Platform Owners and Complementors: The Emergence and Evolution of Platform Firms and The Performance Implications for Organizational Learning, Strategic Alliance, and Vertical Integration Behaviors of Platform Participants

by

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ABSTRACT

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By Kenan Guler,

Dissertation Director:
Dr. Douglas J. Miller

This dissertation examines the impacts of platform firms and platform-mediated business ecosystems in the modern society by utilizing both qualitative and quantitative research methodologies.

Investigating the emergence and evolution of platform firms, the qualitative chapters of the dissertation construct two different grounded theories of platform firms. The first qualitative chapter builds a theory of the emergence of platform firms. Analyzing 52 publicly available interviews with platform entrepreneurs, managers, and venture capitalists, I develop a theory and a process model showing how platform firms come into existence over four consecutive stages: (1) Inefficient Markets and Incumbents, (2) Entrepreneurial Motivation and Enabling Factors, (3) Efficiency-Enhancing Means, and (4) Platform Firms.

Collecting 52 publicly available interviews with platform entrepreneurs, managers, and venture capitalists and 34 review, forum, and analyst articles, I examine the evolution of platform firms in the second chapter of my dissertation. In particular, the process model I built in the second chapter shows that the evolution of platform firms consists of the following stages: (1) Platform Growth, (2) Competition, (3) Adaptive Behaviors, (4) Platform Sustainability, (5) Rebranding Challenges, and (6) Platform Failure.

On the other hand, the quantitative chapters of the dissertation utilize a large-scale video game dataset. The third chapter of my dissertation investigates the performance consequences of alliance and vertical integration behaviors of platform owners and complementor firms. I develop a framework for examining competitive and collaborative behaviors among platform participants noting that platform owners' entry into complementors' space should not always be viewed as an act of competition. The chapter found a positive relationship between alliance behaviors of platform participants and product performance, and a weakening moderating effect of platform maturity on the alliances between platform owners and complementor firms.

Bridging the longstanding exploration-exploitation literature to the platform literature, the last chapter of my dissertation investigates the relationship between organizational learning activities – exploration and exploitation – and alliance performance of platform participants. In particular, the chapter shows that ambidexterity in strategic alliances through partner specialization is positively associated with alliance performance, and finds platform maturity negatively moderates the positive effects of ambidextrous alliances on alliance performance.

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CHAPTER 1: INTRODUCTION

A recent surge of platform research shows that the modern capitalist economy is shaken by platform revolution (Parker and Van Alstyne, 2017; Parker, Alstyne, and Choudary, 2016) and the "taken for granted" competition in the business environment has been transformed into a platform-mediated one (Eisenmann, Parker, and Van Alstyne, 2010; Halaburda, Jan Piskorski, and Yıldırım, 2017). This transformation has not only expanded the boundary of traditional firms to facilitate transaction among firms and individuals who previously did not have an opportunity to transact with each other (Baldwin and Woodard, 2009; Eisenmann *et al.*, 2010; Evans and Schmalensee, 2008; Hagiu, 2006; McIntyre and Srinivasan, 2017; Rochet and Tirole, 2006) but also has blurred the line between “markets” and “firms,” the concepts that explain the “raison d’etre” (the most important reason of existence) of the modern capitalist firm (Coase, 1937, 1970; Williamson, 1975, 1985).

Despite the increasing number of insightful studies in the platform literature (e.g., Jacobides, Cennamo, and Gawer, 2018; McIntyre and Srinivasan, 2017; Parker and Van Alstyne, 2017; Rietveld and Eggers, 2018; Rietveld, Schilling, and Bellavitis, 2018), little attention has been paid to the emergence and evolution of platform firms. Similarly, notwithstanding a few insightful studies (Kapoor and Agarwal, 2017; Rietveld and Eggers, 2018; Rietveld *et al.*, 2018), our understanding of how platform participants achieve and sustain competitive advantage is limited. Building upon the preceding literature stream, this dissertation qualitatively investigates the emergence and evolution of platform firms and quantitatively examines the performance outcomes of behaviors of platform participants. The dissertation consists of two qualitative and two quantitative articles.

In the first qualitative article, I collect 52 publicly available unstructured interviews with 50 founders, top managers, and venture capitalists of platform firms with a theoretical sampling strategy (Glaser and Strauss, 1967) and build a theory of the emergence of platform firms. While a literature stream doesn't have to start with a theory that explains the "raison d'etre" of its fundamental concepts and constructs, it has to develop a theory of existence to convey important takeaways and findings to the next generation of researchers. The first qualitative article of the thesis takes the first step to build a theory of the existence of platform firms and asks one fundamental question: Why do platform firms come into existence? The process model built in the first qualitative article suggests that platform companies come into existence over four consecutive stages: (1) Inefficient Markets and Incumbents, (2) Entrepreneurial Motivation and Enabling Factors, (3) Efficiency-enhancing Means, and (4) Platform Firms.

In the second qualitative article of my dissertation, I use the same 52 publicly available unstructured interviews with 50 founders, top managers, and venture capitalists of platform firms, and collect additional 34 review, forum, and analyst articles to investigate the evolution of platform firms. While we have accumulated a certain amount of knowledge about the growth and evolution of traditional firms since Penrose's (1959) classic "theory of the growth of the firm" and Nelson and Winter's (1982) "an evolutionary theory of economic change," little attention is paid to the evolution of platform firms. As a result, we have little knowledge about whether or not platform firms follow a similar evolutionary path as their traditional counterparts. To better understand the impacts of platform firms on the traditional business environment, the second qualitative article of my dissertation asks: how do platform firms evolve? The evolutionary process model built in the second qualitative study indicates that the evolution of platform firms includes six major categories: (1) Platform Growth, (2) Competition, (3) Adaptive Behaviors, (4) Platform Sustainability, (5) Rebranding Challenges, and (6) Platform Failure. The evolutionary model suggests that the behaviors of platform participants are highly likely to be affected by the lifecycle and maturity of platforms because platform firms achieving the platform sustainability stage often drive out those struggling with rebranding challenges. To better understand the performance outcome of behaviors of platform participants, I design two large scale quantitative studies. In particular, in the quantitative articles, I scrutinize the effects of strategic alliance, vertical integration, and organizational learning (exploration vs. exploitation) behaviors of platform participants on their performance.

The third and fourth articles in my dissertation utilize a unique dataset, which consists of 18,169 video game releases between 1977 and 2017. Accordingly, there are 1,926 video game developers, 547 video game publishers, 10 platform owners and 38 video game platforms. In the third article, I contribute to the scant research on the entry decision of platform owners into the complementors' space, which often views entry as an act of "competition" (Gawer and Cusumano, 2002; Gawer and Henderson, 2007; Zhu and Liu, 2018) or "threat" (Wen and Zhu, 2019). Building upon the early field studies (Gawer and Cusumano, 2002; Gawer and Henderson, 2007) and recent empirical works (Zhu and Liu, 2018; Wen and Zhu, 2019), the paper extends the literature on the performance consequences of possible collaborative and competitive behaviors of platform owners and complementor firms. Consistent with the existing literature, I argue that platform owners may prefer to compete with complementor firms by a vertical integration mode and can produce complementary products for their platforms. However, platform owners' entry into the complementors' zone should not always be viewed as an act of "competition" or a "threat" because the owners often collaborate with complementor firms to develop new products. Focusing on collaborative and competitive behaviors of platform participants, I investigate the extent to which the alliance and vertical integration behaviors of firms in a platform ecosystem yield to superior product performance.

The fourth and last article of the dissertation uses a subsample of the video game dataset and investigates the performance outcome of balancing exploration and exploitation activities through partner specialization in a platform ecosystem. In the paper, I contend that balancing exploration/exploitation activities in an industry or ecosystem through separation of exploration and exploitation across partners in an alliance is positively associated with alliance performance. The hypothesis is built on the fact that, on the same project, one partner's activities can represent exploration while the other partner's activities represent exploitation. Furthermore, a firm can simultaneously specialize in exploration in one alliance and exploitation in a different alliance, thereby effectively separating activities that might lead to internal conflict, yet exhibiting ambidexterity in its approach to the market (Lavie et al., 2011). Using an uncertainty framework, I build a bridge between the longstanding contextual ambidexterity literature and the recent platform literature and show that platform maturity negatively moderates the positive effects of ambidextrous alliances on alliance performance.

Because of the four-paper dissertation format, each chapter is organized as a full article. Accordingly, each paper consists of introduction, theory, methods, results, and discussion sections. In the following chapters, I continue with qualitative and quantitative articles of my dissertation. After these four articles, I conclude the dissertation with a summary and conclusion section.

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CHAPTER 2: TOWARD A THEORY OF PLATFORM FIRM EMERGENCE

ABSTRACT

In recent years, platform firms have become an essential component of the business world. With the increasing number of studies, the impacts of platform firms on the traditional business environment are visible in many industry settings. Yet, little attention has been paid to the origin of these organizations. Analyzing 52 publicly available interviews with platform entrepreneurs, managers, and venture capitalists, I explore the emergence of platform firms. In a rigorous grounded theory-building study, I develop a theory and a process model showing how platform firms come into existence over four consecutive stages: (1) Inefficient Markets and Incumbents, (2) Entrepreneurial Motivation and Enabling Factors, (3) Efficiency-Enhancing Means, and (4) Platform Firms. The model illustrates that platform organizations' impact on the traditional business environment results from developing efficiency-enhancing means. It also highlights the differences between platform firms and traditional firms, and yields important implications for existing theories of the firm.

INTRODUCTION

In recent years, platform organizations have shaken the modern economy (Parker and Van Alstyne, 2017; Parker, Alstyne, and Choudary, 2016) and have transformed the "taken for granted" competition in the business environment into a platform- and ecosystem-mediated one (Cusumano, Yoffie, and Gawer, 2019; Eisenmann, Parker, and Van Alstyne, 2010; Jacobides, Cennamo, and Gawer, 2018). The impact of this transformation can be seen not only in high-technology industries but also through the emergence of platform models in more traditional settings, and even the non-profit sector. Conceptually, a platform organization refers to the owner of a multi-sided platform that enables different parties to transact with one another (Armstrong, 2006; Caillaud and Jullien, 2003; Evans, 2003; Hagiu, 2006; Rochet and Tirole, 2003, 2006). Some recent examples of platform firms' impact include Uber's impact on taxis, Airbnb's effect on the hotel industry, and Amazon's influence on the retail industry. With the increasing popularity of platforms among scholars and media, significant attention has been paid to the impacts of platform organizations on traditional business environments (e.g., Jacobides *et al.*, 2018; McIntyre and Srinivasan, 2017; Parker and Van Alstyne, 2017; Rietveld and Eggers, 2018; Rietveld, Schilling, and Bellavitis, 2018) but much less attention is paid to the origins and emergence of these organizations.

In an extensive qualitative grounded theory-building study, this chapter extends the literature by investigating the emergence of platform organizations and asks: Why do platform firms come into existence? With interest in platforms increasing dramatically in recent years – research on "platform firms" has increased about 15-fold since 2000, tripled since 2010, and doubled since 2013[1] – understanding the unique dynamics of platforms as a viable means of interaction represents a critical next step in this domain. Similarly, a better understanding of the process of platform firm emergence may not only offer insight into the increasing prevalence of platforms, but also guide future scholars studying the evolution of platform organizations.

[Insert Figure 2.1 about here]

To better understand the origin and emergence of platform firms, this study builds a qualitative theory of emergence of platform firms based on five interrelated stages. The chapter defines a *platform firm* as the owner of at least one platform where the firm orchestrates a network of firms and individuals, and coordinates these parties to develop complementary products, services, or technologies to mutually enhance value (Gawer, 2009, 2014). More specifically, it conceptualizes platform firms as having two distinctive characteristics: (1) the existence of at least two distinct user groups deriving value from transacting on the platform and (2) mediating interactions among these groups to facilitate coordination more efficiently and effectively than would bilateral relationships (Evans, 2003). For example, on a ride-sharing platform, Uber makes money by enabling transactions between drivers and passengers. In contrast, traditional taxi companies own cars and hire drivers to provide the same service. While we have accumulated significant knowledge about the emergence of traditional firms since the works of early behavioral theorists (Cyert and March, 1963; March and Simon, 1958; Simon, 2013) and transaction cost economists (Coase, 1937, 1970; Williamson, 1975, 1985, 1991), recent transformation

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[1] This finding is based on the visualization of Google Scholar results when I searched for four terms: (1) "platform firm", (2) "platform firms", (3) "platform company", and (4) "platform companies."

and disruption by platform firms urge us to build a theory of the emergence of the platform firm.

Taking the first step toward a theory of the emergence of the platform firm, this chapter designs a qualitative grounded theory-building study to deeply understand the process of the emergence of platform companies. I collect 52 publicly available interviews with platform entrepreneurs, managers, and venture capitalists. The process model built in the study suggests that platform companies come into existence over four consecutive stages: (1) Inefficient Markets and Incumbents, (2) Entrepreneurial Motivation and Enabling Factors, (3) Efficiency-enhancing Means, and (4) Platform Firms. The first stage of the model, Inefficient Markets and Incumbents represents the unsatisfactory situation where parties pay more for a product or service than what it's worth, mainly because of information asymmetry. The second stage of the model includes two distinct categories, Entrepreneurial Motivation and Enabling Factors. The category of Entrepreneurial Motivation encompasses the founders' rationale for the creation of the platform firms. Enabling Factors describes the circumstances that facilitate platform entrepreneurs' external organization of market forces rather than internally allocate resources. The third stage of the model, Efficiency-enhancing Means, emerges as a result of the interaction among earlier categories in the first two stages. In this stage, platform entrepreneurs use enabling factors to create alternative means to alleviate inefficiency in the existing marketplace resulting from behaviors of the incumbent organizations. The final stage of the model, Platform Firms, represents the birth of platform organizations as an alternative organizational mode which often pushes the traditional business environment toward a platform-mediated one. This transformation mainly occurs when ownership models are converted into a sharing economy, when firms mostly sell intangibles such as “mobility” and “minutes” instead of tangibles, and when different factors enable simple and real-time solutions to complex problems.

Developing a process model that shows why platform firms come into existence, this article makes four vital contributions. First, it is one of the first attempts to examine empirically the specific process of platform firm emergence. Second, the paper addresses existing criticism that platform literature “has taken for granted the existence of the markets that transact through the platform” and “has been of limited use for those looking for insights into why platforms come into existence in the first place (Gawer, 2009: 58)” and extends Jacobides *et al.*’s (2018) theory of ecosystems by highlighting the organizational aspect of platforms. As a response to Gawer (2009), the paper shows that platforms and platform firms come into existence mainly because of inefficient markets and incumbents, entrepreneurial motivation, and enabling factors. Third, the paper contributes to the literature by developing a model that shows how platform firms come into existence over four consecutive stages. This framework suggests that the platform literature largely focuses on the impacts of platform organizations on traditional business environments (e.g., Jacobides *et al.*, 2018; McIntyre and Srinivasan, 2017; Parker and Van Alstyne, 2017; Rietveld and Eggers, 2018; Rietveld *et al.*, 2018) but has offered relatively few insights on the emergence of platform firms. The chapter contributes to the literature by highlighting the impact of platform organizations on traditional settings, but also by explaining the stages that lead to the emergence of platform organizations. Finally, the chapter contributes to the literature by highlighting key differences between traditional firms and platform firms. According to the built theory, enabling a sharing economy, selling intangibles and providing simple and real-time solutions are the main factors that distinguish platform organizations from their traditional counterparts. All four contributions of the paper improve our understanding of platform organizations, and also open up new directions for future research. The paper continues with the theoretical background of platform firms, qualitative methodology, a detailed grounded theory of the emergence of platform firms, and the discussion section.

THEORETICAL BACKGROUND

In this study, platforms refer to multi-sided platforms that enable different parties to transact with one another (Armstrong, 2006; Caillaud and Jullien, 2003; Evans, 2003; Hagiu, 2006; Rochet and Tirole, 2003, 2006). As the owner of a platform[2], platform firms bring together two or more distinct customer groups, with at least one of these groups willing to reach the other group(s) (Evans, 2003), and orchestrate a network of firms and individual innovators, who are often collectively referred to as the platform's "innovation ecosystem" (Adner and Kapoor, 2010; Gawer, 2014; Nambisan and Sawhney, 2011). Accordingly, the platform firm uses its "smart power" to actively stimulate and shape the platform business ecosystem (Williamson and De Meyer, 2012; Yoffie and Kwak, 2006). Studies in the platform literature show that the stimulation and change of a platform ecosystem are affected by connections between platform firms and complementor firms (Ceccagnoli *et al.*, 2012; Cennamo and Santalo, 2013; Gawer and Henderson, 2007), standards and platform interfaces (Gawer, 2014), and rivalries between different platform ecosystems (e.g., Cennamo and Santalo, 2013).

[2] I should note that some platforms are not created or owned by platform firms, but rather they are open-source platforms. Examples of open-source platforms include Linux operating system and WooCommerce e-commerce platform. In the discussion section, I briefly discuss the difference among platform firms, open-source platforms, and blockchain technology.

While some studies highlight the central role of a platform firm in emergence of a platform ecosystem and see the platform owner as the "lead firm" (Williamson and De Meyer, 2012) or "keystone" organization (Iansiti and Levien, 2004), others focus on the value created from platform-mediated user networks (e.g., Cennamo and Santalo, 2013). A fundamental tenet of platform-mediated networks is that the value of platforms increases with the growing number of users (Cennamo and Santalo, 2013). Notably, the growing installed base of customers – the number of current users – is essential for new participants of platforms because the amount of value new entrants can appropriate is directly proportional to the installed base of customers (Eisenmann, 2006; Farrell and Saloner, 1986; Katz and Shapiro, 1986; McIntyre, 2011). Because participants in platforms are dependent on one another to create and appropriate value, the initial liquidity problem is often called a "chicken-and-egg problem" (Caillaud and Jullien, 2003). Given that a customer group is willing to participate in a platform only if its complements exist on the platform, platform firms face substantial direct and indirect network effects (Chen and Xie, 2007). While a large number of users on the same "side" facilitate direct network effects, a large number and variety of goods or users on another side lead to indirect network effects (Bonardi and Durand, 2003; Eisenmann *et al.*, 2010; Evans, 2003; Rochet and Tirole, 2003). Researchers have recently unearthed the asymmetric relationship between different sides of networks. A recent study shows that while the increased installed base of customers has a long-term impact on the growth of applications in a platform, the increased number of applications has only a short-time impact (Song *et al.*, 2017). Yet, the finding that increasing the number of potential matches has both positive and negative effects depending on the availability of outside options (Halaburda, Jan Piskorski, and Yıldırım, 2017) supports the asymmetric relationship in a platform ecosystem.

Quite recently, the focus of platform research has turned to complementor firms. Building upon the business ecosystem literature (e.g., Kapoor, 2014; Kapoor and Lee, 2013), several studies have focused on complementor firms (Kapoor and Agarwal, 2017; Rietveld and Eggers, 2018) and examine the relationship among giving access to complementor firms, control, and innovation (Boudreau, 2010; Parker and Van Alstyne, 2017). The importance of complementor firms is increasing for both platform firms and platform ecosystems because they create a network of innovation to produce complementary goods and services that make a platform more valuable (Ceccagnoli *et al.*, 2012; Gawer and Cusumano, 2002). For example, Ceccagnoli *et al.*, (2012) argue that partnerships between platform firms and complementor firms lead to co-creation of value on a platform ecosystem that eventually increases the performance of the complementor firms as well as benefiting platform firms by extending net benefits to platform adopters.

Despite the insightful findings in the literature on the central role of platform firms, platform-mediated networks and the implications for platform participants and complementors, we still know little about why platform firms come into existence. Analyzing how top management teams and founders of platforms initiate a platform firm business model, this paper attempts to scratch the surface of the process that leads to the existence of platform firms.

METHODS

Investigating the origin of platform firms, this paper mainly follows grounded theory-building guidelines (Glaser and Strauss, 1967; Strauss and Corbin, 1998). Without having any presumptions and hypotheses, the study was started with an open-mindedness but was refined during an 18-month back-and-forth process between the existing literature and the data. This back-and-forth process narrowed down the scope of the research to an important research question: Why do platform firms come into existence? To increase the explanatory and predictive power of the theory, the chapter adopted an inductive bottom-up coding methodology guided by a grounded theory-building study (Glaser and Strauss, 1967; Strauss and Corbin, 1998). The inductive theory-building process started with line-by-line coding and ended with major categories of the study. After several rounds of back-and-forth iteration between data and literature, the foci of the paper emerged on four stages: (1) Inefficient Markets and Incumbents, (2) Entrepreneurial Motivation and Enabling Factors, (3) Efficiency-Enhancing Means, and (4) Platform Firms. Building upon these foci, further iterations between data and the existing literature helped me relate categories to each other and develop a theory of platform firm emergence (Edmondson and McManus, 2007).

[Insert Figure 2.2 about here]

Data Collection and Sample

The study primarily utilizes theoretical sampling, the process of data collection directed by evolving theory rather than a predetermined population (Glaser and Strauss, 1967; Strauss, 1987), to create a rigorous database based on interviews with founders, top executives, and venture capitalists. In the very early stage of the study, the main criteria for selecting interviews was whether individuals were talking about the origin of their platform firm idea. Over an 18-month period, I have watched more than 115 interviews with founders, top managers, and capital providers (venture capitalists) of platform firms. To determine appropriate interviews, I used different combinations of “entrepreneur”, “manager”, "venture capitalist", "platform", "interview", "talk", "platform firm", "platform company", and "platform ecosystem" keywords in an online Google search. I considered any interview conducted since 1995 that involved an interviewer not affiliated with the company as a potential data source. Once reaching theoretical saturation (Glaser and Strauss, 1967; Strauss and Corbin, 1998), I stopped searching for further interviews. However, I didn't include some of these interviews in the analysis for several different reasons. First, some interviews were not relevant to the study and didn't match the main criteria. For example, nine interviews with platform entrepreneurs were not included in the analysis because the content was instead about daily lives of entrepreneurs. Second, if there was redundant information across interviews of the same individuals (30 interviews), the more detailed interview was preferred. And finally, during the trial-and-error process while directing the search to find proper interviews, I eliminated another 24 interviews because these interviews were conducted with traditional firm entrepreneurs. Interviews with traditional firm entrepreneurs except for venture capitalists were excluded from the analysis. As a result, the final sample consists of 52 interviews with 50 individuals, including 43 (Co)-Founders, 5 Venture Capitalists, and 2 Top Managers. The duration of the interviews in the final sample range from 6 minutes to 90 minutes, with an average of 24.71 minutes and a median of 24 minutes. Transcribing video interviews to text resulted in nearly 522 single-spaced pages.

The bulk of the video interview data comes from several major websites including khanacademy.org, under30ceo.com, cleverism.com, and youtube.com. In addition to these primary sources, I utilized other websites such as retireat21.com, forbes.com, fortune.com, wsj.com, and nytimes.com during the trial-and-error theoretical sampling process to direct search by evolving theory. Despite not analyzing all of the watched videos, redundant videos with the same individuals increased the integrity and reliability of the sample. I started to collect the data in early 2017 and continued to collect and analyze further data until late 2018. While all the video interviews were conducted between 2007 and 2017, more than 80% of them were conducted between 2013 and 2015. Thus, on average, the video materials were 3-4 years old when I analyzed them. As the main purpose of conducting these video interviews was to understand how platform entrepreneurs started their business, this was well-aligned with the research question of the paper. I have also collected further data about each person from public and private sources. These sources include LinkedIn, Facebook, Twitter, Crunchbase, Bloomberg, Pitchbook, and Privco.

From the cited sources, I collected data about the following variables: gender, citizenship, education, relevant industry experience, headquarters, and firm type. Accordingly, the following are some individual characteristics in the sample: 49 males and one female; 60% (30 out of 50) US citizens; three college dropouts and 26 individuals with a graduate degree; 72% (36 out of 50) with relevant industry experience. Further, I collected some firm-level characteristics. Although individuals in the sample have been involved in founding at least 122 firms, I only report here their last (or related) firm. The majority of these firms were founded in Silicon Valley, Ca. Correspondingly, the headquarters of these platform firms are in four US States: 92% (46 out of 50) in California, 4% (2 out of 50) in Washington, 2% (1 out of 50) in Texas, and 2% (1 out of 50) in Iowa. To deeply analyze individual characteristics of each firm and scrutinize the origin of platform firms, I divided firms into four categories: (1) Platform firm, (2) Half-platform firm, (3) Inter-platform firm, and (4) Traditional firm. If a firm coordinates transactions of multiple parties and matches supply and demand on a platform ecosystem, it has been coded as a platform firm. Firms that identify potential customers for other companies have been coded as half-platform firms, those that integrate and connect different platforms have been coded as inter-platform firms, and finally, those that do not meet these criteria were coded as traditional firms. While traditional firms only include five venture capitalist firms, there are 31 platform firms, eight half-platform firms, and six inter-platform firms. Table 2.1[3] provides several examples of these firms. The preceding taxonomy organizing firms into four categories calls for further research. Industry-wise, the vast majority of firms are in data analytics, information technology, gaming, software (hardware) development, and online education industries.

[Insert Table 2.1 about here]

Data Analysis

A rigorous qualitative study should at least be assessed on credibility, transferability, dependability, and conformability of the research (Lincoln and Guba, 1985). To meet these rigorous qualitative notions, I follow the commonly accepted standards for a grounded theory-building methodology (Charmaz, 2014; Glaser and Strauss, 1967). The grounded theory process started after collecting the transcripts of initial interviews. I began the grounded theory process with the line-by-line coding of each transcript[4] (Charmaz, 2014; Glaser, 1978). The second stage of grounded theory-building was converting line-by-line coding into open coding (Corbin and Strauss, 1990) by re-reading the transcripts and

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[3] Please see Appendix for full sample.
[4] Often transcripts of each interview were available on the cited websites. In few cases where transcripts were not available, videos were manually transcribed after watching videos for several times.

previous codes. This conversion was done to make the style and structure of the data gain a uniform shape. To compare the emerging categories with the data, a constant comparative method (Glaser and Strauss, 1967) was utilized after open coding. This constant comparison stage was primarily helpful to assemble and gather data under a primitive structure. The tradeoff between the flexibility of open-endedness and the primitive rigidity of early structure lead me to figure out the similarities and differences among emerging themes. Further, these similarities and differences were consolidated through a focused coding stage by using "the most significant and/or frequent earlier codes to sift through a large amount of data" (Charmaz, 2014: 57). This focused coding stage was more directed to select appropriate categories (Glaser, 1978).

[Insert Table 2.2 about here]

The grounded theory-building process continued with axial coding and selective coding. During the axial coding stage, I related categories to subcategories and reassembled the data (Charmaz, 2014; Corbin and Strauss, 1990). Whereas early line-by-line and open coding stages fractured the data and set apart the individual components of the data, focused and axial coding stages reassembled these fractured parts into a unified theory. At the end of the axial and selective coding stages, the data led me to build the foundations of an inductive qualitative theory. The final two stages of the data, selective coding and writing short memos (Glaser, 1978), were particularly helpful for conceiving of different scenarios of the relationship among the emerged categories. Specifically, memos consist of drawn tables, analytic notes, charts and demographic information about each interviewee. Repeating this stage through several iterations improved the initial structure of the data and led me to propose a qualitative theory of platform firm emergence under a unified umbrella.

[Insert Figure 2.3 about here]

TOWARD A THEORY OF PLATFORM FIRM EMERGENCE

Qualitative data analysis revealed four stages that show how platform firms come into existence. These four stages are: (1) Inefficient Markets and Incumbents, (2) Entrepreneurial Motivation and Enabling Factors, (3) Efficiency-Enhancing Means, and (4) Platform Firms. Except for the second stage, the other stages include one category. Because most platform entrepreneurs referred to unsatisfactory conditions prior to founding their platform organizations, I chose to place the category of Inefficient Markets and Incumbents as the first stage in the model. Quite often, entrepreneurs also mentioned such unsatisfactory conditions as a trigger for their entrepreneurial motivation. Thus, I decided to include Entrepreneurial Motivation in the second stage of the model. Similarly, because there was no sign or indication that Entrepreneurial Motivation precedes Enabling Factors but evidence that Enabling Factors played important roles in the creation of Efficiency Enhancing Means, I preferred to include both Entrepreneurial Motivation and Enabling Factors in the second stage of the model. Finally, because of the important roles Efficiency Enhancing Means play in the emergence of platform firms, I selected Efficiency Enhancing Means as the third stage and Platform Firms as the fourth stage of the model. The following section elaborates these stages and categories.

[Insert Table 2.3 about here]

Stage I: Inefficient Markets and Incumbents

This category represents the unsatisfactory situation in which either the supply or demand side pays more for a product or service than what it's worth. Most often a platform firm emerges in inefficient markets and industries that lack innovation for a long time. Lacking innovation in these inefficient industries causes fragmentation of the marketplace, resulting in dispersion and dissolution of different parties. In the data analysis, I coded the main category of inefficient markets and incumbents based on the following four subcategories: (1) Inefficient situation, (2) Fragmented markets, (3) Opportunistic middle-men, and (4) Burden of ownership. An interpretation of early stage codes such as "[we were looking for] an old enough industry to be disrupted" and "I have a lot of frustrations about not having a smooth gaming experience" leads me to create the subcategories of inefficient situation. Secondly, quotes like "we're in [the cities] that are almost all hyper-fragmented marketplaces" make me create the subcategory of fragmented markets, which refers to the situation that no single product is able to completely satisfy a specific need of consumers. The following illustrative quote provides an example of fragmented markets and shows how platform firms arise from fragmented markets.

> **Dennis Fong (Founder of Raptr):** It kind of sucks as a PC gamer to have Battle.net to talk to your Battle.net friends, Steam to talk to your Steam friends, you have League of Legends to talk to your League of Legends friends, it's a bit of a fragmented market. So, we're the only agnostic platform that connects you to all of your friends anywhere.

The third subcategory of opportunistic middle-man is of vital importance for the framework built in the chapter. While existing theories of the firm mainly focus on internal factors such as resources, technology, or transaction costs to explain why firms bring some operations inside but outsource some others, this study reveals that industrial factors play an important role as well. One of the main industrial factors is incumbents' behaviors in an industry. Whereas Williamson's (1975, 1985) tradition of TCE argues that opportunism in a marketplace will lead firms to internalize asset-specific transactions, this research found that incumbents' (or rivals') opportunistic behaviors allow new entrants to enhance trust and transparency in the marketplace by introducing a platform firm governance mode. For example, the following quote is a good example of how entrepreneurs introduce a platform firm governance mode as a response to banks' opportunistic behaviors in credit card fees.

> **Ben Milne (Founder of Dwolla):** I had another company before and essentially, we sold all the product online. I was losing about 55,000 dollars a year in credit card fees, and I started getting really obsessed with how I could get paid through my website without paying credit card fees…[So,] Dwolla's core purpose is to allow anybody with an internet connection secure access to their money and allow them to exchange it with anybody else who can receive it without paying interchange costs.

A similar story comes from the founders of Airbnb, Joe Gebbia and Brian Chesky, who could not afford an apartment but suddenly realized how hotels were full during a major event (*i.e.*, a conference in San Francisco) despite soaring prices. Their simple platform firm idea, providing airbeds and cooking breakfast for guests, disrupted the long-time inefficient hotel industry. Finally, ownership of assets has become a burden in modern life. For example, people in big cities avoid buying a car because car ownership brings more burdens than benefits. Insurance costs, parking problems and getting ticketed make people look for alternative ways to commute. Platform firms make that possible by providing a ground for sharing activities. Therefore, opportunism and inefficient marketplaces may not lead firms to internalize operations but rather to externally organize market forces with a platform firm governance mode.

The discussion shows that some leading markets and industries have over time become inefficient as a result of lacking innovation at the organizational level. Yet, technology-savvy entrepreneurs introduce a platform firm governance mode to replace the existing governance modes or to disrupt highly inefficient markets and industries. I have to note that the disruption of platform firm governance is not limited to for-profit industries such as transportation, education, gaming, and hosting but also takes place in non-profits. For example, the following quote by Beth Schmidt, the founder of Wishbone.org, shows how she reinvigorates inefficient philanthropy and education sectors.

> **Beth Schmidt (Founder of Wishbone.org):** …I started Wishbone to actually send low-income students on these after-school and summer programs…If you look at schools, they're the same as they were how many years ago, and so, that is a big red flag. If you can look at the fact that we are teaching the same way we've taught forever, that's an invitation for innovation. We have this stale system, right now, that needs to be reinvigorated. We need to bring technology and new ideas into the field of [broken] education system…I think non-profits are coming to a new age, and that age is sustainability…

In sum, platform firms originate from inefficient markets where incumbent companies lack innovation for a long time. According to data analysis, lacking innovation for a long time in these markets causes market fragmentation. As a result, motivated, technology-savvy entrepreneurs are needed to connect market forces with a platform firm governance mode.

Stage II: Entrepreneurial Motivation

Entrepreneurial motivation elaborates on why entrepreneurs found a platform firm and details the major drivers of their behaviors. Although this category is not unique to the context of platform firms, it was one of the most prevalent attributes in the early stages of the emergence. Accordingly, three sub-categories under this category are: (1) Future orientation, (2) Advancing a cause, and (3) Solving a problem. The first subcategory of future orientation helps entrepreneurs bring their platform business idea into reality. Future-oriented entrepreneurs are more likely to try a risky and innovative business idea and model. As a governance mode, platform firms, therefore, are more likely to be founded by people who are future oriented. For example, the following early codes made me derive the subcategory of future orientation from the data: (1) “It’s all about what happens tomorrow…So, let’s go invent tomorrow rather than worrying about what happened yesterday” and (2) “We said, let’s go tackle the next frontier.”

Secondly, the subcategory of advancing a cause is still an important motivating factor for entrepreneurs of platform firms. Early codes such as “we wanted to change the world and have huge impacts, so we picked a bigger market to play” and “we wanted to advance the cause of electric vehicles” resulted in the subcategory of advancing a cause during the data analysis stage. Finally, facing a problem often precedes the emergence of platforms. Therefore, the period prior to coming up with a platform business idea includes facing a tough problem and trying to solve it at a massive scale. For example, the following quote shows how entrepreneurs develop a platform firm out of an ignored challenging problem.

> **Marco Zappacosta (Founder of Thumbtack):** ... [So,] we didn’t index on our interest or our passions but instead said, what’s the biggest problem we think we can solve with technology? And, we started thinking and looking, and what we realized was that there was this gigantic local services market with hundreds of millions of customers, tens of millions of professionals and it was very old. There really hadn’t been much innovation in how they found each other, how they came together, how they worked together, and we felt that it was inevitable that technology would help these people...

Marco Zappacosta’s quote can be interpreted as: the inefficient marketplace of local services was fragmented because of “hundreds of millions of customers and tens of millions of professionals” and lacked innovation for a long time. As a result, this fragmented inefficient local services market motivated platform entrepreneurs to use enabling factors such as the technology at hand and improve efficiency in the marketplace through different means. Therefore, in addition to the direct effect of inefficient markets and incumbents on efficiency enhancing means, I believe that there is a potential indirect effect of inefficient markets and incumbents on efficiency-enhancing means through entrepreneurial motivation.

Enabling Factors

This is the category that describes the circumstances that help platform entrepreneurs externally organize market forces rather than internally allocate resources. The category details how the context and timing of founding a platform firm and technological advancement increased the popularity of platform firms and created different means to enhance efficiency in inefficient marketplaces. Marco Zappacosta's quote not only highlights how he and his co-founders come up with a solution to solve the long-time inefficient match-making problem of local professionals but also stresses how technology and context enable them to implement their platform business idea. The category of enabling factors consists of three related subcategories: (1) Computing power and the internet, (2) Context and timing, and (3) Combinatorial experience and innovation. Several brief examples that led to the first subcategory of computing power and the internet include: "computing power behind things and being connected to the internet changes the responsiveness of immediate interaction without latency," "we definitely felt that the intersection of Cloud and mobile was going to generate a fair amount of disruption," and "the internet of things is going to have a renaissance in the later part of the 21st century."

Some early codes that were aggregated under the second subcategory of context and timing include: "every year, the same thing happens… Hotels sell out and people need a place to stay [at the] last minute. So, we thought this was a perfect opportunity [timing] to launch the next version of a better breakfast," "hard to break through noise when lots of companies start," and "every part of your business, running a company, doing a partnership, marketing, whatever, it's actually about putting things in the right context." To highlight how the context and timing of the foundation affect the success of the company, Eren Bali, Co-founder of Udemy, an online education platform, provides the following quote:

> **Eren Bali (Co-Founder of Udemy):** Initially, we were doing some other projects. We had created a 3D simulation for constructions. It was how we started. But I always wanted to work in education, so we built a company that were close, similar to Udemy in terms of supervision in Turkey, almost 8 years ago. So, we launched it, but we realized that wasn't the right time and the right place.

Finally, I included the subcategory of combinatorial experience and innovation as the last subcategory of enabling factors. Early codes in the subcategory of combinatorial experience and innovation include: "having programming, cognitive science, and artificial intelligence background," "merging and integrating disparate subjects such as philosophy, psychology, and architecture," and "Scribd is a combination of previous ideas."

Stage III: Efficiency-Enhancing Means

The stage of efficiency-enhancing means occur as a result of the interaction among three earlier categories in the first two stages of the model. This stage describes disparate means and methods used by entrepreneurs to alleviate inefficiencies in the existing markets. I have to note that the first three categories of the model are not specific to platform organizations but can be applied to any type of traditional firms. However, the interaction among the earlier three categories – inefficient markets and incumbents, entrepreneurial motivation, and enabling factors – has extended (and blurred) the boundaries of existing markets through means provided in this category. Thus, I can argue that these efficiency-enhancing means are the main facilitators of platform firms.

The category of efficiency-enhancing means consists of the following subcategories: (1) Connecting disparate parties, (2) Changing methods and processes, and (3) Building trust and transparency. The first subcategory of connecting disparate parties includes a connection between supply and demand in transactional platforms (Cusumano *et al.*, 2019) but also integration and connection of applications, devices, and software programs. For example, some early stage codes in the subcategory of connecting disparate parties include: “bridging across devices in a very fast, seamless way, leveraging our cloud infrastructure everywhere,” “having a software solution that helps customers find, engage and end up hiring software engineers,” “[willing to] play [a role] in the construction of a medium in a way that lead the individuals, the group, the society, and the community to be a lot better” and “bringing ecosystem of publishers, authors, and readers together.” The following quote by Jonathan Rosenberg, Former Senior Vice President of Products and CEO Advisor at Google, highlights how enabling factors reduced information and transaction costs, and as a result, connected dispersed parties all around world.

> **Jonathan Rosenberg (Former Senior Vice President of Products and CEO Advisor at Google):** … if you think about information costs and transaction costs going to zero which is kind of the Uber example, that's going to spawn massive commerce because every single person in the world can now reach every other person in the world, and as soon as that can happen, the number of things that somebody over here has that he would be willing to sell for a very low price, the number of things that somebody over here would be willing to buy [whether it's a good or a service, or it's a ride in an Uber] is going to expand exponentially because everyone knows what everyone else has, and it becomes very seamless to buy and sell.

The second subcategory under efficiency-enhancing means is changing methods and processes. This subcategory stresses how enabling factors such as computing power, the internet, tablets, context and timing change the way people interact with each other or the way they do something. A few early stage codes that lead to the subcategory of changing methods and processes contain: “we changed the old model of match-making,” “[our new technology] is something that could change how people interact and transact,” and “our recent high-profile investments will change the way you commute forever.” Finally, the third subcategory under efficiency-enhancing means is building trust and transparency. From the data, I realized that changing traditional methods and processes was an important outcome of the interaction among the earlier three categories – inefficient markets and incumbents, entrepreneurial motivation, and enabling factors – but often was not sufficient to enhance efficiency in the existing inefficient markets. Along with connecting disparate parties and changing methods and processes, platform entrepreneurs often mentioned how building trust and transparency was important to transform the existing inefficient markets. Therefore, I placed the subcategory of building trust and transparency under the category of efficiency-enhancing means. A few early codes under the subcategory of building trust and transparency include: “using quickbooks to match lender and business owners with more confidence,” “creating a lending marketplace based on trust and credit,” and “bringing transparency to the marketplace.” For example, the following quote by Marco Zappacosta of Thumbtack highlights how they are willing to bring transparency to the long-time inefficient local services.

> **Marco Zappacosta (Founder of Thumbtack):** By and large, we don’t view ourselves as a way to increase or decrease prices, we want to help bring transparency to this sector such that customers are assured that they’re paying a good price and that the professionals are educated about what the market is going for these days.

Stage IV: Platform Firms

In the most concise form, the platform firms stage is the last stage of the model where platform entrepreneurs transform existing inefficient markets by (re)-organizing market forces. The data analysis shows that subcategories such as sharing economy, selling intangibles, and providing simple and real-time solutions are the factors that differentiate a platform-mediated environment from traditional business environments. The first-order constructs in the data-coding structure show that entrepreneurs in platform firms aim to create an environment to enable and improve sharing experiences. Some early codes aggregated under the subcategory of sharing economy include: "managing the environment and creating a structure that enables sharing," "improving shared mobility experience," and "partnering with the developer and sharing the revenue."

In addition to creating a sharing experience, platform firms also change our perception about products and services. The data show that to enable a better shared experience and remedy inefficiency in existing marketplaces, platform firms often sell intangibles rather than tangible goods. For instance, Brian Wong, the founder of Kiip, an online gaming platform, has founded his platform firm to sell moments instead of tangible products. What Kiip does is to gather game developers, customers and brands on a platform. Instead of putting some annoying ads in achievement moments (e.g., completing a level in a video game), Kiip uses those moments to reward game players and send them sample products. Similarly, platform firms have emerged via the sale of mobility instead of cars. As car ownership becomes a burden in big cities; platform firms came into existence to reduce this inefficiency by matching people willing to supply a service with those willing to use it. Providing a real-time solution with a button click for the problem of car ownership is what makes ridesharing platforms successful. Some example codes about simple and real-time solutions include: "booking houses, apartments, and rooms with a click," "simplifying products worked great," "give me what I want and give it to me right now," and "having an easy to understand, easy to learn and then easy to manage and maintain user interface." The following quote by John Zimmer of Lyft illustrates how entrepreneurs disrupt a long-time inefficient car ownership sector by creating a sharing opportunity and selling intangibles (*i.e., commuting)* by a button click.

> **John Zimmer (Co-Founder of Lyft):** The market every year in the United States is two trillion dollars, the amount people spend on car ownership; and the cars are utilized four percent of the time. It's incredibly inefficient and so there's a massive opportunity to replace car ownership with transportation as a service.

DISCUSSION

This chapter asks a fundamentally important research question: Why do platform firms come into existence? Building a grounded theory based on publicly available interviews with entrepreneurs, managers and venture capitalists of platform firms, I found that platform firms come into existence because the existing incumbents, markets, and industries over time become inefficient as well as because there are motivated entrepreneurs who use enabling factors to disrupt these inefficient marketplaces with a "platform firm" governance mode. The process model shows platform firms come into existence over four consecutive stages: (1) Inefficient Markets and Incumbents, (2) Entrepreneurial Motivation and Enabling Factors, (3) Efficiency-Enhancing Means, and (4) Platform Firms. Using a top management team lens, the study elaborates how platform firms evolve from market and incumbent inefficiency, entrepreneurial motivation, and enabling factors.

While it is true that most traditional firms also originate from market and incumbent inefficiency, entrepreneurial motivation, and enabling factors, the difference regarding the emergence of platform firms comes from developing efficiency-enhancing means and targeting and disrupting the whole inefficient market or industry. In contrast, entrepreneurs in traditional companies often compete based on value or quality of a product and service. Willing to disrupt inefficient markets and incumbents, traditional organizations enter into a marketplace by utilizing a better technology to provide a better-value (e.g., low-cost) or higher-quality (e.g., differentiation) product or service. This entry by traditional entrepreneurs into inefficient markets, at best, may disrupt and replace market leaders in those markets. However, because platform entrepreneurs develop efficiency-enhancing means while entering into a specific market, disruption caused by platform firms affects the whole market and industry, rather than only individual market leaders. Thus, developing efficiency-enhancing means resulting from interaction among inefficient markets and incumbents, enabling factors, and entrepreneurial motivation distinguishes the emerging process of platform firms from the emergence of traditional firms. Efficiency-enhancing means such as connecting disparate parties, changing methods and processes, and building trust and transparency unify fragmented pieces of inefficient markets, remove opportunistic middlemen from the equation, and alleviate the inefficient situation. As a result, these efficiency-enhancing means lead to the emergence of platform firms and disrupt the entire market rather than only market leaders.

The stage of efficiency-enhancing means in the model describes how the emergence process of platform firms differs from the emergence process of traditional firms. Building upon this stage, the last stage of the model, platform firms stage, shows how platform firms differ from their traditional counterparts. In the introduction section, I conceptualized platform firms as having two distinctive characteristics: (1) the existence of at least two distinct user groups interested in transacting with one another on a platform, and (2) mediating interactions among these groups to facilitate coordination more efficiently and effectively than would bilateral relationships (Evans, 2003). The data analysis and process model shows, in addition to these basic differences, there are other fundamental differences between platform firms and traditional firms. Accordingly, these differences include enabling a sharing economy, selling intangibles, and providing simple and real-time solutions.

Major contributions of the study include gathering empirical findings in the platform literature under a framework of platform emergence, extending Jacobides *et al.*'s (2018) theory of ecosystems by underlining the organizational aspect of platforms as well as by using a platform firm lens, and responding to Gawer's (2009) criticism of the two-sided platform literature. The paper shows why we should not take for granted the existence of markets and platforms through explaining the process and mechanisms leading to the emergence of platform firms. The framework developed in the paper reveals that the platform literature mainly focuses on the impacts of platform organizations on the traditional business environment (e.g., Jacobides *et al.*, 2018; McIntyre and Srinivasan, 2017; Parker and Van Alstyne, 2017; Rietveld and Eggers, 2018; Rietveld *et al.*, 2018) and creates a ground to better understand these impacts on the traditional business environment. Finally, the paper contributes to the literature by highlighting how platform firms differ from traditional firms.

Theoretical Implications for Existing Theories

Transaction cost economics. Transaction cost economics (TCE) is the main theory of the firm interested in the existence and boundary conditions of the firm. In the simplest form, TCE states that firms come into existence to the extent the marginal cost of procuring a product from the market is higher than the marginal cost of producing it within the firm

(Coase, 1937). Accordingly, firms attempt to minimize transaction and production costs while considering alternative governance modes (Poppo and Zenger, 1998; Williamson, 1985). Major factors such as uncertainty, information asymmetry, bounded rationality, opportunism, asset specificity, the number of exchange partners, and transaction frequency play important roles in market frictions and firm emergence (Jones and Hill, 1988; Mahoney and Qian, 2013; Williamson, 1985). Thus, high levels of uncertainty and information asymmetry in a marketplace increase the likelihood of opportunistic behavior because decision makers are only boundedly rational. To prevent opportunistic behaviors in the marketplace, agents should internalize frequent asset-specific transactions with small numbers of exchange partners.

Quite similar to the arguments of transaction-cost economics, I found that opportunism and market fragmentation play an important role in the emergence of platform firms. However, the built theory diverges from transaction-cost economics regarding the role of enabling factors and technology. For example, Williamson (1985: 1) states that "contrary to earlier conceptions – where the economic institutions of capitalism are explained by reference to class interest, technology, and/or monopoly power – the transaction-cost approach maintains that these institutions have the main purpose and effect of economizing on transaction costs." Whereas the role of technology and enabling factors is downplayed relative to the role of transaction cost in the emergence of traditional firms by transactional-cost economists, the model built in this study shows that enabling factors and technology can alleviate market frictions and opportunism in a marketplace through efficiency-enhancing means. Similarly, enabling factors and technology can reduce uncertainty, information asymmetry and bounded rationality through building trust and transparency as well as increase the number of available exchange partners through connecting disparate parties. Therefore, neither transaction costs nor enabling factors and technology should be downplayed relative to each other because they play important roles in the emergence of both traditional firms and platform firms. Enabling factors and technology play a particularly important role in the emergence of platform firms because they help platform entrepreneurs minimize transaction and information costs and assume the historical role of price mechanism (Coase, 1937) by organizing market forces rather than internalizing them.

Behavioral theory. 'A behavioral theory of the firm (BTOF)' is the second theory of the firm interested in the existence of the firm. Whereas TCE states that firms come into existence to the extent the marginal cost of procuring a product from the market is higher than the marginal cost of producing it within the firm (Coase, 1937), BTOF views the firm as an information-processing and decision-rendering system (Cyert and March, 1963). Because firms consist of individuals who have conflicting goals, the decision-making process is the main task of a firm (Cyert and March, 1963). However, because of bounded rationality, opportunism, satisficing, and uncertainty-avoidance behaviors of managers, the economic conceptualization of the firm based on profit maximization and perfect knowledge is an inadequate perception of the firm (Cyert and March, 1963). Instead, managers need costly information to make appropriate decision (Ahuja, 2007).

Because the enabling factors and technology category of the process model can reduce uncertainty, information asymmetry, and bounded rationality through building trust and transparency, the process model is highly likely to yield important implications for BOTF. The model indicates that platform firms can analyze a huge amount of data and get automatic insights from this analysis with the help of artificial intelligence. For example, the following quote by Guy Nirpaz of Totango shows how sensors minimize bounded rationality in the decision-making process.

> **Guy Nirpaz (Founder of Totango):** …one of the experiences that I am really kind of a fan of is that if you are an Amazon prime subscriber and you've been trying to watch—I was amazed by that, I was watching an HD movie on Amazon prime and the next day I got an email from Amazon saying 'You're refunded for the movie because you didn't experience 100% HD'. So think about it right, they know what was the experience that I was expecting, I was even unaware of the fact that there was like 2 minutes on the movie that wasn't full HD but they have identified this through their operating system and this is the sensor, they sensed that and then they've created an automated action that turned the experience into a very positive experience…

Although cognitive abilities of human beings will always be limited, artificial intelligence and internet of things-based platform firms can diminish bounded rationality. Therefore, decision-makers can make rational-like decisions because enabling factors and technology decrease transaction and information costs to negligible amounts thanks to building trust and transparency, connecting disparate parties, and changing methods and processes. However, we still need further research to better understand applications of the behavioral theory in a platform ecosystem.

Future Research and Limitations

The study raises some research questions for future consideration. For example, we need some empirical quantitative studies to better understand the relationships among categories developed in the study. Future research can investigate potential direct and indirect effects among the categories and stages. Although we have not seen any major differences in the emergence of platform firms, half-platform and inter-platform firms, we still need future research to unearth the conditions under which inefficient marketplaces, entrepreneurial motivation, and enabling factors lead to the emergence of these governance modes. A promising research avenue can also investigate the relationship between technological innovation and these governance modes. If we accept these new governance modes as an organizational innovation – the adoption of a new administrative idea and system at the organizational level (Chandler, 1977, 1962; Damanpour, 1991; Damanpour and Evan, 1984) – future research can compare and contrast these governance modes to the existing traditional and hybrid governance modes (Makadok and Coff, 2009). Finally, investigating the evolution and failure of platform firms is highly likely to be a promising research avenue for a better understanding of platform firms.

Nonetheless, the study has several limitations. First, because of the time period of the study, the study may be generalizable to entrepreneurial web-based platforms but may or may not be generalizable to older platforms. A future study can replicate the study for older platforms and unearth the generalizability of the study. Second, I use secondary publicly available interviews. Although collecting such interviews helped me gather an extensive dataset, it may also suffer from availability bias. A future study may replicate the study with primary data. Finally, the study can still suffer from success bias. Future research can also investigate the conditions that yield to platform firm failure at the idea stage.

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FIGURE 2.1. Google scholar results for platform firms over years

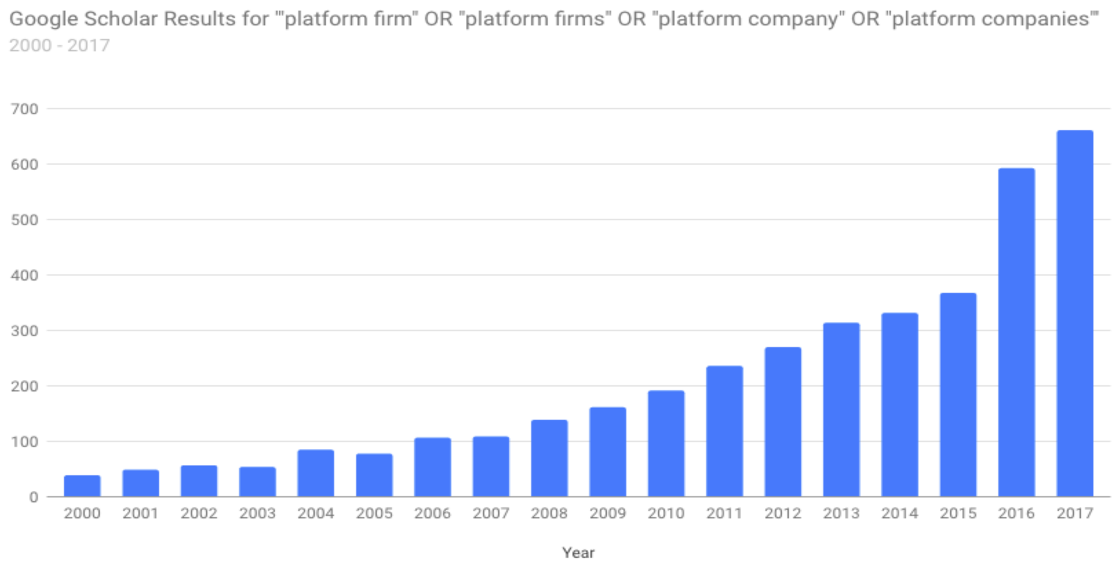

FIGURE 2.2. A model of platform firm existence

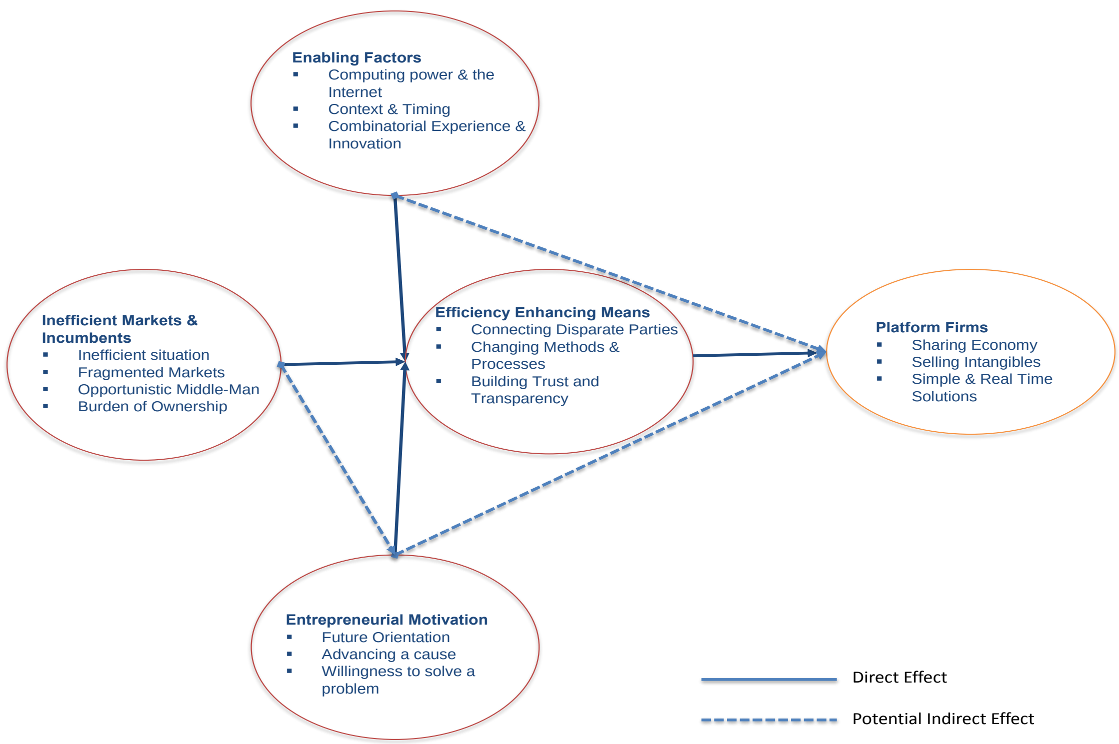

FIGURE 2.3. Data coding structure

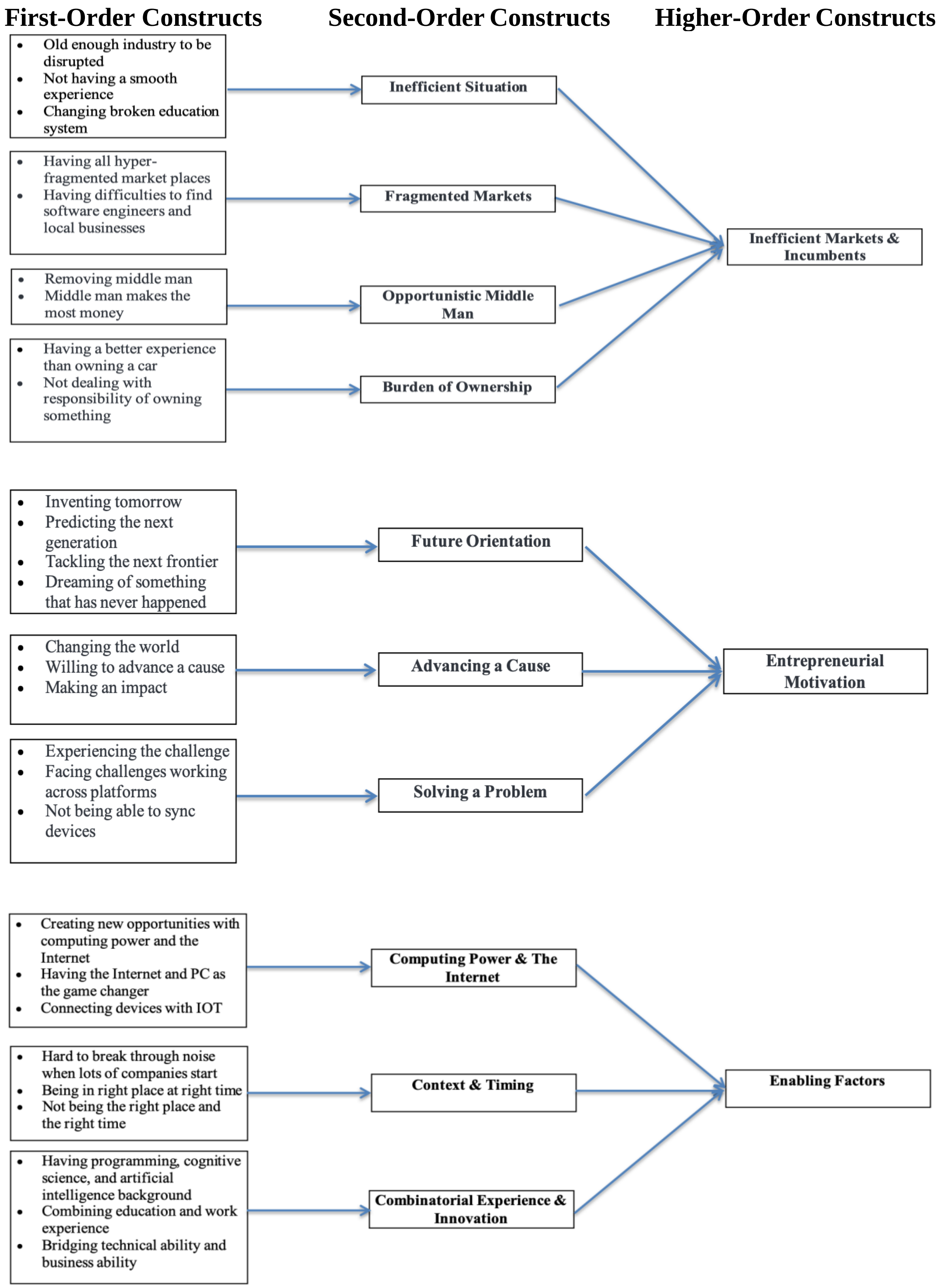

FIGURE 2.3. Data coding structure (Continued)

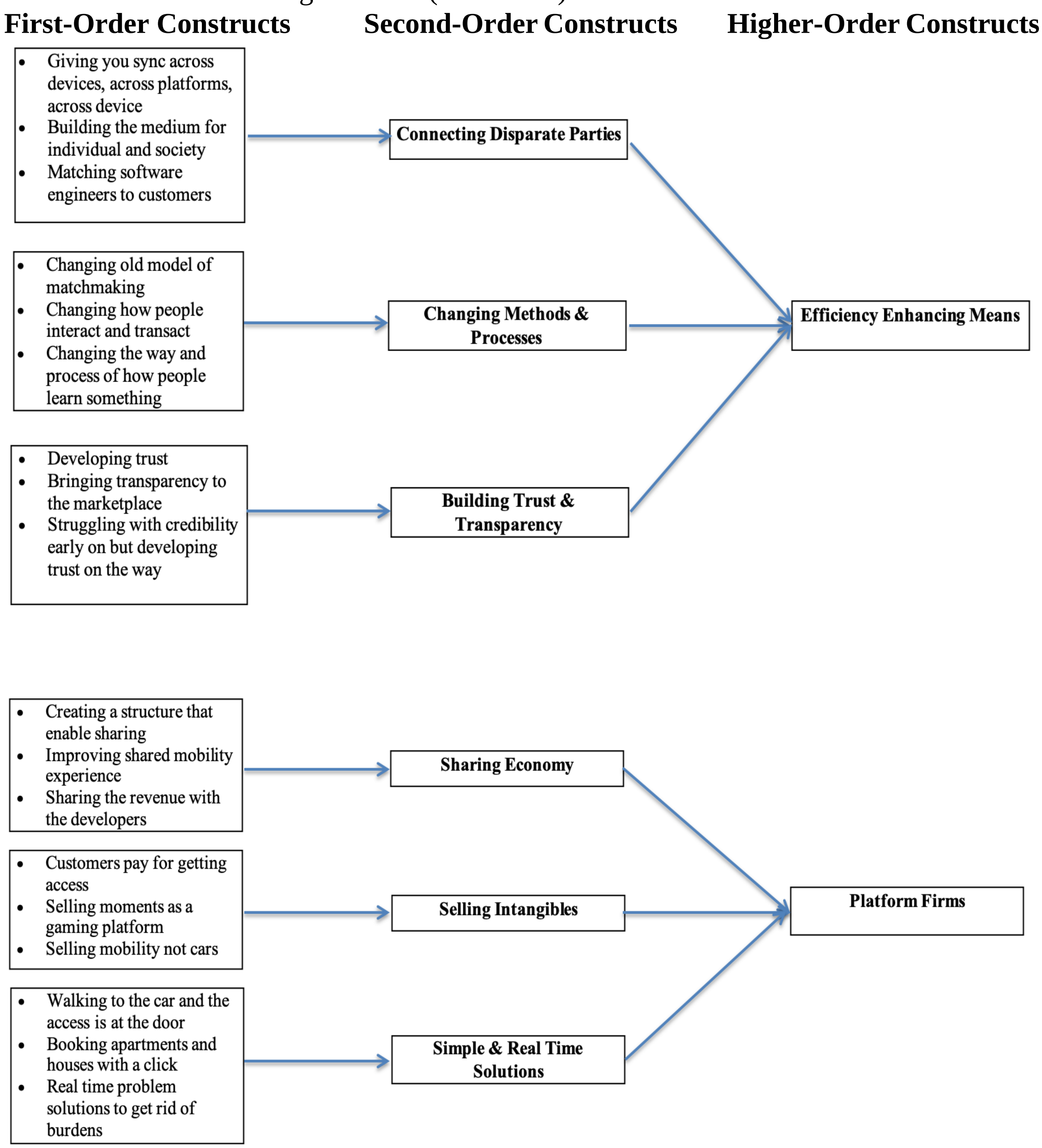

TABLE 2.1. Illustrative sample data

Individual (Title)	Related company /Firm type	Explanation	Headquarter city and state	Duration (Mins)
René Lacerte (Founder and CEO)	Bill.com/Platform	The company matches small companies with their customers	Palo Alto, CA	25
Trip Adler (Co-Founder and CEO)	Scribd/Platform	A digital library platform bringing together publishers, writers, and readers	San Francisco, CA	24
Niklas Lindstrom (Co-Founder)	SKOUT/Platform	Social networking and dating platform	San Francisco, CA	17
Beth Schmidt (Founder)	Wishbone.org /Platform	A non-profit platform company matching poor students with philanthropists	San Francisco, CA	9
Marco Zappacosta (Co-Founder and CEO)	Thumbtack /Platform	Online service platform matching customers with local professionals	San Francisco, CA	20
Brian Wong (Founder and CEO)	Kiip/Platform	A gaming reward platform that brings together game developers, players, and advertising companies	San Francisco, CA	26
Dennis Fong (Founder and CEO)	Raptr/Platform	Social networking platform for video game players	Mountain View, CA	33
Omer Artun (Founder and CEO)	AgilOne/Half-Platform	Enterprise customer data platform that identifies potential customers for businesses	Mountain View, CA	24
Vincent Yang (Co-Founder and CEO)	EverString/Half-Platform	Sales and Marketing platform identifying potential customers	San Mateo, CA	27
Milind Gadekar (Co-Founder and CEO)	CloudOn/Inter-Platform	An online productivity platform that enables people to edit, create, organize and share docs on many platforms including tablets, phones, PC, Dropbox, etc.	Mountain View, CA	28
Mark Lee (Co-Founder and CEO)	Splashtop/Inter-Platform	A productivity software platform that bridges smartphones, tablets, computers, TVs, and clouds by providing remote access	San Jose, CA	22
Alex Taussig (Venture Capitalist)	Highland Capital Partners/Traditional	Traditional venture capitalist firm	Palo Alto, CA	28
Andrew Ogawa (Venture Capitalist)	Quest Venture Partners/Traditional	Traditional venture capitalist firm	Palo Alto, CA	26

Note: Data in the table comes from public sources including LinkedIn, Facebook, Twitter, Crunchbase, and Bloomberg.

TABLE 2.2. Grounded theory coding and explanation

Grounded theory steps	Action taken
Line-by-line coding	Every single page was read and coded line by line.
Open coding	Transcripts and line-by-line codings were re-read to make the style and structure of the data gain a uniform shape.
Constant comparison	Constant comparison was done to compare emerging codes with each other and with the data.
Focused coding	In addition to the standard grounded theory-building stages, a focused coding stage was conducted to highlight the most significant and/or frequent earlier codes (Charmaz, 2014).
Axial coding	Categories and subcategories were related to each other.
Selective coding	This is the period when the final decision was made about major core categories. Main categories were selected, and all other subcategories were related to these categories.
Memo writing	Different scenarios of the relationships among emerged categories were speculated during this stage. Also, this stage includes drawing tables and charts, writing analytic notes and demographic information, and unifying all this information under a unified theoretical umbrella.

Note: Grounded theory building is one of the most popular qualitative methodologies that construct a new theory through gathering and analyzing qualitative data. In contrast to hypothetico-deductive quantitative studies, the grounded theory-building approach is an inductive data-driven method (Charmaz, 2014; Glaser and Strauss, 1967).

TABLE 2.3. Main categories coding description and illustrative quotes

Coding	Coding definition	Illustrative quote(s)
Inefficient markets and incumbents	The unsatisfactory situation when a side pays more for a product or service than what it's worth.	I have started four companies... All four companies are actually community platforms. I just have the passion around bringing people together. And all four, actually, were created to solve my own personal frustrations around something. Obviously, I'm very big gamer so I have a lot of frustrations about things that I think could be or could work more smoothly in gaming. Since no one else is trying to solve those things, I say why don't we just go and do that? (Dennis Fong, Founder of Raptr)
Entrepreneurial motivation	Main drivers of why individuals found a platform firm.	[At the] end of 2009, I left Cisco, and I partnered with a couple of my co-founders who are based in Israel. We said, let's go tackle the next frontier. We wanted clearly to get away from that working. As we look at the space then, we definitely felt that the intersection of Cloud and mobile was going to generate a fair amount of disruption. We were coming at it without a lot of experience in this space, but with the belief that we know what it takes to identify the problem (Milind Gadekar, Co-Founder of Cloudon).
Enabling factors	The circumstances that help platform entrepreneurs externally organize market forces rather than internally allocate resources.	Now at Khan, you've got these amazing new tools that have been built by engineers that work for you, that can-do things that use predictive analytics to figure out what math problems you don't understand. It's a quantum change in learning that we've never seen before…I would also add that if you think about information costs and transaction costs going to zero which is kind of the Uber example, that's going to spawn massive commerce because every single person in the world can now reach every other person in the world…everyone knows what everyone else has, and it becomes very seamless to buy and sell (Eric Schmidt and Jonathan Rosenberg, Top Managers at Google).
Efficiency enhancing means	Disparate means and methods used by entrepreneurs to alleviate inefficiencies in the existing markets.	The app store was not even out yet. The only thing we knew about the app store was the logo, so for me it was just the promise and the opportunity that this was going to transform the way we communicate with each other, share information with each other, and how we get entertainment, how we get news and information. I saw this as a transformation… (Calvin Carter, Founder of Bottle Rocket Apps).
Platform firms	The ultimate-results where platform firms organize market forces by creating a sharing environment.	So, the digital publishing market is growing very quickly… And I think that this entire shift from the ownership model to the access model that we're pursuing is really an exciting change… We're now shifting it at the access model where you pay for access to the library and then the publisher or the author gets paid when the books are actually read. So that creates huge changes in just the overall ecosystem (Trip Adler, Co-Founder of Scribd).

CHAPTER 3: AN EVOLUTIONARY THEORY OF PLATFORM FIRMS

ABSTRACT

Despite recent increasing interest in platforms, platform ecosystems, and platform firms, we still know little about the evolution of platform firms. Conducting a grounded theory-building study on 52 publicly available interviews with platform entrepreneurs, managers, and venture capitalists and 34 review, forum, and analyst articles, I explore the evolution of platform firms. In an extensive inductive qualitative study, I develop a theory and a process model showing evolutionary stages of platform firms. In particular, the process model indicates that the evolution of platform firms consists of the following stages: (1) Platform Growth, (2) Competition, (3) Adaptive Behaviors, (4) Platform Sustainability, (5) Rebranding Challenges, and (6) Platform Failure. I contribute to the literature by constructing an evolutionary model of platform firms, showing why the "winners-take-all" assumption should not be taken for granted, unearthing how platform companies sustain competitive advantage, and discussing factors leading to platform failure.

INTRODUCTION

A recent surge of platform research shows that platform organizations have started to revolutionize the traditional business environment (Parker and Van Alstyne, 2017; Parker, Alstyne, and Choudary, 2016), mainly because digital platforms facilitate transaction among disparate parties and allow complementors to innovate (Cusumano, Yoffie, and Gawer, 2019; Jacobides, Cennamo, and Gawer, 2018; Eisenmann, Parker, and Van Alstyne, 2010) . With each platform firm achieving and controlling a significant percentage of market share in platform-mediated ecosystems, the assumption of "winners-take-all (or-most)" (Cusumano *et al.*, 2019) has gained significant ground among scholars and business intellectuals. Some popular examples of winners who attained approximately 70 percent or more of market share include Microsoft's Windows operating system and Google's internet search technology (Cusumano *et al.*, 2019: 54). While the assumption has been built upon the existence of strong network effects in platform ecosystems (Cusumano *et al.*, 2019; McIntyre and Srinivasan, 2017), some scholars have started to question the validity of the "winners-take-all (or-most)" assumption by highlighting the influence of multi-homing and digital technology (Cusumano *et al.*, 2019).

Despite the increasing number of insightful studies in the platform literature (e.g., Jacobides *et al.*, 2018; McIntyre and Srinivasan, 2017; Parker and Van Alstyne, 2017; Rietveld and Eggers, 2018; Rietveld, Schilling, and Bellavitis, 2018), we still know little about the evolution and growth process of platform organizations. While we have accumulated a certain amount of knowledge about the growth and evolution of traditional firms since Penrose's (1959) classic "theory of the growth of the firm" and Nelson and Winter's (1982) "an evolutionary theory of economic change," we have little knowledge about whether or not platform firms follow a similar evolutionary path as their traditional counterparts. To better understand the impacts of platform firms on the traditional business environment, we should have an evolutionary perspective of platform organizations. Moreover, examining the evolution of platform companies is valuable for not only understanding whether the “winners-take-all” assumption is warranted but also for identifying factors leading to the sustainability of competitive advantages in platform ecosystems. Therefore, aiming to extend the existing literature on the evolution of platform companies, I ask: how do platform firms evolve?

In this study, I define a platform as a multi-sided market that allows disparate parties to transact with each other and build complementary products (Armstrong, 2006; Caillaud and Jullien, 2003; Cusumano *et al.*, 2019; Evans, 2003; Hagiu, 2006; Rochet and Tirole, 2003, 2006). This definition includes both innovation platforms (e.g., Google Android) – platforms that create value by facilitating the development of new complementary products and services – and transaction platforms (e.g., Uber) – those that create value by facilitating the buying and selling of goods and services (Cusumano *et al.*, 2019: 40). For example, Uber, as an owner of a ridesharing platform, enables transaction between drivers and passengers, whereas Google’s Android platform allows application developers to innovate and serve end-users. Given these examples, I define a platform firm as the owner of at least one platform ecosystem.

To better understand the growth and evolution process of platform firms, I build a qualitative grounded theory based on 52 publicly available interviews with platform entrepreneurs, managers, and venture capitalists and 34 review, forum, and analyst articles. The evolutionary process built in the study indicates that the evolution of platform firms includes six major categories: (1) Platform Growth, (2) Competition, (3) Adaptive Behaviors, (4) Platform Sustainability, (5) Rebranding Challenges, and (6) Platform Failure. The first category of the evolutionary process model, *platform growth*, starts with the establishment of a platform company and continues with adapting supply and demand to the changing needs of the environment and with increasing liquidity of activities on a platform. Oftentimes, the platform growth stage continues until platform firms reach a critical mass (Evans and Schmalensee, 2010). Once platform firms achieve a critical mass, they covet a higher market share in relevant areas, become more visible, and attract incumbent firms' attention. As a result, the second stage of the model, *competition*, is initiated either by entrenched incumbent firms who are willing to protect their market shares or by platform firms who are eager to convert their smaller but niche platforms into a general one.

The third stage of the model, *adaptive behaviors*, often follows platform growth and competition stages. In the stage of adaptive behaviors, platform firms choose to follow either a resource re-orchestration or resource redeployment strategy to protect their existing positions or occupy a better position. Depending on the outcome of the stage of adaptive behaviors, platform firms either enter into a shrinking trajectory through struggling with the stage of *rebranding challenges* or enjoy a platform sustainability stage by different means. While the stage of *rebranding challenges* includes problems associated with adaptation, uncertainty, and complexity, the stage of platform sustainability refers to platform firms' changing tasks to keep different sides on the platform through various mechanisms including the creation of recurrent needs, adaptation, and personalization rather than attracting further customers. Even though attracting new customers is still important in this stage, the existing parties on the platform often undertake this responsibility. The platform sustainability stage of the built theory is an important revelation for platform literature because it questions the commonly accepted “winner-takes-all” assumption of the literature. In contrast to this narrative, the theory suggests that even “winners” should strive for keeping different sides on platforms through different mechanisms. Finally, the last stage of the model, *platform failure*, refers to the death and dissolution of platform companies as a result of customer abandonment, network mismanagement, and management problems.

The chapter makes five contributions to the existing literature. First and foremost, it contributes to the platform research (e.g., Parker et al., 2016; Parker & Van Alstyne, 2017; Jacobides et al., 2018; McIntyre & Srinivasan, 2017; Parker & Van Alstyne, 2017; Rietveld et al., 2018; Rietveld & Eggers 2018) by shedding some light on the growth and evolution process of platform companies. Second, the paper contributes to the literature by investigating whether the “winners-take-all” assumption is warranted and yields to an important finding that platform firms can only achieve competitive advantage in platform ecosystems if they are able to reach the platform sustainability stage. Third, it contributes to the literature by developing an evolutionary process model of platform firms and unearthing the differences between the evolution of platform firms and that of traditional firms (Penrose, 1959; Winter and Nelson, 1982). Fourth, the findings of competitive and adaptive behaviors in platform ecosystems yield important implications about the behaviors of platform participants. Finally, the paper contributes to the literature by showing major reasons for platform failures. In the following sections, the chapter will continue with the details of theoretical background, methodology, grounded theory, and discussion.

THEORETICAL BACKGROUND

The primary focus in this study is multi-sided platforms (Armstrong, 2006; Caillaud and Jullien, 2003; Evans, 2003; Hagiu, 2006; Rochet and Tirole, 2003, 2006). I define a platform firm as the owner of at least one multi-sided platform, on which the owner brings multiple parties together (Evans, 2003) and facilitates innovation or transaction (Cusumano *et al.*, 2019). Because platform owners, individual innovators, and end-users play different roles in a platform ecosystem, platform literature indicates that interactions among platform owners, individual innovators, and customers (Ceccagnoli *et al.*, 2012; Cennamo and Santalo, 2013; Gawer and Henderson, 2007), as well as competition among different platforms (e.g., Cennamo and Santalo, 2013), affect the creation of value on platform ecosystems.

With few exceptions, most early studies of multi-sided platforms concentrated on the key role of platform firms. For example, to highlight the importance of platform owners, researchers name platform firms as the “lead firm” (Williamson and De Meyer, 2012) or the “keystone” organization (Iansiti and Levien, 2004). Given the crucial role of platform firms for the platform ecosystems, researchers have put a significant amount of effort into understanding the success of platform owners (e.g., Eisenmann *et al.*, 2010; Gawer and Henderson, 2007; McIntyre and Subramaniam, 2009; Zhu and Iansiti, 2012). In particular, the pricing decisions of platform firms (Hagiu, 2006; Parker and Van Alstyne, 2005; Rochet and Tirole, 2003; Seamans and Zhu, 2013), the rivalry among competing platforms (Armstrong, 2006; Casadesus-Masanell and Llanes, 2011; Economides and

Katsamakas, 2006), and the effects of a growing network (Cennamo & Santalo, 2013; Edelman, 2015; Eisenmann, Parker, & Van Alstyne, 2011) are known to be critical determinants of performance of platform firms.

In addition, building upon early network research, platform researchers investigated how platform-mediated networks create value for platform owners and participants (e.g., Cennamo and Santalo, 2013). Particular attention in this stream of research has been paid to the growing installed-user base (Eisenmann, 2006; Farrell and Saloner, 1986; Katz and Shapiro, 1986; McIntyre, 2011) because the amount of value created is positively correlated with the growing number of end-users (Cennamo and Santalo, 2013). Given the importance of the installed-user base for platform ecosystems, platform owners often face the "chicken-and-egg problem" (Caillaud and Jullien, 2003), which refers to the early liquidity challenges. Once solving the "chicken-and-egg problem," platform owners benefit from both direct network effects – stimulation of additional users on the same side of the platform – and indirect network effects – stimulation of additional users on the opposite side of the platform (Bonardi and Durand, 2003; Eisenmann *et al.*, 2010; Evans, 2003; Rochet and Tirole, 2003).

Finally, recent platform studies examine complementary products and the performance of complementor firms on the platform ecosystems (Kapoor and Agarwal, 2017; Rietveld and Eggers, 2018) as well as the competition between platform owners and complementors when platform owners enter into complementors' space (Gawer and Cusumano, 2002; Gawer and Henderson, 2007; Wen and Zhu, 2019; Zhu and Liu, 2018). Prominent scholars have investigated the impacts of opening/closing platform ecosystems to complementor firms (Gawer, 2009) as well as the influence of giving access and control rights on the innovativeness of platforms (Boudreau, 2010; Parker and Van Alstyne, 2017). As complementor firms undertake responsibility in platform ecosystems in the creation of network effects, complementary products, and services (Ceccagnoli *et al.*, 2012; Gawer and Cusumano, 2002), they increasingly become one of the indispensable components of platforms.

Despite the increasing number of insightful studies and findings, we still do not have a unified framework that places individual findings in the literature within the bigger evolutionary picture. Understanding the unique dynamics of the evolution of platform firms represents an essential task in the creation of this unified evolutionary framework. Therefore, this paper takes the first step to comprehend the evolution process of platform firms.

METHODS

To investigate the evolution of platform firms, I utilize the qualitative grounded theory-building methodology (Glaser and Strauss, 1967; Strauss and Corbin, 1998). I have started the study without having any presumptions. The initial task was to protect my open-mindedness and collect a large and extensive dataset to better understand the evolution of platform firms. Therefore, the study was conducted over two different time periods but extensively refined during a back-and-forth process between existing platform literature and the data. The first period (18 months) of the study mostly focused on the growth of the platform firms, whereas the second period (6 months) of the study was directed to understand the failure of platform firms. During each time period, I continued the back-and-forth process between the literature and data. At the end of the process, I limit the scope of the study to an important research question: how do platform firms evolve?

Because the inductive bottom-up coding technique guided by a grounded theory-building methodology (Glaser and Strauss, 1967; Strauss and Corbin, 1998) helps researchers increase the explanatory and predictive power of a study and allows them to deeply explore different nuances of the research question, I preferred to analyze the data based on commonly accepted grounded theory-building guidelines. I started the study with line-by-line coding. I then utilized the following coding stages: open-coding, constant comparison, focused coding, axial coding, selective coding, and memo-writing. At the end of this process, I came up with major categories of the study. Thus, the foci of the study emerged based on the following categories: (1) Platform Growth, (2) Competition, (3) Adaptive Behaviors, (4) Platform Sustainability, (5) Rebranding Challenges, and (6) Platform Failure. Keeping these categories in mind, I continued further iterations between the platform literature and the data to relate categories to each other and build an evolutionary theory of platform firms (Edmondson and McManus, 2007).

[Insert Figure 3.1 about here]

Data Collection and Sample

To create an extensive qualitative dataset, I use the theoretical sampling technique (Glaser and Strauss, 1967; Strauss, 1987), a sampling method that is guided by emerging theory rather than a prearranged population. I can categorize the data collection into two different stages. At the beginning of the first stage of data collection, the primary criteria for selecting interviews was whether interviewees were mentioning anything about the emergence and growth of their platform business. Having this criterion early on helped me better understand the initial growth of platform companies. Over 18 months, I collected video interview data of more than 115 interviews with founders, top managers, and venture capitalists of platform companies. To find appropriate interview data, I made a Google search using various combinations of the following keywords: "platform firm", "platform company", "platform ecosystem", "platform", "interview", "talk", "entrepreneur", "manager", and "venture capitalist". Because of the availability of data, any interview available on the internet conducted since 1995 has been considered a likely data source. I stopped searching for further interviews once I realized further interviews add little value to the data analysis, which was an indication of reaching theoretical saturation (Glaser and Strauss, 1967; Strauss and Corbin, 1998). Because of relevance, redundancy, and the trial-and-error process, I eliminated 63 video interviews[5] from the analysis. As a result, the final sample at the end of the first stage of data collection included 52 interviews with 50 individuals, including 43 (Co)-Founders, five Venture Capitalists, and two Top Managers. While the video interviews were on average 24.71 minutes, they had a median of 24 minutes and a range from six minutes to 90 minutes. Combining the transcripts of video interviews resulted in a 522 single-spaced page dataset.

The Google search directed me to different websites to collect the data. I collected the majority of the dataset from the following notable websites: khanacademy.org, under30ceo.com, cleverism.com, and youtube.com. Further, other websites such as retireat21.com, forbes.com, fortune.com, wsj.com, and nytimes.com were highly utilized

[5] I didn't include some of these interviews into the analysis for several different reasons. First, some interviews were not relevant to the study and didn't match the main criteria. For example, nine interviews with platform entrepreneurs were not included in the analysis because the content was instead about daily lives of entrepreneurs. Second, if there was redundant information across interviews of the same individuals (30 interviews), the more detailed interview was preferred. And finally, during the trial-and-error process while directing the search to find proper interviews, I eliminated another 24 interviews because these interviews were conducted with traditional firm entrepreneurs. Interviews with traditional firm entrepreneurs except for venture capitalists were excluded from the analysis

during the first stage of data collection. As I started to collect initial data in early 2017, the majority (80%) of video interview data were 3-4 years old. While the earliest interview was conducted in 2007, the latest one was conducted in 2017. Because I suspect that the first data collection stage may suffer from success bias, I started the second data collection stage by searching failed platform companies. While the firms being hosted in the video materials are likely to be successful platform owners, my research shows 11 platform firms out of the initial sample had failed by 2019. Collecting and analyzing 57 single-spaced pages of 34 review, forum, and analyst articles about failed platform firms, I have incorporated my codes from the second stage of data collection into the codes from the video materials with the same methodology. The data on platform firm failure were collected from 20 websites, including TechCrunch, VentureBear, Webarchive, Bloomberg, Cbsnews, Failory, etc. Further data about individuals and companies in the dataset were collected from the following data sources: LinkedIn, Facebook, Twitter, Crunchbase, Bloomberg, Pitchbook, and Privco.

The following individual and company-level data are collected from the abovementioned data sources. The individual-level data show there are 49 men and one woman, 30 US citizens and 20 non-citizens, 26 people with a graduate degree, three college dropouts, and 36 (out of 50) people with relevant industry experience. Further, the interviewees in the data have created at least 122 firms. If I report only relevant platform companies[6], the majority (92% - 46 out of 50) of companies were founded in Silicon

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[6]In the analysis, I divided firms into four categories: (1) Platform firm, (2) Half-platform firm, (3) Inter-platform firm, and (4) Traditional firm. If a firm coordinates transaction of multiple parties and matches supply and demand on a platform ecosystem, it has been coded as a platform firm. Firms that identify potential customers for other companies have been coded as half-platform firms, those that integrate and connect different platforms have been coded as inter-platform firms, and finally, those that do not meet these criteria were coded as traditional firms. While

Valley, Ca. The remaining companies in the sample were founded in three different US states: 4% (2 out of 50) in Washington, 2% (1 out of 50) in Texas, and 2% (1 out of 50) in Iowa. My research indicates the bulk of firms in the sample come from the following industries: information technology, gaming, data analytics, software and hardware development, and online education.

[Insert Table 3.1 about here]
[Insert Figure 3.2 about here]

Data Analysis

This study mainly follows the grounded theory-building standards (Charmaz, 2014; Glaser and Strauss, 1967) to build an evolutionary theory of platform firms. The initial step in the study was to collect transcripts[7] of each interview and article. After collecting transcripts, I began the study with the line-by-line coding (Charmaz, 2014; Glaser, 1978). The open coding stage followed the line-by-line coding stage (Corbin and Strauss, 1990). During the open coding stage, I re-read the transcribed interviews and articles, and previous codes. At the end of the open coding stage, the data started to gain a uniform shape. I then conducted a constant comparative method (Glaser and Strauss, 1967) to compare the initial categories of the study with the data. Several iterations of constant comparative methodology lead to the creation of a primitive structure. After several rounds of iteration between data, emerging categories of the study, and the literature, I consolidated the categories through a focused coding stage – the stage where "the most significant and/or frequent earlier codes

traditional firms only include five venture capitalist firms, there are 31 platform firms, eight half-platform firms, and six inter-platform firms.

[7] Often transcripts of each interview were available on the cited websites. In a few cases where transcripts were not available, videos were manually transcribed after watching videos several times.

to sift through a large amount of data" (Charmaz, 2014: 57). Further, the axial coding stage followed the focused coding stage. In particular, I used the axial coding stage to relate categories to subcategories and collect the fractured data under a theoretical framework (Charmaz, 2014; Corbin and Strauss, 1990). Towards the end of the axial coding stage, I was able to see the foundations of the grounded theory. Finally, I utilized the selective coding and writing short-memo (Glaser, 1978) stages to speculate on different relationships among the categories of the study. I drew tables and charts, took notes, and compared the demographic information of each interviewee during the memo-writing stage. At the end of this process, I came up with a qualitative evolutionary theory of platform firms.

[Insert Table 3.2 and 3.3 about here]

AN EVOLUTIONARY THEORY OF PLATFORM FIRMS

The qualitative grounded theory-building study about evolutions of platform firms revealed the following six categories: (1) Platform Growth, (2) Competition, (3) Adaptive Behaviors, (4) Platform Sustainability, (5) Rebranding Challenges, and (6) Platform Failure. In the following section, I elaborate on each of these categories.

Platform Growth

The first category of the model is the *platform growth* stage. Starting with the emergence of a platform firm, this stage of platform growth results in sustainable platforms by adapting to the environment and increasing the liquidity of activities. Relative to other categories of the model, the platform growth stage has received a higher amount of attention in the existing literature. Three subcategories collected under the platform growth stage are (1) Liquidity, (2) Scalable and non-scalable solutions, and (3) Direct and indirect network effects. A brief literature review shows that researchers have already unearthed chicken-and-egg (or liquidity) problems in the initial phases of founding a platform firm (Caillaud and Jullien, 2003). Some early-stage coding that leads to the subcategory of liquidity includes: “We need to figure out the early traction problem. We have to solve the chicken-and-egg problem.” “In the marketplace, liquidity is the biggest problem.” “Uber Plumber doesn’t have enough liquidity to make it interesting.” Further, we also know that direct and indirect network effects have been a popular research area among platform scholars (Armstrong, 2006; Caillaud and Jullien, 2003; Evans, 2003; Hagiu, 2006; Rochet and Tirole, 2003, 2006). This study confirmed the importance of direct and indirect network effects for platform firms. Particularly, the coding that led to the subcategory of direct and indirect network effects include: “We believe that the network that we have, that connects customers and vendors together, the payables-receivables connection, ultimately does create a supplier network.” “It’s just like bacteria in a Petri dish. So, what you want to do is try to have one customer generate like two customers.” The last subcategory under the platform growth stage is scalable and non-scalable solutions. In addition to the existing known strategies for solving the chicken-and-egg problem (Evans, 2009), this study found another popular solution. The solution is that platform firms early on pursue non-scalable solutions but switch to scalable solutions once a critical mass is reached (Evans and Schmalensee, 2010). Apparently, non-scalable solutions include techniques such as word of mouth, meeting existing users, and increasing the size of the installed user base with the help of family and friends, whereas scalable solutions refer to formal marketing, advertising, and search engine optimization (SEO) techniques. The following are some sample codes for this subcategory: “We knew that we needed to do something a little bit different…one idea was to actually leave our apartment and go out into the world and go meet the people using our website." "It was the word of mouth that ultimately took off." The following quote elaborates how non-scalable solutions are preferred over scalable solutions early on, but scalable solutions work better at the later stages:

> **Eren Bali (Co-Founder of Udemy):** ...And, I was asking these questions to everybody. I would say how did you get the first 100,000 users? How did you solve the initial traction problem? And, the suggestion was: "do things that don't scale." So, meaning, there are things like SEO and advertising are scalable things in getting users. Those tend not to work in the early days of a startup because most of the scalable methodologies are better on the scale.

The main implication of this solution for the chicken-and-egg problem is that early customers on both sides of a market play an important role in legitimizing the platform. Once trust and transparency have been gained through non-scalable techniques such as word of mouth or personal visits, platform firms then switch to scalable techniques such as widespread advertisements or SEO to further scale the platform.

Competition

The second category of the model, *competition*, represents the increasing number of competitive behaviors in platform-mediated industries. Once platform firms gain momentum among users and are on a rising growth trajectory, they become more visible and attract incumbent firms' attention. Similarly, they covet a higher market share. The category of competition is built upon the following two subcategories: (1) Competition by entrenched companies and (2) Expanding a niche platform. Some early-stage codes collected under the subcategory of competition by entrenched companies include: "[…Ending its original service…] While this surely upset many devout Xfire fans, it was rather smart on Xfire to pursue other avenues as by the time Xfire's original service was ended, YouTube and Twitch had quickly begun to rule gaming video media," "Worse still, Levanta, as it tried to switch target audiences, found itself going up against strongly entrenched virtualization management companies like VMware. In addition, far better-known companies such as Hewlett-Packard, IBM, and Sun were moving into data center and virtualization management," "When Eye-Fi first launched, it provided a solution to easily get photos off of a camera for backup or sharing. At this point, many cameras have Wi-Fi built-in, making Eye-Fi's product less appealing than it was when it first launched." Such competition by entrenched companies is an example of platform envelopment (Eisenmann *et al.*, 2010), a situation when a platform company enters into another platform market by combining its own functionality with that of the target platform market.

The second subcategory of expanding a niche platform is another type of competition in platform industries. For example, the following early codes helped me create the subcategory of expanding a niche platform: "To compete with Facebook Messenger, WhatsApp, Skype, and/or Viber, Yahoo made several acquisitions. The new Yahoo Messenger features technology that the company brought over thanks to multiple acquisitions. It has integrated work from not only Flickr, but also Tumblr, Xobni, Cooliris, and Tomfoolery"; "Aiming to be the new Microsoft, Novell engaged in a multi-front war against a larger competitor, with far more resources. Novell bought WordPerfect to compete with MS Word, Quattro Pro to compete with Excel, and announced a dizzying array of additional new initiatives."

Both subcategories – competition by entrenched companies and expanding a niche platform – collected under the main category of competition indicate that platform firms should be ready to compete with different incumbent (or new entrant) companies. However, the data show that platform companies oftentimes are caught unprepared for such a competition. Therefore, they often use adaptive behaviors to get ready for different types of competition in platform industries.

Adaptive Behaviors

The third main category of the model, adaptive behaviors, follows platform growth, and competition stages. I come up with the main category of adaptive behaviors based on the following two subcategories: (1) Resource Re-orchestration and (2) Resource Redeployment. In the stage of adaptive behaviors, platform firms choose one of these strategies to either protect their existing positions or occupy a better position. Some early-stage codes leading to the creation of the subcategory of resource re-orchestration include: "Rebooting its business plan to focus on PC gamers," "announcing an end for console support," and "stopping indexing blogs and sites in languages other than English in order to focus only on the English-language blogosphere." For example, Dennis Fong justifies the resource re-orchestration decision with the following quote:

> **Dennis Fong (Founder of Raptr):** ... "the biggest pain point for PC gamers is the weakness of the platform as a whole. Everybody has a different kind of PC. There are a million different configurations for playing games. We help gamers get the best experience every time they play" and adding "we have reinvented ourselves with a focus on PC gaming".

On the other hand, the second subcategory of resource redeployment is created based on the following early codes: "relaunching a social and professional networking company as a 'workplace chat' application"; "The company's core product was previously an internet search engine for searching blogs. The website stopped indexing blogs and assigning authority scores in May 2014 with the launch of its new website, which is focused on online publishing and advertising"; "…deciding to sunset the Xfire Client and the social site, so we can focus our efforts on the Xfire Tournament Platform." For example, the following quote by Reid Hoffman, the founder of LinkedIn, shows how having re-deployable employees can help platform firms in tough times:

> **Reid Hoffman (Founder of LinkedIn):** ... "So what I had done, because I had imagined this is the way you start a company, is I had drawn out an org chart and said we need people with five to 10 years' experience, doing this, this, and this," [This turned out to be a terrible decision.] [We learnt to hire "generalists" at PayPal because companies evolve; and a perfectly structured team for its initial iteration will immediately fall apart as soon as something fundamentally changes or the company decides to pivot, reinventing itself entirely.][8]

Depending on the outcome of these adaptive behaviors, platform firms either enjoy a platform sustainability stage by different means or enter into a shrinking trajectory through struggling with the stage of *rebranding challenges*.

Platform sustainability stage

An important but largely ignored theme in the platform literature is the concept of platform sustainability, which is defined as the stage when platform firms keep different sides on the platform through various mechanisms, including the creation of recurrent needs, adaptation, and personalization. The preceding three mechanisms are the subcategories that helped me create the main category of platform sustainability. For instance, some early-stage codes of recurrent needs include quotes like: "[Our app] on the app store was generating good money, but we felt we got to figure recurring model out of it… then, we justify it should be a subscription-based." "You have to make people want to come back to the platform." In addition, adaptation to real-time demand and supply is of still significant vitality for platform sustainability. Early-stage codes about adaptation of demand and supply mainly show that platform owners should either subsidize a side of the platform during the time period when the number or variety of a party is significantly below that of

[8] Emphasis added.

its corresponding pair(s) (Eisenmann, Parker, and Van Alstyne, 2006) or create artificial supply until a balance is reached for all parties. For instance, Uber's founder Travis Kalanick explains surge pricing as "a mechanism whereby when demand outstrips supply, the price goes up." Also, the following quote by Sheeroy Desai of Gild shows how artificially created supply can help platform firms sustain their business: "…you've got to create a supply somewhere. I think the best way to get a marketplace going is to create that supply artificially." The last subcategory under the platform sustainability stage is personalization, which basically helps customers explore unknown functions/contents of a platform or get suggestions based on a person's prior search or his/her close friends' interests. For instance, Trip Adler of Scribd discusses how a personalized recommendation engine makes the reader stay on his digital book platform:

> **Trip Adler (Founder of Scribd):** The subscription model really decreases the friction of starting a new book, but we are working by now with a really good recommendation engine, with a really good editorial process that helps you discover books you want to read and also a really nice social layer around reading. So, you can discover things to read through your friends.

The importance of this category comes from the fact that solving the chicken-and-egg or liquidity problem only once during the growth stage most often does not work for platform firms. Rather, platform firms have to sustain their business by keeping all sides on the platform. An important trick here is to create recurrent needs for platform participants and make the platform the main intermediary between demand and supply sides. If demand and supply sides find a way to eliminate the platform as the main intermediary, the platform firm can over time become futile and useless. To avoid such a situation, platform firms should try to create recurrent needs by adopting access and membership business models rather than having a one-time sale model. Therefore, the stage of platform sustainability is indispensable for a better understanding of the evolution of platform firms. The following quote explains how platform companies can achieve the stage of platform sustainability by providing a hook of insurance to keep people on the platform.

> **Andrew Ogawa (Venture Capitalist; Co-Founder of Quest Venture Partners):** …The thing with platforms, though, is that you always have to have some sort of a hook that makes them [people] want to come back to the platform, as opposed to meet someone and then go off the platform and to communicate directly. We have a very interesting startup that we invested in, called DogVacay, which is kind of Airbnb for dogs, pet owners…So, through the platform I can identify someone who's willing to host my dog while I'm on vacation…their hook for their platform is that they provide insurance to the dog sitter and a pet owner, both sides, just in case something happens [*e.g.,* dog got lost]… by providing that hook of insurance, and being able to review and see those reviews, that's what allows people to come back, and not stay off of the platform. So, if you're creating a platform business…you need to make sure that there's a reason why they continue to stay on the platform…

Rebranding Challenges

Like the stage of platform sustainability, the stage of rebranding challenges follows the stage of adaptive behaviors. This stage represents the shrinking trajectory platform firms face when they struggle with different problems resulting from earlier adaptive behaviors. The stage of rebranding challenges is built upon the following subcategories: (1) Adaptation difficulties and (2) Uncertainty and Complexity. For example, the subcategory of adaptation difficulties was built upon quotes: "While the website will continue to operate, it will instead focus its resources towards PC gaming, explaining that recent changes to Xbox Live and PSN have 'repeatedly' broken the site's system. But on the console side, you may have noticed some features stopped updating, as changes to Xbox Live and PSN would repeatedly break our system"; "Another problem was that as virtualization has grown to being an important part of any Linux server farm operation, Levanta's existing software didn't scale well to these new tasks. It did well as the basis for small to medium-sized business appliances. It didn't do half so well at enterprise-sized tasks"; and "The company says that it will not be updating the apps that work with the older cards and platform OS updates may render them non-functioning entirely in the future." On the other hand, the second subcategory of uncertainty and complexity is built upon the following early codes: "taking complexity into account and eliminating noise," "facing constant extermination problem," "never knowing where things are going," and "company could disappear any week." If platform companies do not overcome rebranding challenges, they enter into the platform failure stage.

Platform Failure

The final stage of the model is the stage of platform failure, referring to the death and dissolution of platform companies. The stage of platform failure is created based on the following three subcategories: (1) Customer abandonment, (3) Network mismanagement, and (3) Management problems. For example, some quotes leading to the subcategory of customer abandonment include: "[Referring to EyeFi] … The company abruptly announced on June 30, 2016 that, due to security vulnerabilities present in the cards, all previous generation cards (X2 and before) would cease to be supported by the company's proprietary software after 16 September 2016"; "We appreciate that many non-English bloggers have been long-time users of Technorati and regret that we can no longer provide full services to the vibrant multilingual blogosphere"; and "making a decision to close down its social networking branch." A closely related subcategory is network mismanagement, which includes the following early codes: "not retaining customers," "users have not remained loyal to the network after they have joined the community, they were not attached to the brand," and "being unable to maintain social network at a high level.” For example, the following quote shows how Xfire, a video gamer social networking company that shut down its services in 2016, failed because its resource redeployment decision was not enough to create a sustainable platform.

> In 2003, Xfire released the Xfire Client, the first product to bring the outside world into your games. Since its humble beginnings as a simple chat client, it has steadily grown to enable users to take screenshots, videos, and live broadcasts and share them on the Xfire Social Website. Attracting over 24 million users into a healthy and vibrant community, it set the standard for the socialization of PC Games. We've also seen esports[9] grow from small LAN Parties into a maturing industry. Esports has the potential to grow as large as its real-world counterpart, and at Xfire, we want to be a part of that. For this reason, we have decided to sunset the Xfire Client and the social site so we can focus our efforts on The Xfire Tournament Platform.

Despite reaching a critical mass of 24 million users, Xfire was not able to survive because its adaptive behaviors were not enough to create a sustainable platform. In contrast, these corporate actions resulted in an inverse network effect after initial abandonment of customers because customers lost their trust in the company. Similarly, despite growing from 10,000 users in September 2010 to over three million in May 2011[10], Branchout, a professional network service designed to find a job through close friends, failed because the company could not retain its users and create a recurrent need. Eventually, the company could not create a loyal customer base and failed because of network mismanagement.

Finally, like all traditional companies, platform companies are also failing because of management problems. Some early codes leading to the subcategory of management problems include: “driving out founders out of the management structure and installing incompetent professional managers,” “[The company’s] issues originate from its reported unethical behavior, lack of transparency and outright lies by former CEO and his close

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[9] Esports refers to online video game competitions.
[10] For further details, please see: http://jobsinformo.blogspot.com/2015/10/branchout-post-jobs-on-facebook.html

partners", and "[The company] had other management problems as well." For example, the following quote by Michael Perry, the former senior director of services at Levanta, shows an example of management problems:

> **Michael Perry (Former Senior Director of Services at Levanta): "**I will miss it and what it might have been; but I'll never miss a whole subset of the cast of characters who thought they were above the laws of space and time. No, you were not as it turns out. You made the failure as much as if you drove the car. You simply cannot run the company like it's your personal kingdom. Sorry."

DISCUSSION

The main task in this paper was to investigate the evolution of platform firms. I built a grounded theory and process model based on publicly available interviews and articles with platform entrepreneurs, managers, venture capitalists, and industry analysts. The built grounded theory indicates that the evolution of platform firms includes at least the following categories: (1) Platform Growth, (2) Competition, (3) Adaptive Behaviors, (4) Platform Sustainability, (5) Rebranding Challenges, and (6) Platform Failure. Highlighting the organizational aspect of platforms, the contributions to the literature include the following points.

First and foremost, despite the increasing number of insightful studies and findings (e.g., Parker et al., 2016; Parker & Van Alstyne, 2017; Jacobides et al., 2018; McIntyre & Srinivasan, 2017; Parker & Van Alstyne, 2017; Rietveld et al., 2018; Rietveld & Eggers, 2018), the platform literature lacks a unified picture that shows the evolutionary process of platform firms. Building a qualitative grounded theory, the chapter takes the first step towards a better understanding of the evolution of platform firms and collects individual findings in the literature within a bigger evolutionary framework. Second, along with scholars who started to question the "winners-take-all (or-most)" assumption (Cusumano *et al.*, 2019), the chapter shows that this assumption is only warranted if platform companies achieve a platform sustainability stage. Despite the focus of the platform literature on solving the chicken-and-egg (early traction) problem, the study shows that solving this problem only once is nonetheless not sufficient to keep the platform firm alive. Instead, platform companies should provide a hook and create a recurrent need to make them a sustainable business. Even "winners" should strive for keeping different sides on platforms to create sustainable platforms.

Third, the evolutionary framework of platform firms contributes to the literature by highlighting the differences between the evolution of platform firms and that of traditional firms (Penrose, 1959; Winter and Nelson, 1982). Viewing the traditional firm as a bundle of resources, Penrose (1959) discusses that unused and underutilized resources of firms are a key source of firm expansion and growth (Kor *et al.*, 2016). While this statement can be true for platform companies to a certain extent, we can argue that unused and underutilized resources available in markets are more likely to yield to the expansion and growth of the platform firms. Similarly, if unused and underutilized resources in the core market of a platform firm diminish as a result of competition by other companies, platform companies have to find related unused and underutilized resources in adjacent marketplaces to continue their growth and create a sustainable platform ecosystem. On the other hand, the results yield significant contributions to evolutionary economics. Disputing the classical economic theory that assumes the industry is in an equilibrium and that firms exist to maximize their profits, Winter and Nelson (1982) view firms as a set of organizations guided by organizational routines. In the evolutionary framework of Winter and Nelson (1982), firms attempt to optimize their behaviors rather than maximize their profits.

Occasionally, firms modify their routines by "search" behavior and adapt to new conditions. This evolutionary process often results in the "selection environment," where efficient firms grow at the expense of inefficient ones and drive them out of the business environment. The evolutionary model of platform firms indicates that platform firms may have different routines in each stage of the model. In each stage of the model, platform companies have to adopt a new set of routines to achieve a competitive advantage. For example, the set of routines in the early growth stage of platform companies may be directed towards solving the early traction problem. However, as a result of the competition stage, platform companies have to adapt to the new environment and refine their adaptive behaviors through a "search" behavior. On the other hand, in the platform sustainability stage, platform companies have to develop routines to create a recurrent need and keep different parties on the platform. Therefore, it is likely that platform companies reaching the platform sustainability stage drive out the ones struggling with rebranding challenges.

Fourth, the chapter found that platform companies engage in some adaptive behaviors – resource re-orchestration and resource redeployment – to either protect their existing positions or occupy a better position. Although we have gathered a certain level of knowledge about how resource orchestration and redeployment may affect entry, exit, and acquisition behaviors of traditional firms (Capron, Dussauge, and Mitchell, 1998; Lieberman, Lee, and Folta, 2017; Sirmon *et al.*, 2011), we lack a complete understanding of the effects of these behaviors in a platform ecosystem. Therefore, understanding how these adaptive behaviors affect firm entry, exit, success, and failure in a platform ecosystem can be a potential focus of an interesting future study. Finally, the chapter contributes to the literature by taking the first step towards a better understanding of failures of platform companies. The model indicates that customer abandonment, network mismanagement, and management problems are among top reasons for platform failures. We would definitely benefit from further research about failures of platform companies.

Nonetheless, this study has several limitations. First, the chapter analyzes publicly available interviews and articles. Potentially, the study may suffer from availability bias. Second, although I collect data about both success and failure of platform companies, the analysis still may suffer from success bias. Finally, there may be some other major subcategories and categories that can affect evolution of platform companies. To overcome these challenges, future studies can collect primary data about evolution of platform companies and investigate factors leading to failure of platform companies at the idea stage.

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Figures

FIGURE 3.1. An evolutionary model of platform firms

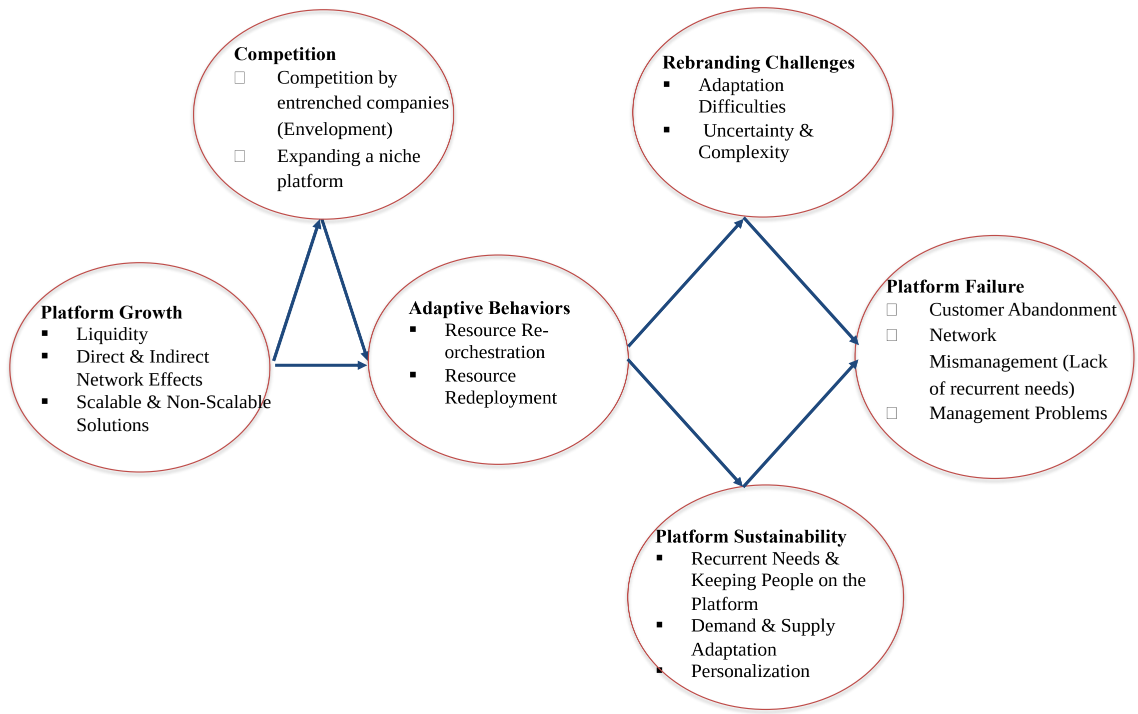

FIGURE 3.2. Data coding structure

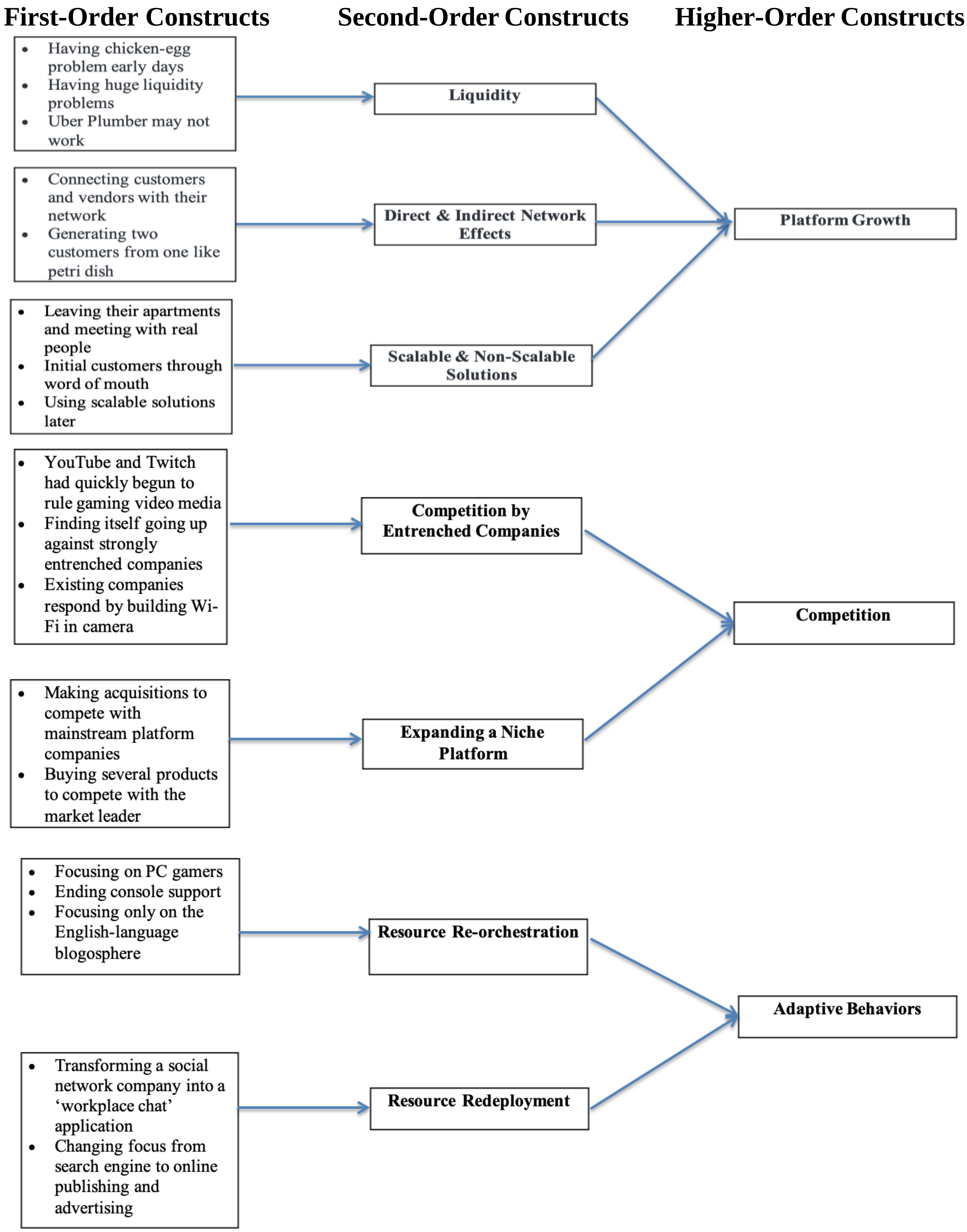

FIGURE 3.2. Data coding structure (Continued)

First-Order Constructs **Second-Order Constructs** **Higher-Order Constructs**

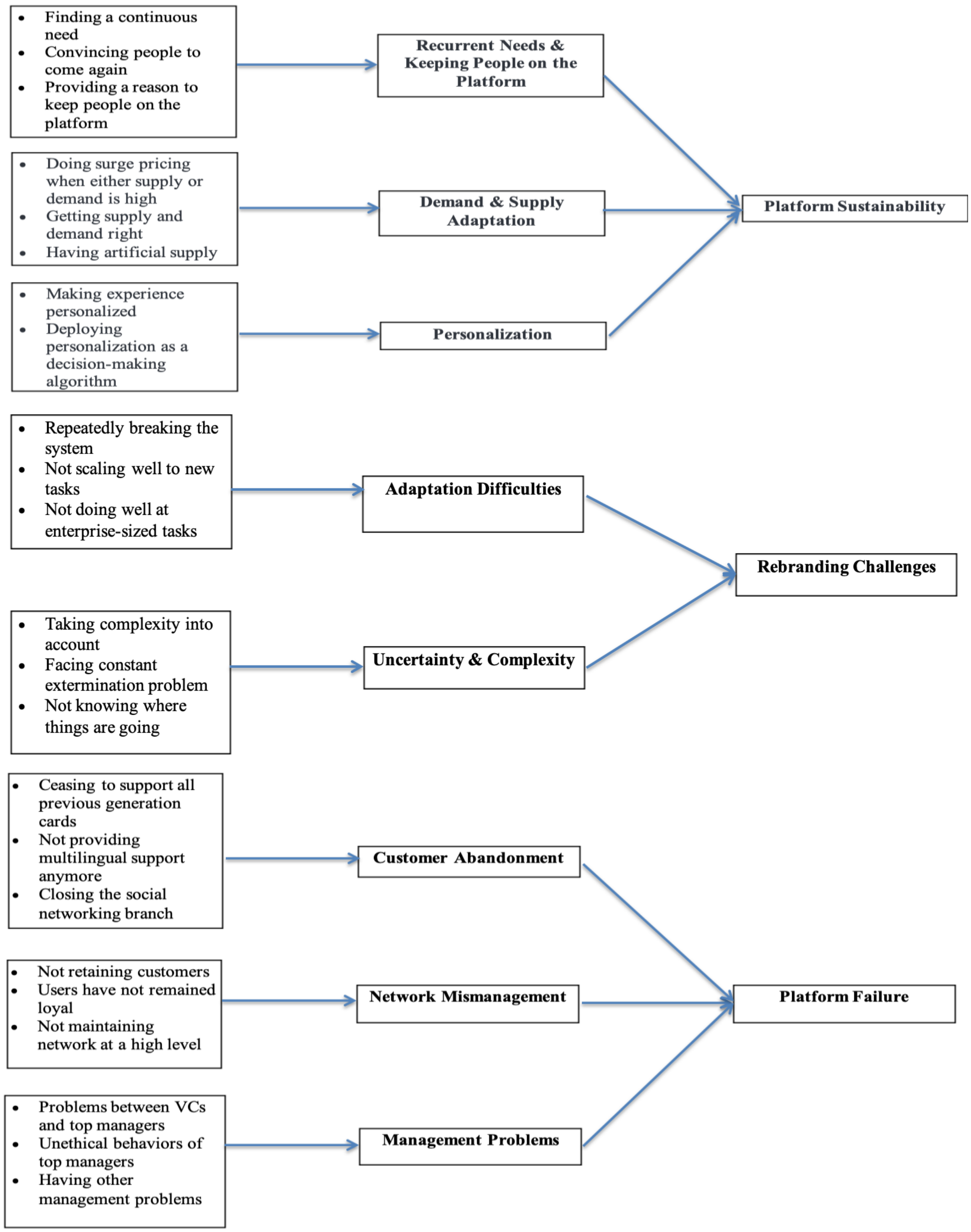

TABLE 3.1. Illustrative sample data

Individual (Title)	Related company /Firm type	Explanation	Headquarter city and state	Duration (Mins)
René Lacerte (Founder and CEO)	Bill.com/Platform	The company matches small companies with their customers	Palo Alto, CA	25
Trip Adler (Co-Founder and CEO)	Scribd/Platform	A digital library platform bringing together publishers, writers, and readers	San Francisco, CA	24
Niklas Lindstrom (Co-Founder)	SKOUT/Platform	Social networking and dating platform	San Francisco, CA	17
Beth Schmidt (Founder)	Wishbone.org /Platform	A non-profit platform company matching poor students with philanthropists	San Francisco, CA	9
Marco Zappacosta (Co-Founder and CEO)	Thumbtack /Platform	Online service platform matching customers with local professionals	San Francisco, CA	20
Brian Wong (Founder and CEO)	Kiip/Platform	A gaming reward platform that brings together game developers, players, and advertising companies	San Francisco, CA	26
Dennis Fong (Founder and CEO)	Raptr/Platform	Social networking platform for video game players	Mountain View, CA	33
Omer Artun (Founder and CEO)	AgilOne/Half-Platform	Enterprise customer data platform that identifies potential customers for businesses	Mountain View, CA	24
Vincent Yang (Co-Founder and CEO)	EverString/Half-Platform	Sales and Marketing platform identifying potential customers	San Mateo, CA	27
Milind Gadekar (Co-Founder and CEO)	CloudOn/Inter-Platform	An online productivity platform that enables people to edit, create, organize, and share docs on many platforms including tablets, phones, PC, Dropbox, etc.	Mountain View, CA	28
Mark Lee (Co-Founder and CEO)	Splashtop/Inter-Platform	A productivity software platform that bridges smartphones, tablets, computers, TVs, and clouds by providing remote access	San Jose, CA	22
Alex Taussig (Venture Capitalist)	Highland Capital Partners/Traditional	Traditional venture capitalist firm	Palo Alto, CA	28
Andrew Ogawa (Venture Capitalist)	Quest Venture Partners/Traditional	Traditional venture capitalist firm	Palo Alto, CA	26

Note: Data in the table come from public sources including LinkedIn, Facebook, Twitter, Crunchbase, and Bloomberg. I use a subsample of the data in a different article about the origin and emergence of platform firms.

TABLE 3.2. Grounded theory coding and explanation

Grounded theory steps	Action taken
Line-by-line coding	Every single page was read and coded line by line.
Open coding	Transcripts and line-by-line codings were re-read to make the style and structure of the data gain a uniform shape.
Constant comparison	Constant comparison was done to compare emerging codes with each other and with the data.
Focused coding	In addition to the standard grounded theory-building stages, a focused coding stage was conducted to highlight the most significant and/or frequent earlier codes (Charmaz, 2014).
Axial coding	Categories and subcategories were related to each other.
Selective coding	This is the period when the final decision was made about major core categories. Main categories were selected, and all other subcategories were related to these categories.
Memo writing	Different scenarios of the relationship among emerged categories were developed during this stage. Also, this stage includes drawing tables and charts, writing analytic notes and demographic information, and unifying all this information under a unified theoretical umbrella.

Note: Grounded theory building is one of the most popular qualitative methodologies that construct a new theory through gathering and analyzing qualitative data. In contrast to hypothetico-deductive quantitative studies, the grounded theory-building approach is an inductive data-driven method (Charmaz, 2014; Glaser and Strauss, 1967).

TABLE 3.3. Main categories coding description and illustrative quotes

Coding	Coding definition	Illustrative quote(s)
Platform growth	The process that starts with an idea to start a platform firm and that evolves into a sustainable platform.	So, originally, we were looking at local mobility and how a third to half of all trips made by Americans are for less than 5 miles; we do them in single occupancy, two to three thousand pound automobiles, and so my idea was to build a small, very efficient electric four-wheel vehicle, that was built from the ground up to be sharable, to occupy a lot of these local needs…[We] realized there was a big gaping hole in mobility that needed to be innovated in, and disrupted…what we learned in the process was that we could do much greater good and have much greater impact if we separate our ideas and became vehicle agnostic and stop trying to build cars…So, we separated the hardware and software that we needed to become vehicle agnostic… we install hardware in every vehicle that we deal with and focus on large groups of assets and fleets… (John Stainfield, Co-Founder of Local Motion).
Competition	The increasing number of competitive behaviors in platform-mediated industries.	Before the internet, local area networks were the big thing. A company called Novell was the first to exploit the trend for connecting systems (local area networks) ultimately becoming "the LAN king" with its NetWare server operating system. Rather than splitting up an expensive hard disk into multiple separate segments, one per workstation, NetWare allowed all workstation to access individual files on a single shared volume. 1990, the company's core product, NetWare, held a commanding 70%+ market share in the networking software space, which was already very large at the time, and growing at a rapid rate. Netware 4 was excellent for small organizations and networks in a local place but rapidly unmanageable for large organizations with multiple sites, particularly if these were in different countries. Windows NT, on the other hand, was a general-purpose OS that natively spoke TCP/IP – or Internet Protocol as we used to call it. It had the familiar Windows user interface, as opposed to the remote-server-console admin of NetWare. The first version of NT, disingenuously called Windows NT 3.1, was quite immature, but adding additional server functionality was much easier (and often cheaper) on Windows NT than on NetWare. Aiming to be the new Microsoft, Novell engaged in a multi-front war against a larger competitor, with far more resources. Novell bought WordPerfect to compete with MS Word, Quattro Pro to compete with Excel, and announced a dizzying array of additional new initiatives. Microsoft finally split with 3COM, developed Windows NT, essentially building Networking into the Operating System (Novell vs. Microsoft).

Adaptive behaviors	Disparate behaviors platform owners use to either protect their existing positions or occupy a better position.	Our history includes providing such services as a blog search engine and authority index helping bloggers and website publishers get their content discovered well before social media redefined discovery. Over the past 6 years, we've grown into a successful ad platform that helps those types of websites earn revenue from that content. With this new website, we hope to shape the conversation of online publishing, specifically around advertising technology and programmatic revenue. You won't find our blog claim process or authority index on this new website, as that technology is being redesigned and optimized to help publishers get discovered by advertisers and earn more for their highly-valued content (Technorati in 2014).
Platform sustainability	The situation where platform firms are able to keep different sides on the platform through various mechanisms.	[At the beginning] we tried then to sell books, but it didn't really work very well, but we've realized subscription was a very good way to help them [publishers and authors] make money…We're building a terrific experience for discovering new books and things to read. The subscription model really decreases the friction of starting a new book, but we are working by now with a really good recommendation engine, with really good editorial process that helps you discover books you want to read and also a really nice social layer around reading. So, we're combining all of this together just to provide a really good experience for discovering things to read… (Trip Adler, Co-Founder of Scribd).
Rebranding Challenges	The shrinking trajectory platform firms face when they struggle with different problems resulting from earlier adaptive behaviors.	When Raptr started out, we offered Steam and XBL achievements and PSN trophy tracking, PC/Xbox 360 gameplay tracking, plus unified buddy lists and chat, a message posted on the website explains. As Raptr grew, we realized there was a big demand for features that improved the PC gaming experience, such as game optimizations, easy Twitch streaming, and lightweight video capture. But on the console side, you may have noticed some features stopped updating, as changes to Xbox Live and PSN would repeatedly break our system. The website had allowed Xbox and PlayStation users to automatically track their playtime and achievements/trophies, but has struggled to keep up with changes introduced to both platform holders' networks following the launch of PS4 and Xbox One (Raptr in 2015)
Platform Failure	The death and dissolution of platform companies.	[BranchOut – a Facebook application designed for finding jobs] was founded by Rick Marini in July 2010, and was, as of March 2012, the largest professional networking service on Facebook. In January 2011, BranchOut's user base grew by a factor of 25, increasing from 10,000 to 250,000. It grew up quickly, from the 400,000 users in December 2011, to over eight million in April 2012. According to Business Insider, Marini believes that the business was wrong when not focusing on retaining customers. At first, the manager was responsible for attracting users, which increased the investor's interest. But its users have not remained loyal to the network after they have joined the community, they were not attached to the brand. Last six months we tried to maintain the social network at a high level. You cannot predict the rapid growth or drastic slowdown of a project. Although you need to deal with many things at the same time, sometimes things just don't go your way as planned and you have no choice (BranchOut Failure)

CHAPTER 4: ENTRY INTO COMPLEMENTORS' SPACE: VERTICAL INTEGRATION AND ALLIANCES OF PLATFORM OWNERS AND COMPLEMENTOR FIRMS

ABSTRACT

This paper investigates the performance consequences of alliance and vertical integration behaviors of platform owners and complementor firms. I develop a framework for examining competitive and collaborative behaviors among platform participants noting that platform owners' entry into complementors' space should not always be viewed as an act of competition. The study found that, in contrast to individual vertical integration of platform owners and complementor firms, alliances between platform owners and complementor firms as well as alliances among complementor firms are positively associated with product performance. Also, it found that platform maturity weakens the positive effects of alliances between platform owners and complementors firms on product performance, whereas there are no moderating effects for alliances among complementor firms.

INTRODUCTION

Recent research in the platform literature shows the platform revolution (Parker and Van Alstyne, 2017; Parker, Alstyne, and Choudary, 2016; Cusumano, Yoffie, and Gawer, 2019) continues to transform the traditional business environment into a platform-mediated one (Eisenmann, Parker, and Van Alstyne, 2010; Kapoor and Agarwal, 2017; McIntyre and Srinivasan, 2017; Jacobides, Cennamo, and Gawer, 2018; Zhu and Liu, 2018; Wen and Zhu, 2019). Researchers often attribute this transformation to the multi-sidedness of platforms because they facilitate interaction among multiple groups of platform participants such as end users and complementor firms (Baldwin and Woodard, 2009; Eisenmann *et al.*, 2010; Evans and Schmalensee, 2008; Hagiu, 2006; McIntyre and Srinivasan, 2017; Rochet and Tirole, 2006). Attracting these constituents to the platform ecosystem plays a vital role in a platform's success because it increases adoption by harnessing network effects, legitimizes the platform by attracting a diverse pool of contributors, eliminates potential concerns, and stimulates the production of unique goods (Boudreau, 2010; Eisenmann, Parker, and Van Alstyne, 2009; West, 2003). Similarly, complementors are often eager to build upon the platform ecosystem because platform owners initially allow them to have a share of the value. However, the research shows that platform owners often enter into complementors' space to appropriate more value from their innovations (Gawer and Cusumano, 2002; Gawer and Henderson, 2007; Zhu and Liu, 2018; Wen and Zhu, 2019). Thus, platform owners face the dilemma of "whether to use vertical integration to capture more value or improve the quality of the platform ecosystem" (Zhu and Liu, 2018: 2621).

The scant research on the entry decision of platform owners into the complementors' space views this action as an act of "competition" (Gawer and Cusumano, 2002; Gawer and Henderson, 2007; Zhu and Liu, 2018) or "threat" (Wen and Zhu, 2019). Building upon the early field studies (Gawer and Cusumano, 2002; Gawer and Henderson, 2007) and recent empirical works (Zhu and Liu, 2018; Wen and Zhu, 2019), this paper extends the literature on the performance consequences of possible collaborative and competitive behaviors of platform owners and complementor firms. Consistent with the existing literature, platform owners may prefer to compete with complementor firms by a vertical integration mode and can produce complementary products for their platforms. However, platform owners' entry into the complementors' zone should not always be viewed as an act of "competition" or "threat" because the owners often collaborate with complementor firms to develop new products. For example, in the video game industry, platform owners (e.g. Microsoft and Nintendo) collaborate with complementor firms in the development and publication of video games. Likewise, complementor firms face the same choice. A complementor firm can collaborate with the platform owner, ally with another complementor firm, or prefer to have a vertical integration mode. For instance, a developer company can collaborate with Nintendo for the publication of its video games, ally with another publisher company, or prefer to publish its games. These examples clarify that platform owners and complementor firms can build complementary products based on four prospective behaviors: (1) vertical integration of platform owners, (2) alliances between platform owners and complementor firms, (3) vertical integration of complementor firms, and (4) alliances among complementor firms. Focusing on these behaviors, the chapter investigates the extent to which the alliance and vertical integration behaviors of firms in a platform ecosystem yield to superior product performance.

The theoretical framework of this chapter is motivated by the literature on performance and success of platform owners and complementor firms (e.g., Eisenmann *et al.*, 2010; Gawer and Henderson, 2007; McIntyre and Subramaniam, 2009; Zhu and Iansiti, 2012); the literature on vertical integration, optimal governance mode, and performance outcomes (Castañer *et al.*, 2014; Rothaermel, Hitt, and Jobe, 2006; Leiblein, Reuer, and Dalsace, 2002; Capron and Mitchell, 2012); and the co-opetition literature (Bengtsson and Kock, 2000; Mathias *et al.*, 2018; Nalebuff and Brandenburger, 1997). The central hypothesis in the study is that, relative to vertical integration of platform owners and complementor firms, collaboration among platform participants is positively associated with product performance. The chapter also predicts the moderating effects of platform maturity: when platforms become more mature, platform owners and complementor firms may identify successful products and prefer to appropriate more value by a vertical integration mode. Overall, the empirical study lends support for all hypotheses but one moderating hypothesis. The study found that platform maturity weakens the positive effects of alliances between platform owners and complementors firms on product performance, whereas there are no moderating effects for alliances among complementor firms.

The global video game industry is the empirical context of the study. As a platform-mediated industry (Shankar and Bayus, 2003), the video game industry fits well to test the hypotheses because major video game console owners (e.g., Microsoft, Nintendo, and Sony) develop and publish games not only by a vertical integration governance mode to compete with complementor firms but also by an alliance mode where they collaborate with some complementor firms. Whereas the existing literature focuses on either the strategies and performance of platform owners (e.g., Eisenmann *et al.*, 2010; Gawer and Henderson, 2007; McIntyre and Subramaniam, 2009; Zhu and Iansiti, 2012) or the performance of complementor firms (Boudreau and Jeppesen 2015, Kapoor and Agarwal 2017, Rietveld & Eggers 2018), this paper investigates product-level performance because it has implications for both platform owners and complementor firms. To see the performance consequences of alliance vs. vertical integration behaviors of platform owners and complementor firms, I gather a unique dataset, which consists of 18,169 video game releases between 1977 and 2017. Accordingly, there are 1,926 video game developers, 547 video game publishers, 10 platform owners, and 38 video game platforms.

The study makes four contributions. First, the paper builds upon the existing literature on platform owners and complementor firms' performance (e.g., Gawer and Henderson, 2007; Kapoor and Agarwal, 2017; Zhu and Iansiti, 2012) and unearths the performance consequences of the relationships between platform owners and complementor firms. Second, along with recent empirical studies (Wen and Zhu, 2019; Zhu and Liu, 2018), the chapter offers empirical evidence on entry decisions of platform owners into the complementors' space and incorporates collaborative behaviors of platform owners and complementor firms into the existing competitive framework. Third, the study contributes to the literature on governance modes – make, buy, or ally decisions – and performance consequences (Castañer *et al.*, 2014; Leiblein *et al.*, 2002; Rothaermel *et al.*, 2006; Capron and Mitchell, 2012) and shows conditions when vertical alliances and vertical integration are more profitable. Finally, the findings in the paper partially echo other research on co-opetition (Bengtsson and Kock, 2000; Hannah and Eisenhardt, 2018; Mathias *et al.*, 2018; Nalebuff and Brandenburger, 1997). While the existing co-opetition research argues that the benefits of cooperation decline over time with market expansion and legitimation and that firms tend to shift their focus from "value creation" and cooperation to "value appropriation" and competition (Bengtsson and Kock, 2000; Mathias *et al.*, 2018; Nalebuff and Brandenburger, 1997), the paper found that this argument is valid for co-opetition between platform owners and complementor firms but not for co-opetition among complementor firms. In other words, according to the paper, even in mature markets, cooperation among complementor firms outperforms vertical integration of a complementor firm.

THEORY

A platform owner is the owner of a multi-sided platform, to which it attracts two or more customer groups and enables interaction between them (Armstrong, 2006; Caillaud and Jullien, 2003; Evans, 2003; Hagiu, 2006; Rochet and Tirole, 2003, 2006; Gawer, 2009). A complementor firm is an organization that builds complementary products, services, or technologies on the platform (Boudreau, 2010; Gawer, 2009; Kapoor and Agarwal, 2017; Parker and Van Alstyne, 2017). Early research on platform ecosystems mostly favored platform owners and investigated their strategies, success, and performance (e.g., Eisenmann *et al.*, 2010; Gawer and Henderson, 2007; McIntyre and Subramaniam, 2009; Zhu and Iansiti, 2012). Recently, researchers have started to address the performance of complementor firms (Boudreau and Jeppesen 2015, Kapoor and Agarwal 2017, Rietveld and Eggers 2018).

The extant literature on platform owners investigates the central role of platform owners in a platform ecosystem (Iansiti and Levien, 2004; Williamson and De Meyer, 2012), the competition among platforms (Armstrong, 2006; Casadesus-Masanell and Llanes, 2011; Economides and Katsamakas, 2006), the pricing decisions of platform owners (Hagiu, 2006; Parker and Van Alstyne, 2005; Rochet and Tirole, 2003; Seamans and Zhu, 2013), the importance of the growing user base for platform-mediated networks and platform owners (Cennamo and Santalo, 2013; Edelman, 2015; Eisenmann, Parker, & Van Alstyne, 2011), and the timing decisions of platform owners' entry into platform ecosystems (Zhu and Iansiti, 2012). Meanwhile, the literature on complementor firms focuses on the success and performance of complementor firms (Kapoor and Agarwal, 2017; Rietveld and Eggers, 2018) and the impacts of access of complementor firms to platform ecosystems (Venkatraman & Lee, 2004; Boudreau, 2010; Parker and Van Alstyne, 2017). While early research connected these two streams of literature by field studies (e.g., Gawer and Cusumano 2002, Gawer and Henderson 2007), there have been few empirical studies that investigate platform owners' entry decisions into complementors' space (Wen and Zhu, 2019; Zhu and Liu, 2018). Nevertheless, along with other studies that acknowledge potential competitive and expropriative behaviors of platform owners (Farrell and Katz, 2000; Huang *et al.*, 2013; Jiang, Jerath, and Srinivasan, 2011), the research on platform owners' entry decisions into complementors' space (Gawer and Cusumano, 2002; Gawer and Henderson, 2007; Wen and Zhu, 2019; Zhu and Liu, 2018) views this action as an act of competition or threat. Instead, this chapter incorporates a collaborative framework into the existing competitive and expropriative framework by showing platform owners' competitive as well as collaborative behaviors in complementors' space.

This study also relates to the literature on vertical integration, optimal governance mode, and performance outcomes (Castañer *et al.*, 2014; Leiblein *et al.*, 2002; Rothaermel *et al.*, 2006; Capron and Mitchell, 2012). Early research in this literature often investigated the role of a make-or-buy decisions in mitigating concerns regarding opportunism and incomplete contracts (Poppo and Zenger, 1998; Mahoney, 1992; Williamson, 1975, 1985). Building upon this tradition, researchers have also examined the performance outcomes of dichotomous make-or-buy decisions (Leiblein *et al.*, 2002; Nickerson and Silverman, 2003; Rothaermel *et al.*, 2006) as well as the performance outcomes of make-or-ally decisions in horizontal collaborations (Castañer *et al.*, 2014), which often happen between incumbents of the same industry (Kogut, 1988). Extending Castañer et al.'s (2014) paper, which focuses on the alliance behaviors between incumbents of the same industry, this paper studies the vertical alliance vs. vertical integration behaviors among platform participants. In platform-mediated industries, vertical alliances can happen in two types: (1) alliances between platform owners and complementor firms and (2) alliances between complementor firms specialized in distinct domains (e.g., in the context, game developers and publishers).

Moreover, the article informs the literature on co-opetition (Bengtsson and Kock, 2000; Mathias *et al.*, 2018; Nalebuff and Brandenburger, 1997), which often investigates collaboration and competition between two or more firms with an inter-temporal approach, by which firms initially collaborate to create a product and then compete to extract profit from that product. Unlike this inter-temporal approach, the co-opetition in the context of the study can happen in the same time period as such: partners can ally on development and publication of a video game while competing on other games that are developed/published either with another partner or with a vertical integration mode. The relationships in the context of the study are different from the existing co-opetition relationships exemplified by the one between Intel and Microsoft (Casadesus-Masanell, Nalebuff, and Yoffie, 2007; Casadesus-Masanell and Yoffie, 2007; Kapoor, 2013) because platform owners in the context of the study are much more powerful than complementor firms – for example, the relationship between Amazon and individual third-party sellers (Zhu and Liu, 2018) – because complementor firms engage in development and publication of the actual products beyond selling them.

In this study, I am interested in the product performance of alliance vs. vertical integration behaviors of platform owners and complementor firms. Because the product performance is likely to be affected by the governance mode of production (Castañer *et al.*, 2014; Leiblein *et al.*, 2002; Rothaermel *et al.*, 2006), I develop hypotheses based on problems and benefits associated with each governance mode. Specifically, I develop Hypotheses 1 and 2 based on the reputational, cost, and expertise benefits of alliances between platform owners and complementor firms, the advantages of domain specialization in vertical alliances, and the problems associated with vertical integration governance modes. Then, I build Hypothesis 3 based on reduction of uncertainty in mature platforms. In the next section, I first develop hypotheses and then provide the details of the research context. Then, I elaborate on the data and analysis techniques. Finally, I conclude with results and discussion.

HYPOTHESES

Alliances and vertical integration of complementor firms

The alliance literature suggests that relative to the vertical integration governance mode, alliances have a "synergistic combination advantage" of pooling resources held by multiple firms (Castañer *et al.*, 2014; Kogut, 1988; Mitchell, Dussauge, and Garrette, 2002; Zajac and Olsen, 1993), as well as a transaction and coordination disadvantage (Castañer *et al.*, 2014; Gulati and Singh, 1998; White and Lui, 2005). In a recent study, Castaner et al. (2014) found that products undertaken through horizontal collaboration achieve higher performance and incur longer time-to-market than those undertaken through autonomous production. In contrast to products undertaken through horizontal collaboration, the products in the research context of the study are undertaken through vertical collaborations. Accordingly, complementor firms in a platform ecosystem may pursue a vertical integration strategy – internalizing development and publication of video games – or a vertical alliance strategy – specializing in either development or publication of video games and finding a specialized partner in the other domain. A similar setting can be found in the bio-pharmaceutical industry between biotechnology and pharmaceutical companies (Paik and Woo, 2017). According to the Transaction Cost Economics (TCE) literature, relative to horizontal collaborations, a vertical integration mode can increase market power and decrease transaction-, uncertainty-, and coordination-related costs (Mahoney, 1992; Poppo and Zenger, 2002; Williamson, 1985) because products undertaken through horizontal alliances often require "technical dialog" (Monteverde, 1995). However, products undertaken through vertical alliances may not face some of these disadvantages because modular activities (e.g., development and publication of video games) are not often specific to each other (Schilling, 2000; Schilling and Steensma, 2001), may not require a high level of technical dialog (Monteverde, 1995), and can benefit from sequential synergies (Dyer, Kale, and Singh, 2004). Thus, it is likely that vertical alliances can benefit from "synergistic combination advantage" by pooling diverse resources from multiple parties (Castañer *et al.*, 2014) and avoid some disadvantages associated with horizontal alliances. As higher levels of diversity often enhance product innovation and quality (Baum, Calabrese, and Silverman, 2000; Mitchell *et al.*, 2002; Singh and Mitchell, 2005; Stuart, 2000), products undertaken through vertical alliances of complementor firms are likely to outperform those undertaken through vertical integration of a complementor firm.

Further, vertical alliances of complementor firms can reap the benefits of specialization in distinct domains. Because specialization in distinct domains or segments is often associated with superior capabilities (Jacobides and Winter, 2005), partners can have richer domain expertise (Becker, 1985; Rosen, 1983). While having domain expertise can help firms better identify their customers' needs (Baker, 1984; Bertrand, Bombardini, and Trebbi, 2014; Eccles and Crane, 1988), gaining deeper domain expertise is often costly (Ferreira and Sah, 2012; Rosen, 1983). Thus, products developed and marketed by alliances of specialized firms are likely to have lower production and marketing costs than products developed and marketed by vertical integration of firms. In addition to the likelihood of decreasing production and marketing costs, superior capabilities developed by domain specialization can also help partners develop and deliver higher quality products to customers. Further, a vertical alliance between specialized firms in distinct domains can also better serve the needs of a niche customer group by integrating certain characteristics in the development stage and creating a better marketing campaign in the publication stage.

Firms in the video game industry can (and often do) create separate subsidiaries for developing and publishing activities, and these subsidiaries may develop specialization in their respective domains. However, vertically integrated firms may fall into competency traps and be reluctant to collaborate on a project because of "Not-Invented-Here syndrome" (Rosenkopf and Nerkar, 2001). Likewise, the Not-Invented-Here syndrome may limit a vertically integrated firm's prospective relationships with other firms. This limitation would be detrimental especially when a product requires a diverse pool of resources held by multiple companies (Kogut, 1988; Mitchell *et al.*, 2002; Zajac and Olsen, 1993). For example, despite not having expertise in a development technology or in a product market, a vertically integrated firm may be reluctant to ally with another firm because of having a high amount of investment in subsidiaries early on. Similarly, compared to alliances among complementor firms, a vertically integrated firm may face tensions and trade-offs for internal resource allocation because either subsidiary may compete for the firm's resources and attention (Christensen, 1997; Ocasio, 1997). Moreover, because alliances are more advantageous for sequential and modular synergies than internalizing tasks with acquisitions (Dyer *et al.*, 2004), alliances across firms specialized in distinct domains are likely to outperform vertical integrations of a firm.

While alliances among complementor firms are likely to outperform vertical integrations of a complementor firm, I contend that alliances among complementor firms are less likely to outperform alliances between platform owners and complementor firms because of the leading role of the of platform owners (Williamson and De Meyer, 2012). Platform owners often control data and intellectual property rights (Boudreau, 2010; Parker and Van Alstyne, 2017) and accumulate a certain level of expertise to deal with technical problems. In addition to the synergistic combination advantage and specialization benefits associated with the alliances among complementor firms, alliances between platform owners and complementors can also benefit from the power and leading position of platform owners. Thus, while, relative to vertical integration of a complementor firm, alliances among complementor firms are likely to be positively associated with product performance, they are likely to be negatively associated with product performance relative to alliances between platform owners and complementor firms.

On the other hand, while vertical integration of complementor firms is less likely to outperform alliances among complementor firms, it may outperform vertical integration of platform owners because platform owners' vertical integration may be seen as a threat by complementor firms and negatively affect the general health of the platform ecosystem (Farrell and Katz, 2000; Gans and Stern, 2003; Gawer and Henderson, 2007; Wen and Zhu, 2019). Similarly, vertical integration of platform owners may discourage potential complementors from joining and using the platform ecosystem. While discouraging potential complementors can limit the quality and innovation on a platform ecosystem, end users would also be reluctant to join such a platform ecosystem. Therefore, relative to vertical integration of a complementor firm, vertical integration of platform owners is likely to negatively affect product performance. Based on the discussion, I hypothesize:

> *Hypothesis 1a:* Relative to vertical integration of a complementor firm, alliances among complementor firms are positively associated with product performance.

> *Hypothesis 1b:* Relative to alliances between platform owners and complementor firms, alliances among complementor firms are negatively associated with product performance.

> *Hypothesis 1c:* Relative to vertical integration of platform owners, vertical integration of complementor firms is positively associated with product performance.

Alliance vs. Vertical integration behaviors of platform owners

Platform owners often enter into complementors' space to maximize profit and appropriate more value from their innovations (Gawer and Cusumano, 2002; Gawer and Henderson, 2007; Wen and Zhu, 2019; Zhu and Liu, 2018). According to the theory, platform owners entering into complementors' space can appropriate more value from their innovations through either a vertical integration behavior or an alliance one. Whereas vertical integration of platform owners would be consistent with the existing literature on entry decisions of the platform owners and be seen as an act of direct competition with complementor firms, alliances between platform owners and complementor firms should also be seen as an act of improving the quality of the platform ecosystem because platform owners share profits with complementor firms and can guide them to solve technical problems.

Because improving and maintaining the general health of platform ecosystems is vital for platforms owners' success and survival (Iansiti and Levien, 2004), platform owners often have to commit to not "squeezing" the profit margins of the complementor firms and to creating a fair ecosystem (Farrell and Katz, 2000; Gans and Stern, 2003; Gawer and Henderson, 2007). For example, Gawer and Henderson (2007) highlight how Intel uses its organizational structure to encourage innovation by complementor firms and to signal its desire to leave a zone for complementors to make money. Thus, in the context of this study, platform owners should be careful with their vertical integrations because having too many products developed/published with a vertical integration mode is likely to squeeze the profit margins of the complementor firms and negatively affect the general health of platform ecosystems. In contrast, allying with some complementor firms can signal "fairness" of platform owners (Gans and Stern, 2003), prevent complementor firms from switching to other platforms (Zhu and Liu, 2018), and attract new complementor firms.

Although a vertical integration mode can help a platform owner preserve and share firm knowledge internally (Grant, 1996) and minimize coordination costs (Poppo and Zenger, 2002), it can also increase bureaucratic, strategic and production costs (Mahoney, 1992). Platform owners may incur bureaucratic and strategic costs when faced with trade-offs among maintaining the general health of the platform ecosystem, solving technical problems, and coordinating activities and allocating resources across multiple units. On the other hand, they may also face increased production costs when complementor firms leave the platform as a result of competitive actions by platform owners. Because it is often not possible and beneficial for platform owners to develop all complementary products by themselves (Zhu and Liu, 2018), allying with complementor firms is often a strategic choice for them to decrease bureaucratic, strategic, and production costs. Consistent with the propositions of the "swimming with sharks" literature, platform owners may engage with smaller complementor firms to create and appropriate more value than they can by themselves (Cox Pahnke *et al.*, 2015; Diestre and Rajagopalan, 2012; Hallen, Katila, and Rosenberger, 2014; Huang *et al.*, 2013; Katila, Rosenberger, and Eisenhardt, 2008).

In addition to reputational and cost-related benefits, alliances between platform owners and complementor firms can benefit from specialization because smaller complementor firms specialized in distinct domains can develop superior capabilities

(Jacobides and Winter, 2005). Because of having deeper domain expertise of complementor firms (Ferreira and Sah, 2012; Rosen, 1983) and technical expertise of platform owners, alliances between platform owners and complementor firms can better identify customer needs and improve product characteristics at development and publication stages. Thus, considering advantages of alliances between platform owners and complementor firms as well as pitfalls of vertical integration of platform owners, I hypothesize:

> Hypothesis 2: Relative to vertical integration of a platform owner, alliances between platform owners and complementor firms are positively associated with product performance.

Platform maturity moderation

Like younger and nascent firms, younger and new platforms are likely to suffer from the liability of newness (Stinchcombe, 1965). As younger firms may face a higher level of task (project) and environmental uncertainty (Williamson, 1985) than established firms, younger platforms may create similar types of uncertainty for complementor firms. Because of the higher likelihood of failure among younger platforms, we can contend that younger platforms are likely to "lack legitimacy until reaching a critical mass" (Hannan and Freeman, 1984; Evans and Schmalensee, 2010) and as a result, they are associated with a higher level of uncertainty. Accordingly, general environmental uncertainty in younger platforms should include technological and market uncertainty. As alliances often "make the most sense" under high levels of technological and market uncertainty (Dyer *et al.*, 2004) and can be a means of risk sharing and collaboration against uncertainty (Dyer and Singh, 1998; Hagedoorn, 1993; Kleinknecht and Reijnen, 1992; Powell, Koput, and Smith-

Doerr, 1996), alliances are more likely than vertical integrations to yield profitable outcomes under higher levels of uncertainty.

Because a higher level of uncertainty in a platform ecosystem is likely to increase the amount of asymmetric information between transacting parties (Reuer and Koza, 2000), we can contend that alliances formed under conditions of asymmetric information are more likely than vertical integrations to yield profitable outcomes (Balakrishnan and Koza, 1993; Reuer and Koza, 2000). However, as the level of uncertainty and the amount of asymmetric information decrease with platform maturity, firms may prefer to have vertical integration to appropriate more value. For example, Zhu and Liu (2018) highlight that Amazon prefers to compete with a complementor firm when its products are successful. This shows that platform participants, both platform owners and complementor firms, can over time identify successful products and strategies and imitate them to capture more value. Provided the fact that in mature platform ecosystems, firms may compete over identified successful products, a vertical integration behavior would minimize coordination problems happening among partners and increase the amount of profit a firm can make from a given product. Therefore, I hypothesize:

> Hypothesis 3a: Platform maturity weakens the positive effects of alliances among complementor firms on product performance.
>
> Hypothesis 3b: Platform maturity weakens the positive effects of alliances between platform owners and complementor firms on product performance.

[Insert FIGURES 4.1 and 4.2 about here]

METHODS

Research Setting and Sample

This study uses the global video game industry as the research setting to test its hypotheses. Because the project-driven global video game industry is mediated by platforms (Shankar and Bayus, 2003), it suits well to test hypotheses about alliance and vertical integration behaviors of platform owners and complementor firms. While platform owners depend on complementor firms to develop and publish video games and have to be fair (Gans and Stern, 2003) to allow complementor firms to make some money, they often are willing to appropriate more value from their innovations (Wen and Zhu, 2019; Zhu and Liu, 2018). In the study context, there are three types of firms which often have distinct tasks: (1) platform owners are the console providers, (2) game developers are the companies that come up with a game idea and develop video games, and (3) game publishers are the companies responsible for distribution and marketing of the products.

I create a video game database from several video game websites, including vgchartz, mobygames, giantbomb, ign, and gamefaqs. Individual game sales data are collected from vgchartz database[11]. Additional company, platform, and game-level products are collected from multiple websites including mobygames, giantbomb, and crunchbase, linkedIn, twitter, facebook, and bloomberg.[12] The original data collected from VGChartz consist of 52,475 unique video game titles. I cross-validated video game titles, genres, platforms, release dates, and some other control variables from other game websites based on platform, year, and title variables. While initial cross-validation was done in "R" program by creating a unique id for each game title based on platform, year, and game title, I also manually cross-validated game titles that include typographical errors or alternate spellings. After I cross-validated the data from multiple websites, I chose to only include

[11] According to Google Scholar, there are over 900 studies based on the VGChartz database.
[12] A company name search on the Compustat and CRSP datasets only shows 10% of the names in the dataset. This can be interpreted as a rough percentage of public companies in the dataset.

game titles that globally sold more than 10,000 units because of missing data for those that sold fewer than 10,000 units. Deletion of data for those that sold fewer than 10,000 units results in full data on 18,169 unique video games across 38 platforms between 1977 and 2017. In the analyses of the panel data, the program dropped 2696 observations because their respective panel group included only one observation; and I deliberately dropped four other observations because they caused "constant omission" in some models. Thus, I have 15,335 video game titles in the final sample, created by 421 video game publisher companies and 1,177 video game developers. Of these games, 1,202 are developed/published by alliances of platform owners and complementor firms, 8,036 games are developed/published by alliances among complementor firms, 617 games are developed/published by vertical integration of platform owners, and 5,589 games are developed/published by vertical integration of a complementor firm.

Dependent Variable

Product Performance. I use game profits – unit sales times retail price minus development costs – as the dependent variable. I collected global unit sales data from VGChartz (as of January, 2019). The data show most individual video games achieve 62% of their lifetime sales in seven months (28 weeks). Thus, video game data from 2018 are intentionally excluded. Collecting the average price[13] for new games for each video game platform from online gaming forums and Electronic Gaming Monthly magazine (see Issue 243, pages 14-15), I created a video game cost simulation based on major factors on a software development company website (https://vironit.com/how-much-does-it-cost-to-make-a-video-game/). Accordingly, the simulation calculates the cost of each video game

[13] The price is adjusted for inflation based on Bureau of Labor Statistics data.

based on the individual game platform and four key characteristics of the game[14] – genre, multiplayer, stereoscopic (3D), and general graphics quality. After calculating an approximate cost for each video game, I computed the dependent variable (game performance) by multiplying game unit sales with average game price per platform and subtracting the estimated cost of each video game. I took the natural logarithm of the dependent variable because it was right-skewed.

Independent Variables

Alliance among complementor firms. The variable is coded "1" if games are developed and published by two different complementor firms and "0" otherwise.

Vertical integration of a complementor firm. The variable is coded "1" if the game is developed and published by the same complementor firm and "0" otherwise.

Alliance between platform owners and complementor firms. The variable is coded "1" if the platform owner is either publisher or developer and "0" otherwise.

Vertical integration of platform owner. The variable is coded "1" if platform owner, publisher, and developer are the same company and "0" otherwise.

Moderating Variables

Platform Maturity. I use weekly platform age as an indicator of platform maturity. I preferred to use weekly age because I also have weekly data for some other variables including total software and hardware sales.

Control Variables

Major factors that affect the performance of a video game include a game's platform, genre, year and month of release, and critic score (Cox, 2014; Rietveld and

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[14] The details of cost computation are provided in the Appendix.

Eggers, 2018). In addition to controlling for these variables, I provide the description of 28 other control variables in Table 4.1. As the study focuses on a single industry, there are no industry-level control variables.

[Insert TABLE 4.1 about here]

Analysis

The decision to engage in an alliance may be endogenous with its structure and performance. Companies may decide to select their partners from a close network or geographical preference as well as internalize the publication or development of a game after a profitable release. To address the possibility of endogeneity, I employ a two-stage Heckman procedure (Sartori, 2003), by which I use the dummy variable of "alliance formation" in the first stage where it takes a value of "1" if the focal firm allies with another firm and a value of "0" if the developer and publisher are the same firm. As inclusion of all variables in both selection and second-stage models may potentially create problems for the Heckman procedure (Hitt et al., 2006), I utilized the recommended exclusion restriction procedure and included "only partner" as the instrumental variable[15] in the first-stage probit model but did not include it in the second-stage equations (Hitt et al., 2006; Shaver, 1998). As a dummy variable, the "only partner" variable is coded as "1" if either the developer or

[15] An instrumental variable is a third variable that is used when some independent variables are likely to be influenced by other unobserved variables (Angrist and Imbens, 1995). As a rule, instrumental variables should theoretically and methodologically be meaningful (Hitt et.al, 2006). Methodologically, I have run several alternative models with other instrumental variables where I included "only partner" as a control variable. While in all cases the variable of "only partner" was significantly related to the decision of alliance formation in the first probit model, it was not statistically significant in any of the second-stage FGLS models. Theoretically, if a firm has only one alliance partner in its lifetime, it will affect the likelihood of allying with the same partner. However, being the only partner of the other firm is less likely to positively or negatively affect the alliance performance because a complementary "only partner" can positively affect the alliance performance, whereas an incompatible "only partner" can negatively affect the alliance performance.

the publisher is the only partner of the other firm, which means the focal firm doesn't have any alliances with a different partner. The descriptive statistics table shows that the instrumental variable of "only partner" has a mean of 0.13, which means nearly 13% of the games in the sample are developed and published by a pair of companies for one of whom the other company is its only partner. Also, looking at the correlation matrix table, we see the variable of "common partners" has the lowest correlation (-0.29) while the variable of age difference has the highest correlation (0.13) with "only partner." After running the selection model with the instrumental variable, I predicted the Inverse Mills Ratio (IMR). Then, I added IMR as a control variable into the second stage FGLS models to eliminate potential endogeneity and partner selection bias (Hitt *et al.,* 2006; Shaver, 1998).

Beyond addressing the likelihood of endogeneity, I have taken the following steps to identify the optimal way to analyze the panel data. First, I conduct a Hausmann test with all control and independent variables to decide whether a fixed-effects or a random-effects regression model fits with the data. As the Hausman test indicates that a fixed-effects model is preferred over a random-effects model, I chose to analyze the cross-sectional time series panel data with publisher-developer fixed effects. Second, I checked Variance Inflation Factors (VIF) after running regression commands to make sure multicollinearity is not a concern for the models. Because VIF scores show that the following three pairs of variables are collinear with each other: "user score – critic score", "hardware life-to-week sales – software life-to-week sales", and "platform age – platform dummies," I dropped "user score" and "hardware life-to-week sales" from the analyses. Because of having platform age as the moderating variable, I preferred to keep a transformed version of it in the models. To get the transformed version of the platform age, I first run an ordinary least square

(OLS) regression where platform age was the dependent variable and platform dummies were the independent variables. After running the OLS regression, I computed residuals from the OLS model and substituted them in the regression models for platform age. Because the rest of the variables have a VIF score less than the commonly accepted threshold (10), the models do not suffer from multicollinearity. The third step was to check for serial correlation and conduct a Wooldridge (2002) test. The results of the Wooldridge (2002) test show the data have serial correlation. Fourth, I carry out a Breusch-Pagan test (Breusch and Pagan, 1979) to see whether I have heteroscedastic data. The results show the data have heteroscedasticity as well. Because of the fact that the feasible generalized least square estimators are more efficient than ordinary least square and generalized least square estimators under heteroscedasticity or serial autocorrelation (Baltagi, 2008; Greene, 2003), I preferred to analyze the data with feasible generalized least square estimators in the regression analysis. I employed *"panels(hetero)"* and *"corr(psar1)"* options after feasible generalized least square regression command (*xtgls in STATA)* to correct for both serial correlation and heteroscedasticity.

RESULTS

While the descriptive statistics and pairwise correlations are provided in Table 4.2, Table 4.3 presents the selection and base models; and Tables 4.4-4.6 report the feasible generalized least square estimators based on an analysis of panel data using cross-sectional times series regressions with publisher-developer fixed effects.

[Insert TABLE 4.2 about here]

Table 4.2 shows the dependent variable has a mean of \$28.4 million and ranges from -\$18.5 million to \$4.2 billion. Looking at Table 4.2, we see 8% of the games are developed by an alliance between platform owners and complementor firms, 57% of the games are developed by an alliance among complementor firms, 3% of the games are developed by vertical integration of the platform owners, and 32% of the games are developed by vertical integration of a complementor firm. While the average number of recurrent ties between publishers and developers is 107.02, the average platform is 275.32 weeks old. The table shows publisher companies are on average 10.49 years older than developer companies. Publisher companies have published 35.58 and 37.73 more games in the same platform and genre, respectively, than developer companies have developed. While 1% of the games have multi-developers and 0.04% of the games have multi-publishers[16], 38% of the games are released with another game on the same day, and there are on average 1.83 games released on the same day. The average user score is 7.15 out of 10; and the average critic score is 68.96 out of 100. Miscellaneous (16.06%) and sports (13.24%) are the two most frequent genres; and Nintendo DS (12.41%) and Sony PS2 (12.15%) are the most frequent platforms. Table 4.2 also shows low correlation between independent and control variables. The lowest correlation in the table is between the vertical integration of platform owners and the vertical integration of a complementor firm (-0.78), whereas the highest correlation in the table is weekly hardware sales and weekly software sales (0.68).

[Insert TABLE 4.3 about here]

The selection Model in the Table 4.3 reports probit regression results and shows

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[16] To calculate the continuous variables for multi-publisher and multi-developer games, I first computed the average value for both publisher and developer sides and then took the difference of the average. For instance, if the publisher is 20 years old, developer 1 is 5 years old, and developer 2 is 10 years old, the age difference for these companies is computed as follows: "20-(10+5)/2=12.5."

that age difference, centrality difference, size difference, publisher average performance, and publisher subsidiary are positively associated with the alliance formation. In contrast, only partner, recurrent partnership, genre experience difference, developer average performance, and developer subsidiary are negatively and significantly associated with alliance formation. The base model in Table 4.3 indicates that platform age, ambidextrous partnership, age difference, genre experience difference, centrality difference, common partners, publisher average performance, developer average performance, multi-developer, publisher subsidiary, developer subsidiary, critic score, multi-release (number and binary), hardware sales, hardware percentage change, all platforms software percentage change, and Inverse Mills Ratio are positively and significantly associated with product performance. On the other hand, the table also shows that recurrent partnership, platform experience difference, being from the same country with the platform owner, multi-publisher, all platforms hardware percentage change, weekly software sales, software percentage change, and software life-to-week sales are negatively and significantly associated with product performance.

[Insert TABLE 4.4 about here]

Table 4.4 reports FGLS regression models of product performance. The table includes all independent variables but excludes one of them in each model. Accordingly, Models in Table 4.4 should be evaluated relative to the excluded variable in each model. Thus, Model 1 in Table 4.4 shows that relative to alliances among complementor firms, alliances between platform owners and complementor firms (β= 0.0991, $p<0.001$) are positively associated with product performance, but vertical integration of platform owners (β= -0.3944, $p<0.001$) and vertical integration of complementor firms (β= -0.2511,

$p<0.001$) are negatively associated with product performance. This result supports Hypotheses 1a and 1b. According to this model, the most profitable scenario is the alliances between platform owners and complementor firms and the second most profitable scenario is the alliances among complementor firms. Looking at Model 2, we see that, relative to vertical integration of platform owners, vertical integration of complementor firms ($\beta= 0.1433$, $p<0.001$) is positively associated with product performance. This result provides statistical support for Hypothesis 1c. Moreover, Model 3 shows that, relative to alliances between platform owners and complementor firms, vertical integration of platform owners ($\beta= -0.4935$, $p<0.001$) as well as vertical integration of complementor firms ($\beta= -0.3502$, $p<0.001$) are negatively associated with product performance. This result supports Hypothesis 2.

Testing the moderating effects of platform maturity, Model 4 shows, relative to the interaction of platform maturity and the first category, alliances among complementor firms, the interaction effects of platform maturity and two other categories – alliances between platform owners and complementor firms ($\beta= -0.0004$, $p<0.001$) and vertical integration of complementor firms ($\beta= -0.0001$, $p<0.01$) – are negatively associated with product performance. This result does not support Hypothesis 3a. In contrast to Hypothesis 3a, the results show, platform maturity does not weaken the positive relationship between alliances among complementor firms and product performance. Model 5 shows that relative to the interaction of platform maturity and the second category, alliances between platform owners and complementor firms, the interaction effects of platform maturity and vertical integration of platform owners ($\beta= 0.0004$, p 0.076) are positively associated with product performance. This result supports Hypothesis 3b. Finally, Model 6 is provided to see the relationship between vertical integration of platform owners and vertical integration of complementor firms. The model shows, relative to vertical integration of platform owners, vertical integration of complementor firms is positively associated with product performance but there are no moderating effects of platform maturity.

Based on these results, the profitability order is: alliances between platform owners and complementor firms > alliances among complementor firms > vertical integration of a complementor firm > vertical integration of the platform owner. While alliances among complementor firms are on average, on both young and mature platforms, more profitable than vertical integration of a complementor firm, platform maturity weakens the positive effects of alliances between platform owners and complementor firms.

Tables 4.5 and 4.6 provide robustness checks. While Table 4.5 reports the FGLS regression models of product performance for platform owners, Table 4.6 reports the models for complementor firms. Models 7 and 8 in Table 4.5, respectively, show that alliances between platform owners and complementor firms (β= 0.1132, $p<0.001$) are positively associated with product performance, and vertical integration of platform owners (β= -0.167, $p<0.001$) is negatively associated with product performance. These results reveal that the product performance of games developed/published by alliances of platform owners and complementor firms is, on average, 11.99% higher than the product performance of other games. In other words, games developed/published by alliances of platform owners and complementor firms make nearly $120,000 more than other games for one million USD profit. Similarly, an interpretation of the coefficient of vertical integration of platform owners indicates that the product performance of games developed/published by vertical integration of platform owners is, on average, 15.38%

lower than the product performance of other games. We can interpret this result as: games developed/published by vertical integration of platform owners make nearly \$154,000 less than other games for one million USD profit. Moreover, Models 9 and 10 in Table 4.5 test the moderation effects of platform maturity. Model 9 shows that platform maturity ($\beta = -0.0003$, $p<0.001$) negatively moderates the positive effects of alliances of platform owners and complementor firms on product performance. On the other hand, Model 10 indicates that platform maturity positively moderates the negative effects of vertical integration of platform owners on product performance, but the moderation is not statistically significant.

Table 4.6 presents the FGLS regression models of product performance for complementor firms. Models 11 and 12 in Table 4.6, respectively, show that alliances among complementor firms ($\beta = 0.0378$, $p<0.001$) are positively associated with product performance, and vertical integration of a complementor firm ($\beta = -0.0242$, $p<0.05$) is negatively associated with product performance. An interpretation of these results reveals that the product performance of games developed/published by alliances of complementor firms is, on average, 3.85% higher than the product performance of other games. In other words, games developed/published by alliances of complementor firms make nearly \$38,500 more than other games for one million USD profit. Similarly, the coefficient of vertical integration of a complementor firm indicates that the product performance of games developed/published by vertical integration of a complementor firm is, on average, 2.39% lower than the product performance of other games. We can interpret this result as: games developed/published by vertical integration of a complementor firm make nearly \$23,900 less than other games for one million USD profit. Moreover, Models 13 and 14 in Table 4.6 test the moderation effects of platform maturity for product performance of complementor firms. Model 13 shows that the interaction effects of platform maturity and alliances among complementor firms (β= 0.0001, $p<0.001$) are positively associated with product performance. The model shows platform maturity positively moderates the positive effects of alliances of complementor firms on product performance. Finally, Model 14 indicates that the interaction effects of platform maturity and vertical integration of a complementor firm (β= -0.00003, p. 0.37) are negatively associated with product performance, but the moderation is not statistically significant.

[Insert Tables 4.5 and 4.6 about here]

DISCUSSION

This study focuses on the platform owner's dilemma of "whether to use vertical integration to capture more value or improve the quality of the platform ecosystem" (Zhu and Liu, 2018: 2621). The study incorporates a collaborative framework into the existing competitive framework that sees platform owners' entry into the complementors' space as an act of competition or threat (Gawer and Cusumano, 2002; Gawer and Henderson, 2007; Wen and Zhu, 2019; Zhu and Liu, 2018). Investigating the performance consequences of alliance and vertical integration behaviors of platform owners and complementor firms, the study found that alliances between platform owners and complementor firms as well as alliances among complementor firms yield a higher product performance than vertical integration of platform owners and complementor firms do. The results show that, in general, alliances between platform owners and complementor firms are the most profitable scenario. Then, the respective order of profitability among the rest of the scenarios is as follows: alliances among complementor firms > vertical integration of complementor firms > vertical integration of platform owners. However, the results also show that platform maturity negatively moderates the positive effects of alliances between platform owners and complementor firms. In contrast to this scenario, platform maturity does not weaken the positive effects of alliances among complementor firms on product performance. We still should cautiously interpret the moderating effects of platform maturity in the study. While both main results and robustness checks show that platform maturity weakens the positive effects of alliances between platform owners and complementor firms, the robustness check does not lend support for a hypothesis that platform maturity weakens the negative effects of vertical integration of platform owners. This should be explained by the nature of binary variables because all other games except the ones undertaken by vertical integration of platform owners are coded as “0” in the robustness check. Thus, the relative category for vertical integration of platform owners in the robustness check does not only include alliances between platform owners and complementor firms but also alliances among complementor firms and vertical integration of a complementor firm. Therefore, we should cautiously state that platform maturity may weaken the negative effects of vertical integration of platform owners relative to the alliances between platform owners and complementor firms but may not weaken them relative to alliances among complementor firms and vertical integration of a complementor firm.

Building upon the existing literature on platform owners’ and complementor firms’ performance (e.g., Gawer and Henderson, 2007; Kapoor and Agarwal, 2017; Zhu and Iansiti, 2012), the study contributes to the literature by unearthing the performance consequences of the relationship between platform owners and complementor firms. Along with recent empirical studies (Wen and Zhu, 2019; Zhu and Liu, 2018), the chapter provides empirical evidence on entry decisions of platform owners into the complementors' space and shows collaboration between platform owners and complementor firms is beneficial for all companies, but vertical integration of either one is likely to yield a lower product performance. Thus, platform owners should carefully decide whether to use a vertical integration governance mode in production of complementary products.

The study also contributes to the literature on governance modes – make, buy, or ally decisions – and performance consequences (Castañer *et al.*, 2014; Leiblein *et al.*, 2002; Rothaermel *et al.*, 2006) and shows vertical alliances between platform owners and complementor firms as well as vertical alliances among complementor firms are more profitable than vertical integration of these parties, but platform maturity weakens the positive effects of alliances between platform owners and complementor firms on product performance. Likewise, the findings contribute to the research on co-opetition (Bengtsson and Kock, 2000; Hannah and Eisenhardt, 2018; Mathias *et al.*, 2018; Nalebuff and Brandenburger, 1997). Whereas the extant co-opetition literature contends that the benefits of alliances decline over time with market expansion and legitimation and that companies shift their focus from "value creation" and cooperation to "value appropriation" and competition (Bengtsson and Kock, 2000; Mathias *et al.*, 2018; Nalebuff and Brandenburger, 1997), the results indicate that shifting their focus from cooperation to competition over time is not beneficial for the relationships among complementor firms but may be beneficial for the ones between platform owners and complementor firms. In other words, even in mature markets and platforms, cooperative behaviors among complementor firms outperform vertical integration behavior of a complementor firm. In contrast, cooperative behaviors between platform owners and complementor firms may become less profitable over time. Moreover, the results also speak to the comparative governance choice focused on alliance vs. acquisition choice (Balakrishnan and Koza, 1993; Mellewigt *et al.*, 2017; Villalonga and McGahan, 2005; Wang and Zajac, 2007). While researchers found that partner-specific alliance experience is likely to lead to the subsequent acquisition of the partner (Mellewigt *et al.*, 2017; Villalonga and McGahan, 2005; Wang and Zajac, 2007), the study indicates that protecting firm boundaries in vertical alliances can be more beneficial for product performance than acquiring the partner firm.

Nonetheless, the study has several limitations. First, because the study is based on a single industry, it may not be generalizable to some other contexts and industries. I believe the results can be generalizable to the industries based on innovation and hybrid platforms (Cusumano *et al.*, 2019) as well as to product-oriented industries such as movie, hardware, and software industries. However, the results may or may not be generalizable to pure transaction platforms. A future study can replicate the study in pure transaction platforms or in a multi-industry context. Second, the cross-sectional panel data do not allow us to test evolutionary hypotheses and see how evolution of alliances affects the performance outcomes of products. Future research based on time series data can help us better understand the effects of alliance evolution on product performance. Third, the analysis still may suffer from availability bias as the study only focuses on products available on the Internet and is only able to perform the analyses for games that sold more than 10,000 units. Similarly, the study assumes that four cost-related variables have similar weight while computing the game cost and that games in the same generations have similar costs. A future study may collect the actual project profit to measure product performance and address these limitations. Finally, the results indicate that if platform owners and complementor firms are from the same country, this is negatively associated with product performance. A future research can investigate the effects of cultural and structural differences among platform participants in the international context and examine the impacts of national groups.

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FIGURE 4.1. Main hypotheses

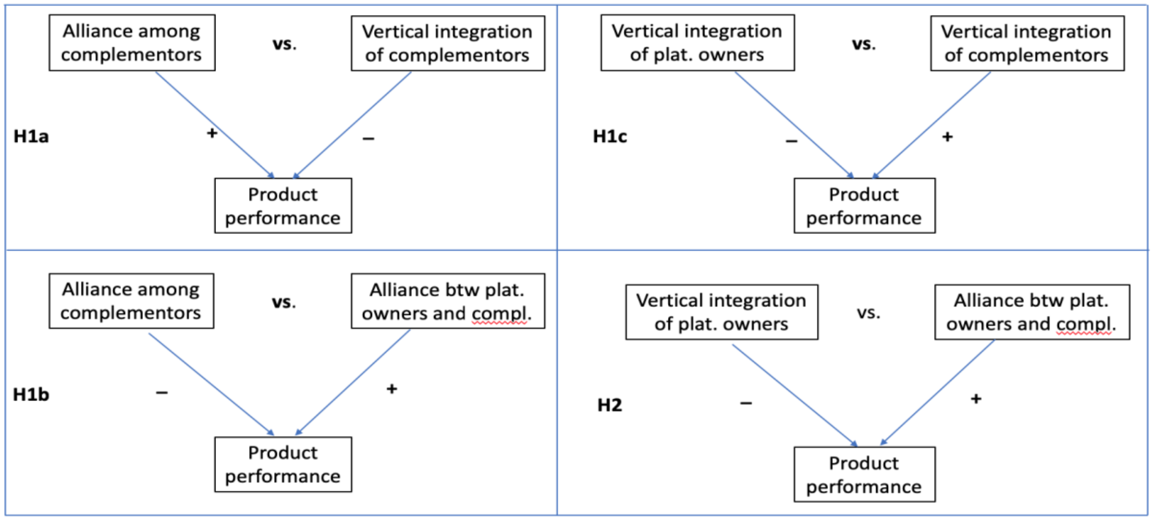

FIGURE 4.2. Moderation hypotheses

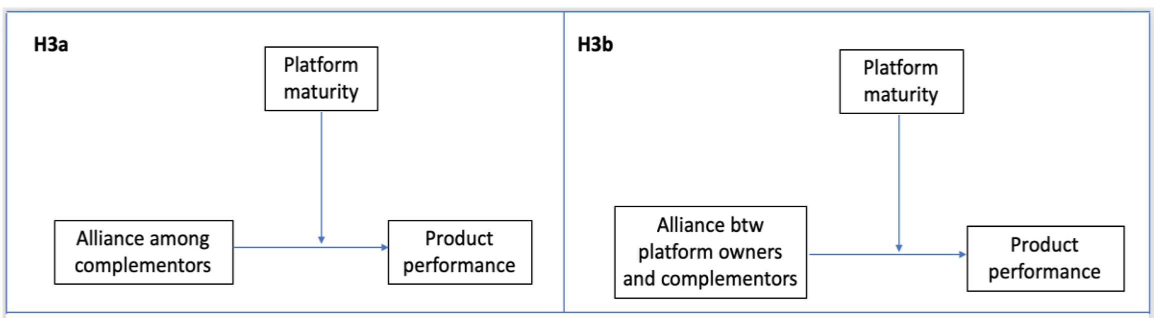

TABLE 4.1. Control variables

Partner size difference	The difference between the number of games published/developed by publisher and developer companies.
Partner age difference	The difference between the ages of publisher and developer companies
Platform experience diff.	This variable represents the difference between the number of games published by publishers and the number of games developed by developers in the same platform.
Genre experience diff.	This variable represents the difference between the number of games published by publishers and the number of games developed by developers in the same genre.
Centrality difference	This variable represents the difference between the number of unique partners publishers and developers have.
Common partners	The number of common partners publishers and developers have.
Publisher avg. performance	Average performance of previous games published by the same publisher.
Developer avg. performance	Average performance of previous games developed by the same developer.
Pub-dev same country	Coded “1” for partners from the same country and “0” otherwise.
Same country platform firm	Coded “1” if the platform company, publisher, and developer are from the same country, and “0” otherwise.
Multi-publisher	Coded “1” if a game is published by multiple companies and “0” otherwise.
Multi-developer	Coded “1” if a game is developed by multiple companies and “0” otherwise.
Publisher subsidiary	Coded as “1” if the publisher of a game was a subsidiary of a larger firm.
Developer subsidiary	Coded as “1” if the developer of a game was a subsidiary of a larger firm.
Multi-release number	The number of games released by the developer/publisher dyad on the focal day.
Multi-release dummy	Coded “1” if the game is released with other games on the same date.
Weekly hardware sales	The number of total hardware units sold one week before the release of the game for the focal platform. This variable and the following three variables related to hardware sales were available for 9,910 game observations. The missing observations were first filled with the average of one week before and one week after sales (999 observations) and then filled with the week averages. It is divided by 100,000 for ease of representation.
Weekly hardware % change	The percentage change of hardware sales one week before the release of the game for the focal platform.
Weekly all platforms hardware % change	The percentage change of hardware sales one week before the release of the game for all platforms. This variable is divided by 1000 for ease of representation.
Weekly software sales	The number of total software sold one week before the release of the game for the focal platform. This variable and the following three variables related to software sales were available for 10,949 game observations. The missing observations were filled with the week averages. It is divided by 100,000 for ease of representation.
Weekly software % change	The percentage change of software sales one week before the release of the game for the focal platform. This variable is divided by 1000 for ease of representation.
Software LTW Sale	Total number of software units sold in a platform’s lifespan until the game release week. It is divided by 100,000 for ease of representation.
Weekly all platforms software % change	The percentage change of software sales one week before the release of the game for all platforms. This variable is divided by 1000 for ease of representation.
Critic score	Professional game critics’ evaluation based on a scale from 0 to 100. 8,961 missing observations were filled with platform-year averages.
Year dummies	Dummy variables for game release year.
Month dummies	Dummy variables for game release month.
Platform dummies	Dummy variables for 38 major gaming platforms such as Game Cube (GC), PC, Xbox, or PlayStation.
Genre dummies	Dummy variables for 16 major gaming genres such as action, sports, simulation, fighting, or racing.

TABLE 4.2. Descriptive statistics and correlation matrix

a. Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1. Performance ($US M)	1																	
2. Alliance decision (Platform owner)	0.2	1																
3. Alliance among complementor firms	-0.12	-0.34	1															
4. Vertical integration (Platform owner)	0.15	-0.06	-0.22	1														
5. Vertical integration (Complementors)	-0.04	-0.2	-0.78	-0.13	1													
6. Platform age (weeks)	-0.03	-0.08	0.06	-0.05	0.01	1												
7. Ambidextrous partnership	0.01	0.05	0.25	-0.08	-0.26	-0.03	1											
8. Recurrent partnership	0.03	-0.12	-0.5	0.14	0.55	-0.02	-0.19	1										
9. Only partner	-0.04	0.08	0.07	-0.07	-0.1	0.04	0.01	-0.18	1									
10. Size difference	0.06	0.28	0.25	-0.09	-0.39	0.02	0.06	-0.25	0.05	1								
11. Age difference	0.15	0.61	0.01	-0.09	-0.33	-0.05	0.06	-0.22	0.13	0.64	1							
12. Platform experience diff.	0.14	0.27	-0.05	0.09	-0.14	0.39	-0.01	0.02	0.02	0.42	0.3	1						
13. Genre experience diff.	0.11	0.16	-0.01	0.01	-0.09	-0.01	-0.01	0.11	-0.02	0.65	0.41	0.38	1					
14. Centrality difference	0.17	0.21	-0.12	0.07	-0.03	0.02	-0.03	0.23	-0.07	0.5	0.28	0.45	0.59	1				
15. Common partners	0.09	-0.05	-0.39	0.13	0.39	-0.03	-0.13	0.65	-0.29	-0.07	-0.11	0.14	0.24	0.45	1			
16. Publisher average perf.	0.43	0.45	-0.25	0.34	-0.12	-0.07	-0.02	0.03	-0.04	0.15	0.45	0.21	0.17	0.18	0.1	1		
17. Developer average perf.	0.41	0.2	-0.2	0.29	-0.02	-0.04	-0.08	0.08	-0.1	0.06	0.14	0.14	0.11	0.14	0.09	0.55	1	
18. Same country	0.04	-0.05	-0.51	0.14	0.52	-0.05	-0.25	0.34	-0.06	-0.16	-0.09	-0.02	0.04	0.01	0.27	0.09	0.11	1
19. Same country platform	-0.01	0.09	-0.41	0.2	0.3	-0.03	-0.18	0.29	-0.03	-0.03	0.05	0.05	0.06	-0.07	0.16	0.14	0.12	0.61
20. Multi-publisher	-0.01	0	0	0.01	0	0.01	-0.01	-0.01	0.01	0	0	0	-0.01	-0.01	-0.01	-0.01	0	0.01
21. Multi-developer	0.02	0.03	0.05	-0.02	-0.07	0	0.05	-0.01	0.02	0.04	0.04	0.01	0.02	0.01	-0.02	0.02	0.01	-0.03
22. Publisher subsidiary	0.06	-0.01	-0.09	-0.01	0.11	-0.03	-0.05	0.09	-0.03	-0.07	-0.08	-0.01	0.08	0.14	0.16	0.02	0.04	0.1
23. Developer subsidiary	0.2	-0.08	-0.33	0.28	0.29	-0.01	-0.11	0.29	-0.11	-0.18	-0.16	0.06	0.07	0.22	0.38	0.18	0.19	0.21
24. Critic score	0.26	0.12	-0.15	0.08	0.06	0.14	-0.06	0.07	-0.03	0.01	0.05	0.08	0.04	0.04	0.08	0.17	0.17	0.1
25. Multirelease (number)	0.1	-0.14	-0.06	0.02	0.14	0.05	-0.06	0.18	-0.1	-0.05	-0.11	0.07	0.09	0.22	0.25	0.04	0.07	0.05
26. Multirelease (binary)	0.04	-0.17	0.02	0	0.08	0.03	-0.05	0.14	-0.1	0.02	-0.1	0.05	0.11	0.19	0.2	-0.02	0.04	0.02
27. Hardware sales (M)	-0.07	-0.05	0.04	-0.06	0.01	0.01	-0.01	0.03	0	0.05	-0.01	0.02	0.06	0.07	0.02	-0.09	-0.06	-0.02
28. Hardware □%	0.02	0.01	0	0	-0.01	-0.02	0	-0.01	0.01	-0.02	-0.01	0	-0.02	-0.02	-0.02	0.02	0	-0.02
29. All platforms hardware □%	0.03	0.01	-0.01	0.01	0	-0.03	0.01	0	-0.01	-0.02	-0.01	0	-0.01	-0.01	0	0	0.01	-0.01
30. Software sales (M)	-0.04	-0.04	0.02	-0.05	0.02	-0.13	-0.01	0.05	-0.01	0.08	-0.01	-0.05	0.09	0.13	0.06	-0.08	-0.04	-0.01
31. Software □%	0	0	-0.01	0.01	0.01	-0.01	-0.01	0.01	0	-0.01	0	0	-0.01	-0.01	0.01	0.01	0.01	0.01
32. Software LTW sales	-0.05	-0.07	-0.01	-0.08	0.08	-0.01	-0.02	0.11	-0.04	0.07	-0.04	0.07	0.11	0.16	0.11	-0.12	-0.05	0.03
33. All platforms software □%	0.02	0.03	-0.01	0.01	0	-0.03	0	-0.01	0	-0.01	0.01	0.01	0	0	0	0.03	0.01	-0.01
34. Year	-0.31	-0.11	0.06	-0.18	0.07	0.21	-0.04	0.15	-0.07	0.16	-0.02	0.08	0.2	0.25	0.19	-0.23	-0.1	0
35. Month	0.07	0	0.02	-0.05	0	-0.02	0.01	0.01	-0.02	0	0	0.01	0.02	0.08	0.03	0.01	0.04	-0.01

Note: Values higher than 0.02 are significant at p<0.05 and those lower than 0.005 are rounded to “0.”

TABLE 4.2. Descriptive statistics and correlation matrix (continued)

	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35
19. Same country platform	1																
20. Multi-publisher	0.01	1															
21. Multi-developer	0	0.04	1														
22. Publisher subsidiary	-0.01	-0.01	-0.01	1													
23. Developer subsidiary	0.04	-0.01	0	0.28	1												
24. Critic score	0.13	0.01	0	0.1	0.11	1											
25. Multirelease (number)	-0.14	-0.01	-0.01	0.15	0.24	0.02	1										
26. Multirelease (binary)	-0.13	-0.01	-0.01	0.12	0.18	0.02	0.7	1									
27. Hardware sales (M)	-0.04	0.01	0.01	-0.04	-0.03	-0.19	-0.01	0.01	1								
28. Hardware □%	-0.02	0	-0.01	-0.01	0	0	-0.01	-0.01	0.13	1							
29. All platforms hardware □%	-0.01	0	-0.01	0	0	0	-0.01	-0.02	0.12	0.44	1						
30. Software sales (M)	-0.07	0	0	0	-0.03	-0.15	0.07	0.1	0.68	0.04	0.05	1					
31. Software □%	0.01	0	-0.01	0.01	0	0	-0.02	-0.02	0.02	0.1	0.05	0.04	1				
32. Software LTW sales	-0.04	0.01	0	0.03	-0.03	-0.08	0.18	0.19	0.15	-0.05	-0.05	0.47	-0.04	1			
33. All platforms software □%	-0.01	0	-0.01	0.01	0	0	-0.01	-0.02	0.02	0.13	0.26	0.09	0.27	-0.04	1		
34. Year	0	0	0.01	0.04	0	-0.06	0.17	0.25	0.23	-0.07	-0.08	0.31	-0.04	0.45	-0.06	1	
35. Month	-0.06	0.01	0.01	0	0.03	-0.04	0.07	0.03	0.18	0.08	0.14	0.16	0.05	0.04	0.14	0.03	1

Note: Values higher than 0.02 are significant at p<0.05 and those lower than 0.005 are rounded to “0.”

b. Descriptive Statistic

	Mean	Std. Dev.	Min	Max
1. Performance ($US M)	28.4	92.1	-18.5	4190
2. Alliance decision (Platform owner)	0.08	0.27	0	1
3. Alliance among complementor firms	0.57	0.5	0	1
4. Vertical Integration (Platform owner)	0.03	0.18	0	1
5. Vertical Integration (Complementors)	0.32	0.46	0	1
6. Platform age (weeks)	275.35	344.13	0	1896
7. Ambidextrous partnership	0.23	0.42	0	1
8. Recurrent partnership	107.02	218.27	1	1253
9. Only partner	0.13	0.33	0	1
10. Size difference	172.3	306.35	-1461	1476.5
11. Age difference	10.49	21.07	-118	123
12. Platform experience diff.	35.58	58.4	-127	1254
13. Genre experience diff.	37.73	54.52	-300	371
14. Centrality difference	99.71	103.53	-36	945
15. Common partners	3.07	2.77	0	16
16. Publisher average perf. (M unit sales)	0.54	0.63	0	6.12

	Mean	Std. Dev.	Min	Max
17. Developer average perf. (M unit sales)	0.51	0.85	0	30.26
18. Same country	0.63	0.48	0	1
19. Same country platform	0.39	0.49	0	1
20. Multi-publisher	0.0004	0.02	0	1
21. Multi-developer	0.01	0.12	0	1
22. Publisher subsidiary	0.07	0.25	0	1
23. Developer subsidiary	0.13	0.33	0	1
24. Critic score	68.97	10.54	13	98
25. Multirelease (number)	1.83	1.51	1	17
26. Multirelease (binary)	0.38	0.48	0	1
27. Hardware sales (M)	0.198	0.196	0	2.102
28. Hardware Δ%	9.85	65.8	-82	3557
29. All platforms hardware Δ%	7.88	39.92	-72	1052
30. Software sales (M)	1.037	1.345	0	14.66
31. Software Δ%	30.55	311.29	-86	12006
32. Software LTW sales	174.93	207.82	0	977.7
33. All platforms software Δ%	11.56	59.33	-78	678
34. Year	2007.03	6.06	1977	2017
35. Month	7.29	3.47	1	12

TABLE 4.3. Selection and base models

Model	**Selection (DV: Alliance Formation)**	**Base**
Platform age (weeks)		0.0084 [0] (0)
Ambidextrous partnership		0.0442 [0.002] (0)
Recurrent partnership	-0.0068 [0] (0)	-0.0001 [0] (0.006)
Only partner	-0.1378 [0.041] (0.001)	
Size difference	0.0036 [0] (0)	0 [0] (0.973)
Age difference	0.0146 [0.001] (0)	0.0004 [0] (0)
Platform experience difference	-0.0002 [0.001] (0.783)	-0.0003 [0] (0)
Genre experience difference	-0.0052 [0.001] (0)	0.0001 [0] (0)
Centrality difference	0.0022 [0] (0)	0.0007 [0] (0)
Common partners	0.0143 [0.011] (0.191)	0.0019 [0.001] (0.005)
Publisher average perf.	0.2051 [0.038] (0)	0.2335 [0.003] (0)
Developer average perf.	-0.1317 [0.024] (0)	0.1848 [0.001] (0)
Same country		-0.0004 [0.002] (0.841)
Same country platfirm		-0.0663 [0.002] (0)
Multi-publisher		-0.6054 [0.17] (0)
Multi-developer		0.0469 [0.006] (0)
Publisher subsidiary	0.2198 [0.064] (0.001)	0.0075 [0.003] (0.03)
Developer subsidiary	-1.1261 [0.051] (0)	0.1607 [0.007] (0)
Critic score		0.0184 [0] (0)
Multirelease (number)		0.0141 [0.003] (0)
Multirelease (binary)		0.0176 [0.004] (0)
Hardware sale		0.0022 [0.001] (0.016)
Hardware □%		0.0001 [0] (0)
All platforms hardware □%		-0.0389 [0.002] (0)
Software sale		-0.0008 [0] (0)
Software □%		-0.0117 [0.002] (0)
Software LTW sale		-0.00003 [0] (0)
All platforms software □%		0.0365 [0.016] (0.024)
Inverse Mills ratio		0.0438 [0.002] (0)
Constant	0.5244 [0.073] (0)	20.2633 [0.434] (0)
Number of observations	18,051	15,335
Number of groups		2,042
Observation per group		
Minimum		2
Average		7.51
Maximum		874
Wald chi2/F value	12752.54	8.76E+07
Pseudo R-squared	0.5476	

The selection model includes Year dummy variables; Base Model and Model 1 include Year, Month, Platform and Genre dummy variables.

Notes: Coefficients are followed by [Standard deviations] and (p-values); Results are based on two-tailed tests.

TABLE 4.4. FGLS regression models of product performance for all companies

Model	1	2	3
Alliance among complementor firms	Excluded	0.3944 [0.031] (0)	-0.0991 [0.002] (0)
Alliance between platform owners and comp. firms	0.0991 [0.002] (0)	0.4935 [0.031] (0)	Excluded
Vertical Integration (Platform owner)	-0.3944 [0.031] (0)	Excluded	-0.4935 [0.031] (0)
Vertical Integration (Complementors)	-0.2511 [0.011] (0)	0.1433 [0.03] (0)	-0.3502 [0.012] (0)
Constant	20.3919 [0.431] (0)	19.9975 [0.429] (0)	20.4909 [0.431] (0)
Number of observations	15,335	15,335	15,335
Number of groups	2,042	2,042	2,042
Observation per group			
Minimum	2	2	2
Average	7.51	7.51	7.51
Maximum	874	874	874
Wald chi2/F value	4.09E+07	4.09E+07	4.09E+07
	The models include all of the control variables in the base model.		

Notes: Coefficients are followed by [Standard deviations] and (p-values); Results are based on two-tailed tests.

TABLE 4.4. FGLS regression models of product performance for all companies (Continued)

Model	4	5	6
Alliance among complementor firms	Excluded	-0.0741 [0.004] (0)	0.3849 [0.032] (0)
Alliance between platform owners and comp. firms	0.0741 [0.004] (0)	Excluded	0.459 [0.033] (0)
Vertical Integration (Platform owner)	-0.3849 [0.032] (0)	-0.459 [0.033] (0)	Excluded
Vertical Integration (Complementors)	-0.2396 [0.011] (0)	-0.3137 [0.013] (0)	0.1453 [0.031] (0)
Alliance among complementor firms * Plat. Maturity	Excluded	0.0004 [0] (0)	-0.0001 [0] (0.822)
Alliance between plat. owners and comp. firms * Plat. Maturity	-0.0004 [0] (0)	Excluded	-0.0004 [0] (0.076)
Vertical Integration (Platform owner) * Plat. Maturity	0.0001 [0] (0.822)	0.0004 [0] (0.076)	Excluded
Vertical Integration (Complementors) * Plat. Maturity	-0.0001 [0] (0.001)	0.0003 [0] (0)	-0.0002 [0] (0.528)
Constant	20.28 [0.433] (0)	20.3541 [0.433] (0)	19.8951 [0.433] (0)
Number of observations	15,335	15,335	15,335
Number of groups	2,042	2,042	2,042
Observation per group			
Minimum	2	2	2
Average	7.51	7.51	7.51
Maximum	874	874	874
Wald chi2/F value	7.2E+06	7.2E+06	7.2E+06
	The models include all of the control variables in the base model.		

Notes: Coefficients are followed by [Standard deviations] and (p-values); Results are based on two-tailed tests.

TABLE 4.5. FGLS regression models of product performance for platform owners

	Alliance vs. Vertical integration of platform owner (Robustness check)			
Model	**7**	**8**	**9**	**10**
Alliance between platform owners and comp. firms	0.1132 [0.003] (0)		0.0984 [0.005] (0)	
Vertical integration		-0.167 [0.03] (0)		-0.1665 [0.031] (0)
Alliance * Plat. Maturity			-0.0003 [0] (0)	
Vertical integration * Plat. Maturity				0.0001 [0] (0.586)
Constant	19.80 [0.432] (0)	20.08 [0.434] (0)	20.05 [0.435] (0)	7.35 [0.614] (0)
Number of observations	15,335	15,335	15,335	15,335
Number of groups	2,042	2,042	2,042	2,042
Observation per group				
Minimum	2	2	2	2
Average	7.51	7.51	7.51	7.51
Maximum	874	874	874	874
Wald chi2/F value	3.24E+07	1.95E+09	3.60E+07	7.68E+09
The models include all of the control variables in the base model.				

TABLE 4.6. FGLS regression models of product performance for complementor firms

	Alliance vs. Vertical integration of complementor firms (Robustness check)			
Model	**11**	**12**	**13**	**14**
Alliance among complementors	0.0378 [0.003] (0)		0.0398 [0.003] (0)	
Vertical integration		-0.0242 [0.011] (0.032)		-0.023 [0.011] (0.044)
Alliance decision * Plat. Maturity			0.0001 [0] (0)	
Vertical integration * Plat. Maturity				-0.00003 [0] (0.37)
Constant	20.29 [0.432] (0)	20.18 [0.432] (0)	20.38 [0.429] (0)	20.17 [0.432] (0)
Number of observations	15,335	15,335	15,335	15,335
Number of groups	2,042	2,042	2,042	2,042
Observation per group				
Minimum	2	2	2	2
Average	7.51	7.51	7.51	7.51
Maximum	874	874	874	874
Wald chi2/F value	4.05E+08	5.74E+07	3.34E+09	1.99E+08
The models include all of the control variables in the base model.				

Notes: Coefficients are followed by [Standard deviations] and (p-values); Results are based on two-tailed tests.

APPENDIX

Because of increasing computer graphics cost in the last several decades[17], video game development cost has exponentially increased. Therefore, an analysis based on "unit sales" may not reveal the accurate performance of a video game. To address the concerns about the increasing cost of new-generation video game platforms, I created a video game cost simulation. The simulation benefits from an existing video game simulation on a software development company website (https://vironit.com/how-much-does-it-cost-to-make-a-video-game/) and takes major cost factors into account. Accordingly, the simulation calculates the cost of each video game based on the individual game platform and four key characteristics of the game[18] – genre, multiplayer, stereoscopic (3D), and general graphics quality. While I collected the average cost of a new game for 18 video game platforms from video game forums, I imputed the cost for the rest of the platforms (20 platforms) by taking the average cost of other platforms of the same generation. In order to create a range for average video game cost, I decided to add and subtract half of the average platform cost[19]. For instance, a video game forum[20] reports the average cost of a video game for Xbox platform as $1.8 million (M). Based on the assumption of adding and subtracting half of the average platform cost, the cost for Xbox video games should range from $0.9 M to $2.7 M. Given the study had four cost-related variables in the simulation, I gave equal weight to genre, multiplayer, stereoscopic, and graphics quality variables and divided the difference between the upper limit (e.g., $2.7 million) and lower limit (e.g., $0.9 million)

[17] Please see: https://www.economist.com/the-economist-explains/2014/09/24/why-video-games-are-so-expensive-to-develop
[18] The details of cost computation are provided in the Appendix.
[19] Subtracting and adding different values including 1/3, 2/3, or 1/4 of the average platform cost does not change the results.
[20] https://vgsales.fandom.com/wiki/Video_game_costs

by four. Therefore, each of these variables would be worth up to ¼ of the difference between the lower limit and the upper limit. Collecting multiplayer and stereoscopic variables from metacritic.com and Google search as necessary, I coded these variables as 0/1 variables. Following the VironIT video game cost simulation, I have coded Strategy and MMO (massive multiplayer-online) genres as 0/1 variables to account for higher cost genres. The graphics quality variable comes from text mining of video game reviews from the He and McAuley (2016) review dataset and the Amazon AWS review dataset.[21] From more than 1.3. million reviews, I extracted each sentence that included the word "graphics." As a result, I singled out 46,000 distinct words (including misspellings) out of nearly 263,000 sentences. To determine the quality of graphics, I initially used Hu and Liu's (2004) sentiment analysis words and individually reviewed the remaining words. As a result, I categorized 7,570 words as positive, 2,269 as negative, and 689 as neutral. While I could link the graphic quality of 3,150 video games based on title-platform pairs after identification of positive, negative and neutral words, I assigned the same graphics quality to the same game titles in different platforms (9,527 titles) because the data show the same video game titles in different platforms have similar graphics quality for over 95.2% of titles. Then, I imputed the missing graphics quality variable with the average graphics quality of the games in the same sequel (i.e., game franchises). For example, I estimated the cost of a stereoscopic and high graphics-quality but single player and lower cost genre video game to be $1.8 million [= $0.9 million (lower limit) + $0.45 million (stereoscopic) + $0.45 million (high graphics-quality)].

[21] https://s3.amazonaws.com/amazon-reviews-pds/tsv/index.txt

CHAPTER 5: BALANCE ACROSS FIRMS: EXPLORATION AND EXPLOITATION IN ALLIANCES BETWEEN PLATFORM PARTICIPANTS

ABSTRACT

The literature identifies different modes of balancing exploration/exploitation activities within and across firms. I develop a framework for examining alliances noting that whether an alliance represents exploration or exploitation for a partner depends on the activity relative to that partner's past activities. Balancing these activities across firms in distinct domains can achieve the benefits of multiple modes while avoiding some pitfalls. I find that alliances in which one partner explores while the other exploits outperform, on average, those alliances in which partners conduct symmetric activities. Also, alliances with both partners exploiting outperform those when both partners explore. Bridging the longstanding exploration/exploitation literature to the platform literature, the study indicates that platform maturity weakens the positive effects of ambidextrous alliances as well as the negative effects of unidextrous exploratory alliances on alliance performance.

INTRODUCTION

How do relative exploration and exploitation activities through partner specialization affect alliance performance? Despite the increasing number of studies about the success of strategic alliances (e.g., Lavie, Haunschild, and Khanna, 2012; Krishnan, Geyskens, and Steenkamp, 2016; Taneri and De Meyer, 2017), it is still true that "the performance of alliances remains one of the most interesting and also one of the most vexing questions" (Gulati, 1998: 309). Not having a uniform indicator of alliance success, scholars have often measured alliance performance by obtaining the performance of only one partner in an alliance (e.g., Parkhe, 1993; Zollo, Reuer, and Singh, 2002), capturing abnormal return to alliance formation (Anand and Khanna, 2000; Kale, Dyer, and Singh, 2002; Sytch, Wohlgezogen, and Zajac, 2018), designing case studies (Doz, 1996) and surveys (Lavie *et al.*, 2012), using a dichotomous variable such as project (drug) approval by the FDA (Hoang and Rothaermel, 2005), proxying alliance duration (Li *et al.*, 2012), or alliance termination (Taneri and De Meyer, 2017). Because alliances are arrangements among different firms who combine resources for creation of products and services (Gulati, 1998), I develop a continuous product-level measure of alliance performance to understand the impact of relative exploration and exploitation activities of partners on the outcome of alliances.

In this paper, I bridge the literature on alliance performance (e.g., Anand and Khanna, 2000; Kale *et al.*, 2002; Krishnan *et al.*, 2016; Lavie *et al.*, 2012; Sytch *et al.*, 2018; Taneri and De Meyer, 2017) to the literature on how firms utilize strategic alliances as a mean of exploration and exploitation activities (Aoki and Wilhelm, 2017; Birkinshaw and Gupta, 2013; Im and Rai, 2008; Zimmermann, Raisch, and Birkinshaw, 2015).

Following Koza and Lewin (1998), researchers suggest that strategic alliances can be formed at any time for either an exploration or exploitation objective. Scholars often use the term "exploration alliances" to describe alliances in upstream activities of the value chain (e.g., R&D alliances) and the term "exploitation alliances" to refer to alliances in downstream activities of the value chain (e.g., marketing alliances) (Grant and Baden-Fuller, 2004; Park, Chen, and Gallagher, 2002; Rothaermel, 2001; Rothaermel and Deeds, 2004). Building upon this stream, scholars argue that a firm exhibits "alliance ambidexterity" if it includes both exploration and exploitation partnerships in its alliance portfolio (Lavie, Kang, and Rosenkopf, 2011; Wassmer, Li, and Madhok, 2017; Yamakawa, Yang, and Lin, 2011; Yang, Zheng, and Zhao, 2014) and that firms can balance exploration/exploitation activities in a single strategic alliance if they have both knowledge-generating upstream activities and knowledge-leveraging downstream activities (Stettner and Lavie, 2014). However, this terminology does not capture the full range of ways in which firms use alliances to simultaneously explore and exploit. Recent literature suggests that the ambidextrous management of interorganizational relationships may include both exploratory and exploitative knowledge-sharing activities between the same set of partners (Im and Rai, 2008)[22] and that single-objective alliances (either exploration or exploitation) may over time expand to reconcile both exploration and exploitation activities (Zimmermann *et al.*, 2015). I contribute to both alliance performance and exploration/exploitation literature streams by (a) clarifying the possibility that, within

[22] Im and Rai (2008) describe exploration as "the exchange of knowledge between firms in a long-term relationship to seek long-run rewards, focusing on the survival of the system as a whole, and pursuing risk-taking behaviors" and exploitation as "the exchange of knowledge between firms in a long-term relationship to seek short-run rewards, focusing on the survival of the components of the system and pursuing risk-averse behaviors" (2008, p. 1283).

a single alliance, the partners can differ in their specialization on exploration vis-à-vis exploitation activities from the beginning, and (b) analyzing the implications of such specialization on alliance performance.

In an alliance relationship, a firm can engage in exploration while its partner emphasizes exploitation, or vice versa. Whether an activity represents exploration or exploitation can be defined *relative to* a given organization or unit, since "certain knowledge, technology, or markets may be new to one organization but familiar to another (Lavie, Stettner, and Tushman, 2010: 115)." For instance, in an alliance between US tire producers and Michelin, radial-tire technology was an exploration for American firms, but the same technology was exploitation for Michelin (Lavie *et al.*, 2010; Sull, 1999). This principle of relativity means the same project – whether R&D or marketing – could represent exploration for one partner and exploitation for the other.

Recognizing that activities in a strategic alliance relationship can be firm-specific, the empirical purpose in this paper is to test the implications for alliance performance of balancing exploration and exploitation through partner specialization. I highlight that in a strategic alliance relationship, partners can conduct asymmetric activities (e.g., one partner explores and the other exploits; an *ambidextrous alliance*) as well as symmetric activities (e.g., both explore or both exploit; a *unidextrous alliance*). The central hypothesis is that balancing exploration/exploitation activities in an industry or ecosystem through separation of exploration and exploitation across partners in an alliance (e.g., *an ambidextrous alliance)* is positively associated with alliance performance. The hypothesis is built on the fact that, on the same project, one partner's activities can represent exploration while the other partner's activities represent exploitation. Furthermore, a firm can simultaneously specialize in exploration in one alliance and exploitation in a different alliance, thereby effectively separating activities that might lead to internal conflict, yet exhibiting ambidexterity in its approach to the market (Lavie *et al.*, 2011). Looking through an uncertainty lens, I draw a bridge between the alliance literature and the recent platform literature to propose that platform age negatively moderates the positive effects of ambidextrous alliances on alliance performance. I also develop hypotheses on the performance outcomes of symmetric exploration and exploitation activities by both partners and investigate the moderating effects of platform maturity. Based on the theoretical framework and hypothetical development, I discuss how firms' preference for exploration, exploitation, or ambidexterity in strategic alliances depends on the partners' goals and competitive context.

To test these hypotheses, I investigate an industry which has pervasive alliance behavior and innovation, the global video game industry. The video game industry is mediated by platforms (Shankar and Bayus, 2003). Recently, the focus of research on platform industries has shifted from the strategies and performance of platform providers (e.g., Eisenmann, Parker, and Van Alstyne, 2010; Gawer and Henderson, 2007; McIntyre and Subramaniam, 2009; Zhu and Iansiti, 2012) to the performance of platform participants[23] who occupy a critical place within the platform ecosystem (Boudreau and Jeppesen, 2015; Kapoor and Agarwal, 2017; Rietveld and Eggers, 2018). I clarify that the performance of a specific alliance between platform participants is another level of analysis

[23] Firms that build off others' platforms are sometimes called "complementor firms" in the existing literature (Boudreau and Jeppesen 2015, Kapoor and Agarwal 2017). Because firms can be "complementors" even in non-platform industries, and platform providers can also build on their own platforms, I use the term "platform participants" to refer to all firms operating in a platform ecosystem.

besides the platform itself, the platform provider, or platform participants. To see how allying firms in a platform ecosystem balance and coordinate exploration/exploitation activities, I collect and triangulate data from multiple sources on 18,169 video game releases between 1977 and 2017. During this period, 1,926 video game developer companies worked with 547 video game publisher companies across 38 platforms.

I make four contributions to the existing alliance literature. First, I contribute to the alliance literature that investigates the performance outcome of organizational and cultural differences (Estrada *et al.*, 2016; Krishnan *et al.*, 2016; Lavie *et al.*, 2012; Prashant and Harbir, 2009; Sytch *et al.*, 2018; Taneri and De Meyer, 2017). I show that, along with organizational and cultural differences (e.g., partner complementarity, partner compatibility, operational and orientation differences), differences in organizational learning – exploration/exploitation – activities positively affect alliance performance. Second, I contribute to the literature on balancing exploration/exploitation activities in an interorganizational context (Aoki and Wilhelm, 2017; Birkinshaw and Gupta, 2013; Im and Rai, 2008; Zimmermann *et al.*, 2015) by showing that ambidexterity in strategic alliances through partner specialization is positively associated with alliance performance. By defining exploration/exploitation activities from the viewpoint of a given firm instead of assigning exploration/exploitation activities to all partners in a relationship, this study is one of the first to examine exploration and exploitation defined relative to a firm’s unique history. Third, I extend the literature on the benefits of ambidexterity in a single or multi-unit context within a firm (e.g., Gibson and Birkinshaw, 2004; Jansen, Simsek, and Cao, 2012; O’Reilly and Tushman, 2008; Simsek *et al.*, 2009) to platform ecosystems and show the boundary conditions of these benefits. The finding that platform maturity negatively moderates the positive effects of ambidextrous alliances on alliance performance shows how ambidexterity can be enabled through platform ecosystems. Fourth, building on the recent trend in the platform literature to measure performance implications for participating firms (Kapoor and Agarwal, 2017; Rietveld and Eggers, 2018), I offer some of the first evidence about alliance financial performance in platform ecosystems. I explain how platform maturity may moderate the relationship between the exploration/exploitation activities of partner firms and alliance performance. Specifically, naming alliances in which both firms are engaged in exploration (exploitation) as *unidextrous exploratory* (exploitative) alliances, I hypothesize that unidextrous exploitative alliances should outperform unidextrous exploratory alliances on average. However, building on more established platforms reduces uncertainty, thereby enhancing the performance of exploratory alliances compared to exploitative alliances. In the next section, I highlight important themes in the exploration/exploitation literature with a specific focus on strategic alliances and then develop new hypotheses. Next, I elaborate on the research context of the study and explain the data and analysis techniques. Finally, the paper concludes with results and discussion.

THEORY

Balance within a firm

Exploiting existing product and customer capabilities helps an individual firm incrementally add new features to its existing capabilities (Tushman and Smith, 2002). On the other hand, exploring new product and customer capabilities ensures long-time survival for a firm and can lead to architectural innovation (Tushman et al. 2010). According to the ambidexterity literature, firms can internally balance these contradictory activities in four different ways: organizational separation, temporal separation, domain separation, or contextual ambidexterity (no separation) (Lavie *et al.*, 2010: 129). Thus, a firm can achieve effective separation of activities by engaging in exploration and exploitation in different organizational units, with internal structure preventing spillover between the units (Christensen, 2013; Taylor and Helfat, 2009); by exploring in one time period and exploiting in another (Brown and Eisenhardt, 1997; Rothaermel and Deeds, 2004; Siggelkow and Levinthal, 2003); or by balancing exploration/exploitation across domains (e.g., customer knowledge vs. technological knowledge) over time (Lavie, Kang, & Rosenkopf 2009, Lavie & Rosenkopf 2006). In contrast to these modes, the contextual ambidexterity literature suggests that organizations can release the tension between exploration and exploitation activities in the same unit by simultaneously combining stretch, discipline, support, and trust (Cao, Gedajlovic, and Zhang 2009, Gibson and Birkinshaw 2004, He and Wong 2004, Jansen et al. 2009, Jansen, Volberda, and Van Den Bosch 2005, Tushman and O'Reilly 1997).

Although an individual ambidextrous firm may ensure both long-term and short-term success by balancing these activities (Gibson and Birkinshaw, 2004; Jansen *et al.*, 2012; March, 1991; Raisch and Birkinshaw, 2008), doing so within a single firm requires inconsistent organizational architectures (Smith and Tushman, 2005), demands different learning modes and practices (e.g., Argyris & Schön 1978, Benner and Tushman 2003, Eisenhardt and Martin 2000), and creates tensions and tradeoffs for resource allocation (March, 1991). Whereas exploratory learning and innovation usually require firms to have experimentation, flexibility, divergent thinking, and increasing variance, exploitative learning and innovation require firms to have efficiency, focus, convergent thinking, and reduced variance (Flynn and Chatman, 2001; Rivkin and Siggelkow, 2003; Smith and Tushman, 2005; Van de Ven, Polley, and Garud, 2008). Because exploration and exploitation activities within a single firm compete for the firm's internal resources and attention (Christensen, 1997; Ocasio, 1997), even the most successful firms can fall into the trap of trading long-term benefits of exploration for short-term benefits of exploitation (Christensen, 1997; Tripsas and Gavetti, 2000). Whereas successful, mature firms face exploitation challenges as exploitation drives out exploration (Benner and Tushman, 2002; Kaplan, Murray, and Henderson, 2003), younger, entrepreneurial firms face similar problems when they are trapped by their exploration activities (Aldrich, 1999; Anderson and Tushman, 2001). Since balancing these activities across firms would prevent problems associated with inconsistent organizational architectures, allow different learning modes and practices, and remove tensions and tradeoffs related to resource allocation, I suggest one way to break out of these traps is to partner with another firm.

Balance across firms

Early research on strategic alliances described multiple purposes for alliances. Alliances can be a means of risk sharing, obtaining access to new markets and technologies, speeding products to market, or pooling complementary skills (Dyer and Singh, 1998; Hagedoorn, 1993; Kleinknecht and Reijnen, 1992; Kogut, 1989; Mowery, Oxley, and Silverman, 1996; Powell, Koput, and Smith-Doerr, 1996). Koza and Lewin (1998) developed a framework in which strategic alliances are a mechanism for firms to jointly exploit their existing knowledge or explore new opportunities. Correspondingly, interfirm alliances help firms share and exchange resources, develop new technologies together, or exploit existing knowledge (Gulati, 1998). To distinguish exploration and exploitation alliances from each other, researchers suggested that strategic alliances in upstream activities of the value chain, such as R&D alliances, can be categorized as *exploration alliances*, whereas alliances in downstream activities of the value chain, such as marketing, licensing, and commercialization alliances are *exploitation alliances* (e.g., Grant and Baden- Fuller 2004, Park et al. 2002, Rothaermel 2001, Rothaermel and Deeds 2004).

Based on these definitions, existing approaches categorize a strategic alliance as either an exploration or exploitation alliance. First, adopting a value-chain definition, scholars in the alliance portfolio literature count the number of exploration and exploitation alliances and suggest that individual firms can balance exploration/exploitation activities in their alliance portfolio (Lavie *et al.*, 2011; Wassmer *et al.*, 2017; Yamakawa *et al.*, 2011; Yang *et al.*, 2014). As alliance ambidexterity refers to the number of exploration/exploitation alliances in the alliance portfolio literature, a single strategic alliance is not allowed to be ambidextrous. Second, the "mode ambidexterity" literature acknowledges that firms can balance exploration/exploitation activities in a strategic alliance mode if they have both upstream (e.g., R&D) and downstream (e.g., commercialization) activities (Stettner and Lavie, 2014). While a single strategic alliance can be ambidextrous according to the mode ambidexterity literature, the notion of relativity between partners (e.g., one partner explores, the other exploits) is not allowed because all partners are assumed to be involved in both upstream and downstream activities. Third, the ambidextrous management/alliance charter literature acknowledges that strategic alliances may include both exploratory and exploitative knowledge sharing activities (Im and Rai 2008) and single-objective (either exploratory or exploitative) alliances can over time be expanded to reconcile both exploration and exploitation activities (Zimmermann et al.

2015). Quite similar to the mode ambidexterity literature, the ambidextrous management/alliance charter literature streams assume that exploratory knowledge sharing in a strategic alliance is exploratory for all partners, and exploitative knowledge sharing is exploitative for all partners. Thus, all three streams of the literature remain silent about whether firms can differ in their specialization on exploration vis-à-vis exploitation and do not account for the principle of relativity (i.e., one partner explores, the other exploits).

Beyond distinguishing exploration/exploitation activities in alliances based on the value chain, researchers also suggest that exploration/exploitation alliances may be classified based on “alliance structure” (Lavie and Rosenkopf, 2006). Regarding alliance structure, exploration alliances refer to a firm’s tendency to seek opportunities by forming alliances with new partners, while exploitation alliances refer to a firm’s efforts to consolidate its alliance portfolio by forming recurrent alliances with a select group of existing partners (Beckman, Haunschild, and Phillips, 2004; Lavie *et al.*, 2011; Lin, Yang, and Demirkan, 2007). Thus, any alliance with a new partner is exploratory, while repeated cooperation with the same partner is exploitative. Subsequently, exploration/exploitation alliances based on alliance structure may create or reinforce a firm’s knowledge base (Beckman *et al.*, 2004), initiate or leverage partnering experiences (Hoang and Rothaermel, 2005), and accumulate trust and reliability between partners (Baum *et al.*, 2005; Chung, Singh, and Lee, 2000; Gulati, 1995; Gulati and Gargiulo, 1999; Li and Rowley, 2002). In this approach, a single alliance cannot be defined as incorporating both exploration and exploitation.

However, I contend that, in an alliance relationship, an individual firm is the main unit that explores new knowledge or exploits its existing knowledge (Lavie *et al.*, 2010).

For each partner in a strategic alliance relationship, exploration refers to developing new products, capabilities, and knowledge, whereas exploitation refers to the refinement and extension of existing products, competencies, and knowledge (March, 1991). Therefore, both asymmetric alliances (one partner explores, the other exploits) and symmetric alliances (both explore or both exploit) are possible. The existing literature does not account for the principle of relativity in strategic alliances mainly because most studies follow the "commercialization" based definition of exploitation (Rothaermel, 2001), which does not comply with the original definition of exploitation that refers to "the refinement and extension of existing products, competencies, and knowledge" (March, 1991: 85). Following the commercialization-based definition, a collaboration between a biotechnology firm and a pharmaceutical company in which the pharmaceutical company commercializes the drugs developed by the biotechnology company should be categorized as an exploitation alliance. However, I believe that, even in this context, partners can specialize in their exploration vis-à-vis exploitation activities based on product and customer knowledge because a biotechnology company can create a new drug while allying with a pharmaceutical company which leverages its existing customer knowledge. Similarly, the same biotechnology company can refine its existing drug knowledge while allying with a pharmaceutical company that explores new customer knowledge. Correspondingly, I highlight that a firm may exploit its existing knowledge in R&D alliances as well as explore new partners in marketing and licensing alliances. Categorization of exploration/exploitation alliances based on value chain position or alliance structure obscures the possibility of relative firm-specific exploration in "exploitation alliances" or firm-specific exploitation in "exploration alliances."

Firms can be expected to consider all these variations as they select alliances and partners that enable them to succeed in the market. While it is possible that one partner could benefit from an alliance while the other partner is hurt by it, in the long run, alliances that perform better overall will lead to increased competitiveness and opportunities for further alliances. Therefore, in the next section, I develop hypotheses about the performance of ambidextrous and unidextrous alliances under common conditions. I use an uncertainty lens and borrow main rationales from the alliance failure literature. Prominent researchers suggest that behavioral and environmental uncertainty are among the main challenges that cause alliance failures (Gulati and Singh, 1998; Sutcliffe and Zaheer, 1998). Behavioral uncertainty results from “strategic non-disclosure, disguise, or distortion of information” by partners (Williamson, 1985: 57) and includes partner and task uncertainty (Santoro and McGill, 2005). Environmental uncertainty refers to “the difficulty in predicting external changes outside the control of the alliance” (Krishnan *et al.*, 2016: 2522) and, in the context of this paper, includes technological and market uncertainty. Consistent with the effects of the type of uncertainty on alliance failure, I offer that they will similarly affect alliance performance. After explaining expected performance differences between ambidextrous alliances and unidextrous alliances in the hypotheses section, I mainly build the rest of the hypotheses based on two types of uncertainty: project (task) uncertainty and platform (environmental) uncertainty.[24] Accordingly, because exploratory projects include a higher level of uncertainty than exploitative ones, I suggest that – among unidextrous alliances – exploratory alliances (both exploring partners) are negatively associated with alliance performance. Then, I hypothesize that relative certainty

[24] I also control for partner uncertainty in the models.

in the environment (e.g., when a platform is more mature) moderates the relationship between ambidextrous alliances and alliance performance as well as the relationship between unidextrous exploratory alliances and alliance performance.

HYPOTHESES

Ambidextrous alliances vs. unidextrous alliances

According to the contextual ambidexterity literature, an ambidextrous firm can simultaneously exploit value from existing markets and competencies and explore new ones (Gibson and Birkinshaw, 2004). Major benefits of ambidexterity within a single firm include, but are not limited to, discovering the unused potential of exploration/exploitation activities (Cao *et al.*, 2009; Jansen *et al.*, 2012), penetrating into existing markets and creating new revenue sources (Jansen *et al.*, 2012), and increasing market share in both existing and new markets (He and Wong, 2004). Because an ambidextrous firm enjoys these benefits, ambidexterity within a single firm is positively associated with firm performance.

While a single ambidextrous firm has to have multiple products, services, markets, or operation modes to explore in one area and exploit in the other, an ambidextrous alliance for creation of products and services can include both exploration and exploitation activities through firm specialization because whether an activity represents exploration or exploitation should be defined relative to a given organization or unit (Lavie et al. 2010). Like an ambidextrous firm, an ambidextrous alliance (i.e., one explores, the other exploits) is likely to help participating firms simultaneously exploit value from existing markets and competencies and explore new ones because the alliance relationship includes both exploration and exploitation activities. All participating firms can benefit from an ambidextrous alliance, mainly because the exploiting partner can find a space to refine its knowledge and competencies in the existing markets while the exploring partner searches for new markets. In addition, firms engaging in ambidextrous alliances can discover the unused potential of exploration/exploitation activities due to specialization in their respective activity. As specialization in either exploration or exploitation activity can help partners develop superior capabilities (Jacobides and Winter, 2005) and gain richer expertise (Becker, 1985; Rosen, 1983), firms engaging in ambidextrous alliances are more likely to discover the unused potential of both exploration and exploitation activities. Penetrating into and increasing the market share in the existing markets can be easier for firms engaging in ambidextrous alliances because such alliances will include the refinement and extension of a partner's existing knowledge and competencies as well as the experimentation of the other partner's with new alternatives. Finally, partners can relatively safely enter into new markets with ambidextrous alliances because the exploiting partner in such alliances may only need to make minor improvements in its existing knowledge and capabilities.

Moreover, from a resource-based view, I infer that complementary exploration/ exploitation activities in the form of mutually supportive, independent activities (Tanriverdi and Venkatraman, 2005; Wang and Zajac, 2007) can create the basis of resource redeployment or recombination for allying companies (Kim and Finkelstein 2009, Sarkar et al.,2001). For instance, in year *t*, firm A may prefer to explore new knowledge and capabilities while its partner firm B is exploiting, and in year *t*+1, firm A may convert its attention to exploit its knowledge and capabilities while firm C is exploring. In both cases, ambidextrous partners will have a chance to explore new products and capabilities as well as exploit the existing ones. Therefore, an ambidextrous alliance can ease resource redeployment or recombination for allying partners. Because complementarity across firms in the interorganizational context can increase the likelihood of successful integration and enhance synergies (Jemison and Sitkin, 1986; Kim and Finkelstein, 2009; Tanriverdi and Venkatraman, 2005; Wang and Zajac, 2007), an ambidextrous alliance based on these complementary activities is highly likely to be positively associated with alliance performance.

In contrast to ambidextrous alliances, a unidextrous alliance (i.e., both firms exploit or both explore) does not provide a ground where firms can reap benefits from simultaneous exploration and exploitation. In other words, a unidextrous alliance is less likely to help firms simultaneously discover the unused potential of exploration/exploitation activities (Cao *et al.*, 2009; Jansen *et al.*, 2012), benefit from both the penetration of existing markets and the creation of new revenue sources (Jansen *et al.*, 2012), increase market share in both existing and new markets (He and Wong, 2004), and conduct complementary exploration/exploitation activities. Therefore, compared to a unidextrous alliance, partners in an ambidextrous alliance are likely to have better alliance performance. Formally stated:

> Hypothesis 1: An ambidextrous alliance (i.e., one partner explores, the other exploits) is positively associated with alliance performance.

Unidextrous alliances: symmetric exploration or exploitation by both partners

The preceding hypothesis is built upon the widely accepted argument that firms need to balance their exploration/exploitation activities to achieve superior performance (He and Wong, 2004; March, 1991; Uotila *et al.*, 2009) and expand that argument to the alliance level. However, the existing literature has not provided substantial evidence beyond the ambidexterity hypothesis and is unclear about whether an emphasis on mostly exploration activities is better for firm/alliance performance than an emphasis on mostly exploitation activities. Instead, researchers have only repeated March's (1991) proposition that an overemphasis on exploration is detrimental to a firm's short-term performance, whereas an overemphasis on exploitation may lead a firm to fall into "competency traps" (Levitt and March, 1988).

Because the theory about the returns from an emphasis on exploration or exploitation is underdeveloped and the limitations of data availability have precluded researchers from theorizing, scholars instead highlight potential pitfalls and advantages of an emphasis on either one. Accordingly, exploration is associated with a high level of uncertainty and risk, variation, experimentation, and discovery, whereas exploitation includes such things as refinement, efficiency, production, and execution (Levinthal and March, 1993; March, 1991). Based on these pitfalls and advantages, the literature suggests that an overemphasis on exploration will yield greater variability in intertemporal performance (He and Wong, 2004; Levinthal and March, 1993; McGrath, 2001) because exploratory projects may have longer tails at both ends of the distribution, which can, on average, lead to a less likely positive outcome (in the middle). However, this less likely positive outcome for exploratory projects does not make these projects less valuable because firms may have to bear costs and losses from early exploratory projects to be able to profit from later exploitative projects.

In addition to variation and longer tails at both ends of the distribution, exploratory projects also include experimentation and discovery (March, 1991). An overemphasis on exploration activities risks spending scarce resources with very little short-term return

(March, 1991). An excessive amount of exploratory activities will limit a firm's ability to tap into the commercial value of their discoveries (Levinthal and March, 1993). Therefore, initial exploratory projects are likely to underperform later exploitative ones. For example, Figure 1 in Uotila et al. (2009) not only shows a curvilinear relationship between relative exploration orientation and firm performance (Tobin's Q) but also that the average value of Tobin's Q for an exploitation orientation is twice as much the average value of Tobin's Q for an exploration orientation.[25]

Even though the preceding discussion is mainly based on exploratory projects developed and marketed by a single firm, the same rationales should also be valid for exploratory projects developed and marketed by alliances of multiple firms. For instance, having too much variation and experimentation during the discovery phase of a product or market capability is likely to be detrimental for alliances between unidextrous exploratory partners. Because all partners in unidextrous exploratory alliances simultaneously conduct exploration, the variation in their alliance performance is likely to make the alliances unstable. In turn, unstable alliances may prevent partners from realizing their full potential as well as from sharing skills and capabilities with partners. In addition, because in a unidextrous exploratory relationship exploitation is limited, partners are likely to bear the cost of experimentation without capturing many benefits of already explored areas. Hence, too much variation and experimentation are more likely to lead to lower alliance performance for unidextrous exploratory alliances than unidextrous exploitative ones.

Although exploratory activities create new areas for individual firms to further

[25] This finding is not explicitly discussed in Uotila et al.'s (2009) paper. Rather, it is interpreted from the Figure 1 on page 227. A high relative exploration orientation suggests that the firm focuses mainly on exploration activities (Uotila et al. 2009).

exploit their existing knowledge and competencies (Brunner *et al.*, 2008), the amount of value creation from exploratory activities is limited because the opportunity for exploitation activities is far greater than that for exploration activities (Benner and Tushman, 2002, 2003). Refining already explored knowledge and capabilities and increasing efficiency of these capabilities through production and execution are likely to increase the alliance performance of unidextrous exploitative partners. Given these rationales, I hypothesize:

> Hypothesis 2: Among unidextrous alliances, exploratory alliances (both partners exploring) are negatively associated with alliance performance.

When alliances exist in a platform-mediated business ecosystem, platform characteristics are the main environmental factors and platform uncertainty is an important environmental factor that affects alliance performance. In the platform literature, reaching a critical mass (Evans and Schmalensee, 2010) often distinguishes successful, mature platforms from new, evolving platforms whose success is uncertain. As platforms mature and reach a critical mass, their main focus transitions from solving the chicken-egg problem (Caillaud and Jullien, 2003) to keeping platform participants on the platform by creating recurrent needs. The chicken-egg problem arises during the initial phases of a platform when the platform is not able to create enough value to attract new customers, as well as it not being efficient and effective for customers to join the platform because there are not enough service/product providers. Once having solved the chicken-egg problem and having reached a critical mass, platforms become more mature and sustainable. Then, allying firms adapt and revise their activities to the more steady-state conditions.

Except for the concept of critical mass (Evans and Schmalensee, 2010), there have been very few studies that shed light on the difference between younger, evolving platforms and mature, sustainable platforms. I contend that younger platforms, like young firms, may suffer from the liability of newness (Stinchcombe 1965). According to Stinchcombe (1965), the liability of newness occurs when younger firms lack resources and legitimacy to develop relationships with other firms. Building upon this fact, researchers have argued that the liability of newness is responsible for a high level of failure among young firms (Bruderl and Schussler, 1990; Freeman, Carroll, and Hannan, 1983). Similarly, I can argue that newer and younger platforms will lack legitimacy until reaching a critical mass (Hannan and Freeman, 1984).

Consistent with the idea that legitimacy problems occur for younger platforms, I consider technological and market uncertainty as the main components of general platform-level uncertainty. As platform owners develop a new platform or update their existing platforms, technological uncertainty associated with new platforms may create problems for participant firms. Because of certain improvements and changes in new platforms, participant firms often have to update their software code with each release of a new platform. For example, Raptr, a social networking company for video game players, in 2015 decided to refocus its resources towards only PC gaming and abandoned support for consoles because changes to Xbox Live and PSN had repeatedly broken their system.[26] Similarly, new platforms may also include a great amount of market uncertainty because of social and cultural characteristics of a target market. For instance, seeking new market opportunities, Uber, as a ride-sharing platform, faced a great amount of market uncertainty while entering into Asian countries and was even partially banned in some of them. Therefore, compared to mature platforms, new platforms are likely to have a greater

[26] For further details, please see: https://www.videogamer.com/news/raptr_to_end_console_support.html.

amount of technological and market uncertainty.

Since young platforms may create problems and uncertainties for platform participants, I suggest that platform maturity is likely to moderate the relationship between ambidextrous alliances and alliance performance as well as the relationship between unidextrous exploratory alliances and alliance performance. The main rationale for this suggestion comes from comparisons across different levels of uncertainty. Given that exploratory projects are more uncertain than exploitative ones, and that younger platforms present more uncertainty than mature platforms, I can state that an ambidextrous alliance on a younger platform will include two levels of uncertainty, one at the project level for the exploring partner and one at the platform level for platform age. In contrast, an ambidextrous alliance on a mature platform will include only one level of uncertainty for the exploring partner at the project level. Moreover, a unidextrous exploratory alliance on a younger platform will include extensive uncertainty at the project level for both exploring partners and additional uncertainty at the platform level, compared to the same type of alliance on a mature platform. Finally, a unidextrous exploitative alliance on a younger platform will only include one level of uncertainty at the platform level, and a unidextrous exploitative alliance on a mature platform will reflect the highest level of certainty when compared to alternative scenarios.

In the first two hypotheses, I argued that, in general, an ambidextrous alliance is likely to outperform a unidextrous alliance, and that, among unidextrous alliances, an exploitative one is likely to outperform an exploratory one. However, I believe that the value of ambidextrous and exploitative alliances can diminish if general environmental uncertainty decreases. As platform-level uncertainty decreases with platform maturity, it is likely that the initial liability of newness for platforms will disappear, and platform participants will start to get used to the platform environment. With increasing levels of certainty in mature platforms, unidextrous exploratory alliances may yield to a higher alliance performance than both ambidextrous and unidextrous exploitative alliances, mainly because exploratory activities by multiple partners can become more valuable in more certain environments.

In contrast, if all partners in an alliance simultaneously conduct exploration activities in younger platforms, they will not only face project uncertainty but also platform uncertainty. Thus, dealing with uncertainty at both project and platform levels may lead companies to lose focus. While it is not always possible to handle uncertainty at either level, partners engaging in unidextrous exploratory alliances in mature platforms will mostly face project uncertainty. In contrast, because of the existence of exploitative activities at the project level in ambidextrous and unidextrous exploitative alliances, partners engaging in such alliances in younger platforms will mostly face platform uncertainty. As a result, despite the main expectation that ambidextrous alliances are more likely than unidextrous alliances to yield a higher alliance performance and that among unidextrous alliances an exploitative alliance is likely to yield a higher alliance performance, I contend that a unidextrous exploratory alliance in mature platforms (low uncertainty) is more likely than an ambidextrous or unidextrous exploitative alliance to yield a higher alliance performance. Thus, I hypothesize:

> Hypothesis 3: Platform maturity weakens (negatively moderates) the positive effect of an ambidextrous alliance (i.e., one partner explores, the other exploits) on alliance performance.

> Hypothesis 4: Platform maturity weakens (negatively moderates) the negative effect of a unidextrous exploratory alliance (both partners

exploring) on alliance performance.

METHODS

Research Setting and Sample

To test hypotheses, I use the global video game industry as the research context. This context suits well to test the hypotheses because it is a project- and product-driven industry where game publishers and developers on different platform ecosystems use exploration and exploitation activities to produce, publish, and market new games as well as benefit from their existing games. I investigate alliances between game publishers and developers – the main participating firms in video game platforms. The success of platforms in the video game industry is directly tied to the performance of platform participant firms and the number and quality of projects/games they develop. To better understand the role of allying participant firms in a platform ecosystem, it is important to distinguish different roles of game publishers and developers. One website explains:

> Publishers are responsible for manufacturing the boxed product, distribution and marketing, and are the ones who advertise the game, arrange press coverage and produce the physical products before delivering them to stores around the world. Unlike publishers, developers are the organizations that come up with the idea for the game; their designers create a detailed design document; their artists produce the environments and characters, and their programmers implement the gameplay as described by the designers.[27]

I collected a unique dataset from five major gaming websites and hundreds of individual game company websites. First, I collected individual game sales data from the VGChartz.com video game database, which is one of two reputable video game sales

[27] See http://www.alteredgamer.com/pc-gaming/49397-what-is-the-difference-between-developers-and-publishers/ for a more detailed description of the difference between publishers and developers.

databases along with NPD. According to Google Scholar, there have been over 900 studies based on the VGChartz database. The original VGChartz dataset includes 52,475 video game titles. I then cross-validated genres, platforms, release date, and various other control variables such as user score and critic score from four other gaming websites: mobygames.com, giantbomb.com, ign.com, and gamefaqs.com. First, I cross-validated variables from these websites in an "R" program by creating a unique id variable based on platform, year, and game title. Second, I manually cross-validated each game title by searching game title and platform name in case titles had typographical errors or alternate spellings. After cross-validation of every video game title from VGChartz, I decided to only include game titles that globally sold more than 10,000 units because some data are not available for those under 10,000 units in sales. These steps result in full data on 18,169 unique video games across 38 platforms between 1977 and 2017. Because this panel study is mainly concerned with the alliance performance of allying publisher-developer companies, the games developed and published by the same company (6,344 observations) are dropped.[28] Similarly, because singleton observations (games developed and published by individual firms who appear as a partner only once) are meaningless in a panel study, the program dropped these observations (2,644). Finally, I dropped an additional 17 observations between 1977 and 1989 because inclusion of year dummies with few observations in early years causes "matrix not positive definite" error in some models. Thus, I have 9,164 video game titles in the final sample, created by 277 video game publisher companies and 1,001 video game developer companies. Of these games, 2,959

[28] I report robustness checks using the full sample in the appendix, addressing the possible endogeneity that could arise because the choice to vertically integrate (both develop and publish) is strategic.

represent ambidextrous alliances and 6,205 are unidextrous alliances following the definitions I describe below. For each company, company-related information such as country and establishment year were collected from mobygames, giantbomb, and crunchbase databases as well as from the individual company websites. If the individual company does not have a website or appear on the preceding databases, I searched on LinkedIn, Twitter, Facebook, and Bloomberg.[29]

Dependent Variable

Alliance Performance. In the product- (or project-) driven game industry, the performance of a game is one of the most important measures of alliance performance between game developers and game publishers because both parties would equally suffer if the game fails. Therefore, I use individual game performance as an indicator for alliance performance. I estimate game profit as unit sales times retail price minus estimated development costs. Global unit sales data come from VGChartz (as of January, 2019), and are precise to the game. Because the data show most titles reach nearly 62% of their lifetime sales in 28 weeks (7 months), I intentionally did not include 2018 video game titles. I collect the average price for a new game for each platform from video game forums and Electronic Gaming Monthly magazine (see Issue 243, pages 14-15), and adjust for inflation. Development cost is estimated as follows. Following a video game cost calculator on a software development company website (https://vironit.com/how-much-does-it-cost-to-make-a-video-game/), I create a video game cost model based on platform and four key characteristics of the game: genre, multiplayer, stereoscopic (3D), and general graphics

[29] A search by name of publishers and developers on the Compustat and CRSP datasets only reveals around 10% of the names in the VGChartz dataset. While many large companies in this industry are public, US-based companies, there are also many private companies, and Japanese and European companies are highly active in the global video game industry.

quality. I was able to find the average cost of game development for 18 video game platforms from video game forums. I then imputed the cost for the remaining 20 platforms using the average cost of games across all platforms of the same generation. I created a range for average video game cost on a platform by adding and subtracting half of the average platform cost.[30] For example, the average video game cost for the Xbox platform is noted as $1.8 million (M) on a video game forum.[31] Accordingly, the range for cost of Xbox video games is assumed to be from $0.9 M to $2.7 M. Next, I divided the difference between the upper limit (e.g., $2.7 million) and lower limit (e.g., $0.9 million) by four to give equal weight to genre, multiplayer, stereoscopic, and graphics quality variables. Thus, up to ¼ of the difference between the lower limit and the upper limit can be added to the lower limit of average platform cost for each of four cost-related variables for an individual game. Multiplayer and stereoscopic characteristics are 0/1 variables. I collected these data from the video game websites listed above, augmented by metacritic.com and Google search as necessary. Following the VironIT cost calculator, I imputed higher costs to games in the Strategy and MMO (massive multiplayer-online) genres than games in all other genres. To create the measure of graphics quality, I performed text mining of video game reviews from the He and McAuley (2016) review dataset and the Amazon AWS review dataset.[32] I extracted each sentence that contains the word "graphics" from more than 1.3 million video game reviews, and identified 46,000 unique words (including misspellings) out of nearly 263,000 sentences. To categorize graphics into high, low, and average quality brackets, I used Hu and Liu's (2004) sentiment analysis words, and then a single rater

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[30] Subtracting and adding different values including 1/3, 2/3, or 1/4 of the average platform cost does not change the results.
[31] https://vgsales.fandom.com/wiki/Video_game_costs
[32] https://s3.amazonaws.com/amazon-reviews-pds/tsv/index.txt

individually reviewed the remaining words. As a result, I coded 7,570 words as positive, 2,269 as negative, and 689 as neutral. Based on these words, the graphics quality of 3,150 video games was linked with title-platform pairs. A comparison of titles across platforms shows that the graphics quality of the same title in different platforms is the same for over 95.2% of titles, so I assigned the same graphics quality value to the same game title in different platforms (9,527 titles) and then replaced missing values with average graphics quality of games in the same franchise (i.e., sequels). For instance, a high-quality graphics and stereoscopic but single player and lower-cost genre game on the Xbox platform is estimated to have a cost of $1.8 million [= $0.9 million (lower limit) + $0.45 million (high-quality graphics) + $0.45 million (stereoscopic)]. Finally, after all computations of the cost-related variables, I multiplied game unit sales with average game price per platform and subtracted the estimated cost of each video game to compute game performance. Because the dependent variable was right-skewed, I took the natural logarithm of it.

Independent Variables

Ambidextrous vs. unidextrous alliances. I computed the first independent variable in two steps. In the first step, I followed Voss and Voss (2013) to measure exploration/exploitation activities within a firm. In the non-profit professional US theater industry, Voss and Voss (2013) measure exploration as the introduction of new products while measuring exploitation as the release of subsequent related products. For each publisher and developer company, I separately coded exploration/exploitation activities. If a company for the first time develops or publishes a game title from a game franchise (or sequel), I coded this as an exploration activity for that company. Subsequent development or publication of games from the same game franchise (or sequel) has been coded as an act of exploitation. For example, if Electronic Arts first released an NHL game in 1998, the first game has been coded as exploration for Electronic Arts, and all subsequent releases of NHL games by Electronic Arts have been coded as exploitation. I have followed a similar strategy for both game developer and publisher companies.

In the second step, I looked at activities of allying game publisher and developer companies. If allying partners conduct asymmetric and complementary activities (e.g., one explores, the other exploits), I coded allying partners as ambidextrous partners. In other cases (i.e., both exploit or both explore), I coded allying partners as unidextrous partners. Finally, in the data analysis, ambidextrous partners were coded as “1” while unidextrous partners as “0”.

Unidextrous exploratory partners vs. Unidextrous exploitative partners. Building upon the preceding independent variable, I further coded unidextrous partners into two subcategories. First, if both partners conduct exploration activities based on game titles and sequels, I coded them as “1”, representing unidextrous exploratory partners and “0” otherwise. Second, I coded allying companies as “1”, representing unidextrous exploitative partners, if both partners conduct exploitation activities and “0” otherwise.

Moderating Variables

Platform Maturity. Platform age is an indicator of platform maturity and sustainability. For each platform in the sample, this variable indicates the age of the platform in weeks as of the game release date. I use weekly platform age because some other control variables including total software and hardware sales are reported weekly.

Control Variables

As has been shown elsewhere (Cox, 2014; Rietveld and Eggers, 2018), major factors that affect the success of a video game are its platform, genre, year and month of release, and critic score. Along with the description of these variables, the description of 29 other control variables is provided in Table 5.1. Because the study is mainly focused on a single industry, industry or market-level control variables are not included.

[Insert TABLE 5.1 about here]

Analysis

The decision to form a partnership may be an endogenous one, in that firms may choose their partners from a close network or a geographical preference. Although the main results of this study do not take this possibility into account, the results based on a larger sample in the Appendix address this possibility and discuss a Heckman (1979) two-stage procedure in detail.

In addition to addressing the possibility of endogeneity, the following steps are taken to identify the best way to analyze the panel data. First, a Hausman test with all control and independent variables was conducted to see whether a fixed-effects or a random-effects regression model fits with the data. Because the Hausman test shows that a fixed-effects model is preferred over a random-effects model, I analyzed the panel data using cross-sectional time series regressions with publisher-developer fixed effects. Second, to ensure the models do not suffer from multicollinearity, I have checked variance inflation factors (VIF) after regression commands. The VIF results show that the following pair of variables are collinear with each other: “user score – critic score”, “hardware life-to-week sales – software life-to-week sales”, and “platform age – platform dummies.” Due to this multicollinearity, “user score” and “hardware life-to-week sales” variables are dropped from the analyses. Because I have platform age as the moderating variable and it is collinear with platform dummies (given year dummies), I first run an ordinary least square (OLS) regression where I have platform age as the dependent variable and platform dummies as independent variables. Subsequently, I computed residuals to substitute for platform age in the regression models. Multicollinearity is not a concern for the remaining variables because they have a VIF score less than the commonly accepted threshold (10). Third, to check for serial correlation, a Wooldridge (2002) test was conducted. Wooldridge test results indicate I have serial correlation in the data. In addition, to check for heteroscedasticity, I performed a Breusch-Pagan test (Breusch and Pagan, 1979). The test shows the data are heteroscedastic. Because the data have serial correlation and heteroscedasticity and because the feasible generalized least square estimators are more efficient than ordinary least square and generalized least square estimators under heteroscedasticity or serial autocorrelation, given the large sample of the study, (Baltagi, 2008; Greene, 2003), I chose the feasible generalized least square estimator in the regression analysis. To correct for both serial correlation and heteroscedasticity, I used *"panels(hetero)"* and *"corr(psar1)"* options after the feasible generalized least square regression command (*xtgls in STATA).*

RESULTS

Table 5.2 reports the descriptive statistics and pairwise correlations and Table 5.3 reports the results of the analysis of the panel data using cross-sectional time series regressions with publisher-developer fixed effect models and feasible generalized least square estimators.

[Insert TABLE 5.2 about here]

Table 5.2 shows the dependent variable has a mean of $29.4 million and ranges from -$18.5 million to $1.8 billion. Looking at Table 5.2, I see the sample includes 29% ambidextrous partners, 27% unidextrous exploratory partners, and 44% unidextrous exploitative partners. While the average platform is 275.24 weeks old, the average number of recurrent ties between publishers and developers is 16.31. On average, publisher companies are 17.21 years older than developer companies. Respectively, publishers have published 44.3 and 46.21 more games in the same platform and genre than developers have developed. While 46% of the partners are from the same country and 27% of partners are from the same country with the platform company, 0.04% of the games have multiple publishers and 2% of the games have multiple developers.[33] The average initial platform price is $373.88 and each platform on average has 1,099 games. The average critic score is 68.25 out of 100, and the average user score is 7.15 out of 10. While the two most frequent game genres are miscellaneous (16.06%) and sports (13.24%), the two most frequent platforms are Nintendo DS (12.41%) and Sony PS2 (12.15%). Table 5.2 also shows low correlations among the independent variables of the study. None of the independent variables have correlations above the commonly accepted threshold level of 0.7. The correlation matrix shows that the highest correlations are the ones between genre experience difference and size difference (0.74) and binary and numeric multi-release variables (0.74). Because deletion of any of these four variables from the analysis does not change the results, I keep and report all of them in the models.

[Insert FIGURE 5.1 and TABLE 5.3 about here]

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[33] To calculate the continuous variables for multi-publisher and multi-developer games, I first computed the average value for both publisher and developer sides and then took the difference of the average. For instance, if the publisher is 20 years old, developer 1 is 5 years old, and developer 2 is 10 years old, the age difference for these companies is computed as follows: “20-(10+5)/2=12.5.”

Table 5.3 consists of feasible generalized least square (FGLS) regression models. Model 1 includes only the control variables, and shows that platform age, genre experience difference, centrality difference, common partners, publisher average performance, developer average performance, developer subsidiary, critic score, multi-release (number), and hardware percentage change are positively and significantly ($p<0.001$) associated with the alliance performance. In contrast, size difference, age difference, platform experience difference, same country, same country platform firm, publisher subsidiary, multi-release (binary), all platforms hardware percentage change, software percentage change, and software life-to-week sales are negatively and significantly ($p<0.005$) associated with alliance performance.

Model 2 in Table 5.3 examines the relationship between ambidextrous partnership and alliance performance. Looking at the model, I see ambidextrous partnership ($\beta= 0.0526$, $p<0.001$) is positively associated with alliance performance. Interpretation of the coefficient of ambidextrous partnership as a result of the exponential value of its coefficient reveals the alliance performance of ambidextrous partners is, on average, 5.4% higher than the alliance performance of unidextrous partners. In other words, for a game that has one million USD profit, ambidextrous partners on average make $54,000 more than unidextrous partners do. This result provides strong support for Hypothesis 1.

I use a subsample of unidextrous alliances in Table 5.3 of Model 3 to test the relationship between exploratory partnership and alliance performance relative to the relationship between exploitative partnership and alliance performance. The model indicates that unidextrous exploratory partnership ($\beta= -0.1032$, $p<0.001$) is negatively and significantly associated with alliance performance. Taking the exponential value of its coefficient will show us that the alliance performance of unidextrous exploratory partners (both partners exploring) is, on average, 9.81% lower than the alliance performance of unidextrous exploitative partners (both partners exploiting). Similar to the previous interpretation, this means that, for a game that has one million USD profit, unidextrous exploratory partners on average make $98,100 less than unidextrous exploitative partners do, providing strong support for Hypothesis 2.

Model 4 tests the moderating relationship of platform age between ambidextrous partnership and alliance performance. The model shows that the interaction effects of ambidextrous partnership and platform age ($\beta = -0.0001$, $p<0.001$) is negatively associated with alliance performance. This result supports the third hypothesis and shows that platform age weakens the positive effect of an ambidextrous alliance (e.g., one partner explores, the other exploits) on alliance performance. In terms of economic interpretation, this result indicates that for every one-week age increase in platform age, relative to the slope of coefficient of unidextrous alliances, the slope of coefficient of ambidextrous partnership decreases by “0.0001.” Looking at FIGURE 5.1, I see inflection point for ambidextrous partnership and unidextrous exploratory partnership is around 450 weeks of age for a platform. On the other hand, Model 5 investigates the moderating relationship of platform age between unidextrous exploratory alliance and alliance performance. The model shows that the interaction effects of unidextrous exploratory alliance and platform age ($\beta = 0.0001$, $p<0.001$) are positively associated with alliance performance. Similarly, this result supports the fourth hypothesis and indicates that platform age weakens the negative effect of unidextrous exploratory partnership on alliance performance. Similarly, this result indicates that for every one-week age increase in platform age, relative to the slope of coefficient of unidextrous exploitative partnership, the slope of coefficient of unidextrous exploratory partnership increases by “0.0001.” FIGURE 5.1 shows that the inflection point for exploitative partnership and exploratory partnership is nearly 320 weeks of platform age. The results show that as a platform matures, the negative relationship between unidextrous exploratory partnership and alliance performance as well as the positive relationship between ambidextrous partnership and alliance performance are weakened.

Models 6-9 in Table 5.4 report robustness check for my hypotheses. Each model in the table contains all independent variables but excludes one of them. Therefore, interpretation of coefficients in each model should be relative to the excluded variable. Model 6 in Table 5.4 shows that relative to unidextrous exploratory partnership, both ambidextrous partnership (β= 0.1188, $p<0.001$) and unidextrous exploitative partnership (β= 0.1062, $p<0.001$) are positively associated with alliance performance. Moreover, Model 7 indicates that, relative to unidextrous exploitative partnership, ambidextrous partnership (β= 0.0126, $p<0.001$) is positively associated with alliance performance. Models 6 and 7 provide statistical support for Hypotheses 1 and 2. Based on Models 6 and 7, I can interpret the profitability order of alliances as: ambidextrous alliances > unidextrous exploitative alliances > unidextrous exploratory alliances. On the other hand, Models 8 and 9 provide robustness checks for moderation hypotheses. Model 8 demonstrates that relative to the interaction effects of unidextrous exploratory partnership and platform age, the interaction effects between platform age and the other two variables – ambidextrous partnership (β= -0.0001, $p<0.001$) and unidextrous exploitative partnership (β= -0.0001, $p<0.001$) – are negatively associated with alliance performance. Finally, Model 9 illustrates that relative to the interaction effect of unidextrous exploitative partnership and platform age, the interaction effect of platform age and ambidextrous partnership (β= -0.00002, p. 0.271) is not significantly associated with alliance performance. Based on Models 8 and 9, I can state that, relative to unidextrous exploratory partnership, platform maturity weakens the positive effects of ambidextrous and unidextrous exploitative alliances on alliance performance. However, based on these results, I cannot state that relative to unidextrous exploitative partnership, platform maturity weakens the positive effects of ambidextrous alliances on alliance performance because the interaction effect of ambidextrous alliances and platform maturity is not statistically significant. These results provide high statistical support for Hypothesis 4 but partial support for Hypothesis 3.

I also conducted robustness checks in several other ways. First, because the study has a right-skewed dependent variable, I ran the regression models by respectively removing the top 1% and 5% of influential values from the dependent variable. Secondly, based on plotting and visualizations, I also ran the regression models by removing influential values from the independent and control variables. Third, I ran the models randomly taking three subsamples of 5,000 observations. And, finally, I had alternative ordinary least square and generalized least square regression models. Except for minor coefficient and p-value changes, the results are robust to these robustness checks.

DISCUSSION

Bridging the longstanding exploration/exploitation literature to the alliance performance and platform literature, this study makes several important contributions to these literature streams. First, I contribute to the alliance literature that investigates the performance outcome of organizational and cultural differences (Estrada *et al.*, 2016; Krishnan *et al.*, 2016; Lavie *et al.*, 2012; Prashant and Harbir, 2009; Sytch *et al.*, 2018; Taneri and De Meyer, 2017) by showing that, along with organizational and cultural differences (e.g., partner complementarity, partner compatibility, operational and orientation differences), differences in organizational learning – exploration/exploitation – activities positively affect alliance performance. Second, I contribute to the literature on balancing exploration/exploitation activities in an interorganizational context (Aoki and Wilhelm, 2017; Birkinshaw and Gupta, 2013; Im and Rai, 2008; Zimmermann *et al.*, 2015) and show that ambidexterity through partner specialization is positively associated with alliance performance. I highlighted that in a strategic alliance, exploration and exploitation activities should not be attributed to all partners in a relationship because partners are likely to conduct asymmetric (e.g., one partner explores and the other exploits) as well as symmetric (e.g., both explore or both exploit) activities. Thus, I contribute to the literature by defining exploration and exploitation activities based on a firm's unique history.

Third, I extend the ambidexterity literature (e.g., Gibson and Birkinshaw, 2004; Jansen, Simsek, and Cao, 2012; O'Reilly and Tushman, 2008; Simsek *et al.*, 2009) to platform ecosystems and show the boundary conditions of ambidextrous and unidextrous alliances. The findings show that relative to unidextrous alliances, ambidexterity through partner specialization is positively associated with alliance performance and that among unidextrous alliances, exploitative ones are positively associated with alliance performance. However, the analysis shows that platform maturity weakens the positive effects of ambidextrous alliances as well as the negative effects of unidextrous exploratory alliances on alliance performance. Using an uncertainty lens, I show dealing with uncertainty at multiple levels (e.g., at both project and platform levels) may not be beneficial for alliances. Fourth, I build on the recent trend in the platform literature to measure performance implications of participating firms (Boudreau and Jeppesen, 2015; Kapoor and Agarwal, 2017; Rietveld and Eggers, 2018) and offer some of the first evidence about alliance financial performance in platform ecosystems. The study improves our knowledge about not only individual firm performance of platform participants but also their alliance performance. Unearthing how platform maturity and age may play a moderating role between firm-specific exploration/exploitation activities and the alliance performance is still another important contribution to the platform literature.

Nonetheless, the study has several limitations that may inspire future research. First, the theory and hypotheses of the study are developed through an uncertainty lens. However, using a capability lens, scholars may develop alternative hypotheses. A future study may investigate how firm- and alliance-specific capabilities affect the relationship between ambidextrous alliances and alliance performance as well as the ones among unidextrous alliances, moderating effects, and alliance performance. Second, the study uses secondary data from public sources, creates a simulation based on average game cost per platform, and computes the performance with average game price per platform. Also, the study assumes that four cost-related variables have similar weight while computing the game cost. Future studies may collect the actual product/project profit to measure alliance performance. Third, despite high statistical significance, the economic significance of platform age moderation may not be high due to small coefficients. Future studies may replicate this study in other platform-mediated ecosystems and see the effects of platform age moderation. Yet, the analysis may still be biased because of data availability. To overcome these limitations, future studies may find a better way to measure alliance performance and collect primary data to see if partner firms deliberately choose symmetric/asymmetric partners in an alliance relationship.

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FIGURE 5.1. Predictive margins of alliance performance

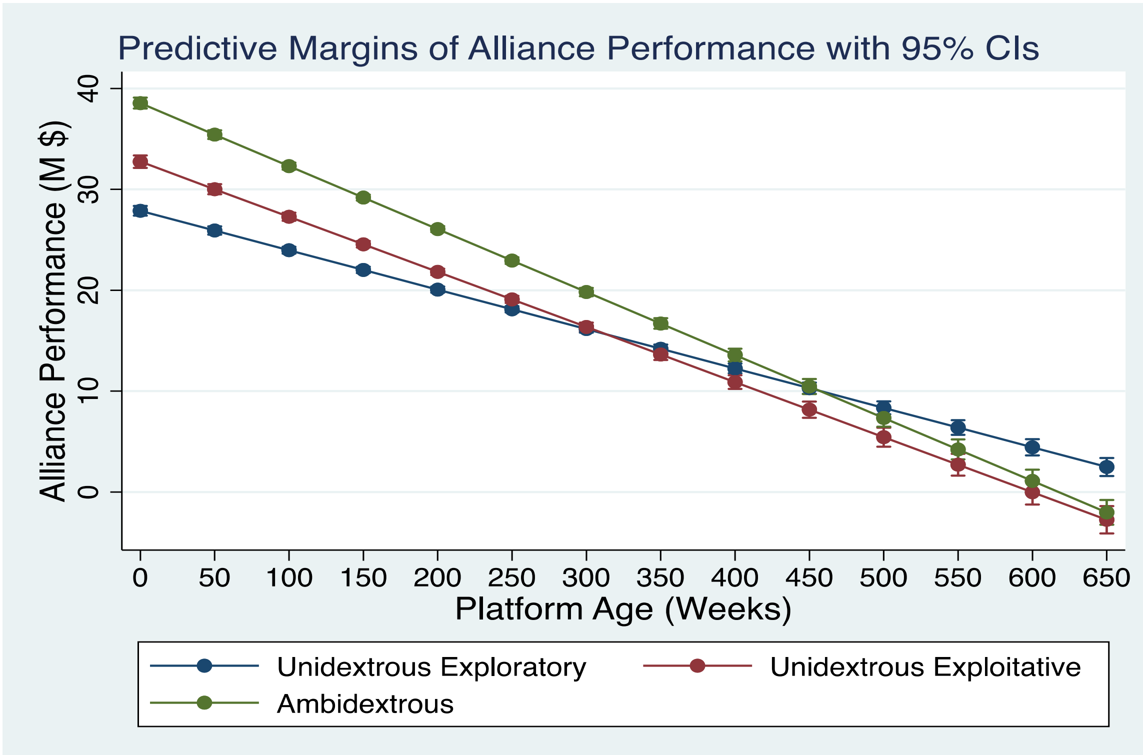

TABLE 5.1. Control variables

Recurrent partnership	**The number of previous ties publishers and developers have**
Partner size difference	The difference between the number of games published/developed by publisher and developer companies.
Partner age difference	The difference between the ages of publisher and developer companies
Platform experience diff.	This variable represents the difference between the number of games published by publishers and the number of games developed by developers in the same platform.
Genre experience diff.	This variable represents the difference between the number of games published by publishers and the number of games developed by developers in the same genre.
Centrality difference	This variable represents the difference between the number of unique partners publishers and developers have.
Common partners	The number of common partners publishers and developers have.
Publisher avg. performance	Average performance of previous games published by the same publisher.
Developer avg. performance	Average performance of previous games developed by the same developer.
Pub-dev same country	Coded “1” for partners from the same country and “0” otherwise.
Same country platform firm	Coded “1” if the platform company, publisher, and developer are from the same country, and “0” otherwise.
Multi-publisher	Coded “1” if a game is published by multiple companies and “0” otherwise.
Multi-developer	Coded “1” if a game is developed by multiple companies and “0” otherwise.
Publisher subsidiary	Coded as “1” if the publisher of a game was a subsidiary of a larger firm.
Developer subsidiary	Coded as “1” if the developer of a game was a subsidiary of a larger firm.
Multi-release number	The number of games released by the developer/publisher dyad on the focal day.
Multi-release dummy	Coded “1” if the game is released with other games on the same date.
Weekly hardware sales	The number of total hardware units sold one week before the release of the game for the focal platform. This variable and the following three variables related to hardware sales were available for 9,910 game observations. The missing observations were first filled with the average of one-week before and one-week after sales (999 observations) and then filled with the week averages. It is divided by 100,000 for ease of representation.
Weekly hardware % change	The percentage change of hardware sales one week before the release of the game for the focal platform.
Weekly all platforms hardware % change	The percentage change of hardware sales one week before the release of the game for all platforms. This variable is divided by 1000 for ease of representation.
Weekly software sales	The number of total software sold one week before the release of the game for the focal platform. This variable and the following three variables related to software sales were available for 10,949 game observations. The missing observations were filled with the week averages. It is divided by 100,000 for ease of representation.
Weekly software % change	The percentage change of software sales one week before the release of the game for the focal platform. This variable is divided by 1000 for ease of representation.
Software LTW Sale	Total number of software units sold in a platform’s lifespan until the game release week. It is divided by 100,000 for ease of representation.
Weekly all platforms software % change	The percentage change of software sales one week before the release of the game for all platforms. This variable is divided by 1000 for ease of representation.
Critic score	Professional game critics’ evaluation based on a scale from 0 to 100. 8,961 missing observations were filled with platform-year averages.
Year dummies	Dummy variables for game release year.
Month dummies	Dummy variables for game release month.
Platform dummies	Dummy variables for 38 major gaming platforms such as Game Cube (GC), PC, Xbox, or PlayStation.
Genre dummies	Dummy variables for 16 major gaming genres such as action, sports, simulation, fighting, or racing.

TABLE 5.2. Descriptive statistics and correlation matrix

b. Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Performance ($US M)	1.00															
2. Ambidextrous partnership	0.02	1.00														
3. Uni. exploratory part.	-0.15	-0.39	1.00													
4. Uni. exploitative part.	0.12	-0.56	-0.54	1.00												
5. Platform age (weeks)	-0.07	-0.02	-0.04	0.05	1.00											
6. Recurrent partnership	0.04	0.02	-0.10	0.07	0.00	1.00										
7. Size difference	0.09	-0.07	-0.11	0.16	0.08	-0.04	1.00									
8. Age difference	0.21	-0.05	-0.03	0.08	-0.01	-0.05	0.57	1.00								
9. Platform experience diff.	0.15	-0.06	-0.09	0.14	0.26	-0.01	0.45	0.31	1.00							
10. Genre experience diff.	0.10	-0.04	-0.12	0.14	0.06	0.00	0.74	0.43	0.35	1.00						
11. Centrality difference	0.15	-0.04	-0.10	0.12	0.06	0.01	0.66	0.35	0.44	0.55	1.00					
12. Common partners	0.08	0.02	-0.15	0.11	0.02	0.23	0.22	0.07	0.13	0.18	0.26	1.00				
13. Publisher average perf.	0.38	-0.03	-0.08	0.10	-0.04	0.02	0.19	0.65	0.23	0.16	0.17	0.12	1.00			
14. Developer average perf.	0.38	-0.08	-0.11	0.17	0.01	0.05	0.12	0.25	0.17	0.10	0.15	0.05	0.36	1.00		
15. Same country	0.04	-0.13	-0.05	0.16	0.02	0.04	0.09	0.15	0.06	0.11	0.00	0.06	0.13	0.09	1.00	
16. Same country platform	0.03	-0.10	-0.08	0.16	0.00	0.08	0.18	0.30	0.15	0.18	0.00	0.08	0.20	0.10	0.67	1.00
17. Multi-publisher	-0.01	-0.01	0.02	-0.01	0.04	0.00	-0.01	0.00	-0.01	-0.01	-0.01	0.00	-0.01	-0.01	0.02	-0.01
18. Multi-developer	0.03	0.05	-0.03	-0.01	-0.03	0.20	0.01	0.01	0.01	0.01	0.01	0.01	0.03	0.02	0.01	0.04
19. Publisher subsidiary	-0.02	-0.01	-0.04	0.05	0.04	-0.02	-0.05	-0.1	-0.04	0.01	0.05	-0.04	-0.05	-0.01	0.08	0.02
20. Developer subsidiary	0.06	0.00	-0.02	0.02	-0.02	0.10	0.00	-0.04	-0.02	0.00	0.03	0.07	0.03	0.04	-0.06	-0.02
21. Critic score	0.26	-0.04	-0.12	0.14	0.00	0.03	0.07	0.11	0.12	0.05	0.06	0.03	0.18	0.16	0.05	0.12
22. Multirelease (number)	0.00	-0.01	-0.07	0.07	0.20	-0.01	0.00	-0.15	0.01	-0.01	0.06	0.05	-0.08	0.00	-0.09	-0.15
23. Multirelease (binary)	-0.07	-0.02	0.00	0.01	0.19	-0.02	0.03	-0.15	-0.02	0.02	0.04	0.03	-0.15	-0.05	-0.08	-0.15
24. Hardware sales (M)	-0.06	-0.02	0.01	0.00	-0.02	0.04	0.06	-0.02	0.02	0.06	0.06	0.01	-0.09	-0.07	0.00	-0.02
25. Hardware Δ%	0.02	0.00	0.00	0.00	-0.02	0.00	-0.03	-0.02	0.00	-0.01	-0.02	0.00	0.00	0.00	-0.01	-0.01
26. All platforms hardware %	0.01	0.01	-0.01	0.00	-0.03	0.00	-0.02	-0.01	0.00	-0.01	-0.01	-0.01	-0.01	0.01	0.00	-0.01
27. Software sales (M)	-0.03	-0.02	0.02	0.00	0.04	0.03	0.1	-0.03	-0.06	0.07	0.11	0.02	-0.09	-0.04	-0.02	-0.04
28. Software Δ%	-0.01	0.00	0.00	-0.01	-0.01	-0.01	-0.01	0.00	0.00	-0.01	-0.01	0.01	0.00	0.00	0.01	0.02
29. Software LTW sales	-0.02	-0.01	-0.02	0.03	0.46	0.01	0.12	-0.05	0.07	0.09	0.13	0.04	-0.10	-0.02	0.00	-0.04
30. All plat. software %	0.02	0.00	0.00	0.00	0.00	0.00	-0.01	0.01	0.00	0.01	-0.01	0.00	0.03	0.01	-0.01	0.00
31. Year	-0.27	-0.05	-0.02	0.07	0.39	0.02	0.23	-0.06	0.06	0.16	0.22	0.07	-0.21	-0.06	-0.02	0.00
32. Month	0.08	0.00	-0.05	0.04	0.01	-0.01	-0.02	-0.02	0.00	-0.01	0.06	0.00	0.01	0.06	0.01	-0.04

TABLE 5.2. Descriptive statistics and correlation matrix (continued)

	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32
17. Multi-publisher	1.00															
18. Multi-developer	0.00	1.00														
19. Publisher subsidiary	0.00	-0.01	1.00													
20. Developer subsidiary	0.00	0.09	-0.02	1.00												
21. Critic score	0.01	0.00	0.05	0.03	1.00											
22. Multirelease (number)	0.00	-0.01	0.04	0.03	-0.01	1.00										
23. Multirelease (binary)	0.02	-0.02	0.03	0.01	-0.04	0.74	1.00									
24. Hardware sales (M)	-0.01	0.02	-0.02	-0.01	-0.19	-0.02	0.01	1.00								
25. Hardware □%	0.00	-0.01	-0.01	-0.01	0.00	-0.01	-0.01	0.16	1.00							
26. All platforms hardware □%	0.00	-0.01	0.00	-0.01	0.01	-0.03	-0.04	0.13	0.51	1.00						
27. Software sales (M)	0.00	0.00	0.03	-0.01	-0.14	0.07	0.11	0.67	0.04	0.05	1.00					
28. Software □%	0.00	-0.01	0.00	-0.01	0.00	-0.02	-0.02	0.03	0.10	0.04	0.05	1.00				
29. Software LTW sales	0.02	-0.01	0.05	-0.01	-0.06	0.24	0.23	0.1	-0.06	-0.05	0.45	-0.04	1.00			
30. All platforms software □%	0.00	-0.01	0.02	-0.01	0.01	-0.03	-0.04	0.03	0.13	0.25	0.09	0.29	-0.03	1.00		
31. Year	0.02	0.00	0.08	0.02	-0.03	0.33	0.36	0.19	-0.07	-0.09	0.33	-0.04	0.47	-0.08	1.00	
32. Month	0.02	0.02	-0.02	0.00	-0.03	0.02	-0.02	0.16	0.08	0.13	0.13	0.06	0.00	0.14	-0.05	1.00

Note: Values higher than 0.02 are significant at p<0.05 and those lower than 0.005 are rounded to “0.”

b. Descriptive Statisti

	Mean	Std. Dev.	Min	Max
1. Performance ($US M)	29.4	72.5	-18.5	1805
2. Ambidextrous partnership	0.29	0.45	0	1
3. Uni. exploratory part.	0.27	0.45	0	1
4. Uni. exploitative part.	0.44	0.5	0	1
5. Platform age (weeks)	275.24	350.44	0	1891.29
6. Recurrent partnership	16.31	54.11	1	1192
7. Size difference	299.45	352.11	-1041	1462.5
8. Age difference	17.21	24.82	-80	121
9. Platform experience diff.	44.3	66.62	-100	1254
10. Genre experience diff.	46.21	63.76	-159	363
11. Centrality difference	110.34	108.15	-26.33	943
12. Common partners	2.39	1.82	0	12.67
13. Pub. avg. perf. (M unit sales)	0.58	0.63	0	5.12
14. Dev. avg. perf. (M unit sales)	0.53	0.93	0	30.26
15. Same country	0.46	0.5	0	1
16. Same country platform	0.27	0.45	0	1

	Mean	Std. Dev.	Min	Max
17. Multi-publisher	0.0004	0.02	0	1
18. Multi-developer	0.02	0.14	0	1
19. Publisher subsidiary	0.05	0.22	0	1
20. Developer subsidiary	0.03	0.18	0	1
21. Critic score	68.25	10.93	17	98
21. Multirelease (number)	1.85	1.28	1	17
23. Multirelease (binary)	0.44	0.5	0	1
24. Hardware sales (M)	0.199	0.193	0	2.03
25. Hardware Δ%	9.78	60.61	-82	1180
26. All platforms hardware Δ%	7.84	40.94	-72	1052
27. Software sales (M)	1.033	1.344	94	14.7
28. Software Δ%	27.84	269.38	-86	12006
29. Software LTW sales (M)	168	203	0	977
30. All platforms software Δ%	11.61	59.53	-78	678
31. Year	2007.45	5.24	1989	2017
32. Month	7.42	3.41	1	12

TABLE 5.3. FGLS regression models of alliance performance

Model	1	2	3
Ambidextrous partnership		0.0526 [0.0017] (0)	
Uni. exploratory partnership			-0.1032 [0.0021] (0)
Platform age (weeks)	0.0031 [0.0005] (0)	-0.0011 [0.0001] (0)	0.0072 [0.0006] (0)
Recurrent partnership	0.00003 [0.0001] (0.743)	0.0001 [0.0001] (0.292)	-0.0005 [0.0002] (0.002)
Size difference	-0.00004 [0] (0)	-0.00005 [0] (0)	-0.00004 [0] (0)
Age difference	-0.0015 [0.0001] (0)	-0.0014 [0.0001] (0)	-0.0022 [0.0001] (0)
Platform experience difference	-0.0002 [0] (0)	-0.0002 [0] (0)	-0.0001 [0] (0)
Genre experience difference	0.0003 [0] (0)	0.0003 [0] (0)	0.0002 [0] (0)
Centrality difference	0.0008 [0] (0)	0.0008 [0] (0)	0.0008 [0] (0)
Common partners	0.0043 [0.0006] (0)	0.0046 [0.0008] (0)	0.0076 [0.0009] (0)
Publisher average perf.	0.2968 [0.0021] (0)	0.2926 [0.0022] (0)	0.2894 [0.0035] (0)
Developer average perf.	0.1967 [0.0011] (0)	0.1973 [0.0013] (0)	0.2184 [0.0036] (0)
Same country	-0.0071 [0.0018] (0)	-0.0029 [0.0019] (0.123)	-0.0442 [0.0026] (0)
Same country platform	-0.0153 [0.0022] (0)	-0.014 [0.0019] (0)	0.0144 [0.0021] (0)
Multi-publisher	-0.0004 [0.1443] (0.998)	-0.0109 [0.1421] (0.939)	0.0238 [0.1137] (0.834)
Multi-developer	0.0024 [0.0058] (0.685)	0.0022 [0.0066] (0.735)	0.1 [0.0036] (0)
Publisher subsidiary	-0.0139 [0.0031] (0)	-0.0167 [0.0035] (0)	0.0134 [0.0027] (0)
Developer subsidiary	0.0904 [0.0061] (0)	0.088 [0.004] (0)	0.0623 [0.0078] (0)
Critic score	0.017 [0.0001] (0)	0.0172 [0.0001] (0)	0.0163 [0.0001] (0)
Multirelease (number)	0.0379 [0.0031] (0)	0.0386 [0.0036] (0)	0.0455 [0.0033] (0)
Multirelease (binary)	-0.0223 [0.0035] (0)	-0.0213 [0.0044] (0)	-0.0494 [0.0039] (0)
Hardware sales	0.0008 [0.0006] (0.216)	0.0019 [0.0009] (0.026)	-0.0068 [0.0004] (0)
Hardware Δ%	0.0001 [0] (0)	0.0001 [0] (0)	0.0001 [0] (0)
All platforms hardware Δ%	-0.1737 [0.016] (0)	-0.1972 [0.0168] (0)	-0.1071 [0.0307] (0)
Software sales	-0.0002 [0.0001] (0.005)	-0.0004 [0.0001] (0.001)	0.0009 [0.0001] (0)
Software Δ%	-0.0385 [0.0033] (0)	-0.0309 [0.004] (0)	-0.0432 [0.0019] (0)
Software LTW sales	-0.0004 [0] (0)	-0.0004 [0] (0)	-0.0003 [0] (0)
All platforms software Δ%	0.0046 [0.0103] (0.654)	0.0246 [0.0143] (0.086)	0.028 [0.0254] (0.27)
Constant	18.812 [0.7793] (0)	17.083 [0.7528] (0)	16 [54.575] (0.769)
Number of observations	9,164	9,164	6,205
Number of groups	1,848	1,848	1,273
Observation per group			
Minimum	2	2	2
Average	4.96	4.96	4.88
Maximum	114	114	109
Wald chi2	2.61E+08	3.09E+09	1.27E+09

Notes: Coefficients are followed by [Standard deviations] and (p-values); Results are based on two-tailed tests;
All models include Year, Month, Platform, and Genre dummy variables.

TABLE 5.3. FGLS regression models of alliance performance (continued)

Model	4	5
Ambidextrous partnership	0.0527 [0.0016] (0)	
Ambidextrous partnership * Plat. Age	-0.0001 [0] (0)	
Uni. exploratory partnership		-0.0982 [0.0022] (0)
Uni. exploratory partnership * Plat. Age		0.0001 [0] (0)
Constant	18.6999 [0.7751] (0)	23.8107 [0.7716] (0)
Number of observations	9,164	6,205
Number of groups	1,848	1,273
Observation per group		
Minimum	2	2
Average	4.96	4.88
Maximum	114	109
Wald chi2/F value	1.02E+08	1.56E+08
	The models include all of the control variables in the base model.	

Notes: Coefficients are followed by [Standard deviations] and (p-values); Results are based on two-tailed tests;
All models include Year, Month, Platform, and Genre dummy variables.

TABLE 5.4. FGLS regression models of alliance performance (Robustness check)

Model	6	7	8	9
Ambidextrous partnership	0.1188 [0.0015] (0)	0.0126 [0.0018] (0)	0.1181 [0.0015] (0)	0.0122 [0.0018] (0)
Uni. exploratory partnership	Excluded	-0.1062 [0.0013] (0)	Excluded	-0.1059 [0.0013] (0)
Uni. exploitative partnership	0.1062 [0.0013] (0)	Excluded	0.1059 [0.0013] (0)	Excluded
Ambidextrous partnership * Plat. Age			-0.0001 [0] (0)	-0.00002 [0] (0.271)
Uni. exploratory partnership * Plat. Age			Excluded	0.0001 [0] (0)
Uni. exploitative partnership * Plat. Age			-0.0001 [0] (0)	Excluded
Constant	19.1823 [0.7721] (0)	19.2886 [0.7721] (0)	19.1455 [0.7714] (0)	19.2564 [0.7713] (0)
Number of observations	9,164	9,164	9,164	9,164
Number of groups	1,848	1,848	1,848	1,848
Observation per group				
Minimum	2	2	2	2
Average	4.96	4.96	4.96	4.96
Maximum	114	114	114	114
Wald chi2/F value	3.56E+08	3.56E+08	6.41E+07	6.4E+07
	The models include all of the control variables in the base model.			

Notes: Coefficients are followed by [Standard deviations] and (p-values); Results are based on two-tailed tests;
All models include Year, Month, Platform, and Genre dummy variables.

APPENDIX

The main purpose of this appendix is to ensure the results are not driven by alternative explanations. The decision to form a partnership may be endogenous with its structure and performance. Firms may choose their partners from a close network or geographical preference as well as decide to internalize the publication or development of game sequels after a successful release. To address these possibilities, I use a two-stage Heckman procedure (Heckman, 1977; Sartori, 2003). In the first stage, I use a dummy dependent variable that takes a value of “1” if a focal firm allies with another firm and a value of “0” if the developer and publisher are the same firm. Because including all variables in both selection and second-stage models can potentially create problems for the Heckman procedure (Heckman, 1977; Sartori, 2003), I used the recommended exclusion restriction procedure and included “only partner” as the instrumental variable in the first stage probit model but did not include it in the second stage equations (Hitt *et al.*, 2006; Shaver, 1998). The “only partner” variable is coded “1” if either the developer or the publisher is the only partner of the other firm; that is, the focal company doesn’t have any alliances with a different partner. An unreported descriptive statistics and correlation matrix table shows the instrumental variable of “only partner” has a mean of 0.1256, which means 12.56% of the games in the sample are developed and published by a pair of companies for one of whom the other company is its only partner. Also, the table shows the variable of “common partners” has the lowest correlation (-0.29) while the variable of age difference has the highest correlation (0.13) with “only partner.” To rule out potential endogeneity and partner selection bias, I add the inverse Mills ratio as a control variable into the second stage FGLS models that investigate the relationship between the independent variables and the alliance performance (Hitt *et al.*, 2006; Shaver, 1998).

As a rule, instrumental variables should theoretically and methodologically be meaningful (Hitt *et al.*, 2006). Methodologically, I have run several alternative models with other instrumental variables where I included “only partner” as a control variable. While in all cases the variable of “only partner” was significantly related to the decision of alliance formation in the first probit model, it was not statistically significant in any of the second stage FGLS models. Theoretically, if a firm has only one alliance partner in its lifetime, it will affect the likelihood of allying with the same partner. However, being the only partner of the other firm is less likely to positively or negatively affect the alliance performance because a complementary “only partner” can positively affect the alliance performance, whereas an incompatible “only partner” can negatively affect the alliance performance.

Table A1 reports one probit and two FGLS regression models. Model i reports the first stage probit regression results and has 18,051 observations of video game titles. Model ii tests the relationship between ambidextrous alliance and alliance performance (H1) and Model iii tests the effects of unidextrous alliance and moderating variables on the alliance performance (H2-H4). Both Model ii and iii have 15,339 video game observations because 2,830 video games were issued by partners who appeared only once in the panel data.

The probit regression Model i shows that size difference, age difference, centrality difference, publisher average performance, and publisher subsidiary are positively and significantly associated with the alliance formation. In contrast, recurrent partnership, only partner, genre experience difference, developer average performance, and developer subsidiary are negatively and significantly associated with alliance formation.

Models ii and iii in Table A1 include all of the control and independent variables plus the IMR. Because of space limits and having similar results, the base model with only control variables, the model that shows the individual effects of unidextrous partnership, and the ones that present the effects of moderating variables are not included in Table A1. However, these models can be provided on request.

Since the control variables in the FGLS models have similar results to the main results of the paper, further discussion of these variables is not provided. Model ii examines the relationship between ambidextrous partnership and alliance performance. Looking at the model, I see ambidextrous partnership ($\beta = 0.037$, $p<0.001$) is positively and significantly associated with alliance performance. Taking the exponential value of the coefficient indicates that the alliance performance of ambidextrous partners is, on average, 3.8% higher than the alliance performance of unidextrous partners. This model provides strong support for Hypothesis 1 and reinforces the main results of the paper.

Model iii tests the relationship between unidextrous partnership and alliance performance as well as the relationship between moderating variables and alliance performance. The model indicates that relative to unidextrous exploratory partnership, both ambidextrous partnership ($\beta = 0.1$, $p<0.001$) and unidextrous exploitative partnership ($\beta = 0.106$, $p<0.001$) are positively and significantly associated with alliance performance. Taking the exponential value of both coefficients shows that the alliance performance of ambidextrous partners is, on average, 10.5% higher, and the alliance performance of unidextrous exploitative partners is, on average, 11.2% higher than the alliance performance of unidextrous exploratory partners. Also, according to the model, relative to the interaction effects of unidextrous exploratory partnership and platform age, the interaction effects between platform age and other two variables – ambidextrous partnership (β= -0.0002, $p<0.001$) and unidextrous exploitative partnership (β= -0.00003, p. 0.066) – are negatively associated with alliance performance. In terms of economic interpretation, this result indicates that for every one-week increase in platform age, relative to the slope of coefficient of unidextrous exploratory alliances, the slope of coefficient of ambidextrous partnership decreases by “0.0001” and the slope of unidextrous exploitative partners decreases by “0.0003.” These results provide further support for Hypotheses 2-4. Overall, the results reveal that relative to unidextrous alliances, ambidextrous alliances are generally positively associated with alliance performance, and that among unidextrous alliances, exploitative alliances are generally positively associated with alliance performance. However, platform maturity weakens the positive effects of these alliances relative to unidextrous exploratory alliances.

Finally, Models ii and iii in the Table A1 include control variables about the vertical integration decision of platform owners and participants. These results are used in a subsequent paper about the entry decisions of platform owners into complementors’ space and the effect of the choice between alliance and vertical integration on product performance. *Vertical Integration* is an ordinal variable which takes four values. Respectively, if games are developed and published by two different firms, the variable is coded as 1; if the game is developed and published by the same firm, it is coded as 2; if the platform owner is either publisher or developer, it is coded as 3; and finally, if platform owner, publisher, and developer are the same company, it is coded as 4. For the sake of transparency, the results of these variables are included in the Appendix. However, because the current study is concerned about the alliance performance of platform participants, games published by the same company are intentionally excluded from the sample.

TABLE A1. Selection model and regression models of alliance performance

	Model i: Selection Model (DV: Alliance Formation)	**Model ii: All partnerships**	**Model iii: Unidextrous partnerships**
Ambidextrous partnership		0.037 [0.001] (0)	0.1 [0.001] (0)
Unidextrous exploratory partnership			Excluded
Unidextrous exploitative partnership			0.106 [0.001] (0)
Platform age (weeks)		0.008 [0] (0)	0.008 [0] (0)
Ambidextrous p.# Plat. Age			-0.0002 [0] (0)
Uni. Exploratory p.# Plat. Age			Excluded
Uni. Exploitative p.# Plat. Age			-0.00003 [0] (0.066)
Recurrent partnership	-0.0068 [0] (0)	0.0001 [0] (0)	0.0001 [0] (0)
Only partner	-0.1378 [0.041] (0.001)		
Vertical Int. (Complementor firms)		-0.246 [0.011] (0)	-0.228 [0.01] (0)
Alliances btw. Platform owner and complementor firms		0.09 [0.003] (0)	0.089 [0.003] (0)
Vertical Int. (Platform owner)		-0.395 [0.032] (0)	-0.364 [0.032] (0)
Size difference	0.0036 [0] (0)	-0.0001 [0] (0)	-0.0001 [0] (0)
Age difference	0.0146 [0.001] (0)	-0.001 [0] (0)	-0.001 [0] (0)
Platform experience difference	-0.0002 [0.001] (0.783)	-0.0003 [0] (0)	-0.0003 [0] (0)
Genre experience difference	-0.0052 [0.001] (0)	0.0002 [0] (0)	0.0002 [0] (0)
Centrality difference	0.0022 [0] (0)	0.001 [0] (0)	0.001 [0] (0)
Common partners	0.0143 [0.011] (0.191)	0.006 [0.001] (0)	0.005 [0.001] (0)
Publisher average perf.	0.2051 [0.038] (0)	0.246 [0.003] (0)	0.244 [0.002] (0)
Developer average perf.	-0.1317 [0.024] (0)	0.19 [0.002] (0)	0.186 [0.001] (0)
Same country		0.009 [0.002] (0)	0.003 [0.002] (0.146)
Same country platfirm		-0.042 [0.002] (0)	-0.047 [0.002] (0)
Multi-publisher		-0.171 [0.226] (0.449)	-0.144 [0.198] (0.466)
Multi-developer		0.039 [0.005] (0)	0.036 [0.004] (0)
Publisher subsidiary	0.2198 [0.064] (0.001)	-0.031 [0.004] (0)	-0.029 [0.003] (0)
Developer subsidiary	-1.1261 [0.051] (0)	0.254 [0.007] (0)	0.249 [0.006] (0)
Critic score		0.018 [0] (0)	0.018 [0] (0)
Multirelease (number)		0.019 [0.002] (0)	0.012 [0.002] (0)
Multirelease (binary)		0.016 [0.003] (0)	0.02 [0.003] (0)
Hardware sale		0.001 [0.001] (0.339)	0.001 [0.001] (0.426)
Hardware Δ%		0.0001 [0] (0)	0.0001 [0] (0)
All platforms hardware Δ%		-0.043 [0.01] (0)	-0.062 [0.002] (0)
Software sale		0 [0] (0.001)	-0.0003 [0] (0.003)
Software Δ%		-0.011 [0.001] (0)	-0.017 [0.002] (0)
Software LTW sale		-0.0003 [0] (0)	-0.0003 [0] (0)
All platforms software Δ%		0.019 [0.016] (0.239)	0.035 [0.011] (0.001)
Inverse Mills ratio		-0.087 [0.007] (0)	-0.079 [0.006] (0)
Year dummies	Y	Y	Y
Month dummies		Y	Y
Platform dummies		Y	Y
Genre dummies		Y	Y
Constant	0.5244 [0.073] (0)	20.335 [0.424] (0)	19.337 [0.408] (0)
Number of observations	18,051	15,339	15,339
Number of groups		2,044	2,044
Observation per group			
Minimum		2	2
Average		7.50	7.50
Maximum		874	874
Wald chi2/F value	12752.54	1.92E+07	4.03E+08
Pseudo R-squared	0.5476		

Note: Coefficients are followed by [Standard deviations] and (p-values); Results are based on two-tailed tests.

CHAPTER 6: SUMMARY AND CONCLUSION

This dissertation consists of two qualitative and two quantitative articles. In the qualitative articles of the dissertation, I investigate the emergence and evolution of platform companies based on 52 publicly available unstructured interviews with 50 founders, top managers, and venture capitalists of platform firms, and 34 review, forum, and analyst articles. While the first qualitative article exclusively focuses on the emergence of platform firms, the second paper concentrates on their evolution. Therefore, I have built two different process models. The first process model about the emergence of platform firms indicates that platform companies come into existence over four consecutive stages: 1) Inefficient Markets and Incumbents, (2) Entrepreneurial Motivation and Enabling Factors, (3) Efficiency-enhancing Means, and (4) Platform Firms. Using a top management team lens, the first qualitative chapter shows how platform firms come into existence as a result of market and incumbent inefficiency, entrepreneurial motivation, and enabling factors. The chapter points out that the differences in the emergence of platform firms come from developing efficiency-enhancing means, targeting and disrupting the whole inefficient market or industry. The discussion in the first qualitative chapter shows that the large-scale disruption of platform firms results from efficiency-enhancing means such as connecting disparate parties, changing methods and processes, and building trust and transparency. As a result of these efficiency-enhancing means, platform firms are able to unify fragmented pieces of inefficient markets, remove opportunistic middlemen from the equation, and alleviate the inefficient situation. Similarly, the chapter shows that the major differences between platform firms and traditional firms include enabling a sharing economy, selling intangibles, and providing simple and real-time solutions.

The second process model built at the end of the second qualitative chapter of the dissertation indicates that the evolution of platform firms includes six major categories: (1) Platform Growth, (2) Competition, (3) Adaptive Behaviors, (4) Platform Sustainability, (5) Rebranding Challenges, and (6) Platform Failure. The main task of the second chapter was to collect the findings in the platform literature under a unified evolutionary framework. The chapter shows that the "winners-take-all (or-most)" assumption is only warranted if platform companies achieve a platform sustainability stage. Despite the majority of studies focusing on solving the chicken-and-egg (early traction) problem, the study shows that solving this problem only once is nonetheless not sufficient to keep the platform firm alive. Platform firms have to provide a hook and create a recurrent need to create a sustainable platform. In other words, even "winners" should strive for keeping different sides on platforms to create sustainable platforms. The chapter shows that unused and underutilized resources available in markets affect the growth and evolution of platform companies and that platform companies have to adopt a new set of routines in each stage of the model to achieve a competitive advantage.

As the evolutionary model built in the second qualitative chapter suggests the behaviors of platform participants are highly likely to be affected by the lifecycle and maturity of platforms, the quantitative chapters of the dissertation scrutinize the effects of strategic alliance, vertical integration, and organizational learning (exploration vs. exploitation) behaviors of platform participants on their performance. Utilizing a large-scale video game dataset, the third chapter of the dissertation focuses on the platform owner's dilemma of "whether to use vertical integration to capture more value or improve the quality of the platform ecosystem (Zhu and Liu 2018, p. 2621) and incorporates a collaborative framework into the existing competitive framework in the platform literature. The chapter found that alliances between platform owners and complementor firms as well as alliances among complementor firms yield a higher product performance than does vertical integration of platform owners and complementor firms. According to the results of the chapter, alliances between platform owners and complementor firms are the most profitable scenario, and alliances among complementor firms are the second. On the other hand, vertical integration of platform owners is the least profitable scenario while vertical integration of a complementor firm is the second least profitable scenario. Also, the chapter found that platform maturity weakens the positive effects of alliances between platform owners and complementor firms on product performance, whereas there are no moderating effects for alliances among complementor firms.

The last chapter of the dissertation focuses on the organizational learning behavior (exploration vs. exploitation) of platform participants and investigates the performance outcome of balancing exploration and exploitation activities through partner specialization in a platform ecosystem. Using a subsample of the video game dataset, the chapter shows that balancing exploration/exploitation activities in an industry or ecosystem through separation of exploration and exploitation across partners in an alliance is positively associated with alliance performance. Similarly, the chapter indicates that among unidextrous alliances, exploitative ones are positively associated with alliance performance. Moreover, the chapter draws a bridge between the longstanding exploration-exploitation literature and the recent platform literature and finds that platform maturity weakens the positive effects of ambidextrous alliances as well as the negative effects of unidextrous exploratory alliances on alliance performance.

In sum, this dissertation is inspired by the question of how recent platform innovation changes the rules of the game for the modern capitalist firm. Utilizing both qualitative and quantitative research techniques, I have investigated the impacts of platform firms and platform-mediated business ecosystem in the modern society and revisited the existing theories of the firm through a platform firm lens. Showing similarities and differences between emergence, evolution, and behaviors of platform firms and traditional firms, I am hopeful that this dissertation will make a meaningful contribution to the literature and open up new research avenues.