies of digital platform ecosystems (Ceccagnoli et al., 2012; Tiwana, 2015a), we focus on one ecosystem to validate our hypotheses; doing so may limit the generalizability of the results. Future research could extend our study to multiple digital platform ecosystems and further examine the impacts of firms' various strategies. Finally, due to underreporting of firms' alliance termination data, we constructed the network using moving window method as suggested by prior literature (e.g., Chi et al., 2010; Lavie, 2007). Future research might employ other methods such as survey and case study to validate the results further.

References

Abrigo, M. R. M., & Love, I. (2015). Estimation of Panel Vector Autoregression in Stata: a Package of Programs. *University of Hawaii working paper*.

Adomavicius, G., Bockstedt, J., & Gupta, A. (2012). Modeling Supply-Side Dynamics of IT Components, Products, and Infrastructure: An Empirical Analysis Using Vector Autoregression. *Information Systems Research, 23*(2), 397-417.

Adomavicius, G., Bockstedt, J. C., Gupta, A., & Kauffman, R. J. (2008). Making Sense of Technology Trends in the Information Technology Landscape: A Design Science Approach. *MIS Quarterly, 32*(4), 779-809.

Agarwal, R., & Tiwana, A. (2015). Evolvable Systems: Through the Looking Glass of IS. *Information Systems Research, 26*(3), 473-479.

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.

Ahuja, G. (2000). Collaboration Networks, Structural Holes, and Innovation: A Longitudinal Study. *Administrative Science Quarterly, 45*(3), 425-455.

Ahuja, G., Jr., F. P., & Mitchell, W. (2009). Structural Homophily or Social Asymmetry? The Formation of Alliances by Poorly Embedded Firms. *Strategic Management Journal, 30*(9), 941-958.

Amabile, T. M., Barsade, S. G., Mueller, J. S., & Staw, B. M. (2005). Affect and Creativity at Work. *Administrative Science Quarterly, 50*(3), 367-403.

Anderson, E. G., Parker, G. G., & Tan, B. (2014). Platform Performance Investment in the Presence of Network Externalities. *Information Systems Research, 25*(1), 152-172.

Andersson, M., & Xiao, J. (2016). Acquisitions of Start-ups by Incumbent Businesses: A Market Selection Process of 'High-quality' Entrants. *Research Policy, 45*(1), 272-290.

Andrews, D. W. K., & Lu, B. (2001). Consistent Model and Moment Selection Procedures for GMM Estimation with Application to Dynamic Panel Data Models. *Journal of Econometrics, 101*(1), 123-164.

Aral, S., & Van Alstyne, M. (2011). The Diversity-Bandwidth Trade-off. *American Journal of Sociology, 117*(1), 90-171.

Arellano, M. (2003). *Panel Data Econometrics*. Oxford, UK: Oxford University Press.

Arellano, M., & Bover, O. (1995). Another Look at the Instrumental Variable Estimation of Error-Components Models. *Journal of Econometrics, 68*(1), 29-51.

Argyres, N., & Bigelow, L. (2010). Innovation, Modularity, and Vertical Deintegration: Evidence from the Early U.S. Auto Industry. *Organization Science, 21*(4), 842-853.

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.

Arora, A., & Nandkumar, A. (2011). Cash-Out or Flameout! Opportunity Cost and Entrepreneurial Strategy: Theory, and Evidence from the Information Security Industry. *Management Science, 57*(10), 1844-1860.

Avgerou, C., & Li, B. (2013). Relational and Institutional Embeddedness of Web-Enabled Entrepreneurial Networks: Case Studies of Netrepreneurs in China. *Information Systems Journal, 23*(4), 329-350.

Avital, M., & Te'eni, D. (2009). From Generative Fit to Generative Capacity: Exploring an Emerging Dimension of Information Systems Design and Task Performance. *Information Systems Journal, 19*(4), 345-367.

Baldwin, C. Y., & Woodard, C. J. (2009). The Architecture of Platforms: A Unified View. In A. Gawer (Ed.), *Platforms, Markets and Innovation* (pp. 19-44). Cheltenham, UK: Edward Elgar.

Bardhan, I., Krishnan, V., & Lin, S. (2013). Business Value of Information Technology: Testing the Interaction Effect of IT and R&D on Tobin's Q. *Information Systems Research, 24*(4), 1147-1161.

Barnett, W. P. (2008). *The Red Queen Among Organizations: How Competitiveness Evolves*. Princeton, NJ: Princeton University Press.

Barroso, A., & Giarratana, M. S. (2013). Product Proliferation Strategies and Firm Performance: The Moderating Role of Product Space Complexity. *Strategic Management Journal, 34*(12), 1435-1452.

Basole, R. C. (2009). Visualization of Interfirm Relations in a Converging Mobile Ecosystem. *Journal of Information Technology, 24*(2), 144-159.

Basole, R. C., & Karla, J. (2011). On the Evolution of Mobile Platform Ecosystem Structure and Strategy. *Business & Information Systems Engineering, 3*(5), 313-322.

Baum, J. A. C., Calabrese, T., & Silverman, B. S. (2000). Don't Go it Alone: Alliance Network Composition and Startups' Performance in Canadian Biotechnology. *Strategic Management Journal, 21*(3), 267–294.

Baye, M. R., & Morgan, J. (2001). Information Gatekeepers on the Internet and the Competitiveness of Homogeneous Product Markets. *American Economic Review, 91*(3), 454-474.

Bayus, B. L., & Agarwal, R. (2007). The Role of Pre-Entry Experience, Entry Timing, and Product Technology Strategies in Explaining Firm Survival. *Management Science, 53*(12), 1887-1902.

Beckman, C. M., Haunschild, P. R., & Phillips, D. J. (2004). Friends or Strangers? Firm-Specific Uncertainty, Market Uncertainty, and Network Partner Selection. *Organization Science, 15*(3), 259 - 275.

Benlian, A., Hilkert, D., & Hess, T. (2015). How Open is This Platform? The Meaning and Measurement of Platform Openness from the Complementors' Perspective. *Journal of Information Technology, 30*(3), 209-228.

Berry, H. (2018). The Influence of Multiple Knowledge Networks on Innovation in Foreign Operations. *Organization Science, 29*(5), 855-872.

Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. (2013). Visions and Voices on Emerging Challenges in Digital Business Strategy. *MIS Quarterly, 37*(2), 633-661.

Bhargava, H. K., Kim, B. C., & Sun, D. (2013). Commercialization of Platform Technologies: Launch Timing and Versioning Strategy. *Production and Operations Management, 22*(6), 1374-1388.

Bohlmann, J. D., Golder, P. N., & Mitra, D. (2002). Deconstructing the Pioneer's Advantage: Examining Vintage Effects and Consumer Valuations of Quality and Variety. *Management Science, 48*(9), 1175-1195.

Boland, R. J., Lyytinen, K., & Yoo, Y. (2007). Wakes of Innovation in Project Networks: The Case of Digital 3-D Representations in Architecture, Engineering, and Construction. *Organization Science, 18*(4), 631-647.

Bonacich, P. (1987). Power and Centrality: A Family of Measures. *American Journal of Sociology, 92*(5), 1170-1182.

Boone, C., Wezel, F. C., & van Witteloostuijn, A. (2013). Joining the Pack or Going Solo? A Dynamic Theory of New Firm Positioning. *Journal of Business Venturing, 28*(4), 511-527.

Boudreau, K. (2010). Open Platform Strategies and Innovation: Granting Access vs. Devolving Control. *Management Science, 56*(10), 1849-1872.

Boudreau, K. (2012). Let a Thousand Flowers Bloom? An Early Look at Large Numbers of Software App Developers and Patterns of Innovation. *Organization Science, 23*(5), 1409-1427.

Boudreau, K., & Jeppesen, L. B. (2015). Unpaid Crowd Complementors: The Platform Network Effect Mirage. *Strategic Management Journal, 36*(12), 1761-1777.

Brahm, F., Tarzijan, J., & Singer, M. (2017). The Impact of Frictions in Routine Execution on Economies of Scope. *Strategic Management Journal, 38*(10), 2121-2142.

Branzei, O., & Vertinsky, I. (2006). Strategic Pathways to Product Innovation Capabilities in SMEs. *Journal of Business Venturing, 21*(1), 75-105.

Bresser, R. K. F. (1988). Matching Collective and Competitive Strategies. *Strategic Management Journal, 9*(4), 375-385.

Burton-Jones, A., & Volkoff, O. (2017). How Can We Develop Contextualized Theories of Effective Use? A Demonstration in the Context of Community-Care Electronic Health Records. *Information Systems Research, 28*(3), 468-489.

Campbell, B. A. (2013). Earnings Effects of Entrepreneurial Expreience: Evidence from the Semiconductor Industry. *Management Science, 59*(2), 286-304.

Carpenter, G. S., Glazer, R., & Nakamoto, K. (1994). Meaningful Brands from Meaningless Differentiation: The Dependence on Irrelevant Attributes. *Journal of Marketing Research, 31*(3), 339-350.

Carpenter, G. S., & Nakamoto, K. (1989). Consumer Preference Formation and Pioneering Advantage. *Journal of Marketing Research, 26*(3), 285-298.

Casciaro, T., & Piskorski, M. J. (2005). Power Imbalance, Mutual Dependence, and Constraint Absorption: A Closer Look atResource Dependence Theory. *Administrative Science Quarterly, 50*(2), 167-199.

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.

Cennamo, C., Ozalp, H., & Kretschmer, T. (2018). Platform Architecture and Quality Trade-offs of Multihoming Complements. *Information Systems Research, 29*(2), 461-478.

Cennamo, C., & Santalo, J. (2013). Platform Competition: Strategic Trade-offs in Platform Markets. *Strategic Management Journal, 34*(11), 1331-1350.

Chellappa, R. K., & Saraf, N. (2010). Alliances, Rivalry, and Firm Performance in Enterprise Systems Software Markets: A Social Network Approach. *Information Systems Research, 21*(4), 849 - 871.

Chen, H., De, P., & Hu, Y. J. (2015). IT-Enabled Broadcasting in Social Media: An Empirical Study of Artists' Activities and Music Sales. *Information Systems Research, 26*(3), 513-531.

Chi, L., Ravichandran, T., & Andrevski, G. (2010). Information Technology, Network Structure, and Competitive Action. *Information Systems Research*, *21*(3), 543-570.

Chua, R. Y. J., Roth, Y., & Lemoine, J.-F. (2015). The Impact of Culture on Creativity: How Cultural Tightness and Cultural Distance Affect Global Innovation Crowdsourcing Work. *Administrative Science Quarterly*, *60*(2), 189-227.

Clark, K. B. (1985). The Interaction of Design Hierarchies and Market Concepts in Technological Evolution. *Research Policy*, *14*(5), 235-251.

Clements, M. T., & Ohashi, H. (2005). Indirect Network Effects and the Product Cycle: Video Games in the U.S., 1994-2002. *The Journal of Industrial Economics*, *53*(4), 515-542.

Cockburn, I. M., & MacGarvie, M. J. (2009). Patents, Thickets and the Financing of Early-stage Firms: Evidence from the Software Industry. *Journal of Economics & Management Strategy*, *18*(3), 729-773.

Coleman, J. S. (1988). Social Capital in the Creation of Human Capital. *American Journal of Sociology*, *94*, S95-S120.

Coleman, J. S. (1990). *Foundations of Social Theory*. Cambridge, MA: Belknap.

Colombo, S. (2013). Product Differentiation and Collusion Sustainability When Collusion Is Costly. *Marketing science*, *32*(4), 669-674.

Corts, K. S., & Lederman, M. (2009). Software Exclusivity and the Scope of Indirect Network Effects in the U.S. Home Video Game Market. *International Journal of Industrial Organization*, *27*(2), 121-136.

Cottrell, T., & Nault, B. R. (2004). Product Variety and Firm Survival in the Microcomputer Software Industry. *Strategic Management Journal*, *25*(10), 1005-1025.

Cox, D. R. (1972). Regression Models and Life-Tables *Journal of the Royal Statistical Society*, *34*(2), 187-220.

Danneels, E. (2002). The Dynamics of Product Innovation and Firm Competences. *Strategic Management Journal*, *23*(12), 1095-1121.

Darwin, C. (1895). *On the Origin of Species*. London: John Murray.

de Reuver, M., Sørensen, C., & Basole, R. C. (2018). The Digital Platform: A Research Agenda. *Journal of Information Technology*, *33*(2), 124-135.

Demsetz, H. (1997). *The Economics of the Business Firm: Seven Critical Commentaries*. Cambridge, UK: Cambridge University Press.

Devaraj, S., & Kohli, R. (2003). Performance Impacts of Information Technology: Is Actual Usage the Missing Link? *Management Science*, *49*(3), 273-289.

Dickson, P. R., & Ginter, J. L. (1987). Market Segmentation, Product Differentiation, and Marketing Strategy. *Journal of Marketing, 51*(2), 1-10.

Diestre, L., & Rajagopalan, N. (2011). An Environmental Perspective on Diversification: The Effects of Chemical Relatedness and Regulatory Sanctions. *Academy of Management Journal, 54*(1), 97-115.

Dowell, G., & Swaminathan, A. (2006). Entry Timing, Exploration, and Firm Survival in the Early U.S. Bicycle Industry. *Strategic Management Journal, 27*(12), 1159-1182.

Dyer, J. H., & Nobeoka, K. (2000). Creating and Managing a High-Performance Knowledge-Sharing Network: The Toyota Case. *Strategic Management Journal, 21*(3), 345-367.

Eaton, B., Elaluf-Calderwood, S., Sørensen, C., & Yoo, Y. (2015). Distributed Tuning of Boundary Resources: The Case of Apple's iOS Service System. *MIS Quarterly, 39*(1), 217-243.

Echols, A., & Tsai, W. (2005). Niche and Performance: The Moderating Role of Network Embeddedness. *Strategic Management Journal, 26*(3), 219-238.

Eisenmann, T. (2006). Internet Companies' Growth Strategies: Determinants of Investment Intensity and Long-Term Performance. *Strategic Management Journal, 27*(12), 1183-1204.

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

Eisenmann, T., Parker, G., & Van Alstyne, M. W. (2006). Strategies for Two-Sided Markets. *Harvard Business Review, 84*(10), 92-101.

El Sawy, O. A., Malhotra, A., Park, Y., & Pavlou, P. A. (2010). Seeking the Configurations of Digital Ecodynamics: It Takes Three to Tango. *Information Systems Research, 21*(4), 835-848.

Enders, W. (2008). *Applied Econometric Time Series*: John Wiley & Sons.

Ethiraj, S. K., & Zhu, D. H. (2008). Performance Effects of Imitative Entry. *Strategic Management Journal*, *29*(8), 797-817.

Foerderer, J., Kude, T., Mithas, S., & Heinzl, A. (2018). Does Platform Owner's Entry Crowd Out Innovation? Evidence From Google Photos. *Information Systems Research, 29*(2), 444-460.

Foros, Ø., Kind, H. J., & Shaffer, G. (2017). Apple’s Agency Model and the Role of Most-Favored-Nation Clauses. *The RAND Journal of Economics, 48*(3), 673-703.

Fosfuri, A. (2006). The Licensing Dilemma: Understanding the Determinants of the Rate of Technology Licensing. *Strategic Management Journal*, *27*(12), 1141-1158.

Fosfuri, A., & Giarratana, M. S. (2009). Masters of War: Rivals' Product Innovation and New Advertising in Mature Product Markets. *Management Science, 55*(2), 181-191.

Fosfuri, A., Lanzolla, G., & Suarez, F. F. (2013). Entry-Timing Strategies: The Road Ahead. *Long Range Planning, 46*(4), 300-311.

Freeman, J., & Hannan, M. T. (1983). Niche Width and the Dynamics of Organizational Populations. *American Journal of Sociology, 88*(6), 1116-1145.

Gabszewicz, J. J., & Thisse, J.-F. (1979). Price Competition, Quality and Income Disparities. *Journal of Economic Theory, 20*(3), 340-359.

Galloway, T. L., Miller, D. R., Sahaym, A., & Arthurs, J. D. (2017). Exploring the Innovation Strategies of Young Firms: Corporate Venture Capital and Venture Capital Impact on Alliance Innovation Strategy. *Journal of Business Research, 71*, 55-65.

Gans, J. S., Hsu, D. H., & Stern, S. (2002). When Does Start-Up Innovation Spur the Gale of Creative Destruction? *The RAND Journal of Economics, 33*(4), 571-586.

Gans, J. S., & Stern, S. (2003). The Product Market and the Market for 'Ideas': Commercialization Strategies for Technology Entrepreneurs. *Research Policy, 32*(2), 333-350.

Gao, G. G., & Hitt, L. M. (2012). Information Technology and Trademarks: Implications for Product Variety. *Management Science, 58*(6), 1211-1226.

Gawer, A. (2014). Bridging Differing Perspectives on Technological Platforms: Toward an Integrative Framework. *Research Policy, 43*(7), 1239-1249.

Gawer, A., & Henderson, R. (2007). Platform Owner Entry and Innovation in Complementary Markets: Evidence from Intel. *Journal of Economics and Management Strategy, 16*(1), 1-34.

Ge, C., Huang, K.-W., & Png, I. P. L. (2016). Engineer/Scientist Careers: Patents, Online Profiles, and Misclassification Bias. *Strategic Management Journal, 37*(1), 232-253.

Ghazawneh, A., & Henfridsson, O. (2013). Balancing Platform Control and External Contribution in Third-Party Development: The Boundary Resources Model. *Information Systems Journal, 23*(2), 173-192.

Ghose, A., & Han, S. P. (2014). Estimating Demand for Mobile Applications in the New Economy. *Management Science, 60*(6), 1470-1488.

Giarratana, M. S., & Fosfuri, A. (2007). Product Strategies and Survival in Schumpeterian Environments: Evidence from the US Security Software Industry. *Organization Studies, 28*(6), 909–929.

Glaser, B. G., & Strauss, A. L. (1967). *The Discovery of Grounded Theory*. Aldine, Chicago: Transaction Publishers.

Goerzen, A., & Beamish, P. W. (2005). The Effect of Alliance Network Diversity on Multinational Enterprise Performance. *Strategic Management Journal, 26*(4), 333-354.

Golder, P. N., & Tellis, G. J. (1993). Pioneer Advantage: Marketing Logic or Marketing Legend? *Journal of Marketing Research*, *30*(2), 158-170.

Goncalo, J. A., Chatman, J. A., Duguid, M. M., & Kennedy, J. A. (2015). Creativity from Constraint? How the Political Correctness Norm Influences Creativity in Mixed-sex Work Groups. *Administrative Science Quarterly, 60*(1), 1-30.

Granados, N., Gupta, A., & Kauffman, R. J. (2010). Information Transparency in Businessto-Consumer Markets: Concepts, Framework, and Research Agenda. *Information Systems Research, 21*(2), 207-226.

Granger, C. W. J., & Newbold, P. (1986). *Forecasting Economic Time Series*. Orlando, FL: Academic Press.

Granovetter, M. (1985). Economic Action and Social Structure: The Problem of Embeddedness. *American Journal of Sociology, 91*(3), 481-510.

Greenwood, B. N., & Wattal, S. (2017). Show Me the Way to Go Home: An Empirical Investigation of Ride-Sharing and Alcohol Related Motor Vehicle Fatalities. *MIS Quarterly, 41*(1), 163-187.

Gulati, R., Lawrence, P. R., & Puranam, P. (2005). Adaptation in Vertical Relationships: Beyond Incentive Conflict. *Strategic Management Journal, 26*(5), 415-440.

Gulati, R., Puranam, P., & Tushman, M. (2012). Meta-Organization Design: Rethinking Design in Interorganizational and Community Contexts. *Strategic Management Journal, 33*(6), 571-586.

Hagiu, A. (2009). Two-Sided Platforms: Product Variety and Pricing Strategies. *Journal of Economics and Management Strategy, 18*(4), 1011-1043.

Hagiu, A., & Wright, J. (2015). Multi-Sided Platforms. *International Journal of Industrial Organization, 43*, 162-174.

Hallen, B. L., Katila, R., & Rosenberger, J. D. (2014). How Do Social Defenses Work? A Resource-Dependence Lens on Technology Ventures, Venture Capital Investors, and Corporate Relationships. *Academy of Management Journal, 57*(4), 1078-1101.

Hansen, L. P. (1982). Large Sample Properties of Generalized Method of Moments Estimators. *Econometrica, 50*(4), 1029-1054.

Hansen, M. T., Mors, M. L., & Løvås, B. (2005). Knowledge Sharing in Organizations: Multiple Networks, Multiple Phases. *Academy of Management Journal, 48*(5), 776-793.

Hillman, A. J., Withers, M. C., & Collins, B. J. (2009). Resource Dependence Theory: A Review. *Journal of Management, 35*(6), 1404-1427.

Hoang, H., & Rothaermel, F. T. (2010). Leveraging Internal and External Experience: Exploration, Exploitation, and R&D Project Performance. *Strategic Management Journal, 31*(7), 734-758.

Hoberg, G., & Phillips, G. (2016). Text-Based Network Industries and Endogenous Product Differentiation. *Journal of Political Economy, 124*(5), 1423-1465.

Hoffmann, W. H. (2007). Strategies for Managing a Portfolio of Alliances. *Strategic Management Journal, 28*(8), 827-856.

Hosmer, D. W., Lemeshow, S., & May, S. (2008). *Applied Survival Analysis: Regression Modeling of Time to Event Data*: Wiley.

Hotelling, H. (1929). Stability in Competition. *The Economic Journal, 29*(153), 41-57.

Hsu, D. H. (2006). Venture Capitalists and Cooperative Start-up Commercialization Strategy. *Management Science, 52*(2), 204-219.

Huang, P., Ceccagnoli, M., Forman, C., & Wu, D. J. (2013). Appropriability Mechanisms and the Platform Partnership Decision: Evidence from Enterprise Software. *Management Science, 59*(1), 102-121.

Huber, T. L., Kude, T., & Dibbern, J. (2017). Governance Practices in Platform Ecosystems: Navigating Tensions Between Cocreated Value and Governance Costs. *Information Systems Research, 28*(3), 563-584.

Hui, K.-L. (2004). Product Variety Under Brand Influence: An Empirical Investigation of Personal Computer Demand. *Management Science, 50*(5), 686-700.

Ibarra, H., & Andrews, S. B. (1993). Power, Social Influence, and Sense Making: Effects of Network Centrality and Proximity on Employee Perceptions. *Administrative Science Quarterly, 38*(2), 277-303.

Inkpen, A. C., & Tsang, E. W. K. (2005). Social Capital, Networks, and Knowledge Transfer. *Academy of Management Review, 30*(1), 146-165.

Isobe, T., Makino, S., & Montgomery, D. B. (2000). Resource Commitment, Entry Timing, and Market Performance of Foreign DirectInvestments in Emerging Economies: The Case of Japanese International Joint Ventures inChina. *Academy of Management Journal, 43*(3), 468-484.

Jacquemin, A. P., & Berry, C. H. (1979). Entropy Measure of Diversification and Corporate Growth. *The Journal of Industrial Economics, 27*(4), 359-369.

Jaffe, A. B. (1986). Technological Opportunity and Spillovers of R & D: Evidence from Firms' Patents, Profits, and Market Value. *American Economic Review, 76*(5), 984-1001.

James, S. D., Leiblein, M. J., & Lu, S. (2013). How Firms Capture Value From Their Innovations. *Journal of Management, 39*(5), 1123-1155.

Johns, G. (2006). The Essential Impact of Context on Organizational Behavior. *The Academy of Management Review, 31*(2), 386-408.

Jones, G. R., & Hill, C. W. L. (1988). Transaction Cost Analysis of Strategy-Structure Choice. *Strategic Management Journal, 9*(2), 159-172.

Kacperczyk, A., & Marx, M. (2016). Revisiting the Small-Firm Effect on Entrepreneurship: Evidence from Firm Dissolutions. *Organization Science, 27*(4), 893-910.

Kale, P., Singh, H., & Perlmutter, H. (2000). Learning and Protection of Proprietary Assets in Strategic Alliances: Building Relational Capital. *Strategic Management Journal, 21*(3), 217-237.

Kalish, S., & Lilien, G. L. (1986). A Market Entry Timing Model for New Technologies. *Management Science, 32*(2), 194-205.

Kallinikos, J., Aaltonen, A., & Marton, A. (2013). The Ambivalent Ontology of Digital Artifacts. *MIS Quarterly, 37*(2), 357-370.

Kaniovski, S. (2005). Product Differentiation and Competitive Selection. *Journal of Evolutionary Economics, 15*(5), 567-580.

Kapoor, R., & Agarwal, S. (2017). Sustaining Superior Performance in Business Ecosystems: Evidence from Application Software Developers in the iOS and Android Smartphone Ecosystems. *Organization Science, 28*(3), 531-551.

Karhu, K., Gustafsson, R., & Lyytinen, K. (2018). Exploiting and Defending Open Digital Platforms with Boundary Resources: Android’s Five Platform Forks. *Information Systems Research, 29*(2), 479-497.

Karimi, J., & Walter, Z. (2015). The Role of Dynamic Capabilities in Responding to Digital Disruption: A Factor-Based Study of the Newspaper Industry. *Journal of Management Information Systems, 32*(1), 39-81.

Katz, M. L., & Shapiro, C. (1994). Systems Competition and Network Effects. *Journal of Economic Perspectives, 8*(2), 93-115.

Kerin, R. A., Varadarajan, P. R., & Peterson, R. A. (1992). First-Mover Advantage: A Synthesis, Conceptual Framework, and Research Propositions. *Journal of Marketing, 56*(4), 33-52.

Khanna, T., Gulati, R., & Nohria, N. (1998). The Dynamics of Learning Alliances: Competition, Cooperation, and Relative Scope. *Strategic Management Journal, 19*(3), 193-210.

Kim, H. J., Kim, I., & Lee, H. (2016). Third-party Mobile App Developers' Continued Participation in Platform-Centric Ecosystems: An Empirical Investigation of Two Different Mechanisms. *International Journal of Information Management*, *36*(1), 44-59.

Kim, J.-H., Prince, J., & Qiu, C. (2014). Indirect Network Effects and the Quality Dimension: A Look at the Gaming Industry. *International Journal of Industrial Organization*, *37*, 99-108.

Kirsch, L. J. (1997). Portfolios of Control Modes and IS Project Management. *Information Systems Research, 8*(3), 215-239.

Klepper, S. (1996). Entry, Exit, Growth, and Innovation over the Product Life Cycle. *American Economic Review*, *86*(3), 562-583.

Klingebiel, R., & Joseph, J. (2016). Entry Timing and Innovation Strategy in Feature Phones. *Strategic Management Journal, 37*(6), 1002-1020.

Kohli, R., & Grover, V. (2008). Business Value of IT: An Essay on Expanding Research Directions to Keep up with the Times. *Journal of the Association for Information Systems, 9*(1), 23-39.

Kruchten, P., Obbink, H., & Stafford, J. (2006). The Past, Present, and Future of Software Architecture. *IEEE Software, 23*(2), 22–30.

Kumar, R., & Nti, K. O. (1998). Differential Learning and Interaction in Alliance Dynamics: A Process and Outcome Discrepancy Model. *Organization Science, 9*(3), 356-367.

Lancaster, K. (1990). The Economics of Product Variety: A Survey. *Marketing science, 9*(3), 189-206.

Landsman, V., & Stremersch, S. (2011). Multihoming in Two-Sided Markets: An Empirical Inquiry in the Video Game Console Industry. *Journal of Marketing, 75*(6), 39-54.

Lane, P. J., Koka, B. R., & Pathak, S. (2006). The Reification of Absorptive Capacity: A Critical Review and Rejuvenation of the Construct. *The Academy of Management Review, 31*(4), 833-863.

Lavie, D. (2006). The Competitive Advantage of Interconnected Firms: An Extension of the Resource-Based View. *Academy of Management Review, 31*(3), 638-658.

Lavie, D. (2007). Alliance Portfolios and Firm Performance: A Study of Value Creation and Appropriation in the U.S. Software Industry. *Strategic Management Journal, 28*(12), 1187-1212.

Lavie, D., Kang, J., & Rosenkopf, L. (2011). Balance Within and Across Domains: The Performance Implications of Exploration and Exploitation in Alliances. *Organization Science, 22*(6), 1517-1538.

Lavie, D., & Rosenkopf, L. (2006). Balancing Exploration and Exploitation in Alliance Formation. *Academy of Management Journal*, *49*(4), 797-818.

Law, K. S., Wong, C.-S., & Mobley, W. H. (1998). Toward a Taxonomy of Multidimensional Constructs. *The Academy of Management Review, 23*(4), 741-755.

Lee, C., Lee, D., & Hwang, J. (2015). Platform Openness and the Productivity of Content Providers: A Meta-Frontier Analysis. *Telecommunications Policy, 39*(7), 553-562.

Lee, G., & Raghu, T. S. (2014). Determinants of Mobile Apps' Success: Evidence from the App Store Market. *Journal of Management Information Systems, 31*(2), 133-170.

Leidner, D. E. (2018). Review and Theory Symbiosis: An Introspective Retrospective. *Journal of the Association for Information Systems, 19*(6), 552-567.

Leidner, D. E., & Kayworth, T. (2006). A Review of Culture in Information Systems Research: Toward a Theory of Information Technology Culture Conflict. *MIS Quarterly, 30*(2), 357-399.

Levie, J. (1995). Strategies for New Venture Growth and Harvest: A Five Year Follow-up of 176 Young Growing Firms in Denmark, Ireland and Scotland. In *Frontiers of Entrepreneurship Research*. Wellesley, MA: Babson College.

Li, S., Shang, J., & Slaughter, S. A. (2010). Why Do Software Firms Fail? Capabilities, Competitive Actions, and Firm Survival in the Software Industry from 1995 to 2007. *Information Systems Research, 21*(3), 631-654.

Li, S. X., & Greenwood, R. (2004). The Effect of Within-industry Diversification on Firm Performance: Synergy Creation, Multi-market Contact and Market Structuration. *Strategic Management Journal, 25*(12), 1131-1153.

Lieberman, M. B., & Montgomery, D. B. (1988). First-Mover Advantages. *Strategic Management Journal, 9*(S1), 41-58.

Liebeskind, J. P. (1997). Keeping Organizational Secrets: Protective Institutional Mechanisms and Their Costs. *Industrial and Corporate Change, 6*(3), 623-663.

Lin, Z. J., Peng, M. W., Yang, H., & Sun, S. L. (2009). How Do Networks and Learning Drive M&As? An Institutional Comparison Between China and the United States. *Strategic Management Journal, 30*(10), 1113-1132.

Lin, Z. J., Yang, H., & Arya, B. (2009). Alliance Partners and Firm Performance: Resource Complementarity and Status Association. *Strategic Management Journal*, *30*(9), 921-940.

Lin, Z. J., Yang, H., & Demirkan, I. (2007). The Performance Consequences of Ambidexterity in Strategic Alliance Formations: Empirical Investigation and Computational Theorizing. *Management Science, 53*(10), 1645-1658.

Love, I., & Zicchino, L. (2006). Financial Development and Dynamic Investment Behavior: Evidence from Panel VAR. *The Quarterly Review of Economics and Finance, 43*(2), 190-210.

Lusch, R. F., & Nambisan, S. (2015). Service Innovation: A Service-Dominant Logic Perspective. *MIS Quarterly, 39*(1), 155-175.

Lynch, J. G., & Ariely, D. (2000). Wine Online: Search Costs Affect Competition on Price, Quality, and Distribution. *Marketing science, 19*(1), 83-103.

Lyytinen, K., & King, J. L. (2002). Around The Cradle of the Wireless Revolution: The Emergence and Evolution of Cellular Telephony. *Telecommunications Policy, 26*(3-4), 97-100.

Mahmood, I. P., Zhu, H., & Zajac, E. J. (2011). Where Can Capabilities Come From? Network Ties and Capability Acquisition in Business Groups. *Strategic Management Journal, 32*(8), 820-848.

Malone, T. W., & Crowston, K. (1994). The Interdisciplinary Study of Coordination. *ACM Computing Surveys, 26*(1), 87-119.

Mantovani, A., & Ruiz-Aliseda, F. (2016). Equilibrium Innovation Ecosystems: The Dark Side of Collaborating with Complementors. *Management Science, 62*(2), 534-549.

March, J. G. (1991). Exploration and Exploitation in Organizational Learning. *Organization Science, 2*(1), 71 - 87.

Markides, C., & Sosa, L. (2013). Pioneering and First Mover Advantages: The Importance of Business Models. *Long Range Planning, 46*(4-5), 325-334.

Markus, M. L., & Loebbecke, C. (2013). Commoditized Digital Processes and Business Community Platforms: New Opportunities and Challenges for Digital Business Strategies. *MIS Quarterly*, *37*(2), 649-653.

McIntyre, D. P., & Srinivasan, A. (2017). Networks, Platforms, and Strategy: Emerging Views and Next Steps. *Strategic Management Journal*, *38*(1), 141-160.

Melville, N., Kraemer, K., & Gurbaxani, V. (2004). Information Technology and Organizational Performance: An Integrative Model of IT Business Value. *MIS Quarterly, 28*(2), 283-322.

Metcalfe, J. S. (1998). *Evolutionary Economics and Creative Destruction*. London, New York: Routledge.

Mithas, S., Ramasubbu, N., & Sambamurthy, V. (2011). How Information Management Capability Influences Firm Performance. *MIS Quarterly, 35*(1), 237-256.

Mone, G. (2013). Beyond Hadoop. *Communications of the ACM, 56*(1), 22-24.

Montgomery, A. L., Hosanagar, K., Krishnan, R., & Clay, K. B. (2004). Designing a Better Shopbot. *Management Science, 50*(2), 189-206.

Morgeson, F. P., Mitchell, T. R., & Liu, D. (2015). Event System Theory: An Event-Oriented Approach to the Organizational Sciences. *The Academy of Management Review, 40*(4), 515-537.

Mowery, D. C., Oxley, J. E., & Silverman, B. S. (1996). Strategic Alliances and Interfirm Knowledge Transfer. *Strategic Management Journal, 17*(S2), 77-91.

Nan, N., & Tanriverdi, H. (2017). Unifying the Role of IT in Hyperturbulence and Competitive Advantage via a Multilevel Perspective of IS Strategy. *MIS Quarterly, 41*(3), 937-958.

Nielsen, P., & Aanestad, M. (2006). Control Devolution as Information Infrastructure Design Strategy: A Case Study of a Content Service Platform for Mobile Phones in Norway. *Journal of Information Technology, 21*(3), 185-194.

Nielsena, B. B., & Gudergan, S. (2012). Exploration and Exploitation Fit and Performance in International Strategic Alliances. *International Business Review, 21*(4), 558-574.

Ondrus, J., Gannamaneni, A., & Lyytinen, K. (2015). The Impact of Openness on the Market Potential of Multi-Sided Platforms: A Case Study of Mobile Payment Platforms. *Journal of Information Technology, 30*(3), 260-275.

Palepu, K. (1985). Diversification Strategy, Profit Performance and the Entropy Measure. *Strategic Management Journal, 6*(3), 239-255.

Panagopoulos, N. G., Rapp, A. A., & Ogilvie, J. L. (2017). Salesperson Solution Involvement and Sales Performance: The Contingent Role of Supplier Firm and Customer–Supplier Relationship Characteristics. *Journal of Marketing, 81*(4), 144-164.

Papyrina, V. (2007). When, How, and with What Success? The Joint Effect of Entry Timing and Entry Modeon Survival of Japanese Subsidiaries in China. *Journal of International Marketing, 15*(3), 73-95.

Park, S. H., Chen, R. R., & Gallagher, S. (2002). Firm Resources as Moderators of the Relationship between Market Growth and Strategic Alliances in Semiconductor Start-ups. *Academy of Management Journal, 45*(3), 527-545.

Parker, G., & Van Alstyne, M. (2017). Innovation, Openness, and Platform Control. *Management Science, Forthcoming*.

Parker, G., Van Alstyne, M., & Jiang, X. (2017). Platform Ecosystems: How Developers Invert the Firm. *MIS Quarterly, 41*(1), 255-266.

Parker, G., & van Alstyne, M. W. (2005). Two-Sided Network Effects: A Theory of Information Product Design. *Management Science, 51*(10), 1494-1504.

Pavlou, P. A., & El Sawy, O. A. (2010). The "Third Hand": IT-Enabled Competitive Advantage in Turbulence Through Improvisational Capabilities. *Information Systems Research, 21*(3), 443-471.

Petkova, A. P., Wadhwa, A., Yao, X., & Jain, S. (2014). Reputation and Decision Making Under Ambiguity: A Study of U.S. Venture Capital Firms' Investments in the Emerging Clean Energy Sector. *Academy of Management Journal, 57*(2), 422-448.

Phelps, C. C. (2010). A Longitudinal Study of the Influence of Alliance Network Structure and Composition on Firm Exploratory Innovation. *Academy of Management Journal, 53*(4), 890-913.

Puranam, P., Singh, H., & Zollo, M. (2006). Organizing for Innovation: Managing the Coordination-Autonomy Dilemma in Technology Acquisitions. *Academy of Management Journal, 49*(2), 263-280.

Qiu, Y., Gopal, A., & Hann, I.-H. (2017). Logic Pluralism in Mobile Platform Ecosystems: A Study of Indie App Developers on the iOS App Store. *Information Systems Research, 28*(2), 225-249.

Raisch, S., Birkinshaw, J., Probst, G., & Tushman, M. L. (2009). Organizational Ambidexterity: Balancing Exploitation and Exploration for Sustained Performance. *Organization Science, 20*(4), 685-695.

Ravindran, K., Susarla, A., Mani, D., & Gurbaxani, V. (2015). Social Capital and Contract Duration in Buyer-Supplier Networks for Information Technology Outsourcing. *Information Systems Research, 26*(2), 379-397.

Raz, O., & Gloor, P. A. (2007). Size Really Matters—New Insights for Start-ups' Survival. *Management Science, 53*(2), 169–177.

Reagans, R., & McEvily, B. (2003). Network Structure and Knowledge Transfer: The Effects of Cohesion and Range. *Administrative Science Quarterly, 48*(2), 240-267.

Rietveld, J., & Eggers, J. P. (2018). Demand Heterogeneity in Platform Markets: Implications for Complementors. *Organization Science, 29*(2), 304-322.

Roberts, N., Galluch, P. S., Dinger, M., & Grover, V. (2012). Absorptive Capacity and Information Systems Research: Review, Synthesis, and Directions for Future Research. *MIS Quarterly, 36*(2), 625-648.

Robinson, W. T., Fornell, C., & Sullivan, M. (1992). Are Market Pioneers Intrinsically Stronger Than Later Entrants? *Strategic Management Journal, 13*(8), 609-624.

Rosenkopf, L., & Padula, G. (2008). Investigating the Microstructure of Network Evolution: Alliance Formation in the Mobile Communications Industry. *Organization Science, 19*(5), 669 - 687.

Rothaermel, F. T., & Deeds, D. L. (2004). Exploration and Exploitation Alliances in Biotechnology: A System of New Product Development. *Strategic Management Journal, 25*(3), 2004.

Rothaermel, F. T., & Hess, A. M. (2007). Building Dynamic Capabilities: Innovation Driven by Individual-, Firm-, and Network-Level Effects. *Organization Science, 18*(6), 898 - 921.

Rothaermel, F. T., & Hill, C. W. L. (2005). Technological Discontinuities and Complementary Assets: A Longitudinal Study of Industry and Firm Performance. *Organization Science, 16*(1), 52-70.

Sabherwal, R., & Robey, D. (1993). An Empirical Taxonomy of Implementation Processes Based on Sequences of Events inInformation System Development. *Organization Science, 4*(4), 548-576.

Sabherwal, R., & Robey, D. (1995). Reconciling Variance and Process Strategies for Studying Information System Development. *Information Systems Research, 6*(4), 303-327.

Sambamurthy, V., Bharadwaj, A., & Grover, V. (2003). Shaping Agility through Digital Options: Reconceptualizing the Role of Information Technology in Contemporary Firms. *MIS Quarterly, 27*(2), 237-263.

Schilling, M. A. (2015). Technology Shocks, Technological Collaboration, and Innovation Outcomes. *Organization Science, 26*(3), 668-686.

Schilling, M. A., & Phelps, C. C. (2007). Interfirm Collaboration Networks: The Impact of Large-Scale Network Structure on Firm Innovation. *Management Science, 53*(7), 1113-1126.

Schmalensee, R. (1982). Product Differentiation Advantages of Pioneering Brands. *American Economic Review, 72*(3), 349-365.

Selander, L., Henfridsson, O., & Svahn, F. (2013). Capability Search and Redeem across Digital Ecosystems. *Journal of Information Technology, 28*(3), 183-197.

Shaked, A., & Sutton, J. (1982). Relaxing Price Competition Through Product Differentiation. *Review of Economic Studies, 49*(1), 3-13.

Shapiro, C., & Varian, H. R. (1998). *Information Rules: A Strategic Guide to the Network Economy*. Boston, Massachusetts: Harvard Business School Press.

Simon, H. A. (1991). Bounded Rationality and Organizational Learning. *Organization Science, 2*(1), 125-134.

Simon, H. A. (1996). *The Sciences of the Artificial*. Cambridge, MA: MIT Press.

Simon, H. A. (2002). Near Decomposability and the Speed of Evolution. *Industrial and Corporate Change, 11*(3), 587-599.

Sims, C. A. (1980). Macroeconomics and Reality. *Econometrica, 48*(1), 1-48.

Singh, R., Mathiassen, L., & Mishra, A. (2015). Organizational Path Constitution in Technological Innovation: Evidence from Rural Telehealth. *MIS Quarterly, 39*(3), 643-665.

Soh, C., Markus, M. L., & Goh, K. H. (2006). Electronic Marketplaces and Price Transparency: Strategy, Information Technology, and Success. *MIS Quarterly, 30*(3), 705-723.

Soh, P.-H. (2010). Network Patterns and Competitive Advantage Before the Emergence of a Dominant Design. *Strategic Management Journal, 31*(4), 438-461.

Song, J., Baker, J., Wang, Y., Choi, H. Y., & Bhattacherjee, A. (2018). Platform Adoption by Mobile Application Developers: A Multimethodological Approach. *Decision Support Systems, 107*, 26-39.

Song, P., Xue, L., Rai, A., & Zhang, C. (2017). The Ecosystem of Software Platform: A Study of Asymmetric Cross-Side Network Effects and Platform Governance. *MIS Quarterly, Forthcoming*.

Sorenson, O. (2000). Letting the Market Work for You: An Evolutionary Perspective on Product Strategy. *Strategic Management Journal, 21*(5), 577-592.

Sorescu, A. B., Chandy, R. K., & Prabhu, J. C. (2003). Sources and Financial Consequences of Radical Innovation: Insights from Pharmaceuticals. *Journal of Marketing, 67*(4), 82-102.

Stern, I., & Henderson, A. D. (2004). Within-business Diversification in Technology-intensive Industries. *Strategic Management Journal, 25*(5), 487-505.

Stuart, T. E., Hoang, H., & Hybels, R. C. (1999). Interorganizational Endorsements and the Performance of Entrepreneurial Ventures. *Administrative Science Quarterly, 44*(2), 315-349.

Su, W., & Tsang, E. W. K. (2015). Product Diversification and Financial Performance: The Moderating Role of Secondary Stakeholders. *Academy of Management Journal, 58*(4), 1128-1148.

Suarez, F. F., Grodal, S., & Gotsopoulos, A. (2015). Perfect Timing? Dominant Category, Dominant Design, and the Window of Opportunity for Firm Entry. *Strategic Management Journal, 36*(3), 437-448.

Suarez, F. F., & Lanzolla, G. (2007). The Role of Environmental Dynamics in Building a First Mover Advantage Theory. *Academy of Management Review, 32*(2), 377-392.

Swaminathan, V., & Moorman, C. (2009). Marketing Alliances, Firm Networks, and Firm Value Creation. *Journal of Marketing, 73*(5), 52-69.

Tambe, P. (2014). Big Data Investment, Skills, and Firm Value. *Management Science, 60*(6), 1452–1469.

Tanriverdi, H., Rai, A., & Venkatraman, N. (2010). Reframing the Dominant Quests of Information Systems Strategy Research for Complex Adaptive Business Systems. *Information Systems Research, 21*(4), 822-834.

Tanriverdi, H., & Lee, C.-H. (2008). Within-Industry Diversification and Firm Performance in the Presence of Network Externalities: Evidence from the Software Industry. *The Academy of Management Journal, 51*(2), 381-397.

Tata, S., & Patel, J. M. (2007). Estimating the Selectivity of *TF-IDF* Based Cosine Similarity Predicates. *ACM SIGMOD Record, 36*(2), 7-12.

Teece, D. J. (1986). Profiting from Technological Innovation: Implications for Integration, Collaboration, Licensing and Public Policy. *Research Policy, 15*(6), 285-305.

Thomas, L. D. W., Autio, E., & Gann, D. M. (2015). Architectural Leverage: Putting Platforms in Context. *Academy of Management Perspectives, 28*(2), 46-67.

Thomaz, F., & Swaminathan, V. (2015). What Goes around Comes around: The Impact of Marketing Alliances on Firm Risk and the Moderating Role of Network Density. *Journal of Marketing, 79*(5), 63-79.

Tilson, D., Lyytinen, K., & Sørensen, C. (2010). Digital Infrastructures: The Missing IS Research Agenda. *Information Systems Research, 21*(4), 748-759.

Tiwana, A. (2009). Governance-Knowledge Fit in Systems Development Projects. *Information Systems Research, 20*(2), 180-197.

Tiwana, A. (2015a). Evolutionary Competition in Platform Ecosystems. *Information Systems Research, 26*(2), 266-281.

Tiwana, A. (2015b). Platform Desertion by App Developers. *Journal of Management Information Systems, 32*(4), 40-77.

Tiwana, A., Konsynski, B., & Bush, A. A. (2010). Platform Evolution: Coevolution of Platform Achitecture, Governance, and Environmental Dynamics. *Information Systems Research, 21*(4), 675-687.

Uzzi, B. (1997). Social Structure and Competition in Interfirm Networks: The Paradox of Embeddedness. *Administrative Science Quarterly, 42*(1), 35-67.

van Angeren, J., Alves, C., & Jansen, S. (2016). Can We Ask You to Collaborate? Analyzing App Developer Relationships in Commercial Platform Ecosystems. *The Journal of Systems and Software*, *113*, 430-445.

van de Ven, A. H. (1992). Suggestions for Studying Strategy Process: A Research Note. *Strategic Management Journal, 13*(S1), 169-188.

Van de Ven, A. H., & Poole, M. S. (1995). Explaining Development and Change in Organizations. *Academy of Management Journal*, *20*(3), 510-540.

Vanhaverbeke, W., Duysters, G., & Noorderhaven, N. (2002). External Technology Sourcing Through Alliances or Acquisitions: An Analysis of the Application-Specific Integrated Circuits Industry. *Organization Science, 13*(6), 714-733.

Vasudeva, G., Spencer, J. W., & Teegen, H. J. (2013). Bringing the Institutional Context Back In: A Cross-National Comparison of Alliance Partner Selection and Knowledge Acquisition. *Organization Science, 24*(2), 319 - 338.

Venkatraman, N., & Lee, C.-H. (2004). Preferential Linkage and Network Evolution: A Conceptual Model and Empirical Test in the U.S. Video Game Sector. *The Academy of Management Journal*, *47*(6), 876-892.

Wadhwa, A., & Kotha, S. (2006). Knowledge Creation through External Venturing: Evidence from the Telecommunications Equipment Manufacturing Industry. *Academy of Management Journal*, *49*(4), 819-835.

Wang, P., Lee, M., Meng, X., & Butler, B. S. (2016). *Toward an Ecology Theory of Creativity in IT Products: A Study of Mobile Device Industry*. Paper presented at the 37th International Conference on Information Systems, Dublin, Ireland.

Wareham, J., Fox, P. B., & Giner, J. L. C. (2014). Technology Ecosystem Governance. *Organization Science*, *25*(4), 1195-1215.

Wasserman, S., & Faust, K. (1994). *Social Network Analysis: Methods and Applications*. Cambridge, UK: Cambridge University Press.

Webster, J., & Watson, R. T. (2002). Analyzing the Past to Prepare for the Future: Writing a Literature Review. *MIS Quarterly, 26*(2), xiii-xxiii.

Wen, W., & Zhu, F. (2019). Threat of Platform-Owner Entry and Complementor Responses: Evidence from the Mobile App Market. *Strategic Management Journal, Forthcoming*.

Wernerfelt, B. (2005). Product Development Resources and the Scope of the Firm. *Journal of Marketing, 69*(2), 15-23.

Wessel, M., Thies, F., & Benlian, A. (2017). Opening the Floodgates: The Implications of Increasing Platform Openness in Crowdfunding. *Journal of Information Technology, Forthcoming*.

Woodard, C. J., Ramasubbu, N., Tschang, F. T., & Sambamurthy, V. (2013). Design Capital and Design Moves: The Logic of Digital Business Strategy. *MIS Quarterly, 37*(2), 537-564.

Woodman, R. W., Sawyer, J. E., & Griffin, R. W. (1993). Toward a Theory of Organizational Creativity. *The Academy of Management Review*, *18*(2), 293-321.

Yang, H., Lin, Z. J., & Lin, Y. L. (2010). A Multilevel Framework of Firm Boundaries: Firm Characteristics, Dyadic Differences, and Network Attributes. *Strategic Management Journal*, *31*(3), 237-261.

Ye, H. J., & Kankanhalli, A. (2018). User Service Innovation on Mobile Phone Platforms: Investigating Impacts of Lead Userness, Toolkit Support, and Design Autonomy. *MIS Quarterly*, *42*(1), 165-187.

Yoo, Y., Henfridsson, O., & Lyytinen, K. (2010). The New Organizing Logic of Digital Innovation: An Agenda for Information Systems Research. *Information Systems Research, 21*(4), 724-735.

Zhang, M., & Gable, G. G. (2017). A Systematic Framework for Multilevel Theorizing in Information Systems Research. *Information Systems Research, 28*(2), 203-224.

Zhang, S., & Markman, A. B. (1998). Overcoming the Early Entrant Advantage: The Role of Alignable and Nonalignable Differences. *Journal of Marketing Research, 35*(4), 413-426.

Zhou, Y. M., & Wan, X. (2017). Product Variety, Sourcing Complexity, and the Bottleneck of Coordination. *Strategic Management Journal, 38*(8), 1569-1587.

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

APPENDICES

Appendix 1. Journal Articles Analyzed in Essay 1

Journal	Number of Articles
Academy of Management Journal	2
Academy of Management Perspectives	1
Business & Information Systems Engineering	1
Decision Support Systems	1
Entrepreneurship Theory and Practice	1
Information & Management	2
Information Systems Journal	4
Information Systems Research	13
Information Technology for Development	1
International Journal of Industrial Organization	3
International Journal of Information Management	2
Journal of Information Technology	6
Journal of Management Information Systems	4
Journal of Marketing	1
Journal of Organizational Computing and Electronic Commerce	1
Journal of Product Innovation Management	1
Management Science	7
MIS Quarterly	8
Organization Science	5
RAND Journal of Economics	1
Research Policy	1
Strategic Management Journal	5
Sustainability	1
Technological Forecasting & Social Change	1
Technovation	1
Telecommunications Policy	2
Telematics and Informatics	1
The Journal of Industrial Economics	1
The Journal of Systems and Software	1
Total	79

Appendix 2. Summary of Empirical Software Platform Business Value Literature

Citation	Method	Platform	Level of Analysis	Dependent Variable	Independent Variables	Theory/Theoretical Idea	Key Findings
(Anderson, Parker, & Tan, 2014)	Analytical Modeling	Video Game	platform	profit	platform performance investment	two-sided market; high performance is a selling point for users, but requires complementors to investment more	Contrary to the “winner-take-all” markets, higher platform performance investments do not always bring competitive advantages.
(Basole & Karla, 2011)	Secondary Data	iOS, Android, BlackBerry, Nokia Ovi, Palm App, Windows	complementor	visualization of mobile platform ecosystems network structure	network measures	social network theory	The network structure of mobile platform ecosystems is continuously evolving.
(Benlian, Hilkert, & Hess, 2015)	Survey	iOS and Android	complementor	continuous intention to contribute	perceived platform openness	tradeoff between control and diversity	Complementors' perceived platform openness affects continuously intentions by increasing their perceived usefulness and satisfaction.
(Bergvall-Kåreborn & Howcroft, 2014)	Qualitative Study of 60 App Developers	iOS and Android	complementor	value capture and creation	coping with diversity, coping with knowledge, coping with structure	Kautz et al. (2007)'s framework of persistent problems and practices in information systems development	The results showed how complementors' app development represents significant changes at the business environment level, and identified the challenges and persistent problems that complementors face.
(Boudreau & Jeppesen, 2015)	Secondary Data	Video Game	platform	platform growth (i.e., development rates)	platform usage; number of unpaid competing complementors	network effects of a different set of motivations for unpaid complementors	Platform usage positively affects the development rates of unpaid complementors. But the increase of unpaid competing complementors will decrease the development rates.

(Boudreau, 2010)	Secondary Data	Handheld computer devices	platform	platform growth (i.e., number of new devices)	platform openness (i.e., give up control; granting access)	stimulate innovation by relinquishing control over core platform resources	Both granting access and giving up control will increase complementors' development rate. The magnitude of granting access is stronger than giving up control.
(Boudreau, 2012)	Secondary Data	Handheld computer devices	multi-level (platform and complementor)	platform product variety; developer product scope and time to release new version	number of producers	two-sided network effects; virtually infinite product space; extensive recombination and reuse; uncertainty and skewed outcomes; low-cost development	Number of complementors (i.e., ecosystem size) positively affects participants' product scope and innovation. Specifically, number of complementors in the same layer decreases innovation, but the number of complementors in other layers increases firm innovation.
(Breznitz, Forman, & Wen, 2018)	Secondary Data	Cloud	complementor	product introduction	VC, VC experience	VCs role in complementing firms' product development on new technological platforms	VC financing positively affects the introduction of new products offered over the cloud. Such effect is stronger for firms backed by VCs with rich experience in the IT industry, but is weaker for firms with experience of developing traditional client/server products.
(Ceccagnoli, Forman, Huang, & Wu, 2012)	Secondary Data	SAP	complementor	sales; likelihood of IPO	platform participation; IP rights; downstream capabilities	ownership of downstream complementary assets versus appropriation	Participation in a major platform ecosystem increases complementors' sales and likelihood of IPO. IP rights and downstream capabilities will amplify such effects.
(Cennamo & Santalo, 2013)	Secondary Data	Video Game	platform	market share	app market competition; apps exclusivity; distinctive positioning	network effects (cause winner-take-all strategy) versus platform competitive position	Aggressively pursuing WTA strategies concurrently decreases the benefits of each strategy. A differentiation strategy improves platform performance when the platform is highly distinctive relative to its competitors.

(Cennamo, Ozalp, & Kretschmer, 2018)	Secondary Data	Video Game	complementor	product quality (i.e., the average Game Rankings score)	multihoming; platform architecture (simple versus complex)	multihoming (expand market reach versus reduce differentiation)	Multihoming reduces app quality on a technologically more complex platform. But games that are released on the complex platform with a delay suffer a smaller drop in quality on complex platforms.
(Clements & Ohashi, 2005)	Secondary Data	Video Game	platform	market share	price, software variety	indirect network effects	Introductory pricing is effective at the beginning of the product cycle, but enhancing software variety is more effective later.
(Constantinides, Henfridsson, & Parker, 2018)	exploratory embedded case study	Android	platform	platform forking	governance of boundary resources	openness versus control	This study presented several strategies of bundling a platform fork from a set of host, forker, and other resources and suggested how to curb exploitation and retain control.
(Corts & Lederman, 2009)	Secondary Data	Video Game	platform	market share; number of complementors	market share; number of complementors	indirect network effects	This study shows the presence of a cross-platform (or generation-wide) network effects.
(den Hartigh, Ortt, van de Kaa, & Stolwijk, 2016)	Exploratory Case Study	Apple; IBM	platform	platform control mode (central control vs. distributed control)	innovativeness; quality; modularity; compatibility; network size, diversity, and governance structure; entry timing; product range; install base; pricing; reputation operational capabilities;	technology management and standardization perspectives; strategic management perspective; and social network theory	Platform owners' design of control modes are affected by the identified technology, network, and strategic factors.
(Eaton, Elaluf-Calderwood, Sørensen, & Yoo, 2015)	Embedded Case Study	iOS	boundary resources	evolution of boundary resources	heterogeneous actors' engagement in tuning	tuning; tension between generativity and infrastructural control	The evolution of boundary resources are shaped and reshaped through distributed tuning. Power has a dualistic role in the distributed tuning.

(Economides & Katsamakas, 2006)	Analytical Modeling	Microsoft; Linux	platform	demand; profit	proprietary vs. open source platform	two-sided network effects	The proprietary system is likely to dominate the open source platform industry both in terms of market share and profitability.
(Eisenmann, Parker, & Van Alstyne, 2011)	Literature Review; Analytical Modeling; Case Study		platform	platform success	platform envelopment	network effects; bundling; tying; economic of scope	Envelopers capture market share by foreclosing an incumbent's access to users; in doing so, they harness the network effects that previously had protected the incumbent.
(Foerderer, Kude, Mithas, & Heinzl, 2018)	Secondary Data	Android	complementor	innovation (product major update)	platform owner's entry	Red Queen competition; attention spillover	The entry of platform owner positively affects the likelihood of complementors' major update.
(Foerderer, Kude, Schuetz, & Heinzl, 2018)	multiple-case study of 4 platforms	enterprise software platforms	platform	knowledge integration across complementors	functional extent; interface design; evolutionary dynamics; knowledge boundaries; boundary resources scope and scale	Carlille's knowledge boundary framework	Platform functional extent, interface design, and evolutionary dynamics, affects knowledge boundaries. In shaping boundary resources, platform owners face the trade-off between knowledge scope and scalability.
(Foros, Kind, & Shaffer, 2017)	Analytical Modeling	iOS	platform	profit	revenue-sharing rule; agency model adoption	market competition	Although agency model increases platform profits, it may not be universally adopted.
(Ghazawneh & Henfridsson, 2013)	Case Study	iOS	boundary resources	design and use of boundary resources	resourcing; securing	generativity	Resourcing and securing are drivers behind boundary resources design and use, and interact with each other in third-party development.
(Ghose & Han, 2014)	Secondary Data	iOS and Android	complementor	demand; revenue	in-app purchase; in-app advertisement; price discount	interconnectivity to external players or choices	In-app purchase increases app demand, but in-app advertisement decreases app demand. Both in-app purchase and in-app advertisement

							increase app revenue. Price discount increases app demand.
(Giessmann & Legner, 2016)	Action Design Research	Cloud	platform	profitability	user segments and their specific value proposition; components and applications; install base relationships; platform and internal governance	two-sided markets; openness; control	This research provides a set of design principles for cloud platforms' business models.
(Goldbach, Benlian, & Buxmann, 2018)	Laboratory Experiment and a Follow-up Field Survey	Android	complementor	continuance intentions; app quality	platform control modes (formal vs. self-control), perceived autonomy	platform control	Platform control mode significantly affects complementors' continuance intention and app quality by enhancing their perceived autonomy.
(Hagiu & Hałaburda, 2014)	Analytical Modeling		platform	profit	information transparency (i.e., inform users about prices charged to developers); market power	market competition	Monopoly platforms have higher information transparency. Platforms with higher competition will have higher profits when users are less informed.
(Hagiu & Spulber, 2013)	Analytical Modeling		platform	profit	first-party content; price	coordination between buyer and seller	Platform owners will invest more (less) in first-party content if they have favorable expectations when first- and third-party content are substitutes (complements).
(Hsieh & Hsieh, 2013)	Field Interview and Literature Review	mobile platforms	complementor	intention to maintain relationship with platform	rewards; service quality; demand; switching costs; identification with platform;	calculative and affective commitment	This study proposed an integrative framework based on calculative and affective commitment to explain why complementors continued participate in a mobile platform ecosystem.

(Huang, Ceccagnoli, Forman, & Wu, 2013)	Secondary Data	SAP	complementor	join in platform ecosystem	IP rights; downstream capabilities	ownership of downstream complementary assets vs. appropriation	IPR and downstream capabilities positively affect complementors' likelihood of joining the platform, and these two effects amplify each other.
(Huber, Kude, & Dibbern, 2017)	Exploratory multiple-case study	two enterprise software platforms	platform	successfully address the tension (i.e., cocreating value vs. governance costs)	platform governance; value cocreation; ecosystem resources; relational capital	complementor diversity versus control	This research presented a process theory of ecosystem-wide governance rules and value creation.
(Kankanhalli, Ye, & Teo, 2015)	Survey	iOS and Android	complementor	intention to create new apps)	tool kit support; trend leadership; extrinsic reward; recognition; enjoyment	user innovation theory and construal level theory	Trend leadership and anticipated extrinsic reward affect both potential and actual users' intentions to innovate. Anticipated recognition and toolkit support affect only actual user innovators, while anticipated enjoyment affects only potential user innovators.
(Kapoor & Agarwal, 2017)	Secondary Data	iOS and Android	complementor	superior performance (in the top 500 list by revenue)	ecosystem complexity; ecosystem experience; platform generational transitions	evolutionary economics perspective of firms: consider the dual search processes of innovation and imitation as shaping performance dynamics	Ecosystem complexity increases complementors' superior performance and such effect will be amplified by ecosystem experience. Platform transitions decreases complementors' likelihood of sustaining superior performance, and that this effect is exacerbated by the extent of ecosystem complexity.
(Kim, Kim, & Lee, 2016)	Survey	iOS	complementor	Continued participation	revenue-sharing; market demand; usefulness of development tools and online forum; review	dedication-based mechanisms	Complementors' relationship benefits (such as revenue-sharing attractiveness, market demand, usefulness of development tools, and review process fairness) positively affect their continued

					fairness; termination costs on setup and learning		participation. Termination cost is positively associated with developers' continued participation by increasing their dependence on the platform.
(Kim, Prince, & Qiu, 2014)	Analytical Modeling; Secondary Data	Video Game	platform	market share; number of complementors	market share; product quality; number of complementors	indirect network effects	The use of aggregate level measures underestimates the indirect network effects by around 30%.
(Lahiri, Dewan, & Freimer, 2010)	Analytical Modeling	iOS and Android	platform	consumer surplus; social surplus	open versus property platforms	complementor diversity versus control	Users in an open platform are more likely to be under-served. Open platforms produce lower consumer surplus and social surplus.
(Landsman & Stremersch, 2011)	Secondary Data	Video Game	platform; complementor	complementor multihoming; platform sales	platform age; platform market share; platform-complementor fit; platform-level multihoming	multihoming (expand market reach versus reduce differentiation)	The negative effect of platform-level multihoming on sales vanishes as platforms mature or gain market share. Platform-level multihoming has stronger impacts on platform sales than the number of applications. Platform market share increases (decreases) seller-level multihoming for mature (nascent) platforms.
(Lee, Lee, & Hwang, 2015)	Secondary Data	iOS and Android	complementor	efficiency	platform openness	control	iOS complementors have a higher average efficiency with low variance within the group; Android complementors have a higher efficiency level than iOS group. Multi-homing complementors have highest efficiency because of the economies of scale.

(Lee & Raghu, 2014)	Secondary Data	iOS	complementor	sales (i.e., survival in the top charts; survival duration; number of apps in the top charts)	product portfolio (i.e., number of apps; number of categories)	scope economics	Complementors' broaden app portfolio positively influence their success in sales.
(Lin, Li, & Whinston, 2011)	Analytical Modeling; simulation	iOS and Android	platform	profit; pricing	complementor innovation and price competition	two-sided network effects; competition	Platforms can charge or subsidize users depending on their willingness to pay for quality. When all complementors innovate, there exists a parameterization under which a higher seller-side access fee stimulates innovation.
(Mäkinen, Kanniainen, & Peltola, 2014)	Secondary Data	Nokia Beta Labs	complementor	adoption dynamics	free beta products	product diffusion model	The adoption dynamics of free beta complementary products in a platform ecosystem follow Gompertz's model rather than the Bass model.
(Mantovani & Ruiz-Aliseda, 2016)	Analytical Modeling		platform	profit	platform investment; quality; open versus closed platform; environment	two-sided network effects; competition	When a market reaches saturation, firms will be trapped in a prisoner's dilemma: higher created value does not translate into greater value capture. Strategies such as in-compatibility may solve the dilemma.
(Miron, Purcarea, & Negoita, 2018)	Case Study	production mgmt software platform	complementor	complementors' perceived risks (i.e., relational risks and performance risks)	transaction costs; controls	transaction cost theory; control theory	Informational controls negatively affect complementors' perceived environmental uncertainty and perceived risks.

(Mollick, 2016)	Quasi-experiment and a longitudinal survey	iOS	complementor	commercialization	affiliation; anticommercial attributes; self-identity	nonmonetary motivation in OSS community; self-identity	Anticommercial attitudes do not affect complementors' commercialization decisions. Instead, entrepreneurial self-identity positively affects the propensity to commercialize.
(Mukhopadhyay, Reuver, & Bouwman, 2016)	Field Survey	Mobile Internet services	owner	safeguard customer relationships; manage interdependencies; access complementary resources	behavioral control, outcome control, input control	control theory	Behavioral and outcome controls positively affect ecosystem leaders' management of dependencies. Input and behavioral controls influence access to complementary resources. Outcome and behavioral controls contribute to platform owners' customer relationships management.
(Msiska & Nielsen, 2018)	Case Study	DHIS2 in Malawi	platform	evolutionary trajectory	socio-technical generativity	generativity	This study shows how the technical attributes of the software platform influences the generativity in concert with human relationships.
(Niculescu, Wu, & Xu, 2018)	Analytical Modeling		platform	profit	platform openness; absorptive capacity of the entrant; intensity of network effects	two-sided network effects; competition	IP sharing is impossible when the network effects are intense. If there is intermediate intensity of network effects, the incumbent opens the technology to the entrants with high absorptive capacity.
(Oh, Koh, & Raghunathan, 2015)	Analytical Modeling	mobile (network operator and mediated networks)	platform	ecosystem's generativity; platform provider's profitability	revenue-sharing	bargaining; generativity	This study developed a new bargaining model demonstrating how value can be appropriated between the platform owner and complementors.
(Ondrus, Gannamaneni, & Lyytinen, 2015)	Case Study	mobile payment	platform	market potential (i.e., critical mass of users)	platform openness at three levels: provider, technology, and user	two-sided network effects	Platform openness at the three levels overall can improve market potential; but all have their positive and negative consequences.

(Parker & Van Alstyne, 2017)	Analytical Modeling		platform	profit	platform openness; IP duration	openness vs. control; duration of third-party complementors' rights	This study analytically derived the optimal platform openness and IP duration.
(Parker, Van Alstyne, & Jiang, 2017)	Analytical Modeling		platform	platform innovation; profit	number of developers	code spillovers	Firms with more complementors are more likely to innovate using open external contracts than closed vertical integration.
(Pon, Seppälä, & Kenney, 2014)	Case Study	Google, Amazon, and Xiaomi	platform	firms' establishment of bottlenecks for platform control	gatekeeper roles (i.e., service creation environment; profile/identity management; service provisioning)	the openness characteristics of platforms create the challenge of control point	Using theories of bottlenecks and gatekeeper roles, this study found some specific strategies of platform control such as service creation environment, profile/identity management, service provisioning, billing information.
(Qiu, Gopal, & Hann, 2017)	Grounded Theory Study	iOS	complementor	complementor's management of logics of profession and markets	logic of profession, logic of the markets, and logic synthesis	institutional logics in platform ecosystems	Complementors manage the inherently opposed but coexisted logics of profession and markets, which is theorized as logic synthesis.
(Rietveld & Eggers, 2018)	Secondary Data	Video Game	complementor	sales	platform life cycle; complementor novel innovation (i.e., new IP)	the heterogeneity between early and late platform adopters to identify counterintuitive dynamics for complements	Later entrants have lower sales than those launched earlier because of the preference differences between early and late adopters. Such negative effect is stronger for novel games.
(Selander, Henfridsson, & Svahn, 2013)	Case Study	Sony Ericsson	complementor	innovation habitat	capability search; capability redeem	network effects; generativity	Complementors cannot rely on a single platform for addressing all relevant layers of innovation.
(Song, Baker, Wang, Choi, & Bhattacherjee, 2018)	Interpretive case study and Field Survey	Mobile platform	complementor	adoption	platform innovativeness, openness, advantage, and compatibility); market	IT adoption theories	This research has developed an interpretive theory of IT platform adoption. In addition, the study shows that network externalities have stronger influences on complementors'

					potential; developer tools; marketability; social influence		adoption decision of platforms than end-users.
(Song, Xue, Rai, & Zhang, 2017)	Secondary Data	Firefox	platform	app number; app diversity; user usage	platform governance (i.e., app review time; platform update frequency)	value creation and capture	Cross network effects of the user-to-developer and developer-to-user are asymmetric. App review time and platform updates significantly moderate such asymmetric cross network effects.
(Tanriverdi & Lee, 2008)	Secondary Data	Operating Systems platform	platform	sales growth; market share	platform relatedness; product-market relatedness	network externalities	Related diversifications across platforms and across software product-markets amplify and mutually affect each other. Combing the two strategies improves sales growth and market share, but implementing only platform-related diversification has negative effects.
(Tiwana, 2015a)	Survey and Secondary data	Firefox	complementor	market performance (i.e., number of users; rating)	extension modularization; input control; evolution rate	modular systems theory; control theory	Complementarity between input control and complementors' modularization positively influence complementary performance.
(Tiwana, 2015b)	Survey and Secondary data	Firefox	complementor	platform desertion	app decoupling; interface standardization; decision rights delegation; coordination costs	modular systems theory; coordination	App decision rights and app microarchitecture influences an app's platform desertion, by affecting the coordination costs.
(Tiwana, 2018)	Survey and Secondary data	Blackberry OS	complementor	competitive lead (i.e., an app's lifetime rating relative to competitors)	platform synergy; modularity; monolithicity	platform synergy—the degree to which an app leverages an evolving platform's capabilities; architectural near-	Modularity in an app's external architecture and monolithicity in its internal architecture jointly influence complementors' competitive lead.

						decomposability	
(van Angeren, Alves, & Jansen, 2016)	Secondary Data	Android, Google Chrome, Microsoft Office 365, Internet Explorer	complementor	variation of platform ecosystem network structure	complementors' interform relationships, entry barriers, partnership model, domain of the software platform	interconnectivity of the software industry	Lower entry barriers to the app store will be positively related to the number of app developers that populates a commercial platform ecosystem. The use of a partnership model to govern a commercial platform ecosystem and strong customer demand for related applications in an ecosystem will be positively related to its network density.
(Venkatraman & Lee, 2004)	Secondary Data	Video Game	complementor	developers' choices to launch games for game platform	network density overlaps and embeddedness; platform dominance and newness	coordination	Density overlap positively affects participation, but platform embeddedness negatively influences participation. Dominance and newness (i.e., platform age) of the platform positively affects complementors' participation.
(Wang, Lai, & Chang, 2016)	Survey and Simulation	Mobile network operators (e.g., iOS)	platform	number of users, number of developers	app discoverability; localized apps; app diversity; customer services; revenue-sharing; app review; promotion and user analysis support; market value	two-sided network effects	Platforms should exploit resources to sense and seize emerging opportunities, and reconfigure their resources in a dynamic market to rebuild their core competences for sustaining competitive advantages.

(Wareham, Fox, & Giner, 2014)	Case Study	ERP software platform	platform	three salient tensions that characterize the ecosystem: standard–variety, control–autonomy, and collective–individual	platform governance mechanisms	generativity; control	This study identified conditions in which complementary logics are overshadowed by contradictory logics and suggest the effective governance mechanisms.
(Ye & Kankanhalli, 2018)	Survey and Secondary data	iOS and Android	complementor	user service innovation (measured by number of apps created)	lead userness, design autonomy, toolkit support	user innovation theory and work design literature	Lead userness, toolkit support, and design autonomy independently and jointly influence users' quantity of innovation.
(Zhou & Song, 2018)	Secondary Data	Firefox	platform	market share	quantity, quality, and diversity of new apps, app updates; competitive entry	two-sided network effects; low entry barriers	The positive effect of number of complementors on platform performance is greater before than after competitive entry. Quality is more important than diversity in affecting platform performance PP after than before competitive entry.
(Zhou, Song, & Wang, 2018)	Secondary Data	Firefox	complementor	app performance	app update speed	ecology theories	Complementors' app update speed positively affects their performance. Frequent platform update and intraspecific negatively moderate the relationship between app update speed and app performance. Interspecific mutualism and developer capability amplify the effectiveness of app update speed.
(Zhu & Iansiti, 2012)	Analytical Modeling; Secondary Data	Video Game	platform	platform success	product quality; indirect network effects; consumer expectations	two-sided network effects	Xbox (new entrant) had disadvantage of quality but advantages on strength of indirect network effects and consumers' discount factor than PlayStation 2 (incumbent).

Appendix 3. Conceptual Research Related to Software Platforms

Citation	Research Focus	Method	Level of Analysis	Theoretical Perspectives	Deliverable
(de Reuver, Sørensen, & Basole, 2018)	A research agenda for software platforms research	Conceptual	Platform; Boundary resources	Digital artifacts; Generativity	Conceptualization of software platforms and non-software platforms; Identifying main issues, risks, and recommendations for software platform scholars in terms of concepts, scoping, and methodology; Suggesting six questions for future research;
(Gawer, 2014)	Integrating two-sided markets and technological architecture view of platforms	Conceptual	Platform	Two-sided markets and network effects; Platform architecture	Conceptualization of technological platforms from economics (i.e., two-sided market) and engineering design (i.e., platform architecture) perspectives; Classification of technological platforms into internal, supply-chain, and industry platforms; Developing a framework describing platform innovation and competition;
(Constantinides et al., 2018)	Concomitantly discuss platforms and digital infrastructures	Conceptual and Literature Review	Platform	Platform architecture (i.e., layered modular architecture); Governance	Summary of key insights from the literature; Identifying five themes and opportunities for future research; Discussing implications for policy making;
(McIntyre & Srinivasan, 2017)	Extant perspectives of platforms and a research agenda	Literature Review	Platform	IO economics; Technology management; Strategic Management	Summary of extent perspectives of platforms research; Developing a research agenda focusing on the relative impacts of network effects and platform quality, drivers of indirect network effects, and attributes of complementors, and leveraging complementor dynamics for competitive advantage;
(Tiwana, Konsynski, & Bush, 2010)	The evolutionary dynamics of software platforms and their ecosystems	Conceptual	Platform	Platform architecture; Governance (or control)	A framework incorporating platform architecture, governance, and environmental dynamics to explain platforms' evolutionary dynamics; Suggesting four theoretical lenses for future

					research; Developing five future research questions;
(Yoo, Henfridsson, & Lyytinen, 2010)	The new type of product architecture: layered modular architecture	Conceptual	Platform (product owners)	Digital artifacts; Generativity	A conceptual framework describing digital innovation enabled by layered modular architecture; Identifying two new research themes and suggesting future research questions under these two themes;
(Lusch & Nambisan, 2015)	Service innovation (or value co-creation) from a service-dominant logic perspective	Conceptual	Platform	Modular architecture; Rules of exchange	Proposed a broadened view of service innovation, where value is co-created as resource integration process, diver actor roles, and supportive environment; Identifying key research themes in service innovation and offer a research agenda;
(Agarwal & Tiwana, 2015)	Red Queen competition and information systems evolvability	Conceptual	Not explicitly specified	Systems architecture	Describing Red Queen competition, systems architecture, and information systems evolvability;
(Thomas, Autio, & Gann, 2015)	Theorize architectural leverage and use it to understand platform evolution	Literature Review	Platform	Logics of leverage; Architectural openness	Identifying four research streams, including organizational platforms, product family platforms, market intermediary platforms, and platform ecosystems; Theoretical logics of each stream of research; Developing the concept of architectural leverage by integrating the theoretical logics of leverage and architectural openness;
(Nambisan, 2017)	Software entrepreneurship—the intersection of software technologies and entrepreneurship	Conceptual	Complementor	Digital artifacts and infrastructure; Openness; Generativity	Summary of two broad implications for software entrepreneurship, including less bounded entrepreneurial processes and outcomes and less predefined locus of entrepreneurial agency; Identifying six themes for future research;
(Ghazawneh & Henfridsson, 2015)	A paradigmatic analysis of software application marketplaces	Conceptual	Platform	Control and functionality scope	A typology distinguishing four types of software application marketplaces: closed, censored, focused, and open marketplaces;

Appendix 4. Development of Platform and Complementary Capabilities

Constructs	Illustrative Variables from Related Literature
Platform Capabilities	
Intermediarity	***Platform Investments (or Platform Quality)***: superior performance is a selling point for end users, but the increased technological complexity increases complementors' efforts and costs (Anderson et al. 2014; Zhu & Iansiti 2012). ***Motivating Complementors***: signaling and reputational motivations drive the investments and development activities of complementors (Boudreau & Jeppesen 2015). ***Combination of WTA Strategies***: simultaneously pursuing same intense distinct WTA strategies may trigger conflicting incentives for complementors (Cennamo & Santalo 2013). ***Platform Positioning***: differentiate using distinct positioning instead of focusing on space with largest number of consumers is more beneficial (Cennamo & Santalo 2013). ***App Non-Exclusivity (or Multihoming)***: non-exclusive apps allow complementors to reach broader market than a single platform's install base, and therefore triggering indirect network effects between users of competing and incompatible hardware platforms (Corts & Lederman 2009; Landsman & Stremersch 2011). ***Pricing***: platform owners can facilitate network effects through discriminate and strategic pricing toward direct users and complementors (Clements & Ohashi 2005; Economides & Katsamakas 2006; Lahiri et al. 2010; Lin et al. 2011). ***Revenue-Sharing Rules***: revenue-sharing between platform owner and complementors affect retail prices and complementor participation (Foros et al. 2017). ***Levels of Information (or Transparency)***: different levels of information on users and complementors affect matching and platform profits (Hagiu & Halaburda 2014). ***Toolkit Support***: toolkit helps complementors better identify market needs and develop products that satisfy user preferences (Kankanhalli et al. 2015; Ye & Kankanhalli 2018). ***App Quality***: the effects of user install base on number of complementors is stronger for middle-quality apps; while the impacts of app variety on user utility will be stronger for high-quality apps (Kim et al. 2014). ***App Review***: long app review time will weaken the long-term cross network effects from users to complementors (Song et al. 2018).
Evolvability	***Number of Complementors***: the virtually infinite expanse of possibilities allows for ever-expanding variety; the low tendency of consolidation exists in a weak selection environment (Boudreau 2012; Parker et al. 2017). ***Strategically Adding Complementors*:** the increase of differentiated complementors raises complementors' investment incentives; while adding complementors to already-served app areas crowds out complementors' innovation incentives (Boudreau 2012). ***Platform Owner Entry (or First-Party Content, or Competitive Entry)***: platform owner entry (or other types of competitive entry) poses a competitive threat and pushes complementors engaging in innovation outputs (Foerderer et al. 2018; Hagiu & Spulber 2013; Zhou & Song 2018). ***Distributed Tuning***: the evolution of boundary resources involves cascading actions of accommodations and rejections of interconnected actors and artifacts (Eaton et al. 2015).

	Platform Envelopment: a multi-platform bundle through envelopment can leverage shared user relationships to offer revolutionary functionality (Eisenmann et al. 2011). ***Resourcing***: the process that describes how the diversity and scope of a software platform is enhanced by boundary resources (Ghazawneh & Henfridsson 2012). ***Ecosystem Complexity***: the increase of ecosystem complexity directly affects complementors' internal complexity with respect to its innovation decisions (Kapoor & Agarwal 2017). ***Platform Updates and Generational Transitions***: the transition of new generations or platform updates introduces new market opportunities for complementors and increases competitive dynamics (Kapoor & Agarwal 2017; Song et al. 2018). ***Platform Openness***: open platforms not only trigger innovation, but also transfer risks to complementors and facilitate competitive dynamics (Boudreau 2010; Lee et al. 2015; Ondrus et al. 2015; Parker & Van Alstyne 2017; Parker et al. 2017). ***Intellectual Property Sharing***: open a proprietary technology platform allows and facilitates same-side co-opetition in a market with network effects (Niculescu et al. 2018). ***Architectural Leverage***: platform owners can achieve ecosystem-specific benefits by combining different levels of architectural openness with three types of leverages—production, innovation, and transactional leverage (Thomas et al. 2015). ***Platform Architecture***: platform architecture, such as decomposition, design rules, and modularity, measures how the ecosystem is partitioned into a platform and a set of complementary modules that are decoupled and can be resembled (Tiwana et al. 2010). ***Layered Modular Architecture***: the hybrid between modularity and layered architecture adds the generativity attributes to the platform ecosystem (Yoo et al. 2010).
Stability	***Relinquishing Control***: granting complementors permissions to use the platform, while ensuring the interoperability with the platform and with each other (Boudreau 2010; Parker & Van Alstyne 2017). ***Securing***: the process of the control over the focal platform and its related products and services is increased (Ghazawneh & Henfridsson 2012). ***Ecosystem-wide Governance Rules***: ecosystem governance defines the ease of access to defined technical resources and market resourcing depending on partnership levels, which can help solving salient tensions such as standard-variety, control-autonomy, and collective-individual (Huber et al. 2017; Wareham et al. 2014). ***Practicing Ecosystem-wide Governance Rules***: it includes passively executing rules, passively executing rules while emphasizing values, proactively executing rules, violating values by amending rules, and stretching rules while favoring values (Huber et al. 2017). ***Managing Platform Forking***: a forker can exploit the platform's boundary resources and complements to create a competing platform business. Platforms should strategically curb such exploitation and retain control (Karhu et al. 2018). ***Boundary Knowledge***: the tradeoff of providing knowledge at the right scope and scale, while allowing for the knowledge scalability across the entire ecosystem (Foerderer et al. 2018). ***Incompatibility and Exclusivity***: third-party complementors can improve innovation, but may not translate into greater value when the market reaches saturation (i.e., known as a prisoner's dilemma). Incompatibility and exclusivity

	with complementors may be ways to solve the dilemma (Mantovani & Ruiz-Aliseda 2016). ***Platform Governance***: it describes who makes what decisions about a platform. Governance practices such as input control, decision rights partitioning, and ownership affects the platform owner's abilities of retaining sufficient control (Tiwana et al. 2010; Tiwana 2015a; 2015b).
Complementary Capabilities	
Creativity	***Narrowed and Specialized Product Scope***: complementors' product scope tends to remain narrow and specialized, because of the diseconomies of scope (Boudreau 2012). ***Logic Synthesis***: complementors need to manage the inherent opposed but coexisted logics in their entrepreneurial activities—logic of the profession and logic of the markets—to identify market niche and achieve success (Qiu et al. 2017). ***Entry Timing***: the differences of user preferences between early adopters and late adopters affect complementors' value creation and which types will be most successful (Rietveld & Eggers 2018). ***Innovation Capabilities***: complementors' capability of searching platform boundary resources and redeeming (i.e., developing, distributing, and monetizing) their products and services influences their performance (Selander et al. 2013).
Interconnectivity	***Relation to Venture Capitals (VCs)***: the involvement of VCs reduces uncertainty and assimilates external knowledge, information, and resources (Breznitz et al. 2018). ***Relation to Multiple Platforms (Multihoming)***: multihoming expands complementors' market, but may reduce differentiation among competing platforms; complementors can achieve balance by offering different quality levels across platforms (Cennamo et al. 2018; Landsman & Stremersch 2011; Tanriverdi & Lee 2008; Venkatraman & Lee 2004). ***Relation to External Players***: in-app purchase option increases app demand, while the in-app advertisement option decreases app demand (Ghose & Han 2014). ***Relation to the Platform (Ecosystem Experience)***: experience in a platform ecosystem increases complementors' accumulation of knowledge and dynamic learning (Kapoor & Agarwal 2017). ***Product Scope***: complementors' number of categories, number of apps, and related diversification across market segments in their product portfolio can facilitate the scope of economics (Lee & Raghu 2014; Tanriverdi & Lee 2008). ***Modularization***: complementary apps' modularity—the extent to which the apps are loosely coupled and interacts with the focal platform through standardized interfaces—affects their abilities of evolving, coordination costs, and business value creation (Tiwana 2015a; 2015b). ***Architectural Near-Decomposability***: complementors' independence from the platform and interdependencies within the app influences their capabilities of leveraging the platform's capabilities (Tiwana 2018). ***Coordination Costs***: complementors should spend efforts on managing dependencies with the platform, which affects their value creation (Tiwana 2015b; Venkatraman & Lee 2004). ***Platform Synergy***: the extent to which complementors leverage the platform's capabilities (Tiwana 2018). ***Connections to Other Complementors***: a complementor's collaborative relationships with their peers affects the entry barriers of the ecosystems and create value for complementors (van Angeren et al. 2016).

Appropriability	***Intellectual Property Rights (IPRs)***: IPRs such as copyrights and patents help complementors to deter imitation and prevent entry once imitation occurred (Ceccagnoli et al. 2012; Huang et al. 2013). ***Downstream Capabilities***: help complementors to better defend its "territory" (Ceccagnoli et al. 2012; Huang et al. 2013). ***Revenue-Sharing Rules***: fair revenue-sharing rules promise the amount of complementors' own gains in proportion to their inputs (Foros et al. 2017; Kim et al. 2016; Oh et al. 2015)

Appendix 5. Examples of Hadoop-Related Startups' Business Description

Firm	Time	Product (Business) Description
DataStax	2012Q2	*DataStax offers products and services based on the popular open-source database, Apache Cassandra™, which solve today's most challenging big data problems. DataStax Enterprise combines the performance of Cassandra with analytics powered by Apache Hadoop.*
DataStax	2013Q1	*DataStax powers the apps that transform business for more than 200 customers, including startups and 20 of the Fortune 100. DataStax delivers a massively scalable, flexible and continuously available big data platform built on Apache Cassandra™. DataStax integrates enterprise-ready Cassandra, Apache Hadoop™ for analytics and Apache Solr™ for search across multi-datacenters and in the cloud.*
HStreaming LLC	2013Q3	*HStreaming LLC provides the most scalable real-time continuous data analytics platform powered by Hadoop. HStreaming enables organizations to realize the full value of data by analyzing, visualizing, and acting on massive data correctly and in real-time. HStreaming adds real-time processing and ETL capabilities to Hadoop consolidating the full big-data life cycle including pre-processing, ETL, storage, analytics, post-processing, and archival on a single platform. HStreaming is compatible with all major Hadoop distributions.*
Hortonworks	2016Q1	*Hortonworks is a commercial vendor of Apache Hadoop, the preeminent open source platform for storing, managing, and analyzing big data. Hortonworks Data Platform, powered by Apache Hadoop, provides an open and stable foundation for enterprises and a growing ecosystem to build and deploy big data solutions. Hortonworks is the trusted source for information on Hadoop, and together with the Apache community, Hortonworks is making Hadoop more robust and easier to install, manage, and use. Hortonworks provides unmatched technical support, training, and certification programs for enterprises, systems integrators, and technology vendors.*
SkyTap	2015Q4	*Skytap's enterprise customers gain on-demand, self-service access to Cloudera's leading open source distribution of Apache Hadoop, including the Cloudera Enterprise free edition, which can be used to deploy and manage physical or virtual clusters of up to 50 nodes. Skytap's Cloudera Hadoop templates are ideal for enterprise developers, testers, data scientists and IT professionals who are interested in quickly learning more about Hadoop, experimenting with its capabilities, and developing proof-of-concepts for big data offerings.*

Appendix 6. Examples of Public Firms' Hadoop-Related Product Description

Firm	Time	Official Description of Hadoop-Related Products
Google	2014Q1	*Google continues to build on its Cloud Storage platform by offering Apache Hadoop developers a simpler way to manage big data clusters and file system through a new Google Cloud Storage Connector for Hadoop. This connector is meant to allow developers to focus on their data processing logic instead on managing a cluster and file system.*
Amazon Web Services	2010Q1	*Amazon Elastic MapReduce is a web service that enables businesses, researchers, data analysts and developers to easily and cost-effectively process vast amounts of data. It utilizes a hosted Hadoop framework running on the web-scale infrastructure of Amazon Elastic Compute Cloud (Amazon EC2) and Amazon Simple Storage Service (Amazon S3).*
Teradata	2012Q3	*Teradata Aster Big Analytics Appliance is the industry's first unified big analytics appliance. The Teradata Aster Big Analytics Appliance brings together open source Apache Hadoop and Teradata Aster into a single highly- integrated and optimized appliance. With the Teradata Aster patented SQL-MapReduce and Aster SQL-H, the Teradata Aster Big Analytics Appliance provides users with transparent access to Hadoop and provides unique business analytics to a broad set of knowledge workers. The appliance offers pre-packaged ready-to-run analytical functions such as digital marketing optimization, social network analysis, fraud detection, and analysis of machine-generated data in just hours.*

Appendix 7. Top 30 Keywords in Hadoop Firms' Product Description in Selected Periods

Time	Keyword List
2010 4th Quarter	data, analytics, hadoop, develop, enterpris, platform, big, search, elastic, manag, system, access, busi, custom, process, servic, web, apach, applic, cloud, cluster, cost, digit, file, languag, massiv, power, secur, storage, support
2013 4th Quarter	data, analytics, hadoop, big, enterpris, busi, cloud, manag, platform, softwar, custom, apach, servic, applic, deploy, develop, integr, system, databas, power, perform, environ, support, comput, cost, insight, real, access, distribut, server
2015 4th Quarter	data, hadoop, analytics, big, enterpris, platform, busi, cloud, manag, softwar, servic, custom, system, apach, develop, applic, deploy, integr, perform, cost, databas, storag, access, lead, scale, power, real, environ, infrastructur, process

Appendix 8. Representative Platform Ecosystem Literature from Complementors' Perspective

Study	Focus	Theoretical Lens	Data	Dependent Variable	Platform	Findings
Ceccagnoli et al. (2012)	Whether participation in platform ecosystems improves the performance of independent software vendors (ISVs), and how appropriable mechanisms will influence the benefit	Research on innovation commercialization, appropriability, and markets for technology	Longitudinal archival data	Sales, likelihood of Initial Public Offering (IPO)	SAP	Participating in a major platform ecosystem will increase an ISV's sales and likelihood of IPO. In addition, these impacts will be strengthened by the ISV's intellectual property rights (IPR) and downstream capabilities.
Huang et al. (2013)	Impacts of ISVs' IPR and downstream capabilities on their entry into platform ecosystems	Tradeoff between the expectation of higher profits and the potential risks	Longitudinal archival data	ISVs' entry into a platform ecosystem	SAP	IPR and downstream capabilities positively affect ISVs' decisions to join a major platform ecosystem. In addition, the impact of IPR is greater for the ISVs with lower downstream capabilities.
Selander et al. (2013)	How complementors participate across digital ecosystems	Ecosystem metaphor	Historical case data	Complementors' participation across digital ecosystems	Sony Ericsson	Complementors benefit from participating across digital ecosystems and pursuing a pluralistic strategy.
Lee & Raghu (2014)	Effects of app portfolio management on the success of app developers	Product portfolio management, scope economics	Longitudinal archival data	Success in product sales	iOS	App developers with broader offers across multiple categories are more likely to survive in the top charts.
Tiwana (2015a)	How input control and a module's modularization jointly affect its performance	Modular systems theory	Survey data and archival data	Market performance	Firefox	A module's modularization and the focal platform's input control jointly affect its market performance, by inducing the product evolution.
Tiwana (2015b)	How an app's microarchitecture and app decision rights jointly influence its	Modular systems theory	Survey data and archival data	Platform desertion	Firefox	App decision rights delegation weakens the negative impact of app decoupling on coordination cost, but strengthens the

	desertion of a platform ecosystem					influence of app interface standardization on reducing coordination cost.
Foerderer et al. (2018)	Influences of platform owner's entry on the complementors' product update	"Red Queen" dynamics	Longitudinal archival data	Apps' major update	iOS	App developers are more likely to update their apps and release new apps in the affected market category after platform owner's entry.
Wen & Zhu (2019)	Complementors' responses to the threat of platform owner's entry	Literature on firms' reaction to the entry threat, platform owner's entry into complementary markets, and competition and innovation	Longitudinal archival data	App update, app price	Android	App developers reduce their innovation effort on the affected apps and increase their prices in response to the threat of platform owner's entry
Kapoor & Agarwal (2017)	Influences of the structural and evolutionary features of platform ecosystems on complementors' sustainability of superior performance	Perspectives on evolutionary economics	Longitudinal archival data	Apps' sustainability of superior performance	Android, iOS	Ecosystem complexity positively affects app developers' likelihood of sustaining their superior performances, and this effect will be strengthened by apps' ecosystem experience. However, platform transitions negatively influence app developers' sustainability.
Qiu et al. (2017)	How the two field-level institutional logics (of profession and markets) are created in platform ecosystems	Theory of institutional logic	Field observations and qualitative data	App developers' two-way logic synthesis	iOS	A theoretical model of field-level professional and market logics operating in a platform ecosystem is proposed.

References (For Appendices)

Agarwal, R., & Tiwana, A. (2015). Evolvable Systems: Through the Looking Glass of IS. *Information Systems Research, 26*(3), 473-479.

Anderson, E. G., Parker, G. G., & Tan, B. (2014). Platform Performance Investment in the Presence of Network Externalities. *Information Systems Research, 25*(1), 152-172.

Basole, R. C., & Karla, J. (2011). On the Evolution of Mobile Platform Ecosystem Structure and Strategy. *Business & Information Systems Engineering, 3*(5), 313-322.

Benlian, A., Hilkert, D., & Hess, T. (2015). How Open is This Platform? The Meaning and Measurement of Platform Openness from the Complementors' Perspective. *Journal of Information Technology, 30*(3), 209-228.

Bergvall-Kåreborn, B., & Howcroft, D. (2014). Persistent Problems and Practices in Information Systems Development: A Study of Mobile Applications Development and Distribution. *Information Systems Journal, 24*(5), 425-444.

Boudreau, K. (2010). Open Platform Strategies and Innovation: Granting Access vs. Devolving Control. *Management Science, 56*(10), 1849-1872.

Boudreau, K. (2012). Let a Thousand Flowers Bloom? An Early Look at Large Numbers of Software App Developers and Patterns of Innovation. *Organization Science, 23*(5), 1409-1427.

Boudreau, K., & Jeppesen, L. B. (2015). Unpaid Crowd Complementors: The Platform Network Effect Mirage. *Strategic Management Journal, 36*(12), 1761-1777.

Breznitz, D., Forman, C., & Wen, W. (2018). The Role of Venture Capital in the Formation of a New Technological Ecosystem: Evidence from the Cloud. *MIS Quarterly, 42*(4), 1143-1169.

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.

Cennamo, C., Ozalp, H., & Kretschmer, T. (2018). Platform Architecture and Quality Trade-offs of Multihoming Complements. *Information Systems Research, 29*(2), 461-478.

Cennamo, C., & Santalo, J. (2013). Platform Competition: Strategic Trade-offs in Platform Markets. *Strategic Management Journal, 34*(11), 1331-1350.

Clements, M. T., & Ohashi, H. (2005). Indirect Network Effects and the Product Cycle: Video Games in the U.S., 1994-2002. *The Journal of Industrial Economics, 53*(4), 515-542.

Constantinides, P., Henfridsson, O., & Parker, G. G. (2018). Introduction—Platforms and Infrastructures in the Digital Age. *Information Systems Research, 29*(2), 381-400.

Corts, K. S., & Lederman, M. (2009). Software Exclusivity and the Scope of Indirect Network Effects in the U.S. Home Video Game Market. *International Journal of Industrial Organization*, *27*(2), 121-136.

de Reuver, M., Sørensen, C., & Basole, R. C. (2018). The Digital Platform: A Research Agenda. *Journal of Information Technology, 33*(2), 124-135.

den Hartigh, E., Ortt, J. R., van de Kaa, G., & Stolwijk, C. C. M. (2016). Platform Control During Battles for Market Dominance: The Case of Apple versus IBM in the Early Personal Computer Industry. *Technovation, 48-49*, 4-12.

Eaton, B., Elaluf-Calderwood, S., Sørensen, C., & Yoo, Y. (2015). Distributed Tuning of Boundary Resources: The Case of Apple's iOS Service System. *MIS Quarterly, 39*(1), 217-243.

Economides, N., & Katsamakas, E. (2006). Two-Sided Competition of Proprietary vs. Open Source Technology Platforms and the Implications for the Software Industry. *Management Science*, *52*(7), 1057-1071.

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

Foerderer, J., Kude, T., Mithas, S., & Heinzl, A. (2018). Does Platform Owner's Entry Crowd Out Innovation? Evidence From Google Photos. *Information Systems Research, 29*(2), 444-460.

Foerderer, J., Kude, T., Schuetz, S. W., & Heinzl, A. (2018). Knowledge Boundaries in Enterprise Software Platform Development: Antecedents and Consequences for Platform Governance. *Information Systems Journal, Forthcoming*.

Foros, Ø., Kind, H. J., & Shaffer, G. (2017). Apple's Agency Model and the Role of Most-Favored-Nation Clauses. *The RAND Journal of Economics*, *48*(3), 673-703.

Gawer, A. (2014). Bridging Differing Perspectives on Technological Platforms: Toward an Integrative Framework. *Research Policy, 43*(7), 1239-1249.

Ghazawneh, A., & Henfridsson, O. (2013). Balancing Platform Control and External Contribution in Third-Party Development: The Boundary Resources Model. *Information Systems Journal, 23*(2), 173-192.

Ghazawneh, A., & Henfridsson, O. (2015). A Paradigmatic Analysis of Digital Application Marketplaces. *Journal of Information Technology, 30*(3), 198-208.

Ghose, A., & Han, S. P. (2014). Estimating Demand for Mobile Applications in the New Economy. *Management Science, 60*(6), 1470-1488.

Giessmann, A., & Legner, C. (2016). Designing Business Models for Cloud Platforms. *Information Systems Journal*, *26*(5), 551-579.

Goldbach, T., Benlian, A., & Buxmann, P. (2018). Differential Effects of Formal and Self-control in Mobile Platform Ecosystems: Multi-method Findings on Third-party Developers' Continuance Intentions and application quality. *Information & Management, 55*(3), 271-284.

Hagiu, A., & Hałaburda, H. (2014). Information and Two-Sided Platform Profits. *International Journal of Industrial Organization, 34*, 25-35.

Hagiu, A., & Spulber, D. (2013). First-Party Content and Coordination in Two-Sided Markets. *Management Science, 59*(4), 933-949.

Hsieh, J.-K., & Hsieh, Y.-C. (2013). Appealing to Internet-based Freelance Developers in Smartphone Application Marketplaces. *International Journal of Information Management, 33*(2), 308-317.

Huang, P., Ceccagnoli, M., Forman, C., & Wu, D. J. (2013). Appropriability Mechanisms and the Platform Partnership Decision: Evidence from Enterprise Software. *Management Science, 59*(1), 102-121.

Huber, T. L., Kude, T., & Dibbern, J. (2017). Governance Practices in Platform Ecosystems: Navigating Tensions Between Cocreated Value and Governance Costs. *Information Systems Research, 28*(3), 563-584.

Kankanhalli, A., Ye, H. J., & Teo, H. H. (2015). Comparing Potential and Actual Innovators: An Empirical Study of Mobile Data Services Innovation. *MIS Quarterly, 39*(3), 667-682.

Kapoor, R., & Agarwal, S. (2017). Sustaining Superior Performance in Business Ecosystems: Evidence from Application Software Developers in the iOS and Android Smartphone Ecosystems. *Organization Science, 28*(3), 531-551.

Kim, H. J., Kim, I., & Lee, H. (2016). Third-party Mobile App Developers' Continued Participation in Platform-Centric Ecosystems: An Empirical Investigation of Two Different Mechanisms. *International Journal of Information Management, 36*(1), 44-59.

Kim, J.-H., Prince, J., & Qiu, C. (2014). Indirect Network Effects and the Quality Dimension: A Look at the Gaming Industry. *International Journal of Industrial Organization, 37*, 99-108.

Lahiri, A., Dewan, R. M., & Freimer, M. (2010). The Disruptive Effect of Open Platforms on Markets for Wireless Services. *Journal of Management Information Systems, 27*(3), 81-110.

Landsman, V., & Stremersch, S. (2011). Multihoming in Two-Sided Markets: An Empirical Inquiry in the Video Game Console Industry. *Journal of Marketing, 75*(6), 39-54.

Lee, C., Lee, D., & Hwang, J. (2015). Platform Openness and the Productivity of Content Providers: A Meta-Frontier Analysis. *Telecommunications Policy, 39*(7), 553-562.

Lee, G., & Raghu, T. S. (2014). Determinants of Mobile Apps' Success: Evidence from the App Store Market. *Journal of Management Information Systems, 31*(2), 133-170.

Lin, M., Li, S., & Whinston, A. B. (2011). Innovation and Price Competition in a Two-Sided Market. *Journal of Management Information Systems*, *28*(2), 171-202.

Lusch, R. F., & Nambisan, S. (2015). Service Innovation: A Service-Dominant Logic Perspective. *MIS Quarterly, 39*(1), 155-175.

Mäkinen, S. J., Kanniainen, J., & Peltola, I. (2014). Investigating Adoption of Free Beta Applications in a Platform-Based Business Ecosystem. *Journal of Product Innovation Management, 31*(3), 451-465.

Mantovani, A., & Ruiz-Aliseda, F. (2016). Equilibrium Innovation Ecosystems: The Dark Side of Collaborating with Complementors. *Management Science, 62*(2), 534-549.

McIntyre, D. P., & Srinivasan, A. (2017). Networks, Platforms, and Strategy: Emerging Views and Next Steps. *Strategic Management Journal*, *38*(1), 141-160.

Miron, E.-T., Purcarea, A. A., & Negoita, O. D. (2018). Modelling Perceived Risks Associated to the Entry of Complementors’ in Platform Enterprises: A Case Study. *Sustainability, 10*(9), 1-18.

Mollick, E. (2016). Filthy Lucre? Innovative Communities, Identity, and Commercialization. *Organization Science, 27*(6), 1472-1487.

Msiska, B., & Nielsen, P. (2018). Innovation in the Fringes of Software Ecosystems: The Role of Socio-Technical Generativity. *Information Technology for Development*, *24*(2), 398-421.

Mukhopadhyay, S., Reuver, M. d., & Bouwman, H. (2016). Effectiveness of Control Mechanisms in Mobile Platform Ecosystem. *Telematics and Informatics*, *33*(3), 848-859.

Nambisan, S. (2017). Digital Entrepreneurship: Toward a Digital Technology Perspective of Entrepreneurship. *Entrepreneurship Theory and Practice*, *41*(6), 1029-1055.

Niculescu, M. F., Wu, D. J., & Xu, L. (2018). Strategic Intellectual Property Sharing: Competition on an Open Technology Platform Under Network Effects. *Information Systems Research, 29*(2), 498-519.

Oh, J., Koh, B., & Raghunathan, S. (2015). Value Appropriation between the Platform Provider and App Developers in Mobile Platform Mediated Networks. *Journal of Information Technology*, *30*(3), 245-259.

Ondrus, J., Gannamaneni, A., & Lyytinen, K. (2015). The Impact of Openness on the Market Potential of Multi-Sided Platforms: A Case Study of Mobile Payment Platforms. *Journal of Information Technology, 30*(3), 260-275.

Parker, G., & Van Alstyne, M. (2017). Innovation, Openness, and Platform Control. *Management Science, Forthcoming*.

Parker, G., Van Alstyne, M., & Jiang, X. (2017). Platform Ecosystems: How Developers Invert the Firm. *MIS Quarterly, 41*(1), 255-266.

Pon, B., Seppälä, T., & Kenney, M. (2014). Android and the Demise of Operating System-Based Power: Firm Strategy and Platform Control. *Telecommunications Policy, 38*(11), 979-991.

Qiu, Y., Gopal, A., & Hann, I.-H. (2017). Logic Pluralism in Mobile Platform Ecosystems: A Study of Indie App Developers on the iOS App Store. *Information Systems Research, 28*(2), 225-249.

Rietveld, J., & Eggers, J. P. (2018). Demand Heterogeneity in Platform Markets: Implications for Complementors. *Organization Science, 29*(2), 304-322.

Selander, L., Henfridsson, O., & Svahn, F. (2013). Capability Search and Redeem across Digital Ecosystems. *Journal of Information Technology, 28*(3), 183-197.

Song, J., Baker, J., Wang, Y., Choi, H. Y., & Bhattacherjee, A. (2018). Platform Adoption by Mobile Application Developers: A Multimethodological Approach. *Decision Support Systems, 107*, 26-39.

Song, P., Xue, L., Rai, A., & Zhang, C. (2017). The Ecosystem of Software Platform: A Study of Asymmetric Cross-Side Network Effects and Platform Governance. *MIS Quarterly, Forthcoming*.

Tanriverdi, H. n., & Lee, C.-H. (2008). Within-Industry Diversification and Firm Performance in the Presence of Network Externalities: Evidence from the Software Industry. *The Academy of Management Journal, 51*(2), 381-397.

Thomas, L. D. W., Autio, E., & Gann, D. M. (2015). Architectural Leverage: Putting Platforms in Context. *Academy of Management Perspectives, 28*(2), 46-67.

Tiwana, A. (2015a). Evolutionary Competition in Platform Ecosystems. *Information Systems Research, 26*(2), 266-281.

Tiwana, A. (2015b). Platform Desertion by App Developers. *Journal of Management Information Systems, 32*(4), 40-77.

Tiwana, A. (2018). Platform Synergy: Architectural Origins and Competitive Consequences. *Information Systems Research, Forthcoming*.

Tiwana, A., Konsynski, B., & Bush, A. A. (2010). Platform Evolution: Coevolution of Platform Architecture, Governance, and Environmental Dynamics. *Information Systems Research, 21*(4), 675-687.

van Angeren, J., Alves, C., & Jansen, S. (2016). Can We Ask You to Collaborate? Analyzing App Developer Relationships in Commercial Platform Ecosystems. *The Journal of Systems and Software*, *113*, 430-445.

Venkatraman, N., & Lee, C.-H. (2004). Preferential Linkage and Network Evolution: A Conceptual Model and Empirical Test in the U.S. Video Game Sector. *The Academy of Management Journal, 47*(6), 876-892.

Wang, J., Lai, J.-Y., & Chang, C.-H. (2016). Modeling and Analysis for Mobile Application Services: The Perspective of Mobile Network Operators. *Technological Forecasting and Social Change*, *111*, 146-163.

Wareham, J., Fox, P. B., & Giner, J. L. C. (2014). Technology Ecosystem Governance. *Organization Science, 25*(4), 1195-1215.

Wen, W., & Zhu, F. (2019). Threat of Platform-Owner Entry and Complementor Responses: Evidence from the Mobile App Market. *Strategic Management Journal, Forthcoming*.

Ye, H. J., & Kankanhalli, A. (2018). User Service Innovation on Mobile Phone Platforms: Investigating Impacts of Lead Userness, Toolkit Support, and Design Autonomy. *MIS Quarterly*, *42*(1), 165-187.

Yoo, Y., Henfridsson, O., & Lyytinen, K. (2010). The New Organizing Logic of Digital Innovation: An Agenda for Information Systems Research. *Information Systems Research*, *21*(4), 724-735.

Zhou, G., & Song, P. (2018). Third-Party Apps (TPAs) and Software Platform Performance: The Moderating Role of Competitive Entry. *Information & Management*, *55*(7), 801-911.

Zhou, G., Song, P., & Wang, Q. (2018). Survival of the Fittest: Understanding the Effectiveness of Update Speed in the Ecosystem of Software Platforms. *Journal of Organizational Computing and Electronic Commerce*, *28*(3), 234-251.

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