ESSAYS ON PLATFORM ECOSYSTEMS

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ESSAYS ON PLATFORM ECOSYSTEMS

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To my parents

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SUMMARY

There has been a tremendous increase in the number and variety of ecosystems. Extant literature has paid more attention to platform owners within ecosystems. In this dissertation, I focus on complementors and try to understand their capabilities and strategies. First, I review the literature and summarize existing research that spans across the three phases of the ecosystem namely nascent, growth and technological change. I highlight some of the gaps in existing research, especially those concerning the nature and role of complementors within the ecosystem. I use empirical studies based on the Enterprise Resource Planning (ERP) Platform Ecosystem to address some of these gaps. More specifically, in one study, I look at the complementor strategy of multihoming and explore the role played by complementor capabilities in terms of their human capital and ecosystem learning facilitated by the complementor's prior platform partnership in multihoming. In another study, I examine the relationship between platform level competition and complementor performance. When an incumbent platform faces competition from an entrant platform, it tends to engage in steering activities that are aimed at supporting its complementors and dissuading them from joining the rival platform. I analyze the potential role of steering in complementor performance and its differential impact based on the complementors's human capital profile.

CHAPTER 1. INTRODUCTION

This dissertation is aimed at learning about complementors and the role played by them in platform ecosystems. There has been a tremendous increase in the number and variety of ICT enabled ecosystems over the last few decades that have together given rise to what we now relate to as the digital economy. On the one hand, while traditional strategy literature has offered vast insights into the origin and sustenance of firm competitive advantage, many of its theories have seldom been applied to ecosystems. On the other hand, though the ecosystem literature has been burgeoning over the last several years, it has brought with it its own set of concepts, methods, and terminologies. This has led to a fundamental question: Is the ecosystem a phenomenon or theory? There is a need for a reconciliation between these two seemingly disparate literatures. How can we enrich our understanding of ecosystems by bringing in theoretical insights from the broader strategy literature? What can the broader strategy literature learn from exploring ecosystems? My own dissertation is an attempt in this direction.

In the first chapter, I review the extant literature on ecosystems. The purpose of this review is to explore the literature to better understand how different types of firms cooperate and compete to create and capture value in the ecosystem. Scholars in this field have focused on what may be thought of as three distinct phases that together constitute the lifecycle of the ecosystem namely nascent, growth and technological change. Accordingly, I employ this three-phase framework and focus on the major papers that pertain to each of the phases of the ecosystem.

The review enables us to identify some of the gaps in the literature, the filling of which could form potential avenues for future research. I summarize below the major learnings from the review and pertinent questions raised by it. First, ecosystem business models differ from traditional business models especially with regard to the complexity involved in value creation and appropriation in an environment characterized by fragmented yet overlapping property rights. In such environments, firms need to learn how to balance cooperation and competition in order to achieve their strategic objectives. For example, cooperation among competing firms through standard setting organizations and industry consortia enhances the chances of technology adoption through follow on innovation. Participation in such groups provides individual firms an opportunity to have their say in the technology's evolutionary trajectory and, in turn, enables those firms to competitive effectively in later stages.

Second, the traditional technology lifecycle approach is useful but incomplete when technologies are systemic and embedded in ecosystems. This is especially true of platform ecosystems that involve complementary technologies. Transition from one technology generation to another is shaped by the challenge faced by the new technology in creating an ecosystem and opportunity available to the old technology to leverage on its existing ecosystem.

Third, the literature has focused more on platform owners and has extended the same organization level analysis to analyzing them in the context of ecosystems. It looks at the ecosystem from a demand side perspective and focuses on the platform owner's problem of balancing the two sides of the ecosystem namely complementors and customers in the presence of network effects. In order to develop a more complete understanding of ecosystems, we may need to move beyond platform owners and focus on other players such as complementors that play a crucial role in the origin, growth, and sustenance of ecosystems. Some of the specific questions related to the role of complementors include the following. How do complementors help in resolving bottlenecks in nascent ecosystems? How do bottleneck shifts affect complementors? How do complementor capabilities affect their response to growth in the ecosystem? How do complementors affect the growth of the ecosystem? How do complementors impact and are impacted by technological change? How platform owner actions affect complementors? How complementor actions affect platform owners?

In the next two chapter of my dissertation, I try to understand more about complementors and possibly answer some of these questions. I address two main gaps in the current literature highlighted by the review. First, existing literature is dominated by a demand side perspective on ecosystems and is less informative on the supply side. I take a supply side perspective and try to understand how complementor capabilities affect their ability to respond to changes in the ecosystem. In particular, I focus on human capital as a source of complementor capabilities and the evolution and reinforcement of those capabilities over time through ecosystem learning i.e. learning from the platform owner and customers. Second, I look at how platform level competition affects complementors. In particular, I look at how an increase in platform level competition benefits complementors and improves their performance. Further, I look at how the ability to internalize such benefits various across complementors based on their human capital.

I use the Enterprise Resource Planning (ERP) platform ecosystem setting and focus on a period marked by industry consolidation and intense rivalry between the principal platform owners SAP and Oracle to test my theoretical assertions. For this purpose, I built a novel dataset by combining data from a variety of sources including archived websites, press releases, 10K reports, National Establishment Times Series, and LinkedIn. In the second chapter, I focus on the phenomenon of multihoming, a complementor's decision to affiliate with multiple platforms. Finding answers related to what causes multihoming and how it impacts the complementor can be especially tricky given that human capital investment by the complementor may be correlated with the benefits of affiliating with a different platform. To address this concern, I make use of a positive demand shock in the ERP platform ecosystem in the mid 2000's, which was plausibly exogenous to the SAP complementors in my sample. An increase in demand on a rival platform (Oracle) should encourage complementors of the focal platform (SAP) to multihome into the rival platform (Oracle). However, I find that not all complementors are capable of multihoming. In particular, those complementors that are narrowly specialized in their pre-shock human capital lack the dynamic and integrative capabilities required to multihome. Further, longer duration of prior partnership (with SAP) enables better ecosystem learning that facilitates multihoming. However, such benefits reinforce the advantage of generalist complementors that have wider variety of human capital in multihoming and leave behind the specialists once again.

In the third chapter, I look at how platform level competition for growth in installed base affects complementors. In the case of two-sided platform ecosystems, in the presence of cross-side network effects, the growth of a rival platform's installed base on one side of the market is likely to hurt complementors of the focal platform on the other side of the market. However, platform owners would be more willing to share value with complementors when faced with competition from another platform to dissuade them from joining the rival platform. We do find empirical evidence consistent with the latter in the ERP platform ecosystem setting. When faced with competitive threat from a rival platform (Oracle) that intends to grow its installed base through acquisitions, the focal platform (SAP) engages in ‘steering’, activities aimed at promoting the complementor, supporting its development efforts, and, thus, encouraging it to stay away from the rival platform. While steering improves the performance of all SAP complementors, on average, specialist complementors tend to be worse off than others. Further, we find that these results continue to hold even after accounting for multihoming as a potential explanation for superior generalist performance.

CHAPTER 2. VALUE CO-CREATION AND APPROPRIATION WITHIN ECOSYSTEMS

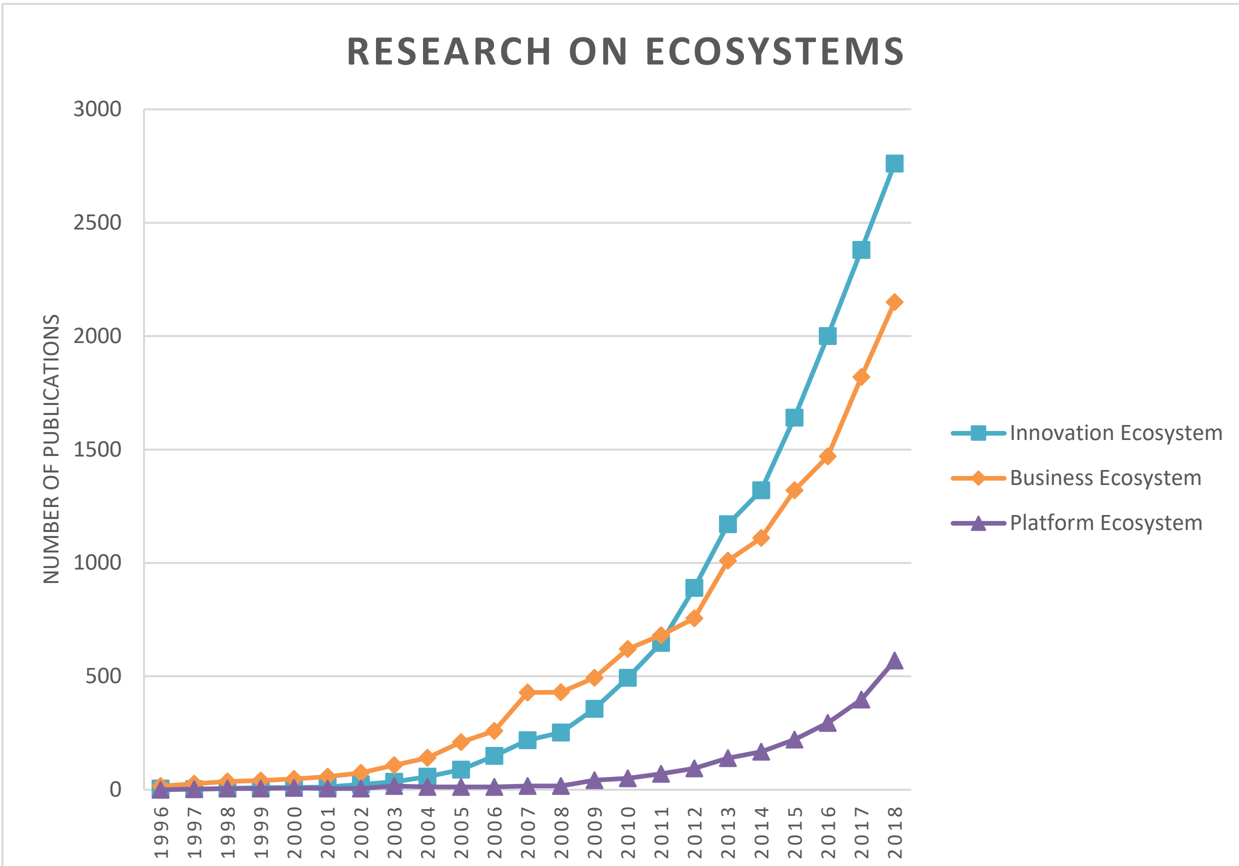
2.1 Introduction

Firms such as Apple, Google, Amazon, and Microsoft have become very successful in recent years largely due to their ability to create, build and manage their ecosystems.[1] Fast growing firms such as Uber, Airbnb and Spotify are now trying to emulate the model in diverse industries and are building ecosystems along with their partners to get there.[2] The literature is also catching up with the trend (refer to figure 2.1.) as researchers in the field of strategic management increasingly try to embrace the new business reality dominated by ecosystems. This, in turn, is beginning to get reflected in the kind of research questions asked and the methodologies adopted in answering them.[3]

The field of strategic management has primarily been concerned with the origin and sustenance of firm competitive advantage and the consequent heterogeneity in firm performance. Over the years, performance heterogeneity has been attributed to the industry (Porter, 1980; McGahan and Porter, 1995) as well as firm level elements such as resources (Barney, 1991; Wernerfelt, 1984), routines (Nelson and Winter, 1982) and dynamic capabilities (Teece, Pisano, and Shuen, 1997). But, more recently, the ecosystem has emerged as a pertinent level of analysis (Teece, 2007; Adner and Kapoor, 2010). The

[1] Seven of the world's top ten companies (by market capitalization) as of 2018 are ecosystem based companies.
[2] As per CB Insights, as much as 70% of start-ups valued at $1 billion or above (unicorns) are platform companies.
[3] One concern related to research on ecosystems has been the concomitant rise of terminologies that are often seen as unique to ecosystems, limiting the broader applicability of its findings. This aspect is discussed in more detail in a later section.

ecosystem may be thought of as a loosely governed network[4] that includes firms that occupy the core of the ecosystem, upstream suppliers that provide components that are combined into the product core and downstream complementors whose offerings are combined with the core by customers based on their needs.[5]



Source: Google Scholar

4 Jacobides, Cennamo and Gawer (2018) distinguishes between ecosystem governance and alliance network governance

5 In addition, standard setting organizations (SSOs), research universities/ laboratories and legal and regulatory authorities act as support institutions and influence the nature and growth of innovation within the ecosystem (Teece, 2007). In the next section, we list the major players that form part of the ecosystem.

Figure 2.1. Research on Ecosystems over Time

Note: The number of publications in any given year is based on the number of search hits in Google Scholar that matches the particular variant of the term ecosystem. In the research literature, the term business ecosystem is used in a very broad sense and may often involve a platform and witness rapid innovation or both. However, some researchers prefer to use the term platform ecosystem to imply that the entire ecosystem is built around one or more platforms at its core and still others choose innovation ecosystem to stress on the pivotal role played by innovation in fostering growth within such an ecosystem. In order to ensure comprehensiveness, the present review shall include papers that assume all three variants of the ecosystem definition.

Table 2.1 Rise in Research on Ecosystems

Period	Total number of publications		
	Innovation Ecosystem	Business Ecosystem	Platform Ecosystem
Since 1996	14527	13307	2166
Since 2010	13301	10938	2004

Note: Similar to figure 2.1, the number of publications in any given year is based on the number of search hits in Google Scholar that matches the particular variant of the term ecosystem. It may be seen that the number of publications that use these terms has grown tremendously in recent years.

The purpose of this review is to explore the literature on ecosystems to better understand how different types of firms compete and cooperate to shape its business model across the different phases namely nascent, growth, and technological change that together constitute the lifecycle of an ecosystem. This shall also enable us to identify some of the gaps in the existing literature and potential avenues for future research. We briefly discuss below what we mean by an ecosystem's business model, how the traditional technology lifecycle approach is useful but incomplete when technologies are systemic and embedded in ecosystems, and why we need to move away from our focus on platform owners alone when it comes to studying ecosystems.

A business model outlines the way in which value is created, captured and shared within any business ecosystem (Teece, 2010). Even though the concept in itself is not new, in recent years, the proliferation of the internet has led to a concomitant rise and spread of new business models (Zott, Amit and Massa, 2011) marked by the presence of one or few platform owners and numerous suppliers/complementors and value co-creation through a complex network of relationships among them (Bresnahan and Greenstein, 1999). Value creation and capture in these new digital ecosystems pose very different challenges compared to those faced in the industrial economy (Teece, 2018).

S-curves have often been used to depict the inter-temporal dynamics of technology diffusion at the level of the industry (Foster 1986; Utterback, 1994). While this approach has been highly useful in understanding technology diffusion (Rogers, 2003; Hall, 2004) and technology change (Christensen, 1997), it has largely taken a technology first approach and ignored the role of the ecosystem in which it is embedded (Adner and Kapoor, 2016). In particular, on the one hand, complements could accelerate adoption of a new technology by generating network effects. For example, the availability of complements through the iTunes store enabled the adoption of the Apple iPod (Yoffie and Rossano, 2012). Similarly, the availability of battery switching stations could increase the adoption of electric vehicle technology (Avci, Girotra, and Netessine, 2014). On the other hand, the inability of complements to adapt to change could impede the technology's adoption by slowing its performance. For example, the inability of game developers to adapt could force console makers to stay behind the technology frontier (Claussen, Essling, and Kretschmer, 2015). Similarly, the hesitation of handset makers in moving away from the manufacturing of older generation of handsets with lower battery life disrupted mobile operations during the transition from 2G to 3G mobile services (Ansari and Garud, 2009).

Prior work on ecosystems has mostly focused on the platform owner and its strategies (Iansiti and Levien 2004; Eisenmann, Parker, and Van Alstyne, 2009) and the complementor has often been missing or relegated to a minor role. In essence, this has led to extension of the same organization level analysis to the new realm of ecosystems where the strategies of the central firm continues to dominate the analysis. However, more recently, researchers have begun to look at complementors' strategies (Ceccagnoli et. al., 2012) and the sustenance of their competitive advantage (Kapoor and Agarwal, 2017). It is important to research about complementors not only to know more about complementors themselves but to understand how they influence the creation and appropriation of value within the ecosystem across its different phases and the sustenance of the ecosystem's business model.

Recent reviews on ecosystems have laid emphasis on bridging and integrating divergent perspectives on ecosystems. Gawer (2014) explores the conceptualization of platforms either as two-sided markets or modular technology architectures. McIntyre and Srinivasan (2017) talks about industrial organization economics, technology management and strategic management perspectives and the need for studies to integrate these different strands for research. While acknowledging these divergent perspectives on ecosystems, the present review shall lay emphasis on how this relates to the evolution of ecosystems across different phases starting with nascent and moving on to growth and technological change and what this means for value creation and appropriation by not just platform owners but complementors.

The review shall begin with the ecosystem paradigm and identify its distinguishing features namely multi-sidedness, network effects and modularity. Next, it shall identify the players that together constitute the ecosystem. Following this, an ecosystem phase based framework would be proposed; the players that form part of the ecosystem (especially complementors) would be integrated into the framework; and the literature shall be reviewed to identify theoretical postulates and empirical results that fit with various elements of this framework. This shall be followed by a concluding section that summarizes the discussion in the previous sections and identifies the key takeaways for researchers from the review.

2.2 The Ecosystem Paradigm

Within the strategy literature, two models have dominated our thinking concerning the creation and sustenance of firm competitive advantage. The former is that of the firm which possesses valuable and rare resources (Barney, 1991) and has the unique capabilities (Teece, Pisano, and Shuen, 1997) to exploit these resources to its advantage. The latter is that of the industry (Porter, 1980) composed of various forces in the form of competitors, suppliers, buyers, substitutes, and (threat of) new entrants that together shape the firm's value creation and appropriation opportunities.

2.2.1 *Phenomena or Theory.*

But recently, a set of phenomena that has consistently played out across a wide range of industries and that has reshaped those industries in profound ways has been loosely understood as ecosystem strategy. Researchers have also been motivated to study such occurrences more closely because they now represent significant economic value within the broader economy.[6] However, it is still unclear whether these phenomena simply represent temporalities within industries that fit a Schumpeterian world view or they have the potential to result in a paradigm shift in theories (Kuhn, 1962) concerning the firm as the locus of value creation and appropriation and the industry as a grouping of competing firms that influence the nature and extent of such value creation and capture.

2.2.2 *Distinguishing Features*

Three features of ecosystems have often been highlighted to ontologically delineate them from traditional industries.[7] The first concerns multi-sidedness (Armstrong, 2006) that introduces the possibility that a firm could capture value by (potentially) charging multiple groups that occupy different parts of the value chain at the same time. For example, in a traditional automobile supply chain, a firm engaged in assembly pays its suppliers for raw materials or components, transforms these raw materials and combines these components into a final product for which it charges from end users. But, in the case of multi-sided markets such as credit cards, the firm can charge a fee from both sides

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6 As per the Bureau of Economic Analysis, the digital economy largely comprised of ecosystems accounted for 6.9 percent of the U.S. gross domestic product, or $1.35 trillion in 2017.

[7] Note that not all ecosystems share all three features though it is common to observe more than one feature operating within an ecosystem at the same time.

namely the merchants that accept card payments and end users that subscribe to those cards as a payment option.

The second feature is that of network effects (Katz and Shapiro, 1985), which may simply be understood as the benefits that accrue to an individual buyer from others purchasing/ subscribing to the same product/ service. While network effects have been prevalent in many industries such as telephone communication or cab services over a long period of time, the digital economy has brought them to the fore. A unique aspect of ecosystems that are also two-sided markets is the possibility of cross-side network effects i.e. the benefits that accrue to members on one side of the market from having more members on the other side of the market. This makes it possible for intermediaries that govern the two sided market to subsidize one side at the expense of the other side, resulting even in free goods/ services in some cases (Parker and Van Alstyne, 2005).

The third feature is modularity (Baldwin and Clark, 2000). Modularity is an approach toward designing a complex system in a manner that allows for high degree of technical interdependence within a component but limited technical interdependence across components. It allows for the possibility to design and deploy components with limited knowledge concerning the technical complexity of other components that may potentially interact with the focal component. A simple example in software programming is an application programmable interface (API) that allows the developer to combine multiple software components say a map for navigation and a social network to connect with friends to create a custom app that enables one to track or share real time location information. In this example, the modular nature of the components and the readily accessible APIs to connect them relieves the developer that aims to make such a connection from the knowledge concerning the complex code built into the map or the social network.

It is important to pay attention to these features to not only understand the nuances of value creation and appropriation within ecosystems but to set boundaries on theories concerning ecosystems. While some would argue that these features are embedded more or less in every major industry that we are interested in as scholars, two aspects concerning the observed prevalence of these features help us with both sense making and limiting the scope of our theory. First, these features seem to be more pronounced in some industries rather than others in determining both opportunities and risks associated with value creation and value capture. Second, these features tend to be, more often than not, associated with technologically intensive markets rather than others.

2.2.3 Players within the ecosystem

2.2.3.1 Platform owner.

The platform owner occupies a prominent position within the business network that makes up the ecosystem and often times owns the core platform or governs the critical value chain around which the ecosystem is built. Within the literature, depending on the context, platform owners have been referred to as platform leaders (Gawer and Cusumano, 2002), keystone firms (Iansiti and Levien, 2004) or platform owners (Gawer and Henderson, 2007; Ceccagnoli et. al., 2012). Most ecosystems comprise of just one or a few owners. Examples include Apple and Google in the mobile application ecosystem, SAP and Oracle in the ERP ecosystem, Uber and Lyft in the online based urban mobility ecosystem and so on. Platform owners play an important role in shaping the future of their ecosystem through several strategic decisions such as choosing between open and closed innovation (Chesborough, 2003); determining the level of modularity of the core product or service (Baldwin and Clark, 2000); and cooperating with other owners in standard setting (Shapiro, 2000; Farrell et. al., 2007; Simcoe, 2012; Axelrod et. al; 1995).

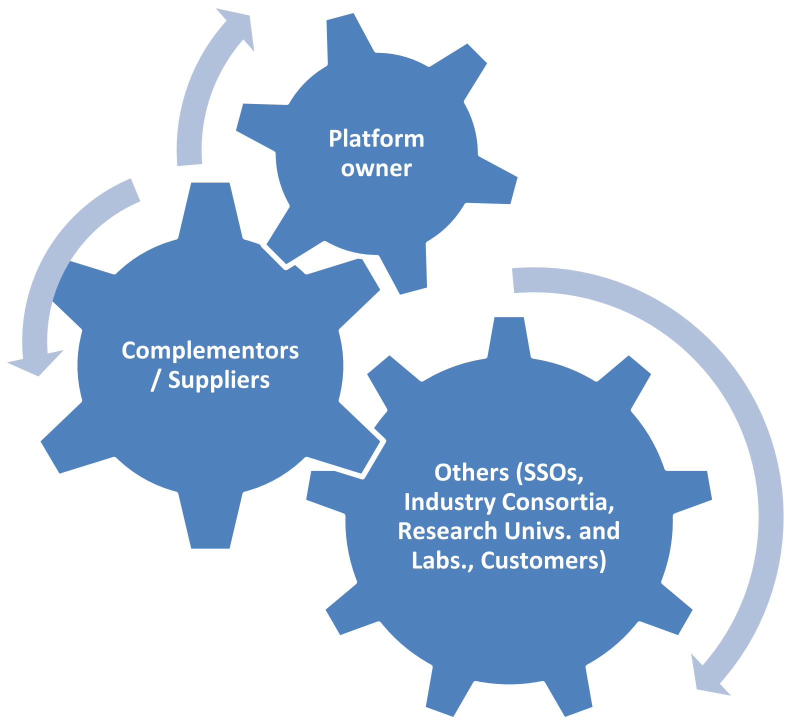

Figure 2.2 Players in the Ecosystem

2.2.3.2 Complementors or Suppliers.

While the terms suppliers and complementors sometimes tend to be used interchangeably, it is important to draw a distinction between the two to better understand the location of value creation and appropriation. In the context of an ecosystem, suppliers may simply be understood as firms that make the components that go into the core product that is bundled together by the platform owner. In the automobile industry, for example, supplier parks are redefining firm boundaries and a huge chunk of the production is now carried out by suppliers in the ecosystem instead of the core companies (Sako, 2009). On the other hand, complementors may be thought of as firms that create products that add value to the core product (Brandenburger, and Nalebuff, 1996) and that are often bundled along with the core product by customers. For example, there are more than a million apps on Apple's iOS and Google's Android platforms today. While a handful of apps are built by Apple and Google themselves, a vast majority of them are actually built by complementors. Customers may choose to download certain applications and bundle them with the core product, which is the smartphone in this case, to derive value from the ecosystem. Even though value addition by the marginal complementor or supplier, in isolation, may not be significant, the combined effect of a huge number of complementors or suppliers can be tremendous. The willingness of complementors or suppliers to partner with platform owners and invest in relational capital not only affects knowledge transfer and individual complementor profitability but influences the overall growth of innovation and helps in achieving scale within the ecosystem.

2.2.3.3 Other Players.

Apart from platform owners, complementors and suppliers that play an important role in ecosystems, we can think of grouping of players in industrial consortia and standard setting organizations, support institutions such as research universities and laboratories, and customers as an integral part of the ecosystem. This review shall not focus directly on the incentives of these players but shall nevertheless include the players in the discussion to the extent that they relate to shaping the value creation and appropriation opportunities across the three ecosystem phases.

2.3 Phases of an Ecosystem – A Review

Three major sequential phases of the ecosystem namely nascent, growth and technological change have been of interest to researchers. To understand what we mean by these three phases, let us consider the wireless telecommunication ecosystem. The nascent phase of this ecosystem involves the creation of the enabling technologies, resolution of technical and other issues that impede coordination among these technologies, cooperation and competition among players in the ecosystem to influence the emergence of standards that govern the interoperability and use of these technologies. The growth phase entails the adoption of wireless telecommunication by end users on the one side and the supply of hardware, software, and applications by suppliers and complementors on the other. Technological change phase refers to a period during which wireless telecommunication moves from one generation to another. This could adversely affect the existing patterns of value creation and capture and the sustenance of competitive advantage of existing players in the ecosystem, a possibility that we shall discuss in detail later. Following a major technology change, the ecosystem once again undergoes a nascent phase corresponding to the new technology generation followed by growth, resulting in a new ecosystem cycle.

Figure 2.3 Phases of an Ecosystem

Focus on a specific phase of the ecosystem has allowed researchers to better understand the unique challenges confronted by firms in that phase and explore the potential opportunities available to them to resolve some of those challenges. A review of the papers that pertain to each of these phases can help us take stock of some of the well-established facts as well as track newly emerging trends within each of the phases. Hence, in this section, we shall look at each of these phases in detail.

2.3.1 Nascent Phase

We have considerable understanding of how individual firms behave in the very early stages that start right from founding based on the entrepreneurship literature (Zoltan and Audretsch, 2006). While the scope of the entrepreneurship literature is much broader, it has stressed more on new modes of value creation through innovation that can potentially disrupt existing industries but offers a limited perspective on value appropriation. In high technology industries, value appropriation not only depends on the potential ability to create value through a core technology asset but the presence of co-specialized complementary assets (Teece, 1986). To this, Teece (2006) adds complementary technologies that could influence value appropriation. Hence, the question of how firms relate to their ecosystems in the presence of various complementarities becomes important (Teece, 2018).

The ecosystem context has its own challenges that makes it unique in some respects. This also makes it important for us to pay attention to the nascent phase in the context of the ecosystem. First, ecosystems shift the locus of value creation outside the organization (Parker, Van Alstyne, and Jiang, 2017) which necessitates participants in the ecosystem to ensure that interdependent components that are complementary are brought together to offer a coherent final product or service. Second, and related, ecosystems are required to overcome bottlenecks that hamper the overall performance of the ecosystem (Eisenhardt and Hannah, 2018). Third, there is a tension between the opportunity to create additional value by opening up the ecosystem to others and the ability to capture value that gets created in the ecosystem (Chesborough, 2003). We shall elaborate on each of these aspects in the following paragraphs.

The first aspect concerns interdependencies among multiple entities in the ecosystem. One major problem faced by firms engaged in the development of system technologies laden with interdependencies is the potential fragmentation and overlap of intellectual property that could derail follow on innovation as well as adversely affect the sustenance of competitive advantage of firms that are part of the ecosystem (Rysman and Simcoe, 2008). Hence, a strand of the literature on the early stage of innovation has focused on standard setting organizations (SSOs) to understand how firms balance competition and cooperation within nascent ecosystems.

Participation in industry consortia and standard setting exercises not only enhances an individual firm's ability to have a say in the evolutionary trajectory of a new technology but also the arrival of a standard enhances the chances of adoption through follow on innovation (Rysman and Simcoe, 2008; Leiponen, 2008). Hence, it becomes important for policy makers to ensure the ready accessibility of institutions such as SSOs and other industrial consortia to large incumbents as well as small and resource constrained players. While effective institutions and standard setting enhance the cumulative impact of individual innovations (Furman and Stern, 2011), it may be noted that vendors could manage to create high switching costs even in the presence of open standards by manipulating compatibility (Chen and Forman, 2006). We discuss more about the implications of (lack of) compatibility in a subsequent section that focuses on technology.

Nascent ecosystems are often confronted with bottlenecks that could hamper the widespread adoption of the product/ service. The firm that successfully resolves the bottleneck gets to appropriate value from the ecosystem. Bottlenecks are closely related to value creation and capture within an ecosystem. While resolution of bottlenecks leads to value creation and enables adoption of the overall technology system, the control of bottlenecks is important to ensure value capture. This often creates a tension in nascent ecosystems especially when there is technological complementarity within the ecosystem. On the one hand, the ability of the innovator to appropriate value can be challenged if the complement created by a different player in the ecosystem ends up becoming a bottleneck asset. On the other, the innovator may lack the capabilities to create the complement by themselves.

Bottlenecks may be understood as narrow points within a complex system that obstruct efficient flow within the system. Bottlenecks may be broadly classified as technical and strategic (Baldwin, 2015). Technical bottleneck may be thought of as an impediment that arises from physical properties of the system that limits its overall performance. For example, in the case of the electric vehicle ecosystem, the charging capacity of the batteries may be seen as a bottleneck that stems the performance of the electric vehicle, affecting the growth of the overall ecosystem. On the other hand, a strategic bottleneck is an 'artificial' bottleneck introduced by a firm that first creates values by solving the technical bottleneck and then captures value by controlling access over the solution.

"What Apple has done since the launch of the iPhone is tell all iPhone owners and iPhone app developers that if they want to buy and sell apps, they have to go through the App Store," ... "So Apple has set up this app store as a bottleneck where everyone in the iPhone ecosystem must transact."[8]

In the above example, the core product (the iPhone) composed of the OS and underlying hardware has a limited set of standard functionalities, which forms a technical bottleneck. One way to address this issue is to allow for the building of applications that enhance the core functionalities and enable users to perform a wide range of meaningful tasks. This value creation could potentially happen within the firm or through a community of developers and given the vast array of applications it makes more sense to open this to complementors. However, Apple's decision to allow sales of these applications only

[8] These quotes from Vaheesan, Legal Director at the Open Markets Institute, in Liptak and Nicas (2019) illustrate the use of strategic bottlenecks as an effective means to appropriate value from the ecosystem

through its app store represents a strategic bottleneck that enables the effective capture of value.

This is further complicated by the possibility that bottlenecks could change over time (Hannah and Eisenhardt, 2018). The paper shows that in the case of the solar ecosystem, finance was the initial bottleneck, owing to the high cost of solar panels. Over time, the cost of solar panels kept coming down and reached below $2/ watt by 2009. However, the costs incurred in acquiring a customer still remained quite high (~$2000 per customer). This shifted the bottleneck from finance to sales. Once, residential solar became more popular, customers generally became more aware of the value of the technology and this brought down the spending on sales. However, installation costs still remained quite high and now formed more than half of the total costs. Hence, by 2013, the bottleneck again shifted from sales to installation. As seen above, bottlenecks can shift continuously within nascent ecosystems and within relatively short periods of time. This requires firms to think more carefully about their competitive as well as cooperative strategies in order to be able to sustain their advantage in the ecosystem.

The limited literature on nascent ecosystems offers little guidance to complementors on the strategies that they ought to pursue within the ecosystem. First, it is not clear whether complementors can successfully align with platform owners and create value by resolving bottlenecks. On the one side, complementary technologies are required for the successful adoption of nascent ecosystem. On the other, complementors could appropriate most of the value created by occupying the bottleneck. Such tensions could not only result in failure of the complementor but threaten the survival of the overall ecosystem. The unsuccessful attempt by a company called Better Place to complement the

EV ecosystem is a case in point. Through the provision of battery swapping services, the company successfully managed to resolve the twin bottlenecks that hampered the adoption of electric vehicles – the low range of the vehicle coupled with a high amount of time required for recharging. However, after raising close to a billion dollars, the company ended up as a failure. Users who had bought the car by counting on the complementary services of battery swapping were adversely affected by this, putting an end to the ecosystem, as originally conceptualized. The above case also illustrates how the resolution of a technical bottleneck is a necessary but not a sufficient condition for value capture (Baldwin, 2015).

Second, we do not know much about the relationship between timing of entry of complementors into the ecosystem and consequent performance. While there is a rich literature on first-mover advantages (and disadvantages) it is not clear how it applies to complementors faced with the prospect of partnering within nascent ecosystems. Apart from the risk that a nascent ecosystem may not take off and become mainstream, there is the risk that a particular technology may not become the standard and/ or widely adopted. Complementors need to make their choices regarding entry in the face of these dual risks. To illustrate, the electric vehicle ecosystem in itself may fail to become mainstream owing to resurgence of the older fossil fuel powered ecosystem or the emergence of still another ecosystem powered by Hydrogen, for example. To add to this risk, either the charging standard or the battery swapping standard adopted initially may fail to emerge as the dominant design adopted by the ecosystem. Hence, we need to understand the risks and entry choices of complementors more thoroughly.

Third, we do not know much about the co-evolution of capabilities of platform owners and complementors within nascent ecosystems over time. For example, how do bottleneck shifts affect complementor capabilities? Certain bottlenecks shifts could help reinforce the existing capabilities of complementors while other shifts could render them obsolete. It is important to understand more clearly the nuances of such changes in different settings and across time.

2.3.2 Growth Phase

As per the industrial organization literature, value appropriation is tied to early entry advantages (Lieberman and Montgomery, 1986), reinforcing of these advantages by setting up facilities for mass production (Christensen and Greene, 1976), marketing, and service and by making constant improvements by going down the learning curve (Spence, 1981). While the literature has stressed on the role played by supply side economies of scale in the growth of firms in traditional industries, the narrative on newer industries built on a digital backbone such as e-commerce, social media, entertainment, and urban mobility has been dominated by a demand side perspective that lays emphasis on network effects (Katz and Shapiro, 1985) and customer switching costs (Farrell and Shapiro, 1988). This change in thinking has also influenced how we value firms based on their growth potential. One striking example that illustrates this change is the valuation premium enjoyed by Uber over many traditional automobile companies. Even though Uber does not own a single factory or count employees on its rolls, factors that are associated with supply side scale economies, it is seen as a company that can transform mobility through aggregation of demand for such services at an unprecedented scale.

The literature on network effects has been built on theoretical models (Katz and Shapiro 1985; Rochet and Tirole, 2003; Armstrong, 2006) that have highlighted the tradeoffs faced by platform owners in balancing the two sides of the market namely complementors/ suppliers and customers. Empirical work has demonstrated the existence of network effects and measured the size of such effects in settings such as video games (Shankar and Bayus, 2003; Clements and Ohashi, 2005) and mobile telecommunications (Fuentelsaz, Maicas and Polo, 2012). An important implication from this literature is that the prevalence of network effects along with switching costs in an industry has the potential to tip the entire industry toward one or few players, a trend that could be very hard to reverse. For example, one of the reasons attributed to Blackberry's failure is its inability to effectively manage its ecosystem (Jacobides, 2013). In spite of its superior core product offerings, it failed to attract application developers on one side by opening up the ecosystem and expand beyond its niche of business users on the other by appealing to the mass market.

While the demand side view on ecosystems has enabled us to explain, to some extent, the tremendous growth of certain industries within a relatively short time period, more recently, researchers have begun to question some of the assumptions made in the theory. For example, Cennamo and Santalo (2013) demonstrate that winner-takes-all (WTA) strategies may not always be effective in improving platform owner's performance. Rietveld and Eggers (2018) find that cross-side network effects may not apply uniformly. They show that heterogeneity in demand in terms of early and late adopters of the core platform could affect the sales of complementors on the other side of the ecosystem.

Researchers have also called into question the undue emphasis on quantity alone that network effects is based on. Afuah (2013) cautions against the undue emphasis on network size alone and stresses the role of network structure and conduct. According to the paper, structural elements such as members' centrality, structural holes, network ties, possibility of transactions and the number of roles each member plays; and conduct such as opportunism, signaling, and perceptions of trust could play an important role in determining ecosystem outcomes. Others have stressed that the quality and variety of applications might be equally if not more important in determining platform level competitive outcomes. For example, Boudreau (2012) finds that increase in the producers of software applications increases the variety of applications produced on the platform. However, later cohorts seem to generate lesser quality applications and, also, there is crowding among similar applications. Still others have shown analytically the counterintuitive possibility that platform owners could actually create value by limiting the choice of applications on their platform (Casadesus-Masanell and Halaburda, 2014).

While the emphasis of the literature on ecosystem has often been on prescriptions to platform owners to grow their ecosystem, there has been less research on what it entails for the growth of complementors. For example, complementors may often be unpaid and yet driven by several motivations other than sales such as signaling about reputation, hobbies etc. These could in turn affect how they respond to platform growth (Boudreau and Jeppesen, 2015). Also, less is known about the supply side such as in terms of the capabilities of the complementors to exploit demand side changes in the growth phase of the ecosystem (Venkataraman, Ceccagnoli and Forman, 2018).

Unlike the strategy literature that lays emphasis on resources (Wernerfelt, 1984; Barney, 1991), knowledge (Grant, 1996), and dynamic capabilities (Teece, Pisano, and Shuen, 1997) of firms, the ecosystem literature has thus far relied more on output measures concerning complementors such as quantity, quality and pricing and offers very little insight on the capabilities of complementors, the nature of the knowledge production process within and across complementors, and, finally, how it relates to the growth of the broader ecosystem.

In an environment in which firms increasingly rely on external application developers to grow their ecosystem (Parker, Van Alstyne, and Jiang, 2017), it becomes important to understand the sources of complementor knowledge and capabilities. Further, to develop a better understanding of ecosystem growth, there is a need to combine supply side and demand side perspectives and look at how complementors' dynamic capabilities and integrative capabilities (Helfat and Raubitschek, 2018) affect their response to demand side changes.

More recently, researchers have pointed out some of the limitations in the existing literature and have brought focus to complementor capabilities and sustenance of complementor competitive advantage. A fundamental question faced by potential complementors concerns whether they should partner and join an ecosystem. Ceccagnoli et. al. (2012) finds that firms with a greater stock of intellectual property and those with stronger downstream capabilities are more likely to join a platform. This suggests that complementors see the threat of appropriation by the platform owner as a major concern with regard to their partnership decision.

Another complementor strategy that has attracted attention of scholars is that of multihoming, a phenomenon wherein a complementor decides to partner with more than one platform (Bresnahan and Greenstein, 1999; Cennamo, Ozalp, and Kretschmer, 2018; Venkataraman, Ceccagnoli and Forman, 2018). Complementors may decide to partner with multiple platforms for a variety of reasons. First, it could be that the benefit from being able to expand into a related platform and serve a larger network of end users outweighs the costs. Second, a decision to partner with multiple platforms may actually stem from a threat from the platform owner with whom the complementor has an ongoing relationship. Third, in the face of technological change[9], there is a possibility that complementors that are stuck with a single platform may be rendered obsolete. An interesting aspect concerning multihoming is that it not only affects the marginal complementor but a joint decision by several complementors to multihome has the potential to stem the tendency of the overall market to tip toward a single platform, as we discussed above.

Ecosystem growth considerations could favorably or adversely affect platform owner-complementor relationships. On the one hand, platform owners may choose not to enter complementor markets to encourage growth and use commitment mechanisms based on a combination of organizational structure and processes to signal their intent to complementors who may be wary of joining them (Gawer and Henderson, 2007). On the other hand, as ecosystems mature and growth slows, platform owners may be tempted to enter and 'envelop' related markets (Eisenmann, Parker, and Van Alstyne, 2011). Platform

[9] Refer to the next section for a more detailed discussion on technological change as a phase of the ecosystem.

envelopers grow their market by foreclosing the incumbent's access to users. Envelopments could involve incumbent-entrant pairs that are complements, substitutes or unrelated.

2.3.3 Technological Change

The origin of technology change, in itself, can be quite complex, and has been attributed to a combination of advancements in science, economic factors, institutional changes, and resolution of unsolved problems that block technology paths (Dosi, 1982). Here, we are particularly interested in the potential of technology change to alter the nature of value creation and appropriation and challenge the sustenance of competitive advantage of incumbents.

First, and perhaps the most obvious, the extent of the change affects firm adaptation. While incremental or continuous changes favor incumbents, radical or discontinuous changes favor entrants and enable them to dislodge incumbents (Tushman and Anderson, 1986). Second, and more subtle, the nature of the change as it relates to component level changes or the manner in which components are recombined, referred to as architectural, can affect the incumbent’s ability to adjust to the change (Henderson and Clark, 1990). The above two scenarios assume that the new technology is invariably superior in performance to the old technology that it replaces. Third, there could be instances in which the nature of demand across customer segments affects change, leading to a new technology that is initially inferior in performance disrupting the old technology (Christensen, 1997). The literature has relied more on technology push and demand pull based explanations but it has offered a limited perspective on how it is affected by the ecosystem in which it is embedded.

According to Adner and Kapoor (2016), transition from one technology generation to another is shaped by the challenge faced by the new technology in creating an ecosystem and opportunity available to the old technology to leverage on its existing ecosystem. For example, in the case of gasoline powered automobiles, component improvements such as more efficient internal combustion engines combined with complementor improvements such as cleaner fuels have enabled them to prolong the ecosystem. At the same time, electric vehicles have challenges related to improving the quality of components especially given their limited experience,[10] and ensuring the availability of complements in the form of charging stations.

As illustrated above, both the emergence challenge faced by the new ecosystem and the extension opportunity available to the existing ecosystem enable incumbents to sustain their competitive advantage. However, there could also be instances in which the ecosystem constraints the ability of the incumbent to adapt. For example, Afuah (2000) argues that the existing capabilities of suppliers and complementors may be rendered obsolete in the phase of technological change and this could in turn affect the performance of the focal firm.

Similar to differences in customer expectations (Christensen, 1997), differences in complementor capabilities could introduce competing pressures on the platform owner in an ecosystem. As illustrated in the case of Intel (Gawer and Cusumano, 2002), some complementors would like the platform owner to move faster to the next technology generation. Other complementors might want the platform owner to continue with the old

[10] The Wall Street Journal article titled Quality Woes a Challenge for Tesla's High-Volume Car talks about Tesla's struggles with production

technology generation. These pressures are further complicated by platform level competition. To be able to compete effective with competitors, platform owners may like to set their technology level closest to the frontier (Claussen, Essling, and Kretschmer, 2015). However, pressure from certain segments of complementors might push them to settle for a lower level.

An aspect of technological change that is especially relevant to ecosystems is the level of compatibility across different platforms and across generations of the same platform. Platform owners could increase or decrease the level of compatibility of their platform with regard to other platforms or older generations of the same platform to encourage or discourage porting of applications on the one side and switching of users on the other.

Adner, Chen and Zhu (2016) focuses on compatibility with other platforms. The paper uses the case of Apple iPad and Amazon Kindle to illustrate how an entrant or incumbent may use technology compatibility as a lever in orchestrating the ecosystem. The paper also highlights the tradeoff faced by entrants in such ecosystems. On the one hand, entrants need to try and differentiate their core product from others to appeal to customers, which could make the product less compatible with others. On the other, they need to ensure the availability of complements that work well with the product, which forces them to make their product more compatible.

Compatibility with other platforms could also have an impact on complementor strategies. While complementors have several incentives to multihome (as discussed earlier), they also face tradeoffs while designing their products for multiple platforms that often differ in their architectures (Cennamo, Ozalp, and Kretschmer, 2018). This in turn leads to a situation where multihoming complements have lower-quality in a more complex platform. However, complements that are introduced on the more complex platform with a delay suffer a smaller drop in quality.

Kapoor and Agarwal (2017) and Kretschmer and Claussen (2016), on the other hand, focus on generational transitions and how it affects complementors. Kapoor and Agarwal (2017) uses the mobile ecosystem setting to show that complementors are adversely affected every time there is a generational transition. This could be due to the failure to quickly adapt to the changes that come with every transition. Although companies try their best to ensure backward compatibility (Kapoor and Agarwal, 2017: P. 535), it still becomes difficult to ensure that app developers on the one side and users on the other are on the same stable version.

Kretschmer and Claussen (2016) studies the US market on video consoles and explores the dual role played by backward compatibility in generational transitions. On the one side, backward compatibility plays a positive role by enabling the ready availability of complements without having to rebuild them. On the other, backward compatibility has a negative effect on the entry of new complements. Thus, compatibility has important implication not only for individual complementors but for overall ecosystem innovation and growth.

2.4 Discussion and Conclusion

The ecosystem as a concept is still evolving. Based on what we have seen, we know more about platform owners and their strategies while we have less insights on complementors and their strategies. Unlike the strategy literature that has stressed on the supply side factors such as resources and capabilities, the literature on ecosystems is dominated by a demand side perspective. To address these concerns, future research needs to focus more on complementors and how they relate to the ecosystem. Following are a few examples of unanswered questions. What is the source of complementor capabilities? Why and when do complementors engage in strategies such as multihoming? How do complementor strategies relate to their own performance? How do complementor strategies affect platform performance and tipping of the ecosystem?

There has been considerable growth in research on each of the different phases of the ecosystem. However, there has been less research that synthesizes the product lifecycle approach and the locus of value creation and value appropriation in the ecosystem. Clements and Ohashi (2005) is perhaps a notable exception. According to the paper, in the video game ecosystem, a focus on hardware pricing is an effective strategy in the introductory stage while software variety becomes more important later on in the lifecycle. They also show that there is an inertia with respect to sales in the software market that is not observed in the hardware market. In other words, software providers continue to exploit the installed base of existing hardware users even when the demand for new hardware has slowed. We need more such research that cuts across ecosystem phases. How does early imprinting in nascent ecosystems affect the ecosystem's growth trajectory? How does technological change affect growth in the number of complements and the quality of complements?

The growth of the ecosystem literature has also been accompanied by a set of terminologies such as two-sidedness, network effects, modularity, tipping, multihoming, steering, envelopment etc. While this has enhanced our ability to understand the workings of ecosystems, on the one hand, it has also made it difficult to compare ecosystem strategies with other traditional strategies such as alliances and networks, vertical and horizontal integration, economies of scale and scope etc. Also, research on ecosystems often uses outcomes measures such as application rankings, number of installations, and user ratings. It is not clear how these relate to traditional measures of performance such as sales and profits. We feel that the next phase of research should be aimed at integration of the ecosystem literature with the broader strategy literature with an aim to harmonize theories, terminologies, and measures, where possible. How can we enrich our understanding of ecosystems by bringing in theoretical insights from the broader strategy literature? What can the broader strategy literature learn from ecosystems? This is essential to not only build a more complete theory of ecosystems (Jacobides, Cennamo, and Gawer, 2018) but, in some ways, a more complete theory of the firm (Alchian and Demsetz, 1972; Williamson, 1975).

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CHAPTER 3. MULTIHOMING WITHIN PLATFORM ECOSYSTEMS: THE STRATEGIC ROLE OF HUMAN CAPITAL

3.1 Introduction

Across industries such as gaming, mobile, business software, e-commerce and credit cards, the nature of competition has shifted from product-based to platform-based competition (Bresnahan and Greenstein, 1999; McIntyre and Srinivasan, 2016; Choudary, Van Alstyne, and Parker, 2016). A platform ecosystem may be thought of as taking a "hub and spoke" form composed of a central product that is connected to complementors that contribute toward building around it through their product or service offerings (Jacobides, Cennamo, and Gawer, 2018; Adner and Kapoor, 2010; Gawer, 2014).[11]

Within this context, a key strategic decision for many potential complementors is whether to affiliate with a particular platform. A related question is whether complementors should affiliate with multiple platforms, or multihome. These decision have important implications for the performance of many software firms (Ceccagnoli *et al*., 2012; Kapoor and Agarwal, 2017) and the quality of their products (Cennamo, Ozalp, and Kretschmer, 2018; Claussen, Kretschmer, and Mayrhofer, 2013). An evolving literature has explored how platform owners can influence the value to potential complementors of affiliating with the platform by shaping the costs of coordinating with the platform and ecosystem

[11] In this way, our definition of platforms shares more with the "engineering view" of platforms as described by Gawer (2014), which emphasizes that platforms are technological architectures that facilitate innovation. This is in contrast to the "economics perspective" which sees platforms as a vehicle for market exchange.

(Boudreau, 2010; Gawer, 2014; Kapoor and Agarwal, 2017; Tiwana, 2015).[12] However, so far there has been relatively little exploration of how the strategic actions taken by potential complementors can shape their benefits of affiliating with a platform (Ceccagnoli *et al*., 2012; Kapoor and Agarwal, 2017). In particular there is relatively little understanding of how complementor actions can shape the coordination costs—and in turn overall benefits—of affiliating with a platform.[13] This is an important gap in knowledge, as understanding the interrelationships between platform affiliation and other decisions will have important performance implications for many software firms.

We study the decisions of software firms to multihome across enterprise resource planning (ERP) ecosystems. Our core research question asks whether and how ex ante differences in a complementor's human capital influences the decision to multihome, and how the impact of these differences are shaped by learning that takes place during the relationship with the existing platform. To answer this question, we take as our starting point that a firm's human capital will affect its ability to pursue its strategies (Castanias and Helfat, 1991, 2001; Mayer, Somaya, and Williamson, 2012). ERP involves the automation of a firm's business processes through software. As a result, unlike software written for consumers, producing for an ERP platform requires knowledge and skills not only related to technology such as programming languages. In particular, it also requires knowledge and skills related to the functional business processes defined in the software as well as the industry of customers in which the software is used. Further, the diversity of

[12] The cited papers represent examples of recent empirical testing of theoretical work that has explored themes related to modularity, openness, complexity, and control in a much longer stream of theory work. For some examples, see Anderson et al. (2013), Baldwin and Clark (2000), Sanchez and Mahoney (1996), Parker and Van Alstyne (2018), Parker, Van Alstyne, and Jiang (2018), and Tiwana *et al* (2010).
[13] Notable exceptions include Kapoor and Agarwal (2017), Cennamo, Ozlap, and Kretschmer (2018), and Agarwal and Kapoor (2018). We discuss our relation to these papers in further detail below.

knowledge and overlapping knowledge boundaries induce cospecialization among diverse forms of human capital and raise the costs of acquiring these skills on the external market (Grant, 1996; Kogut and Zander, 1992, 1996; Carlile, 2002; Nickerson and Zenger, 2004). In short, we hypothesize that firms who are generalists—i.e., those possessing multiple types of cospecialized human capital—will be more likely to multihome.

Our focus on knowledge and learning allows us to examine another important question for complementors: how learning that occurs as a result of affiliating with the existing (home-) platform influences the probability of multihoming. As the result of repeated interactions with the platform owner and the existing ecosystem, complementors learn how to more effectively produce for the platform and meet the needs of platform customers. Some kinds of learning are more transferable to the new platform, such as organizational knowledge and competences that facilitate spanning boundaries across the ecosystem. We therefore hypothesize that over time that complementors will be more likely to multihome. However, as the platform partnership evolves, the key mechanism that provides an advantage to generalists to begin with will become more important over time. That is, knowledge accumulation at the intersection of diverse forms of human capital as well as the development of organizational competences in integrating knowledge across boundaries provide an additional source of learning for generalists that increase their propensity to multihome relative to specialists as the existing partnership evolves.

We test our ideas using a unique event that occurred within the enterprise resource planning (ERP) platform ecosystem: a shock to the size of the installed base of one platform vendor, Oracle, triggered by a short period of intense platform-level acquisitions.[14] We

14 Starting in the year 2004, Oracle initiated a series of acquisitions starting with that of PeopleSoft for more than $10 billion, which was then the largest ever acquisition across technology-based industries.

study the decisions of small SAP complementors as a response to this shock,[15] allowing us to examine how ex ante differences in human capital and learning with the existing platform lead to heterogeneity in response to this event. We take advantage of employee-level data from LinkedIn to create a unique measure of human capital specialization. Our analysis uses an unbalanced panel composed of 226 firms corresponding to 1020 observations spread across the years 2001-2006.

Our empirical findings inform the relationship between human capital specialization, duration of relationship with the existing platform, and the decision to multihome. Consistent with our theory, we find that firms specialized in one form of human capital are less likely to multihome after the demand shock. Similarly, we demonstrate that the usefulness of a given form of human capital to multihoming increases with the addition of any other form of human capital involved in the software development process, providing empirical support for cospecialization among diverse forms of human capital in integrating complementary software solutions with a platform.

We further find that the longer the duration of prior partnership, the more likely a complementor will multihome. However, this relationship is stronger for generalists. We explore the robustness of these relationships to a variety of alternative specifications and measurement strategies. In particular, while it is challenging to disentangle the effect of internal firm learning and sources of learning associated with complementor activities within the existing ecosystem, we show that this relationship is robust to the inclusion of a proxy for internal firm learning.

15 To ensure homogeneity within the sample, we restrict our sample to relatively small firms with less than 5000 employees when they enter the sample.

We leverage existing strategy research, mostly originating from the knowledge-based view of the firm (Grant, 1996; Kogut and Zander, 1992, 1996), to contribute to recent research within the platform ecosystem literature that has explored how knowledge barriers and coordination costs influence the benefits and costs of affiliating with a platform. Most research on this topic has explored topics around how choices of the platform owner shape these costs through decisions related to the technical architecture and openness of the platform (e.g., Gawer, 2014; Boudreau, 2010; Tiwana, 2015). In particular, prior work has focused primarily on how technological features such as distance from the technological frontier (Anderson, Parker, and Tan, 2013; Claussen, Essling, and Kretschmer, 2015), modularity (Sanchez and Mahoney, 1996, Tiwana, 2015), and the extent of connectedness between the platform and its components (Kapoor and Agarwal, 2017) —influences the costs of affiliating with and innovating on a platform.

Within the platform strategy literature, our research builds in particular on recent work that has examined how the characteristics of complementors and their strategic decisions interact with the architecture of the platform to shape the costs of affiliation. These have included the experience of complementors (Kapoor and Agarwal, 2017), the connectedness of complementors to the platform and broader ecosystem (Agarwal and Kapoor, 2018), the nature of the vertical relationships between the platform and complementor (Cennamo, Ozalp, and Kretschmer, 2018), and the use of development tools (Cennamo, Ozalp, and Kretschmer, 2018). While we similarly focus on "supply-side" features of complementors, our research is unique in its focus on their human capital, a key and thus far unexplored issue. In this way, our research will have important implications for the human capital and platform affiliation decisions of software firms.

Our results also have implications for platform owners. Understanding where and when firms multihome is important because it influences market-level outcomes such as the likelihood whether a market will tip and become a winner-take-all market (e.g., Corts and Lederman, 2009; Landsman and Stremersch, 2011). Prior research on multihoming has focused on demand-side explanations for multihoming, in particular the role of cross-side network effects (e.g., Corts and Lederman, 2009; Rochet and Tirole, 2003; Rysman, 2007). However, our results show that even when cross-side network effects are growing, not all complementors may be able to respond quickly and seize the opportunity (Teece, 2007).

While much of the recent empirical work on platform ecosystems has focused on consumer markets such as mobile applications and video games (e.g., Kapoor and Agarwal, 2017; Agarwal and Kapoor, 2018; Cennamo, Ozalp, and Kretschmer, 2018), our focus on complementarities among human capital investments will have implications across a wide range of enterprise software markets. This focus on enterprise software is valuable for several reasons. First, enterprise software platforms are economically important—one recent estimate put the size of the SAP "economy" at $204 billion (Mirchandani, 2014) and another recently argued that Salesforce and its partner ecosystem will generate more than $859 billion in new revenues worldwide by 2022 (Prince, 2017). Further, the problem of integrating applications with business processes enabled by platforms will be a significant one for many rapidly growing platforms that connect devices enabled by the "Internet of Things" (Iansiti and Lakhani, 2014).

3.2 Theoretical Framework

3.2.1 Strategic Human Capital

Our theory used to explain multihoming is based on a microfoundational approach toward firm capabilities. Prior literature has shown that the nature of a firm's human capital and how individuals endowed with different skills interact will affect a firm's overall ability to pursue its strategies (Castanias and Helfat, 1991, 2001; Mayer, Somaya, and Williamson, 2012). We build on this literature and focus on the human capital deployed in developing solutions for a platform's customers. This approach lets us consider both the nature of skills residing in the individual and the mechanisms through which individual knowledge gets combined to form firm capabilities. Knowledge, in this context, does not reside in a single person, but is distributed across individuals. Hence, organizational knowledge comes not only from individuals who are specialized in a task, but also from the various activities that relate the tasks and combine them into a productive routine (Nelson and Winter, 1982). In line with recent discussions on the microfoundations of strategy research, we analyze interactional effects associated with human capital on firm-level decisions (Barney and Felin, 2013).

3.2.2 Developing a Complementary Solution – An Illustration

Complementors to platform ecosystems must combine multiple types of human capital to interface with the platform. We provide a motivating example to clarify this issue. Company XYZ is a typical complementor within an ERP platform ecosystem who is developing an accounting solution for the retail industry. Producing software that is complementary to ERP and integrating it with the platform requires multiple skills. First, there is a need to understand the retail industry. Each industry has a unique set of business processes and accounting systems and the complementor must capture these nuances while recording transactions. Hence, XYZ must possess the necessary industry knowledge industry to serve the needs of its customers.

Second, the functionality provided by the accounting solution needs to be implemented within a particular ERP platform. XYZ must have the skills to understand the functionalities and processes of the underlying platform, and then extend these functionalities in ways that will both serve its customers and seamlessly integrate with the platform.[16]

Third, development of complementary products and services for a platform requires individuals who have significant knowledge about the technical complexity involved in creating a software solution. Examples include coding skills related to developing the graphical user interface, logic for manipulating the data, and structures for storing data.

To summarize, developing an accounting solution for the retail industry on an ERP platform requires our company XYZ to invest in three different forms of human capital. We depict the interrelationships between these different forms of human capital in Appendix Figure A3.1. As we will discuss next, this puts firms specialized in any one form of human capital at a disadvantage when seeking to multihome.

3.2.3 Modularity and Interdependencies among Human Capital

An open question is whether modular platform architectures reduce the need for complementors to invest in multiple types of human capital. Modularity enables

[16] For example, knowledge of how the platform handles multi-currency accounting might help the platform to develop country-specific solutions.

independence across technical modules even though there could be interdependence within each module (Baldwin and Clark, 2000). Modular designs within platforms can facilitate more widespread participation from complementors by reducing the set of technical interdependencies among modules (e.g., Tiwana *et al*., 2010). This means that while the core product and the complementor solution can have technical interdependencies within themselves, there are minimal technical interdependencies between the core product and the complementor solution. This reduces the costs to complementors of technically integrating their solution with the underlying platform. Thus, the use of modularity within a platform can reduce the needs for complementors to invest in certain kinds of technical human capital.

While modularity brings down technical interdependencies, it does not automatically resolve the interdependencies between the technical aspects of the solution and other aspects such as those related to functions, processes, and industry. This often requires firms to draw their knowledge boundaries broader than the operational technical boundaries (Colfer and Baldwin, 2016) and invest not only in technical human capital but also in functional and industry human capital. As industry experts (Jacobson, 2005) put it,

> *"The ins and outs of the system are byzantine ... you at least need the industry knowledge" ...*
> *"Many of the individuals entering this field are business majors who have limited programming skills but are knowledgeable in their fields and in business process re-engineering. This also means that industry or functional knowledge is the most important prerequisite for a consultant."*

This is consistent with recent work suggesting that technological skills may be necessary but not sufficient to build capabilities in software development (Chatterjee, 2017). In the case of ERP platform ecosystems, the underlying costs of affiliation are high because firms are required to master not only the technical challenges of interfacing with the platform but also the industry environment of the platform's users and their business processes, leading to interdependencies in the corresponding task structure. In short, modular platform architectures do not obviate the need for complementors to invest in multiple types of human capital to produce for a platform.

3.2.4 Knowledge Decomposability and the Coordination Problem

The interdependencies highlighted above have important implications for a complementor's decision to affiliate with a platform. Since knowledge required to develop software in these ecosystems often cuts across the three forms of human capital, it is complex and non-decomposable (Simon, 1962). To absorb and apply such knowledge, firms are required to bring together diverse forms of human capital, which leads to difficulties in coordination (Carlile, 2002, 2004).

For example, since all technical consultants undergo similar professional training and are also trained in similar tasks at the workplace, they tend to share a certain common language. However, when technical consultants and functional consultants try to interact, communication becomes more difficult because of the lack of a common language (Grant, 1996). Second, lack of expertise in the other field impairs the ability to track performance. For example, technical consultants may have a private incentive to overestimate the effort needed to implement a certain design made by the functional consultant. And, functional consultants may be unable to gauge the exact level of effort needed to complete a specific technical task. This could lead to other potential problems that get manifested in the form of shirking and free-riding.

3.2.5 Generalist vs. Specialists and Multihoming

The existence of these coordination costs motivates our first hypothesis regarding the advantages of generalists over specialists in multihoming. This argument is based on the premise that the fundamental task of an organization is to coordinate the efforts of many individual specialists (Grant, 1996; Kogut and Zander, 1992, 1996). There are several ways that firms can achieve these aims. They can put in place internal knowledge sharing initiatives and suitably reward employees for articulating some of their tacit knowledge in common forums. Further, they can rotate jobs so that individuals with varied expertise are able to coordinate with each other more frequently. In sum, given the size of coordination costs and the nature of the mechanisms to reduce them, it would be difficult for firms that are specialized in a particular form of human capital to replicate them by contracting for them on external markets.

In other words, due to the nature of knowledge and associated coordination costs, the different forms of human capital required to multihome are cospecialized. With cospecialization, the marginal impact of possessing a certain form of human capital at the firm level on the ability to multihome is likely to be improved by an increase in any of the other forms of human capital involved in software development. That is, firms with deep expertise in all key forms of human capital are better equipped for integrating their solution with the platform. Firms who specialize in only one form of human capital are therefore less likely to multihome. To summarize, we formulate the following hypothesis.

Hypothesis1: The higher the specialization in any one form of human capital, the lower the firm's propensity to multihome.

3.2.6 Ecosystem Learning and Multihoming

The two-sided nature of platform ecosystems has unique implications for complementor learning. Complementors learn not only independently – e.g. when learning how to interact as a team (e.g., Reagans, Argote, and Brooks, 2005) – but also learn from two sources within the ecosystem: the platform owner and the customers that the complementors serve through the platform.[17]

Complementors learn as a result of their interactions with the platform owner, using them to refine their software development process to ensure that the software solution is synchronized with the platform owner's core product. One source of such learning will come from the need for complementors to respond to changes in the platform (Kapoor and Agarwal, 2017; Foerderer *et al*., 2017). For example, ecosystem complexity will often increase over time, increasing the interactions between complementor products and those of other components within the ecosystem (Kapoor and Agarwal, 2017). Within the context of enterprise software, changes in the interfaces to and functionality within the core platform can require changes by the complementor (Foerderer *et al*., 2017). Complementors who produce for platform ecosystems such as enterprise software also seek certification from the platform owner as to the quality of the solution and its ability to interface with the core platform (Ceccagnoli *et al*., 2012; Huang *et al*., 2013).

All of these interactions between the complementor and members of the platform ecosystem require the exchange of knowledge across significant knowledge boundaries (Carlile, 2004). Knowledge-sharing and associated supporting routines between platform

[17] While here we focus on "external learning" with partners within the ecosystem, we will later explore the robustness of our analysis to controls for "internal learning" that does not require coordination with partners.

owners and their partners will critically determine the extent of value co-created in the context of business software ecosystems (Sarker *et al*., 2012; Grover and Kohli, 2012). These activities can involve semi-formalized interactions that enable brokering between the platform owner and complementor, as well as individualized knowledge boundary resources that facilitate frequent exchange of information between the platform and complementors (Foerderer *et al*., 2017). Complementors develop over time complementary interaction routines enhancing their absorptive capacity that allow them to transfer valuable knowledge across organizational boundaries (Dyer and Singh, 1998). These routines can also be deployed when multihoming.

Complementors also learn from their interactions with customers who are affiliated with the platform. In the case of enterprise software, the implementation of software built by complementors and associated business process innovation requires complementary innovation by users (Bresnahan and Greenstein, 1996; Von Hippel, 2005). Complementors will develop routines to facilitate interaction with customers. They will also learn best practices for different types of customers. Because complementors are often smaller firms who are resource constrained, we argue that these learning opportunities are facilitated by partnering with a platform and participating in the ecosystem. When the platform owners license the core product they will often suggest complementary solutions from third party firms, thereby generating leads for complementors (e.g., Wilcox and Yemen, 2011) and opportunities for learning from customers.

Through repeated engagements, complementors will develop competencies around spanning boundaries with customers. Knowledge transfer between ERP complementors and clients is arduous, and there are specific practices that can be applied to facilitate learning and knowledge transfer between complementors and clients (Ko, Kirsch, and King, 2005). Complementors not only learn how to interact with a specific customer but build a broader capability that can be deployed in other customer facing projects in the future (Ethiraj *et al*., 2005).[18]

More broadly, the process of engaging in repeated development projects enables complementors to understand how to deploy their human capital in a way that makes it efficient to handle such boundary spanning activities. Complementors will be able to transfer many of the lessons learned from these engagements to a new platform, thereby increasing the benefits to multihoming. To summarize, we predict that learning acquired over time from 'external' sources in the ecosystem, namely platform owners and customers, increases the (net) benefits to multihoming.[19] We therefore formulate the following hypothesis:

Hypothesis 2: The longer the duration of partnership with a given platform, the greater the propensity of the firm to engage in multihoming.

[18] An example of knowledge exchange between a complementor and client is the case of The Hershey Company. In 1997 Hershey decided to replace its mainframe systems with SAP's ERP product along with complementary solutions for inventory, transportation, supply chain and forecasting applications from software provider Manugistics. For Manugistics to succeed in the implementation, it needed to understand the SAP system and the data that was generated as output from or had to be fed as input into SAP. Repeated participation in such challenging integration with the platform owner reinforced Manugistics' integration learning and enabled the complementor to learn how to integrate its solution with any platform. The Hershey case also illustrates the complexity of the ERP platform ecosystem and provides a cautionary tale on how ERP deployments could go wrong if platform owners, complementors, and customers fail to come together and address the challenges concerning integration.

[19] Beyond these mechanisms, we acknowledge that longer partnership duration may be associated with higher transaction costs due to increased relationship-specific investments by the complementor. We discuss how this possibility along with other alternative mechanisms could affect our empirical findings in a later section.

3.2.7 The Interaction between Partnership Duration and Human Capital

Despite the benefits from ecosystem learning, we argue that the impact of partnership duration will not be the same across all complementors. It is useful here to summarize the key mechanism behind hypothesis 1. As pointed out earlier, integrating a solution with a platform involves not only the accumulation of technical, functional or industry knowledge but involves the understanding of elements that lie at the intersection of these different aspects. Major problems that specialized knowledge poses to organizations are actually found at such knowledge boundaries (Carlile, 2002). When the problem being solved is complex and less-decomposable (Simon, 1962), high interaction across the three forms of human capital becomes important, giving rise to cospecialization. Given this context, firms pursuing a market form of governance are at a disadvantage in integrating knowledge (Nickerson and Zenger, 2004), which, as hypothesized earlier, also put them at a disadvantage in multihoming.

However, as the partnership evolves, the key mechanism that provides an advantage to generalists in multihoming to begin with will become more important due to path dependence in knowledge accumulation and organizational learning. Indeed, even though partnership duration is likely to improve learning in complementors on average, specialists will tend to learn less than generalists.

Prior literature suggests that firms can develop an organizational competence in spanning boundaries of diverse professional and organizational settings (Grant, 1996; Kogut and Zander, 1992; Nonaka, 1994; von Hippel, 1988). Knowledge accumulated over a period of time can also be shaped through path-dependence of organizational knowledge development (Levinthal and March, 1993; Sydow *et al*., 2009). For generalists, such organizational competence will be the result of two interrelated processes. First, generalists will expand their internal knowledge base at the intersection of the different forms of human capital. Second, organizational knowledge will be reinforced over time as generalists draw on and use knowledge integration practices aimed at reducing coordination costs stemming from the possession of more diverse human capital (Orlikowski, 2002). Path-dependency may be located in both the knowledge base of the firm and in the associated knowledge management routines carried out to transfer and share knowledge (Coombs and Hull, 1998). Both of these sources of knowledge can be leveraged by generalists when affiliating with a different platform ecosystem.

Specialists, in turn, will not be able to accumulate knowledge at the intersection of different forms of human capital. Moreover, while they may be able to develop knowledge integration practices to reduce coordination costs in cooperation with ecosystem partners, these practices are costlier to be implemented using market transactions and cannot easily be leveraged with a different set of partners as required by multihoming. Hence, we predict that, even though ability to multihome improves with partnership duration on average, firms specialized in one form of human capital would be less able to take advantage of the accumulated knowledge and knowledge integration practices in the new setting.

Hypothesis 3: The impact of partnership duration with a platform on multihoming is reduced if the firm is specialized in any one form of human capital.

3.3 Data and Methodology

3.3.1 Empirical Setting.

We test these hypotheses in the ERP platform ecosystem setting. Within the ERP ecosystem, SAP and Oracle are the dominant platform owners that develop and license the core ERP product to end customers. Just as developers develop apps in the mobile ecosystem and choose whether to do so only on Apple or Android or both (multihome), ERP complementors face similar choices with regard to SAP and Oracle. However, products and services on the ERP platform are complex and require some combination of functional, technical and industry human capital to deliver solutions.

We use a key feature of our research setting: the ecosystem witnessed a series of platform-level acquisitions by Oracle during our sample period. We exploit Oracle's acquisitions as a change in the benefits of multihoming that SAP complementors are heterogeneously able to take advantage of based on the skill characteristics of their employees prior to the change.

3.3.2 Sample

We have built a comprehensive dataset on the ERP platform ecosystem based on several secondary data sources. The dataset covers the years 2001-2006 that marked the rise of Oracle as an ERP platform owner and the subsequent intense rivalry between SAP and Oracle. This is especially important given that we are interested in events that shift the value of multihoming. We discuss this aspect in more detail in the identification section.

To identify complementors and their multihoming decisions, we first obtained a list of SAP partners. SAP maintains an active partner website that contains information on complementors that offer solutions based on the SAP ERP product. However, limiting the partners to ones from the current SAP's partner website is likely to induce a survivorship bias. Hence, we augmented the list of firms by adding exhibitors from past SAP SAPPHIRE and SAP Insider annual meetings.

We decided to focus on US-based complementors in order to ensure that firms within the sample are comparable and because some of our control variables are available only for US firms. We use press releases data from Factiva to identify the year of partnership formation with SAP. We relied on keyword based searches to identify the press releases related to both SAP and the complementor firm. We took each firm from the list of SAP complementors built earlier and checked for the earliest date in which the firm and SAP occurred together in a press release. The assumption made here is that if a complementor is mentioned along with SAP in a press release, the partnership between SAP and the complementor is at least as old as the press release. After comparing the press release information obtained from Factiva with the one from Lexis Nexis for 10% of the sample, we found Factiva to be much better in terms of both coverage and precision. Hence, we chose to use Factiva. The same approach was used for obtaining the year of multihoming (affiliating with the Oracle platform).

For obtaining detailed micro-level data on human capital, we downloaded CVs of both present and past employees of the partner firms from a popular online professional network. We also obtained data on firm sales and firm size from the National Establishment Time Series (NETS) database. It is a time series of the archival Dun and Bradstreet (D&B) database and contains information on close to 50 million unique establishments between

1990 and 2013. The dataset covers both private and public establishments and contains information on the establishment tree that enables us to aggregate sales and employee data to the firm level. We matched the list of SAP partners with the NETS database and ended up with 1,012 DUNS numbers for headquarters which corresponded to 45,339 target establishments. We used the tree structure to aggregate the establishment data back to the firm level. We retained only those complementor firms that had less than 5000 employees at the time of partnering with SAP to reduce the extent of unobserved heterogeneity in the sample. The unit of observation in our sample is the firm-year.

3.3.3 Dependent Variable

The dependent variable is multihoming which takes either zero or one as its value. Multihoming starts with zero when a complementor firm enters into a partnership with the SAP ERP platform and turns into one if and when the firm enters into a partnership with the Oracle platform. If the firm never multihomes, the variable remains at zero until the end of the sample.

3.3.4 Independent Variables

We seek to investigate how firms' ex ante endowments of human capital allow them to take advantage of new opportunities for multihoming. We construct separate variables corresponding to each of these three types of human capital specialization: functional, technical and industry. Here we provide an overview of our approach; more details are available in the Appendix.

First, we identify a set of keywords that are associated with a specific form of human capital. We identify keywords for the different forms of human capital from resources that are publicly available on SAP's own support website.[20]

Second, we search within the employee CV data for the keywords identified above and count all relevant instances of their appearance. To do this, we first identify the individuals employed with the sample company in a given year. Next, we count the total number of appearances of each of the keywords (identified earlier) within the CVs of the relevant individuals. The number of keywords found in a CV may depend on its total length. To control for this effect, we divide the keyword match count by the number of words in the CV. In order to account for the obsolescence of knowledge over time, we limit ourselves to the knowledge accumulated over the five years prior to the firm-year under consideration. We repeat this procedure for each and every individual identified as a valid employee of the focal firm in a given year.

Third, we aggregate the individual capabilities to the firm level to obtain a firm-year measure for each form of human capital. We first add up the skills across the employees and then bring the skill values to the per-employee level by dividing by the number of employees in the sample. Though more complex aggregation approaches are possible, this simple form of aggregation is consistent with the microfoundational view of firm strategy (Barney and Felin, 2013). For each of the three types of human capital, we compute the stock as of 2001 and then create a dummy variable that is equal to one when the value of that type of human capital exceeds the 75th percentile within its category. We provide further details on these three variables below.

[20] For example, SAP architecture-related terms such as ABAP and NetWeaver and coding languages such as Java and C++ correspond to technical human capital; Automotive, Utilities and Banking are some of the industries where these ERP products are implemented; and Materials Management (MM) and Plant Maintenance (PM) are some of the functional modules within the ERP product.

3.3.4.1 Technical Human Capital

Technical human capital enables the firm to develop an understanding of the technical architecture of a platform. This knowledge is useful in developing code fragments that interact with and add value to the underlying platform.

3.3.4.2 Functional Human Capital

Functional human capital is essential to grasp the business process flows built into an ERP platform. An end-to-end business process usually involves several steps that are carried out by individuals spread across an organization. It often cuts across several modules within the ERP platform as well as those built by complementors. An individual specialized in functional human capital understands the particular way in which a business process such as procure-to-pay is implemented within the ERP platform.

3.3.4.3 Industry Human Capital

Knowledge-based work is often carried out with a certain industry context (Mayer, Somaya and Williamson, 2012). The same is true for the development and deployment of ERP-based products and services. Industry human capital may simply be thought of as the skills required to adapt such products and services to an industry context.

3.3.4.4 Specialized Firm

We designate as specialist firms those who are above the 75th percentile in one and only one of the human capital measures described above. Our measure of specialist firm is equal to one when the firm is specialized in only one type of human capital, and zero otherwise.

3.3.4.5 Acquisition Time Window (ATW)

In order to capture the effect of announcements regarding platform-level acquisitions by Oracle, we use a dichotomous variable that is equal to one during the ATW (which is defined as three years immediately following the first acquisition related announcement, which occurred in 2004) and is zero otherwise.

3.3.4.6 Duration of Partnership (Duration)

The duration of partnership is equal to the number of years spent with the SAP platform as of the start of the ATW.

3.3.4.7 Control Variables

We control for the number of firm employees and total firm sales. It has been shown in the literature that these two variables control for a vast array of firm capabilities and, hence, have considerable potential to influence firm strategies. In our setting, we can think of firm sales as a proxy for the quality of the complementor product.

3.3.5 Identification

A potential challenge that we face is omitted variable bias: human capital investment measures at the firm level may be correlated with the benefits of affiliating with a different platform. Rather than examine the in-sample correlation between human capital investment and multihoming, we fix our human capital variables at pre-sample levels and instead examine heterogeneity in response to an exogenous demand shock that increased the benefits of joining the Oracle platform, based upon the ex-ante human capital investments within the firm.

We use a *fixed effects* model that controls for time invariant firm-level unobservables and *time dummies* that control for events that are common across firms in any given year. Our identification strategy relies on the assumption that, even if the shock could have been anticipated, it is difficult for firms to change their human capital mix in the short run using the labor market because it takes time for teams to learn to work together.[21]

Our exogenous shock is based upon a series of acquisitions made by Oracle. Starting in 2004 with the acquisition of PeopleSoft, Oracle made a series of application platform acquisitions to inorganically increase its market share within a short period of time (Bloomberg, 2011). The acquisition of PeopleSoft was initially valued at $11 billion, which was then the largest ever acquisition within the IT industry. This attracted the attention of antitrust authorities both in the US and Europe. But, in 2004, the US courts ruled in favor of Oracle and against the Department of Justice. This was soon followed by a similar judgement in Europe. Not only were these developments pivotal in Oracle's inorganic growth strategy, but they also represented a strong signal for complementors thinking about partnering with Oracle. They meant that Oracle partners had access to significantly larger demand than had previously been the case.

While partnering with Oracle represented a significant opportunity, joining the new platform was not an easy undertaking for SAP partners. We make use of heterogeneity

[21] We test the robustness of this assumption by replacing the HC values obtained as of the beginning of the sample (2001) with the HC values based on the last year of the sample (2006). We find that there is no systematic variation in the HC values across the years and our initial results continue to hold.

across firms in human capital to identify how different pre-acquisition firm characteristics related to human capital influenced a change in the propensity to multihome during and after the acquisitions. Indeed, even though all firms are subject to the exogenous shock, according to our theory, the ones that are highly specialized in any one form of human capital are expected to be less responsive to the shock.

3.3.6 Estimation Methodology

We use a panel data linear probability model (LPM) with firm level fixed effects (Wooldridge, 2001) for estimation. Our use of the LPM rather than a nonlinear model (e.g., probit or logit) reflects several considerations. Most importantly, the LPM will deliver consistent estimates of the parameter of interest (Angrist and Pischke, 2009). A major drawback will be the existence of heteroskedastic standard errors, which we address using robust standard errors. The LPM allows us to difference out the firm-level fixed effects without loss of observations in our dataset (as would be the case with a probit or logit, for example). Further, the linear model allows for more straightforward interpretations of implied marginal effects from our parameter estimates: Our models include interaction terms, and the signs of the interaction terms do not identify the signs of the marginal effects in nonlinear models (Ai and Norton 2003; Hoetker, 2007; Wiersema and Bowen 2009; Zelner, 2009). Further, while models such as the conditional fixed effects logit allow conditioning on firm effects, they are not amenable to the computation of marginal effects (Greene, 2017). Last, nonlinear models may be inconsistent when there are a large number of zeroes in the dependent variable, as there are in our sample (King and Zeng, 2001). In the Appendix we provide results from survival models and they are qualitatively robust.

We treat multihoming as the final absorbing state under the assumption that a multihoming partner does not leave the new platform ecosystem (Oracle) at a later point in time. The continued presence of these partners on the Oracle partner site confirms our assumption. Hence, we delete all observations post-multihoming and structure the data as an unbalanced panel. Further, we drop firms who partnered with SAP after the ATW, as there will be no variation in the key variables of interest: the interaction of the ATW with human capital and the duration of partnership. In sum, we have 1020 observations from 226 firms.

3.4 Results

Table 3.1 shows the basic summary statistics while Table 3.2 reports the correlations. Specialized firms constitute approximately 30% of our sample. The mean of partnership duration prior to the start of the ATW is approximately 4.6 years. As one might expect, the correlation between the logged values of employee count and sales is quite high.

Table 3.1 Descriptive Statistics

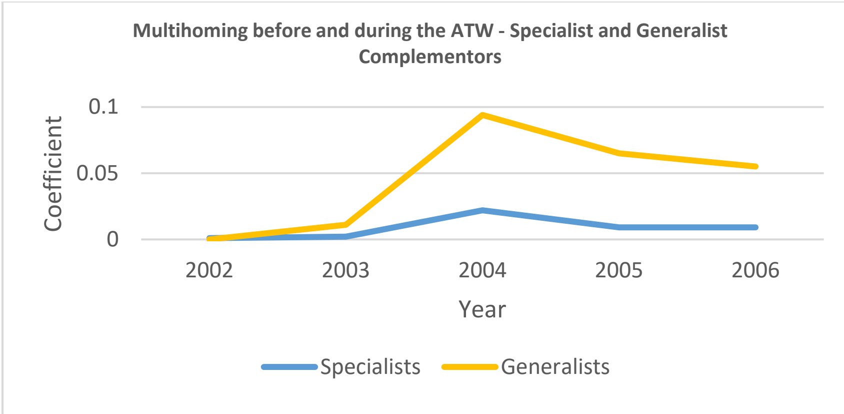
Variable	Description	Mean	Std. Dev.	Min	Max
Multihoming	Dichotomous variable (equals 1 when the firm multihomes and stays 0 otherwise)	0.029	0.169	0	1
Log Employees	Log Transformation of Number of Employees	2.504	2.753	0	12.35
Log Sales	Log Transformation of Sales Revenues	9.936	7.637	0	24.23
Specialist Firm	Firms above the 75th percentile on only one of the three forms of Human Capital namely Technical, Functional or Industry	0.300	0.458	0	1
Partnership Duration	Duration of Partnership with SAP (difference between the year 2004 and the start of partnership)	4.571	2.391	0	10
Age at Partnership	Firm age at the beginning of partnership with SAP	3.586	4.408	0	15
Technical HC	Firms above the 75th percentile on Technical HC	0.253	0.435	0	1
Industry HC	Firms above the 75th percentile on Industry HC	0.250	0.433	0	1
Functional HC	Firms above the 75th percentile on Functional HC	0.249	0.433	0	1

Number of Firms: 226; Number of Observations: 1020

Table 3.2 Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Multihoming	1								
(2) Log Employees	-0.02	1							
(3) Log Sales	-0.01	0.85	1						
(4) Specialist Firm	0.00	0.00	-0.01	1					
(5) Partnership Duration	0.12	0.14	0.12	0.00	1				
(6) Age at Partnership	0.05	0.42	0.58	-0.11	-0.17	1			
(7) Technical HC	-0.06	-0.11	-0.08	0.1	-0.09	-0.08	1		
(8) Industry HC	-0.07	-0.02	-0.08	0.08	-0.08	-0.08	0.27	1	
(9) Functional HC	-0.05	0.04	0.02	0.19	0.08	-0.08	0.16	0.17	1

Our shock is relevant. In Figure 3.1, we show graphically that the ATW had a positive effect on multihoming. The coefficients plotted in the graph are based on a linear regression with multihoming as the dependent variable and the sample year dummies as independent variables. We also interact the *specialized firm* variable with every year dummy. We clearly find that (1) there is an increase in multihoming during the time window and (2) the coefficients for *specialized firm*s x *year dummy* are lower than those of *other firms* x *year dummy* during the window.



Note: Each point on the above graph represents the coefficient on the year dummy corresponding to the two types of complementors. The values are relative to the base year of 2001 for generalist complementors.

Figure 3.1 Effect of the Acquisition Time Window on Multihoming

Table 3.3 H1: Effect of the Acquisition Time Window on Multihoming for Specialists vs Generalists

Dependent Variable: Multihoming	(1) Specialized Firm	(2) With controls
Log Employees		0.005
		(0.006)
		[0.373]
Log Sales		-0.003
		(0.002)
		[0.083]
Specialist Firm X ATW	-0.056	-0.057
	(0.022)	(0.022)
	[0.010]	[0.010]
Constant	-0.012	0.006
	(0.010)	(0.009)
	[0.233]	[0.531]
Firm FE	Y	Y
Year FE	Y	Y
Observations	1,020	1,020
Number of Firms	226	226
R-squared	0.067	0.070
R-squared (with effect of fixed effects)	0.616	0.617

Robust standard errors clustered by firm in parentheses; p-values in brackets.
ATW: Acquisition time window (2004-2006). Estimates based on the linear probability model.

We next present our regression results. We first present results showing the effects of specialization and duration separately and use these as the source of tests for Hypothesis 1 and 2. However, each of these models contain omitted variables: duration in the case of tests for the effects of specialization and vice versa. Our full model, that is consistent with our theoretical framework, is the one that contains the effects of specialization, duration, and their interaction. These will represent the primary results of the paper.

Our first set of regression results include the interaction of our dummy for specialist firm with a separate indicator for whether the observation is in the ATW. The results in Table 3.3 show that specialized firms have a lower propensity to multihome after the ATW shock by 5.6 (p-value 0.010) to 5.7 (p-value 0.010) percentage points, which is in line with hypothesis 1.

In our motivation for Hypothesis 1 we describe how the reason for the weaker response of specialists to the demand shock is due to the need for all three types of human capital in order to produce for the new platform. To examine the empirical salience of this explanation, we use our data to test for the presence of complementarities among the three sources of human capital. Table 3.4 captures the interaction effects among the different measures of human capital and ATW.[22]

Specialization in any of the three types of human capital—technical, functional, and industry—is associated with a weaker response to the demand shock. That is, the coefficient estimates of each of these variables with ATW is negative. However, the three-way interactions between any of the two types of human capital and the ATW are positive.

[22] Note that individual effect of the HCs in themselves are not identified since we employ a fixed effects regression with pre-shock HC values corresponding to each firm.

Table 3.4 H1: Effect of the Acquisition Time Window on Multihoming depending on different HC profiles

Dependent Variable: Multihoming	(1) Technical HC - Functional HC Interaction	(2) Functional HC - Industry HC Interaction	(3) Technical HC - Industry HC Interaction
Log Employees	0.007	0.008	0.004
	(0.006)	(0.006)	(0.006)
	[0.285]	[0.218]	[0.476]
Log Sales	-0.003	-0.004	-0.003
	(0.002)	(0.002)	(0.002)
	[0.132]	[0.087]	[0.176]
Technical HC X ATW	-0.058		-0.049
	(0.031)		(0.034)
	[0.065]		[0.151]
Functional HC X ATW	-0.084	-0.090	
	(0.022)	(0.023)	
	[0.000]	[0.000]	
Technical HC X Functional HC X ATW	0.061		
	(0.032)		
	[0.062]		
Industry HC X ATW		-0.088	-0.077
		(0.022)	(0.020)
		[0.000]	[0.000]
Industry HC X Functional HC X ATW		0.090	
		(0.023)	
		[0.000]	
Technical HC X Industry HC X ATW			0.051
			(0.035)
			[0.139]
Constant	-0.002	0.001	0.003
	(0.010)	(0.010)	(0.009)
	[0.865]	[0.879]	[0.776]
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	1,020	1,020	1,020
Number of Firms	226	226	226
R-squared	0.082	0.090	0.077
R-squared (includes fixed effects)	0.622	0.626	0.620

Robust standard errors clustered by firm in parentheses; p-values in brackets.
ATW: Acquisition time window (2004-2006). Estimates based on the linear probability model.

This provides evidence in support of complementarity between the different forms of human capital. For example, column 1 shows that if a firm only has technical human capital then the likelihood of multihoming after the ATW declines by 5.8 percentage points (p-value 0.065). However, if the firm also has functional human capital then the net effect of possessing both forms of human capital is approximately 0.

Table 3.5 H2 & H3: Effect of the Acquisition Time Window on Multihoming depending on partnership duration and its interaction with Specialists vs Generalists

Dependent Variable: Multihoming	(1) Duration	(2) Duration-Specialization Interaction
Log Employees	0.004	0.006
	(0.006)	(0.006)
	[0.512]	[0.349]
Log Sales	-0.003	-0.004
	(0.002)	(0.002)
	[0.125]	[0.058]
Specialist Firm X ATW		0.038
		(0.047)
		[0.419]
ATW X Partnership Duration	0.006	0.011
	(0.004)	(0.006)
	[0.155]	[0.063]
Specialist Firm X ATW X Partnership Duration		-0.018
		(0.008)
		[0.024]
Constant	0.012	0.016
	(0.009)	(0.010)
	[0.180]	[0.090]
Firm FE	Y	Y
Year FE	Y	Y
Observations	1,020	1,020
Number of Firms	226	226
R-squared	0.061	0.076
R-squared (includes fixed effects)	0.613	0.620

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

ATW: Acquisition time window (2004-2006). Estimates based on the linear probability model.

This is consistent with the views of an industry expert that we interviewed (quoted below) and reiterates the point that in our context different forms of HC are cospecialized. In particular, these results emphasize the importance of knowledge of business processes and the industry to ERP systems in addition to technical knowledge.

> *"The business analyst [functional HC] acts as some kind of a bridge between the industry consultants and the software developers [technical HC]"*

We next analyze the results corresponding to hypothesis 2 concerning the impact of partnership duration on multihoming. Column 1 shows that the interaction term between ATW and duration is positive (p-value 0.155). To understand the economic impact of partnership duration on multihoming, we computed the predicted probability of multihoming for firms before and after the shock based upon whether or not their partnership duration was above the median. For firms whose partnership duration is below the median, the demand shock increased the predicted probability of multihoming by 2.8 percentage points—from 1.0% to 3.8%. For those whose partnership duration is above the median, the demand shock increased the predicted probability by 6.0 percentage points—from 0.1% to 6.1%. This is consistent with hypothesis 2.

The second column in Table 3.5 includes the interactions between duration, specialization, and ATW. This is our fully specified model and represents the primary results of our paper. We find that the marginal effect of partnership duration on the likelihood of multihoming is lower for specialized firms (coefficient -0.018; p-value 0.024), which is in line with the prediction from Hypothesis 3. To understand the size of these effects, we compute the marginal effects of ATW for firms with partnership duration below and above the median, but also compare the results for specialists and generalists.

As a result of the demand shock, the predicted probability of multihoming increases by 2.9 percentage points for specialists with short term partnership and by 0.6 percentage points for specialists with long term partnerships. In contrast, however, as a result of the demand shock the predicted probability of multihoming increases by 2.7 percentage points for generalists with short term partnerships but increases by a sizeable 8.4 percentage points for generalists with long term partnerships. In short, the marginal effects of duration during the ATW are larger for generalists than specialists, which is consistent with H3.

We can also use these results as a source of tests for Hypothesis 1 and 2. Evaluating the marginal effect of being a specialist at the mean value of partnership duration (4.571) yields a marginal effect of -0.044 (=0.038 – 0.018*4.571, p-value = 0.048), which is consistent with Hypothesis 1. The difference between the marginal effect of being a specialist for long and short duration is striking. When duration is 0, the marginal effect of being a specialist is 0.038 (p-value 0.419), while when duration is at the 75th percentile (duration=7) the marginal effect is -0.088 (p-value 0.001).

We next discuss whether our results for the fully specified model provide support for Hypothesis 2. The marginal effect of partnership duration at mean values of being a specialist (0.3) is equal to 0.006 (=0.011-0.018*0.3, p-value = 0.177), which is similar to the estimate in column 1 of Table 3.5 in economic and statistical significance. Thus the point estimate is consistent with Hypothesis 2, but not at conventional thresholds of statistical significance. This result is in part because a significant portion of the sample is comprised of specialists who receive fewer benefits from partnership duration. Among generalists, the marginal effect of duration is 0.011 (p-value=0.063).

3.4.1 Robustness Checks

3.4.1.1 Nonlinear Models

In our baseline models we use the LPM to examine the effects of specialization and duration on multihoming. As robustness we model these effects using hazard models. These directly model time to event, relaxing the normality assumption imposed in linear regression and providing an approach to address censoring (Hosmer and Lemeshow, 1999). We use the Cox proportional hazard model. The Cox model is semiparametric, making no assumptions of the baseline hazard over time and assuming that covariates multiplicatively shift the baseline hazard function. We present the estimates from the Cox model in Table A1.10. Directionally the estimates of the key parameters in the Cox models are similar to those in the baseline linear models. However, because the Cox is a nonlinear model with interactions, we cannot use the signs of the coefficients to directly test hypotheses (Ai and Norton, 2003). To test hypotheses and to understand the economic effects of changes in our key variables on outcomes, we study the effects of a change in our key variables on the log of the hazard rate. In other words, we examine the semi-elasticities of the hazard rate with respect to a change in each of the key variables of interest.

We will briefly discuss the results of the fully specified model. The semi-elasticity of going from being a generalist to being a specialist when duration is 0 is actually positive, with a value of 2.124 (p-value 0.019). However, at the 75th percentile of duration (Duration=7 years) the semi-elasticity of becoming a specialist is negative, -1.814 (p-value 0.048). Similarly the semi-elasticity of increases in partnership duration for generalists is

0.320 (p-value 0.000), while that for specialists is -0.424 (p-value 0.140). The value of learning for generalists is greater than that for specialists. In short, the results of our estimates using the Cox model is supportive of our hypotheses.

3.4.1.2 Other Robustness Checks

We carried out a number of other robustness checks. We check whether our results are sensitive to changes in length of the ATW, alternative ways of measuring partnership duration, and alternative cut-offs to our specialization dummy. Our results are robust to all of these changes. We further carry out a falsification exercise using an alternative time window to ATW in which there was not a demand shock to the Oracle platform ecosystem. In particular, we re-estimate the baseline model replacing the ATW window using a window indicating the dot com bubble. Our baseline results do not hold during this time window. Detailed results for all of these analyses are included in the Appendix.

3.5 Alternative Explanations

In this section we discuss three alternative explanations that have the potential to shape multihoming decisions and our results. We are unable to rule out the possibility that these explanations have some effect on our estimates. However, as we described in further detail below, we show these explanations often work against the findings in our paper, making it harder for us to find evidence in support of our hypotheses and the mechanisms described. They are also unable to provide an explanation for our complete set of results.

3.5.1 Different types of learning

In our development of hypothesis 2 we emphasized the learning that occurred through repeated interactions with platform owner and customers. However, we are unable to observe these interactions directly. Rather our measure of learning is based on the partnership duration. Other types of learning could take place over time and which could facilitate the delivery of enterprise software. In particular, repeated interaction in prior engagements can lead to better team learning (Reagans, Argote and Brooks, 2005). Over time there is a solidification of roles and responsibilities within a complementor team and team members develop a sense of familiarity with regard to both the division of tasks and the coordination among those tasks. Such familiarity enables the team to arrive at a better division of labor. Also, teams tend to codify collective knowledge enhancing the performance of repetitive tasks (Zollo and Winter, 2002).

Though this latter type of learning is not dependent on the length of affiliation with the platform ecosystem, it will increase over time. As a result, it is a possible alternative explanation for the results that are in support of H2. To examine the salience of this alternative hypothesis, we explore a robustness check in which we include an additional variable that is equal to the age of the firm prior to the start of the partnership with the platform ecosystem. The logic of this variable is that it will capture early stage learning that will be particularly salient to the formation and coordination of teams. The mean of this variable is 3.6 years, with max 15. The correlation of this variable with partnership duration is low (-0.17). In column 2 of Appendix Table A1.6 we show that adding this variable does not affect the estimates in support of H2. Further, in column 3 of that table we re-estimate our full model on the subset of firms whose age at partnership is greater than 4 years. The logic behind doing this is that these firms will have already completed some team learning prior to the formation of the partnership. As a result, the estimates for partnership duration are less likely to be contaminated by the effects of this type of early stage team learning. The parameter estimates for the key variables related to specialization and learning are qualitatively similar in this subsample in terms of economic and statistical significance. This lends further credence to the view that our estimates are capturing learning that occurs as a result of engagements with members of the platform ecosystem. We further note that while we are unable to rule out the effects of internal team learning influencing our partnership duration variable, such an explanation based upon team learning would be unable to explain our results in support of H3.

3.5.2 Relationship-Specific and Cospecialized Investments

Another alternative explanation is that our results reflect the effects of relationship-specific or cospecialized investments with the platform. For example, in a software development context such as ours, it has been shown that firms develop both relationship-specific capabilities as well as general capabilities through repeated engagements (Ethiraj *et al*., 2005). In our context, complementors may develop capabilities and routines for working with the platform owner and may refine these over time. While some of these capabilities and routines may be transferable to a new platform—a possibility that we describe in our motivation for Hypothesis 2—some may not be transferable and so the value of these capabilities and routines may be far less valuable in the new setting. However, if learning is relationship-specific, then that would lead to a prediction of a negative or no relationship between partnership duration and multihoming, not the positive relationship that we observe.

A related issue is that our measure of specialization could be capturing relation-specific investments in a particular type of human capital. For example, prior work has emphasized the costs of integrating the software code between the platform and complementor (e.g., Anderson, Parker, and Tan, 2013; Cennamo, Ozalp, and Kretschmer, 2018; Claussen, Essling, and Kretschmer, 2015; Gawer, 2014). Our measure of specialization – and our test of H1 – could therefore reflect the implications of technical investments that are specific to the platform. We explore this possibility in Table 3.4, in which we decompose human capital into its three constituent parts—technical human capital, functional human capital, and industry human capital. A key implication of the results in that table is that complementors need multiple types of human capital to multihome. In fact, the table shows that while the combination of technical and functional (column 1) and industry and functional (column 2) human capital both influence the likelihood of multihoming, technical and industry does not (column 3). In other words, the empirical evidence suggests that it is functional, not technical, human capital that is necessary for multihoming. This is consistent with our earlier discussion about the importance of functional knowledge to the development of enterprise software.

3.5.3 Why do firms become specialists?

Our results use variance in the extent to which complementors have general or specialized human capital at the beginning of our sample to determine the likelihood that they will respond to an exogenous shock by multihoming. Given the benefits to becoming a generalist, one question is whether firms choose to become specialists for reasons that could influence our results.

Our research design does not enable us to determine the reasons for why firms become specialists or generalists. However, it does enable us to control for some obvious sources of bias that might arise from endogenous selection into being a generalist. Our baseline estimates all use firm-level fixed effects, and our human capital computations are based on the stock up to 2001, the first year of our sample. As a result, we control for many sources of bias that could arise from firm-level time-constant unobservables that might influence selection into being a generalist. Further, our use of static human capital measures mean that they will not be changing in our sample in response to time-varying factors that might influence the likelihood of multihoming.

While our empirical approach controls for firm-level time-invariant factors, there may exist time-varying factors that are differentially correlated with human capital investments and that could influence the likelihood of multihoming. For example, resource-constrained complementors could choose to specialize in a particular type of human capital because it enables them to build a higher quality product, even when specialization makes it more difficult to integrate with the platform. However, if specialists have a higher quality product this would lead to a prediction that they would have a higher likelihood of multihoming in response to the demand shock, which is the opposite of what we observe. In other words, the presence of time-varying unobserved quality in the complementor's products or solutions would induce a positive bias on the effect of human capital specialization on multihoming, while we find a negative effect. As for the case of transaction costs, while important omitted variables may affect the size of the analyzed effects, our qualitative findings remain robust due to the direction of the associated biases.

In short, our estimation strategy allows us to control for many sources of bias that would arise from endogenous human capital investment decisions. While we acknowledge that understanding the reason for these decisions are of independent interest, we leave examination of this issue to future research.

3.6 Discussion and conclusions

We investigate the responses of complementors to a demand-side opportunity arising from the consolidation of a competing platform. Complementors are more likely to multihome when they possess a set of cospecialized complementary assets. Complementors' responses also depend upon the duration of their partnership with the pre-existing platform. The evidence supports the view that there is learning that occurs as a result of partnership with the existing platform and this learning influences the response to the new opportunity. However, the response to learning is also greater for complementors with the requisite cospecialized assets. In particular, the evidence supports the view that complementors who are generalists develop capabilities at integrating knowledge across diverse forms of human capital and this increases their propensity to multihome relative to specialists.

We contribute to a line of research within the platform ecosystem literature that explores how knowledge barriers and coordination costs influence the value of affiliating with a platform. In contrast to much of the work in this area that has focused on the implications of platform owner actions (e.g., Anderson, Parker, and Tan, 2013; Claussen, Essling, and Kretschmer, 2015; Gawer, 2014; Boudreau, 2010; Tiwana, 2015) we build on recent work that has focused on the characteristics of complementors and their strategic decisions (Kapoor and Agarwal, 2017; Agarwal and Kapoor, 2018; Cennamo, Ozalp, and Kretschmer, 2018). However, by focusing on the human capital of complementors, we approach these questions from a unique perspective.

Our research is also related to work on related diversification, in particular that work which has explored the decisions of IT software and hardware firms to diversify by offering multiple products on the same platform or the same product on multiple platforms (Stern and Henderson, 2004; Tanriverdi and Lee, 2008; Cottrell and Nault, 2004). While much of the prior work in this area examines how the diversification strategy of these firms at a particular point in time influence performance, we focus on how the possession of key cospecialized complementary assets and learning that has taken place on home ecosystem influences the decision to affiliate with another platform. In this way, we follow earlier work that has emphasized how knowledge, resources, and capabilities accumulated in one product market can be extended into related product markets (Penrose, 1959; Helfat and Eisenhardt, 2004; Døving and Gooderham, 2008). In particular, our approach is informed by approaches that argue that firms can possess both core product knowledge and integrative knowledge that can facilitate coordination across production chains (Helfat and Raubitschek, 2000). While we similarly emphasize how knowledge of how to integrate in an inter-firm relationship can be applied in new contexts, we also highlight in particular the accumulation of knowledge at the intersection of three forms of human capital and the organizational competencies that arise from integrating knowledge across boundaries.

Further, our research also has implications for the broader strategy literature. In particular, firm response to environmental change has been of interest to a wide range of scholars. While most of the prior focus has been on response to technological change (Tushman and Anderson, 1986; Henderson and Clark, 1990; Christensen, 1997), response to demand side changes has been of interest to scholars more recently. Researchers in this stream have looked at both its theoretical implications (Adner and Levinthal, 2001) and tested them empirically in different settings such as the medical device (Chatterji and Fabrizio, 2012) and defense industries (Agarwal and Wu, 2015). We complement this prior work by studying the strategic role played by human capital in heterogeneous organizational response to demand side changes in the enterprise software industry.

Our study has implications for managers thinking about sourcing and deploying talent. If the deployment of knowledge did not require coordination across workers, then firms could obtain the necessary skills to multihome by contracting for labor or acquiring them directly through the labor market. However, the necessary knowledge arises from repeated coordination among individuals belonging to the organization and, hence, becomes embedded in the organizing principles that govern coordination (Kogut and Zander, 1992). Internal organization not only solves the problem of motivation among individuals but brings about better communication efficiency (Williamson, 1975: P. 25). This becomes especially important when firms try to deal with uncertainty or respond to changes in the demand environment within a relatively short period of time

> *"It can be a challenge especially for small companies … it is very hard to get product knowledge and process knowledge transferred to new employees"*

As illustrated by the above quote from an industry expert, bringing in new individuals from the market and getting them accustomed to a complex routine takes time. It makes it hard for firms to exploit the labor market to respond to rapid changes, forcing them to rely on redeployment of existing human capital.

Our study also has some limitations. Given the nature of our data and the sources of variation that we observe, there may be competing factors at work that could influence our results. As we describe in further detail above, increases in partnership duration may also be correlated with internal team learning that leads to improvements in the ability of complementors to develop and market new software. Further, our results may also be influenced by complementor investments that are specific to the existing platform. These factors are likely to work against our results and we provide some empirical tests to help circumscribe how they might influence our estimates. However, we are unable to quantify their effects.

Firms make strategic decisions related to the nature of their human capital investments in response to a variety of internal and external factors. By focusing on pre-sample human capital and using firm-level fixed effects, our research design controls for many potential sources of omitted variable bias that could influence both human capital decisions and multihoming. However, it is also similarly unable to speak to the reasons that firms choose a specific human capital profile. This is an important set of questions. We hope that our results will encourage further investigation into these questions, as well related inquiries into the causes and implications of human capital decisions by complementors, in future research.

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3.8 Appendix

3.8.1 Robustness Checks

Table 3.6 Alternative Measure: Longer ATW - Five Years (2004-2008)

Dependent Variable: Multihoming	Specialized Firm	Technical HC - Functional HC Interaction	Functional HC - Industry HC Interaction	Technical HC - Industry HC Interaction
Log Employees	0.002	0.003	0.003	0.001
	(0.003)	(0.003)	(0.003)	(0.003)
	[0.422]	[0.329]	[0.250]	[0.791]
Log Sales	-0.002	-0.001	-0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
	[0.066]	[0.151]	[0.089]	[0.250]
Specialist Firm X Longer ATW	-0.047			
	(0.018)			
	[0.010]			
Longer ATW X Technical HC		-0.049		-0.041
		(0.026)		(0.028)
		[0.058]		[0.143]
Longer ATW X Functional HC		-0.070	-0.074	
		(0.019)	(0.019)	
		[0.000]	[0.000]	
Longer ATW X Technical HC X Functional HC		0.052		
		(0.027)		
		[0.050]		
Longer ATW X Industry HC			-0.072	-0.063
			(0.018)	(0.017)
			[0.000]	[0.000]
Longer ATW X Industry HC X Functional HC			0.075	
			(0.019)	
			[0.000]	
Longer ATW X Technical HC X Industry HC				0.043
				(0.028)
				[0.132]
Constant	-0.010	-0.015	-0.013	-0.011
	(0.009)	(0.010)	(0.009)	(0.009)
	[0.261]	[0.119]	[0.170]	[0.207]
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	1,412	1,412	1,412	1,412
Number of Firms	226	226	226	226
R-squared	0.064	0.075	0.082	0.071
R-squared (includes fixed effects)	0.618	0.622	0.625	0.621

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

Longer ATW: Longer Acquisition time window (2004-2008). Estimates based on the linear probability model.

Table 3.7 Alternative Measure: Shorter ATW - Two Years (2004-2005)

Dependent Variable: Multihoming	(1) Specialized Firm	(2) Technical HC - Functional HC Interaction	(3) Functional HC - Industry HC Interaction	(4) Technical HC - Industry HC Interaction
Log Employees	0.011	0.013	0.014	0.009
	(0.010)	(0.010)	(0.010)	(0.010)
	[0.278]	[0.197]	[0.174]	[0.355]
Log Sales	-0.006	-0.005	-0.006	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)
	[0.092]	[0.110]	[0.092]	[0.172]
Specialist Firm X Shorter ATW	-0.065			
	(0.026)			
	[0.014]			
Shorter ATW X Technical HC		-0.065		-0.054
		(0.038)		(0.041)
		[0.088]		[0.185]
Shorter ATW X Functional HC		-0.098	-0.105	
		(0.027)	(0.027)	
		[0.000]	[0.000]	
Shorter ATW X Technical HC X Functional HC		0.069		
		(0.039)		
		[0.081]		
Shorter ATW X Industry HC			-0.101	-0.089
			(0.026)	(0.024)
			[0.000]	[0.000]
Shorter ATW X Industry HC X Functional HC			0.104	
			(0.027)	
			[0.000]	
Shorter ATW X Technical HC X Industry HC				0.057
				(0.042)
				[0.170]
Constant	0.019	0.011	0.014	0.014
	(0.010)	(0.011)	(0.011)	(0.010)
	[0.060]	[0.328]	[0.215]	[0.172]
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	823	823	823	823
Number of Firms	226	226	226	226
R-squared	0.077	0.091	0.102	0.086
R-squared (includes fixed effects)	0.632	0.638	0.642	0.636

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

Shorter ATW: Shorter Acquisition time window (2004-2005). Estimates based on the linear probability model.

Table 3.8 Alternative Measure: Specialist Firm - 90th and 95th Percentile

Dependent Variable: Multihoming	(1) Specialist - 90th	(2) Specialist - 95th
Log Employees	0.003	0.003
	(0.006)	(0.006)
	[0.643]	[0.560]
Log Sales	-0.003	-0.003
	(0.002)	(0.002)
	[0.138]	[0.136]
Specialist Firm (90th) X ATW	-0.039	
	(0.026)	
	[0.134]	
Specialist Firm (95th) X ATW		-0.055
		(0.014)
		[0.000]
Constant	0.006	0.005
	(0.009)	(0.009)
	[0.515]	[0.574]
Firm FE	Y	Y
Year FE	Y	Y
Observations	1,020	1,020
Number of Firms	226	226
R-squared	0.062	0.061
R-squared (includes fixed effects)	0.614	0.614

Robust standard errors clustered by firm in parentheses; p-values in brackets.
ATW: Acquisition time window (2004-2006). Estimates based on the linear probability model.
Specialist Firm (90th): Firms are specialists when they are above the 90th percentile on only one form of HC
Specialist Firm (95th): Firms are specialists when they are above the 95th percentile on only one form of HC

Here, we use the 90^{th} and 95^{th} percentiles of the human capital distribution to identify highly specialized firms, instead of the 75^{th} percentile in our original measure, and repeat our analysis. We find that the initial results are robust to these alternative definitions.

Table 3.9 Alternative Measure: Partnership Duration – Longer and Shorter Partnerships

Dependent Variable: Multihoming	(1) Duration	(2) Duration-Specialization Interaction
Log Employees	0.003	0.004
	(0.006)	(0.006)
	[0.660]	[0.552]
Log Sales	-0.003	-0.004
	(0.002)	(0.002)
	[0.153]	[0.069]
Specialist Firm X ATW		0.035
		(0.032)
		[0.273]
Partnership Duration X ATW	0.067	0.111
	(0.023)	(0.029)
	[0.004]	[0.000]
Specialist Firm X Partnership Duration X ATW		-0.149
		(0.044)
		[0.001]
Constant	0.020	0.028
	(0.008)	(0.009)
	[0.019]	[0.002]
Firm FE	Y	Y
Year FE	Y	Y
Observations	1,020	1,020
Number of Firms	226	226
R-squared	0.076	0.105
R-squared (includes fixed effects)	0.620	0.632

Robust standard errors clustered by firm in parentheses; p-values in brackets.
ATW: Acquisition time window (2004-2006). Estimates based on the linear probability model.

Here, we use as an alternative measure for partnership duration. Those firms that have partnered with SAP for five or more years at the start of the acquisition time window are said to be in a high-duration partnership while others are assumed to be in a low-duration partnership. We use a dummy variable to denote partnership duration that takes either of two values, high (1) or low (0). We find that our initial results based on H2 and H3 are robust to these alternative definitions.

3.8.2 Alternative Explanations

Table 3.10 Alternative Explanation: Dot-com Bubble and Multihoming

	(1)
Dependent Variable: Multihoming	
Log Employees	-0.016
	(0.013)
	[0.251]
Log Sales	-0.003
	(0.003)
	[0.455]
Specialist Firm X Dot-com Bubble	0.107
	(0.080)
	[0.184]
Constant	0.022
	(0.015)
	[0.126]
Observations	310
Number of Firms	130
R-squared	0.150
R-squared (includes fixed effects)	0.524

Robust standard errors clustered by firm in parentheses; p-values in brackets.
Dot-com Bubble: Year 2001 when firms pursued risky strategies. Specialized Firm: Based on the year 1999.
Estimates based on the linear probability model.

Table 3.11 Alternative Explanation: Internal versus External Learning

Dependent Variable: Multihoming	(1) Partnership Duration	(2) Duration-Specialization Interaction	(3) Duration-Specialization Interaction Age at Partnership>4
Log Employees	0.001	0.003	-0.008
	(0.005)	(0.005)	(0.016)
	[0.824]	[0.534]	[0.623]
Log Sales	-0.002	-0.003	0.029
	(0.002)	(0.002)	(0.019)
	[0.318]	[0.138]	[0.140]
Age at Partnership X ATW	0.005	0.007	0.029
	(0.004)	(0.005)	(0.011)
	[0.216]	[0.124]	[0.011]
Specialist Firm X ATW		0.087	0.320
		(0.048)	(0.132)
		[0.070]	[0.018]
Partnership Duration X ATW	0.008	0.016	0.035
	(0.004)	(0.006)	(0.016)
	[0.073]	[0.011]	[0.034]
Specialist Firm X ATW X Age at Partnership		-0.010	-0.027
		(0.005)	(0.011)
		[0.057]	[0.015]
Specialist Firm X ATW X Partnership Duration		-0.021	-0.037
		(0.007)	(0.017)
		[0.006]	[0.033]
Constant	0.006	0.011	-0.415
	(0.011)	(0.011)	(0.263)
	[0.605]	[0.321]	[0.118]
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	1,020	1,020	354
Number of Firms	226	226	84
R-squared	0.067	0.088	0.154
R-squared (includes fixed effects)	0.616	0.625	0.658

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

ATW: Acquisition time window (2004-2006). Estimates based on the linear probability model.

Table 3.12 Alternative Explanation: Relationship-Specific and Co-specialized Investments

Dependent Variable: Multihoming	(1) Technical HC	(2) Functional HC	(3) Industry HC	(4) Three HCs
Log Employees	0.002	0.007	0.005	0.007
	(0.006)	(0.006)	(0.006)	(0.006)
	[0.669]	[0.227]	[0.442]	[0.298]
Log Sales	-0.002	-0.004	-0.003	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)
	[0.204]	[0.077]	[0.150]	[0.126]
Technical HC X ATW	-0.048			-0.023
	(0.022)			(0.022)
	[0.027]			[0.290]
Functional HC X ATW		-0.070		-0.058
		(0.018)		(0.016)
		[0.000]		[0.000]
Industry HC X ATW			-0.067	-0.050
			(0.017)	(0.015)
			[0.000]	[0.001]
Constant	0.003	0.002	0.003	0.001
	(0.009)	(0.009)	(0.009)	(0.010)
	[0.754]	[0.844]	[0.746]	[0.949]
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	1,020	1,020	1,020	1,020
Number of Firms	226	226	226	226
R-squared	0.066	0.075	0.073	0.086
R-squared (includes fixed effects)	0.616	0.619	0.618	0.624

Robust standard errors clustered by firm in parentheses; p-values in brackets.
ATW: Acquisition time window (2004-2006). Estimates based on the linear probability model.

It may be seen that all the three different forms of HC namely technical HC, functional HC and Industry HC have a negative impact on multihoming when subject to the demand shock.

3.8.3 Alternative Specification

Table 3.13 Alternative Specification: Survival Model – Cox

Dependent Variable: Multihoming	(1) Specialist Firm	(2) Partnership Duration	(3) Duration-Specialization Interaction
Log Employees	-0.059	-0.086	-0.091
	(0.107)	(0.107)	(0.111)
	[0.582]	[0.421]	[0.412]
Log Sales	0.015	0.016	0.023
	(0.040)	(0.040)	(0.041)
	[0.704]	[0.692]	[0.570]
Specialist Firm X ATW	-0.689		2.124
	(0.626)		(0.903)
	[0.271]		[0.019]
ATW X Partnership Duration		0.205	0.321
		(0.081)	(0.064)
		[0.011]	[0.000]
Specialist Firm X ATW X Partnership Duration			-0.745
			(0.292)
			[0.011]
Observations	1,020	1,020	1,020
Marginal Effects (ey/dx)			
Specialist Firm	-0.689 (0.626) [0.271]		-1.280 (0.963) [0.184]
Specialist Firm (Duration = 0)			2.124 (0.903) [0.019]
Specialist Firm (Duration = 7)			-1.814 (0.918) [0.048]
Partnership Duration		0.205 (0.081) [0.011]	0.097 (0.099) [0.326]
Partnership Duration (Specialist Firm = 1)			-0.424 (0.288) [0.140]
Partnership Duration (Specialist Firm = 0)			0.320 (0.064) [0.000]

Coefficient Estimates; Robust standard errors clustered by firm in parentheses; p-values in brackets.
ATW: Acquisition time window (2004-2006). Estimates based on the Cox survival model.

The table shows the results based on the Cox proportional hazard model and columns (1), (2) and (3) correspond to our hypotheses H1, H2, and H3 respectively. The marginal effects are elasticities (and denoted by ey/dx).

3.8.4 Interpretation of Results

MH Propensity	**Type of Complementor** Generalist	Specialist
Time Period		
Before ATW	0.000	-0.003
During ATW	0.068	0.012

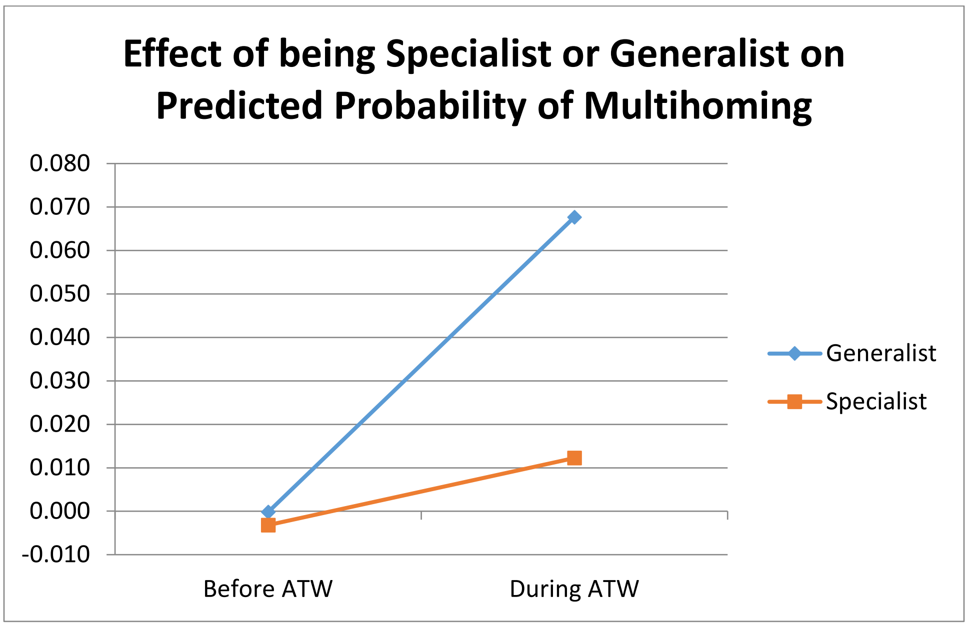

Figure 3.2 Specialization and Multihoming

The figure helps interpret the results corresponding to Hypothesis 1 better. It shows the predicted probabilities of multihoming for specialist and generalist firms, before and during the ATW. We find that both specialist and generalist are more likely to multihome during the ATW when compared to the period before the ATW. But, generalist firms are much more likely to respond to the shock than specialist firms.

MH Propensity	Partnership Duration	
	Short Term	Long Term
Time Period		
Before ATW	0.010	0.001
During ATW	0.038	0.061

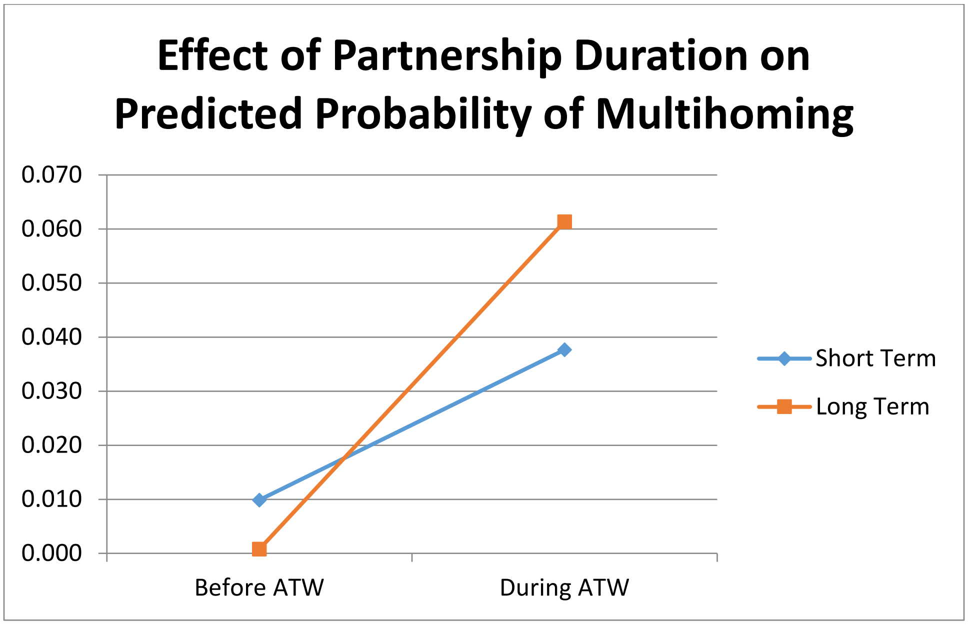

Figure 3.3 Partnership Duration and Multihoming

The figure helps interpret the results corresponding to Hypothesis 2 better. It shows the predicted probabilities of multihoming for firms with short term and long term partnerships, before and during the ATW. The median number of years of prior partnership is five years in our sample. We designate those partnerships that were for five or more years as long term and others as short term. We find that both types of firms are more likely to multihome during the ATW when compared to the period before the ATW. While the increase is negligible for firms with short term partnerships, long term partners are much more likely to multihome in response to the shock.

Specialist Complementors

MH Propensity	Partnership Duration: Short Term	Partnership Duration: Long Term
Time Period		
Before ATW	0.015	-0.006
During ATW	0.044	0.000

Generalist Complementors

MH Propensity	Partnership Duration: Short Term	Partnership Duration: Long Term
Time Period		
Before ATW	0.009	0.002
During ATW	0.036	0.086

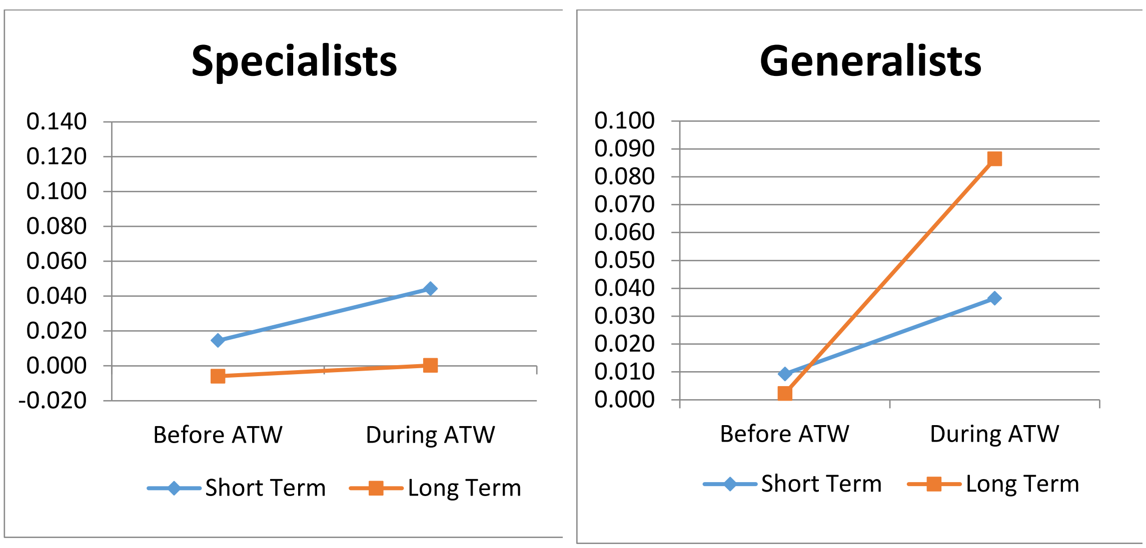

Figure 3.4 Partnership Duration and Multihoming – Specialist versus Generalist Firms

The left panel in the figure corresponds to specialists among the complementors while the right panel corresponds to the generalists. During the ATW, generalists with long term prior partnership are the most likely to multihome (0.086).

3.8.5 *Computation of Human Capital*

Technical HC, Functional HC, and Industry HC are related in the following way:

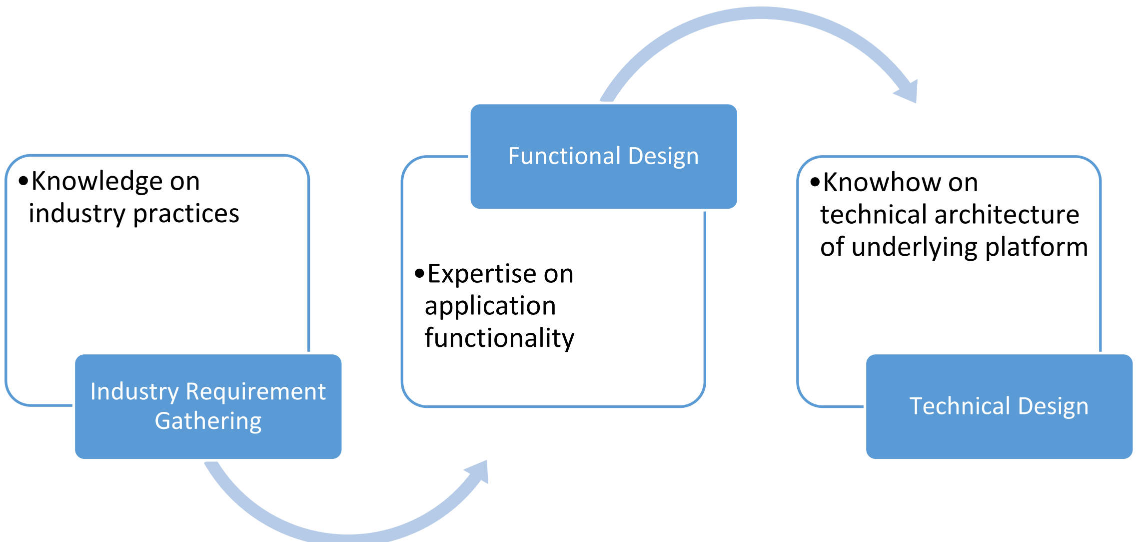

Figure 3.5 Coordination among skills required to integrate a software solution into an ERP platform

In order to determine the values of Technical HC, Functional HC and Industry HC for a given complementor in the year 2001, we proceed in the following manner.

A typical CV in our sample would be similar to the one shown below for reference.

Jessica Claire

190 Peachtree Street NE Atlanta GA 30303 +1-908-909-908

Jessica.claire@mailbox.com

SUMMARY

SAP FICO consultant with over 20 years experience, working in multiple industries (Oil & Gas, Logistics, Engineering and Construction) in various capacities, primarily technology implementation and support. Led several full life-cycle projects with phased rollouts as well as short-term engagements and upgrades. Has also been responsible for instructor-led train the trainer projects and post go-live support.

EDUCATION

Georgia Institute of Technology, Atlanta, GA 1996

- **B.S. in Engineering Major: Information Technology**

Georgia State University, Atlanta, GA 2010

- **Masters in Business Administration Major: Information Technology Management Minor: Marketing**

JOB DESCRIPTION

❖ Principal Consultant
Radiant Technologies, Houston, TX
(Sep 2012 - Present)

- Oversee the development of SAP HANA Cloud based offerings aimed at SMBs offering engineering and construction services.
- Analyzed the competitive landscape in the area of cloud based ERP and recommended a strategic roadmap for our products.
- Developed customer use cases on successful digital transformation.

❖ Lead Consultant
Radiant Technologies, Houston, TX
(June 2008 – Sep 2012)

- Led the roll out of SAP in 15 Countries as part of a transformational project for an Oil & Gas MNC.
- Involved in the preparation of Business Requirement Document (BRD), Functional Design Document (FDD), Blueprinting, Configuration, Functional specs (FS).
- Supported user acceptance testing, integration testing, and change management for implementation.
- Headed the QA team and guided team members in delivering quality output.
- Anchored PMO level meetings to monitor progress of the phased roll out across countries.

❖ Senior Consultant
Apriso, Atlanta, GA
(Mar 1998 – June 2008)

- Gathered business requirements from ERP end-users and developed and implemented SAP FICO based solutions to transform their IT landscape.
- Co-responded to RFPs; documented as-is and to-be system landscape; and provided solution architecture.
- Serviced clients across multiple verticals – Logistics, Engineering and Construction.

❖ Software Development Engineer
IBM, Atlanta, GA
(July 1996 – Feb 1998)

- Involved in coding, testing, documentation and implementation of modules based on Mainframe based inventory management system for a retail giant.

Human capital related words are mentioned on a person's CV in two different sections namely the summary section and the skills section that pertains to each of the firms employed in.

In our example, the text in the summary section is as below.

SAP FICO consultant with over 20 years experience, working in multiple industries (Oil & Gas, Logistics, Engineering and Construction) in various capacities, primarily technology implementation and support. Led several full life-cycle projects with phased rollouts as well as short-term engagements and upgrades. Has also been responsible for instructor led train the trainer projects and post go-live support.

The text in the job description section corresponding to Apriso is as below.

- Gathered business requirements from ERP end-users and developed and implemented SAP FICO based solutions to transform their IT landscape.
- Co-responded to RFPs; documented as-is and to-be system landscape; and provided solution architecture.
- Serviced clients across multiple verticals – Logistics, Engineering and Construction.

We first make a collection of words from the summary and remove all the stop words from the text. Please refer to Table A3.1 for a list of commonly occurring stop words that are filtered out before natural language processing.

Next we count the number of words pertaining to the three different HC measures. Table A3.2 provides the list of keywords corresponding to the three types of HC. These words have been derived from a dictionary of terms pertaining to the ERP ecosystem available in the public domain.

First, we look into the summary text for words corresponding to the functional HC measure from the dictionary of terms. In our example, the term SAP FICO is found and counts toward the functional HC measure.

Second, we look for terms corresponding to the technical HC measure. We find that there are no terms in the summary that correspond to the technical HC measure.

Third, we look for industry specific terms and find five terms in the summary namely oil, gas, logistics, engineering and construction that correspond to verticals that count toward our industry HC measure.

Next we divide the three counts by the number of words in the summary to control for the length of the summary.

Functional HC count = 1

Technical HC count = 0

Industry HC count = 5

Total number of words in summary = 57

Number of words after removing stop words = 43

After dividing by the number of words, we get the following measures for this particular employee.

Functional HC corresponding to the summary section is given as

Functional_HC_Summary_Section = 1/43 = 0.023

Similarly, Technical HC and Industry HC are found to be

Technical_HC_Summary_Section = 0/43 = 0

Industry_HC_Summary_Section = 5/43 = 0.116

Please note that the summary section is common across jobs. So, we allocate only the fraction of the skills corresponding the five years prior to 2001.

The functional HC from the summary section corresponding to the complementor (Apriso) in the year 2001 contributed by this employee is given as

Functional_HC_Summary_Section_Apriso_2001 = 5/20*0.023 = 0.006

In a similar manner, we have,

Technical_HC_Summary_Section_Apriso_2001 = 5/20*0 = 0

Industry_HC_Summary_Section_Apriso_2001 = 5/20*0.116 = 0.029

Now, we repeat the same procedure for the job description section and obtain the counts as below.

Functional HC count = 1

Technical HC count = 0

Industry HC count = 3

Total number of words in the job description section pertaining to Apriso = 45

Number of words after removing stop words = 36

By dividing by the number of words, we get the following measures

Functional_HC_Job_Desription_Section = 1/36 = 0.028

Technical_HC_ Job_Desription _Section = 0/36 = 0

Industry_HC_ Job_Desription _Section = 3/36 = 0.083

Please note that the job description section is common across all the years spent on the job. So, we allocate only the fraction of the skills corresponding to the five years prior to 2001. Also, note that some employees sometimes give the exact month of transition from one job to another as in our example here but others choose to provide only the year. To keep things uniform, we allocate 0.5 years each to the two companies whenever an employee switches between them.

Total years spent by the employee in Apriso = 0.5 (corresponding to the year 1998) + 9 (corresponding to the years 1999-2007) + 0.5 (corresponding to the year 2008) = 10

Among these years, the relevant number of years when computing the employee's HC at Apriso in 2001 is 3.5 given by adding 0.5 (corresponding to the year 1998) and 3 (corresponding to the years 1999-2001).

So, we have

Functional_HC_Job_Desription_Section_Apriso_2001 = 3.5/10 * 0.028 = 0.01

Technical_HC_ Job_Desription _Section_Apriso_2001 = 3.5/10 * 0 = 0

Industry_HC_ Job_Desription _Section_Apriso_2001 = 3.5/10 * 0.083 = 0.029

Combining the two, the three HC values for Apriso in the year 2001 contributed by the given employee are given as

Functional_HC _Apriso_2001 = 0.006 + 0.01 = 0.016

Technical_HC_Apriso_2001 = 0 + 0 = 0

Industry_HC _Apriso_2001 = 0.029 + 0.029 = 0.058

We repeat the above procedure for all the employees in the sample that are employed with Apriso in 2001.

The total values corresponding to the three forms of HC are thus obtained as,

Total_Functional_HC _Apriso_2001 = 0.0365

Total_Technical_HC_Apriso_2001 = 0.767

Total_ Industry_HC _Apriso_2001 = 0.146

We finally bring the three forms of HC to the per employee level by dividing the number of employees in the sample.

Number of employees in the sample = 36.5 (Note that the number is fractional because of transition of employees during the year)

Functional_HC _per_employee_Apriso_2001 = 0.0365/36.5 = 0.001

Technical_per_employee _HC_Apriso_2001 = 0.767/36.5 = 0.021

Industry_per_employee _HC _Apriso_2001 = 0.146/36.5 = 0.004

It may be noted here that we actually use logged values of these measures to account for the skewness of the overall distribution of three HCs across firms. The steps followed in the computation of the human capital measures is summarized in Figure A3.1. shown below.

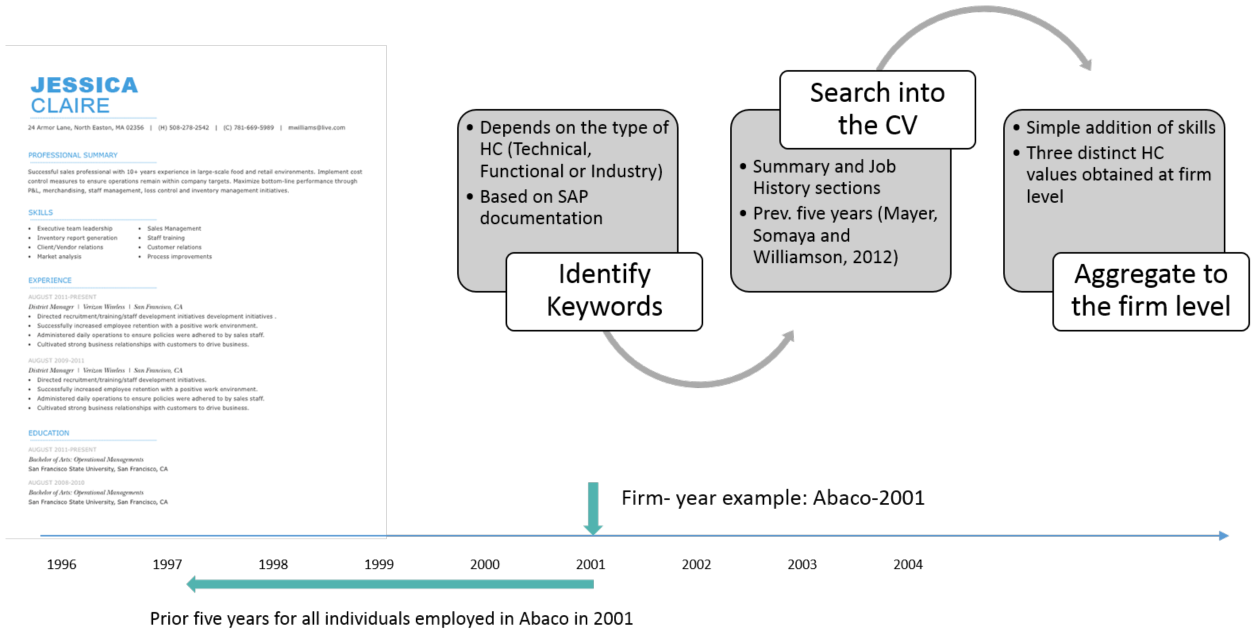

Figure 3.6 Measurement of Human Capital

Table 3.14 List of Stop Words

a	don't	in	she'd	wasn't
about	down	into	she'll	we
above	during	is	she's	we'd
after	each	isn't	should	we'll
again	few	it	shouldn't	we're
against	for	it's	so	we've
all	from	its	some	were
am	further	itself	such	weren't
an	had	let's	than	what
and	hadn't	me	that	what's
any	has	more	that's	when
are	hasn't	most	the	when's
aren't	have	mustn't	their	where
as	haven't	my	theirs	where's
at	having	myself	them	which
be	he	no	themselves	while
because	he'd	nor	then	who
been	he'll	not	there	who's
before	he's	of	there's	whom
being	her	off	these	why
below	here	on	they	why's
between	here's	once	they'd	with
both	hers	only	they'll	won't
but	herself	or	they're	would
by	him	other	they've	wouldn't
can't	himself	ought	this	you
cannot	his	our	those	you'd
could	how	ours	through	you'll
couldn't	how's	ourselves	to	you're
did	i	out	too	you've
didn't	i'd	over	under	your
do	i'll	own	until	yours
does	i'm	same	up	yourself
doesn't	i've	shan't	very	yourselves
doing	if	she	was	

Table 3.15 List of Keywords

Technical HC	Industry HC	Functional HC
ABAP	Aerospace	SAP FICO
Netweaver	Defense	SAP MM
SAP BASIS	Automotive	SAP SD
Java	Banking	SAP PP
Javascript	Chemicals	SAP BI
HTML	Consumer Products	SAP SRM
SQL	Engineering	SAP CRM
Database	Construction	SAP HCM
Code	Operations	SAP BW
Coding	Healthcare	SAP FI
Programming	Higher Education	SAP PS
Technical	Research	SAP PM
Architecture	High Tech	Financial Accounting
C	Industrial Machinery	Materials Management
C++	Insurance	Sales and Distribution
Websphere	Life Sciences	Production Planning
J2EE	Media	Business Intelligence
	Mill Products	Supplier Relationship Management
	Mining	Customer Relationship Management
	Oil	Human Capital Management
	Gas	Business Warehouse
	Professional Services	Project System
	Public Sector	Plant Maintenance
	Retail	Functional
	Sports	
	Entertainment	
	Telecommunications	
	Transportation	
	Logistics	
	Utilities	
	Wholesale Distribution	

CHAPTER 4. PLATFORM COMPETITION AND COMPLEMENTOR PERFORMANCE

4.1 Introduction

Platform based ecosystems are driving innovation and transforming several industries such as e-commerce, urban mobility, hospitality, communication and so on (Evans, Hagiu and Schmalensee, 2006). This has consequences for both the nature of value creation and value appropriation with those industries (Teece, 2007). Ecosystems involve various types of dependencies and complementarities that determine the value-add of the overall ecosystem (Jacobides, Cennamo, and Gawer, 2018). An open set of questions within this literature is whether and how complementors benefit from competition among platform owners.

On the one side, a logic based entirely on cross-side network effects, which has dominated our thinking on two-sided markets, would suggest that growth of a rival platform's installed base would hurt complementors of the focal platform. On the other, the dynamics of value creation and value capture within ecosystems would suggest that platform owners would be more willing to share value with complementors when faced with competition from rivals to dissuade them from joining the rival platform. This has implications not only for the complementors but also for the 'tipping' of the overall market toward a dominant platform, leading to a winner-takes all (WTA) (Shapiro and Varian, 1998; Parker, Van Alstyne, and Choudary, 2016; Bresnahan, Orsini, and Yin, 2014).

The literature on two-sided markets has stressed the role of demand-side economies of scale and the existence of cross-side network effects (Shankar and Bayus, 2003, Clements and Ohashi, 2005), which has been seen as central to achieving WTA. However, the pursuit of WTA approaches has been shown to be not always beneficial, resulting at times in lowering of platform performance (Cennamo and Santalo, 2013). We complement this study and show that the performance of complementors affiliated to a platform could still improve when the rival platform increases its installed base. We reason that this could arise from ‘steering’ – activities pursued by the incumbent platform to encourage complementor sales, share the value created, and potentially discourage them from multihoming into the rival platform (Rochet and Tirole, 2003). Further, we argue that the resultant positive effect on performance varies across complementors and depends, in particular, on their heterogeneous ability to internalize the value created based on the scope of their human capital. Rietveld and Eggers (2018) show that demand-side heterogeneity in terms of early and late platform adopters affect complementor sales. Here, we argue that the difference could also arise from supply-side factors particularly in terms of heterogeneity in complementor skills. Finally, we posit that, in spite of the potential for steering by the incumbent platform, complementors that still go on to multihome would tend to benefit from potential access to the combined installed base of the rival platforms.

Research within platform ecosystems has been more concerned with platform owner strategies (Iansiti and Levien, 2004) and has dealt with questions on openness of innovation (Boudreau, 2010), standard setting (Rysman and Simcoe, 2008), ecosystem regulation and governance (Tiwana et. al., 2010). Less attention has been paid toward the role of complementors within these ecosystems (Ceccagnoli et. al., 2012; Kapoor and Agarwal, 2017). However, rapid advances in ICT in recent years have enabled numerous complementors to join the platform owner in value co-creation. Successful businesses are increasingly relying on the external developer ecosystem to generate value (Parker, Van

Alstyne, and Jiang, 2017). Hence, it becomes important for researchers to study complementors in order to better understand their capabilities and strategies.

The sustainability of superior performance is determined by environmental factors such as structure and change that are common across firms as well as the unique capabilities and purposeful action of individual firms operating within that environment. For example, Kapoor and Agarwal (2017) deals with the former and uses ecosystem complexity (structure) and generational transitions (change) to characterize the platform ecosystem environment. In this paper, we look at how a complementor's capabilities in terms of its human capital and its decision to partner with multiple platforms (henceforth referred to as multihoming) affect its performance when there is a change in the platform ecosystem environment. We build a theory based on three inter-related elements namely the strategic value of the firm's own human capital, the role played by complementor's decision to multihome, and the shift in competition among platform owners, to explain differential complementor performance.

We use the ERP platform ecosystem setting to test our assertions. We use a sample of SAP complementors and supplement firm level data on sales, employees, partnership duration and multihoming strategy with novel micro-level data on human capital extracted from employee CV's and aggregated to the firm level. Our findings may be summarized as follows. First, we find that, on average, an increase in platform level competition benefits complementors. Second, specialist complementors benefit less than generalist complementors from this change in competition. Third, complementors that multihome tend to perform better than others in periods of increased competition among platform owners. We performed a number of checks to ensure the robustness of these results to alternative specifications and variable definitions. While it is difficult to disentangle the effect of human capital specialization and multihoming from other complementor characteristics, we try to show that our results are robust to the inclusion of interactions of platform level competition market with duration of partnership with the incumbent platform and age of the complementor prior to partnership

The paper makes a number of contributions to the literature on platform ecosystems as well as the broader strategy literature. First, this is one of the few empirical studies that looks at the impact of platform competition on complementor performance. While prior literature has looked at platform owner strategies or the impact of platform owners' strategies on rival platforms (Cennamo and Santalo, 2013), our paper brings the focus to the complementor's performance. In this way, it joins a stream of literature that has tried to understand the drivers of complementor competitive advantage in the form of intellectual property and downstream capabilities (Huang et. al, 2012), technology change (Kapoor and Agarwal, 2017) and demand-side heterogeneity (Rietveld and Eggers, 2018). Second, it draws on a rich theoretical literature that has focused on demand side drivers of platform ecosystems (Rochet and Tirole, 2003; Parker and Van Alstyne, 2005; Armstrong, 2006) and combines this with supply side perspectives in the form of complementor capabilities and the complexity of integration with the platform. Third, the traditional strategy literature has emphasized the role of the firm's investment in its own resources (Wernerfelt, 1984; Barney, 1991) and capabilities (Teece et. al., 1997) in attaining and sustaining competitive advantage. Recently, the strategic role played by a firm's human capital in sustainable competitive advantage has been emphasized (Barney and Felin, 2013). In our paper, we aggregate micro-level human capital data to the firm level and designate firms as specialists (and generalists). In particular, we try to answer how generalist and specialist firms that differ in terms of their scope of human capital are affected differently by changes in their environment.

4.2 Theory and Hypotheses

4.2.1 Average Effect of Platform Competition

The modular nature of platform ecosystems (Baldwin and Clark, 2000) enables value co-creation by platform owners and the numerous complementors that partner with them. But there is uncertainty over the extent to which platform owners are willing to share this co-created value with the complementors (Gawer and Cusumano, 2002). This leads to co-opetition between platform owners and complementors. On the one hand, platform owners need to cooperate with complementors by opening up their platform and sharing knowledge with them to enable them contribute toward value creation. On the other, platform owners need to compete with complementors in negotiating and appropriating the overall value created in the ecosystem.

When there is less platform level competition, platform owners may try to 'squeeze' value from complementors. Also, they may be less interested in promoting complementor solutions and more focused on selling their own core product. In some situations, platform owners may even try to enter directly into complementor markets in order to be able to appropriate more value from the ecosystem (Eisenmann and Parker, 2011). However, when faced with competition, platform owners would be more willing to promote complementor solutions in order to attract customers to their platform. Also, they would be more willing to share the value that is created in the ecosystem. In situations where platforms owners charge a transaction fee, they may lower the fee charged to one side of the platform (Parker and Van Alstyne, 2005). But, in modular software platforms, this may take other sophisticated forms such as additional support for software development[23]; better interface to the platform's underlying architecture; and promotion of complementor solutions to end customers. These are aimed at easing the effort of complementors and influencing them to pay less attention to rival platform owners. In the case of enterprise software, for example, SAP introduced the SAP Community Network in 2004 to enable interaction among SAP customers and complementors in the SAP ecosystem. It also made available a community of SAP experts on the network to connect and collaborate with. Over the years, the community evolved into a repository of technical, functional and business knowledge related to the development, deployment and integration of enterprise software. SAP also released the NetWeaver technology platform in 2004 that had been announced back in 2003. The aim of the platform was to reduce complexity and the costs of integrating with the platform. This was aimed at boosting the market share of the SAP platform through adoption of the technology by complementors and, in turn, the customers. In response to the growing demand for information on SAP NetWeaver, SAP launched a 50-city worldwide tour that took place throughout 2004 and used the interactions to explain more about the ease of integration achievable through Netweaver to complementors and customers. This reiterates the notion that successful firms are often better at orchestrating their ecosystem rather than trying to do everything themselves (Gawer and Cusumano,

[23] SAP started the SAP Developer Network (subsequently called the SAP Community Network) within weeks of Oracle's initial announcement to acquire PeopleSoft back in 2003. SAP assured the community that it would bring in its experts to engage with the ecosystem and resolve queries of its members. The subsequent enthusiastic participation in the ecosystem is captured in the form of queries raised over time (shown in the appendix).

2002). In summary, we should find the average effect of platform competition on complementor performance to be positive.

H1: Increased platform competition has a positive effect on complementor performance.

4.2.2 Generalist versus Specialists

Even though platform competition is beneficial to complementors on average, generalists would tend to benefit more than specialists. Software development not only requires technical skills, which has often been discussed in the literature, but also domain knowledge (Chatterjee, 2017). We unpack domain knowledge further into functional skills that captures the functionalities of the platform and the application that complementors provide and industry skills that pertain to the specific industry for which the application is built. The presence of all three skills within the firm makes it easier to develop and implement applications for customers in the ecosystem. While modularity brings down the need for technical interdependencies, functional and other interdependencies remain (Baldwin and Clark, 2000). The idea that organizational ties mirror the underlying technical dependencies alone does not hold in software development in open collaborative environments (Colfer and Baldwin, 2016). This requires such firms to often draw their knowledge boundaries broader than their immediate operational boundaries. The co-specialized nature of these skills also makes it harder to contract on the individual skills in the ecosystem. It becomes especially harder in a dynamic and hyper-competitive environment. Since, generalists are less dependent on the broader ecosystem for resource deployment, they have the dynamic capabilities to react to the change in their environment (Teece et. al., 1997). On the other hand, specialists are less capable of reacting to changes in demand and appropriating value from the ecosystem. Generalists may be thought of as possessing better integrative capabilities i.e. the ability to integrate knowledge across different human capital dimensions through effective communication and coordination (Helfat and Raubitschek, 2018). While it may make sense to specialize and lower the coordination costs across human capital, certain firms may be more willing to invest in diverse forms of human capital and remain as generalists in order to be able to better react to changes in the environment. Further, the tendency to remain as generalists may be particularly more pronounced in ecosystems that are built on system technologies characterized by complementarities (Helfat and Campo-Rembado, 2016). While we acknowledge the possibility that some of the skills could be brought in from outside, internal governance not only solves the problem of private incentives but also brings also results in efficient communication. This makes it better than a market form of governance for skills, which can be thought of as a second-best form of contracting. To sum up our arguments, even if additional value gets created within the ecosystem, specialists are at a disadvantageous position in negotiating over that value (Grossman and Hart, 1986; Hart and Moore, 1990).

Hence, we would expect the following.

H2: When platform competition increases, the performance of generalist complementors increases more than that of specialist complementors.

4.3 Data and Methodology

4.3.1 Setting

We use the ERP platform ecosystem setting to test our hypotheses. The global enterprise software market is expected to reach $575 billion by 2024.[24] The US continues to remain the largest market for enterprise software. The digital economy, of which enterprise software is a crucial component, has been growing at 4.3 times the broader US economy over the last 20 years (1997-2017)[25]. Oracle and SAP are the leading platform owners who control a significant portion of the ERP platform ecosystem. In this way, they are comparable to iOS and Android in the mobile ecosystem. Also, just as Android has been trying to catch with iOS across markets in recent years, in the case of the ERP system, SAP may be seen as the incumbent back in the early 2000's and Oracle as the new entrant trying to improve its market share and catch up with SAP.

Different forms of enterprise software such as those employed in inventory control, warehouse management etc. have been around for decades. However, the notion of an ERP ecosystem began when SAP transitioned from mainframes to a client-server architecture in the mid 1990's. The new architecture enabled complementors to build applications on the SAP platform and add value to the core product. This is again somewhat similar to the case of the mobile ecosystem where transition from feature phones to smartphones suddenly enabled numerous complementors to develop apps on the mobile platform.

[24] As per Global Forecast reports from ResearchandMarkets.com.
[25] Source: Bureau of Economic Analysis (BEA)

The mid 2000's marked the most interesting phase of competition within this ecosystem. Oracle, the other major platform owner within this ecosystem decided to acquire many of the other ERP platforms in order to strengthen its own capabilities and to give a tough competition to the then market leader SAP. Even though SAP continued to hold on to its leadership position, the relative market share of Oracle improved substantially over this period and it emerged as a very close second.

Oracle brought in a top executive with expertise in investment banking and, beginning in 2004, embarked on a series of acquisitions worth several billion dollars to boost its market share on the customer side and signal its commitment to complementors on the other side. Its first major acquisition was that of PeopleSoft, a leader in human capital management software, which had itself acquired JD Edwards, another major legacy ERP vendor, only a year before. Oracle's offer to PeopleSoft which was in excess of $10 billion was then the highest for any acquisition within the IT industry. Other notable acquisitions that followed include iFlex, a banking solution provider, in 2005; Siebel, which had expertise in Customer Relationship Management segment of ERP, in early 2006 and; BEA systems, which had expertise in enterprise applications as well as middleware, in 2008. Oracle was so successful in making so many acquisitions and making inroads into all the different industries and functional segments within ERP that SAP, which made just two acquisitions during the same period, was forced to rethink its own strategy or growing organically later on.

4.3.2 Sample

The dataset has been built from several secondary data sources. The data covers the 2001-2006 period which saw a lot of competition between SAP and Oracle to dominate the market. The evolution of competition between the two leading platform owners in the market makes it an ideal time period to test the impact of platform level competition on complementor performance.

Our sample is composed of US based SAP complementors. The decision to limit our sample to US based complementors is to ensure considerable homogeneity across the sample. We first identified SAP partners from the SAP website dedicated to ecosystem partners. Even though SAP provides accurate information on all its complementors on this website, limiting the sample to these partners alone would lead to a survivorship bias. Also, as stated earlier, we are interested in those complementors that were active in the early and mid-2000s and for whom multihoming was indeed a strategic choice. Hence, we decided to expand the list of complementors by making use of data from SAP's annual meetings. SAP's annual meetings are aimed at connecting with both sides of the market namely the complementors and the end-customers. Complementors sign up as exhibitors to showcase their products and settings during these meetings. We searched for the list of such exhibitors on the internet archives of various SAP meeting related web pages and obtained the complete list of exhibitors for the years 1996-2009 for SAP SAPPHIRE and 2000-2006 for SAP Insider.

In order to get the year of partnership formation with SAP and Oracle, we relied on press releases from Factiva. After comparing the press releases obtained from Factiva with those from other sources such as Lexis Nexis, we found Factiva to be much better and decided to continue with it for the rest of the sample. In order to determine firm specialization in human capital, we required micro-level human capital data from the time. We had to extract this data from LinkedIn that provides information on both present and past employees of complementors in our sample. We would like to note here that this method is novel within the strategy literature even though CVs have sometimes been used to study start-up founders and top management teams within other literature streams.

Finally, we matched our sample with proprietary data from the National Establishment Time Series (NETS) database, which is actually a time series of the yearly Dun and Bradstreet (D&B) database. We were able to obtain the complementors' sales (dollar revenues) and size (employee count) data for the years 1990 to 2013 based on this approach. We also limit our sample to relatively small complementor firms. This is for two reasons. One, large complementors may possess several additional upstream and downstream capabilities that could influence their bargaining power relative to the platform owner. Second, there is a possibility that some large complementors may have been kept in confidence by Oracle while going in for some of the acquisitions. The observation unit used for analysis is firm-year. Our panel consists of 235 firms sampled during the 2001-2006 period and is unbalanced by construction since firms enter the partnerships at different points of time.

4.3.3 Dependent Variable

4.3.3.1 Log Sales

Log transformation of sales revenues (in dollars) of the complementor as of a given year. In order to measure the sustained effect on performance, we also use lead values of the dependent variable. First, it could be that the effect is more pronounced in some years than others. In our case, it may be reasonable to expect complementors to take time to react to the steering activities pursued by SAP. Second, it may be noted that it is quite common to use lagged values of independent variables in other settings for similar purposes. Here, we use the lead values of the dependent variable, instead, in accordance with our theory that SAP reacts with steering to the initial announcement of acquisitions by Oracle, which take up to two years to reflect as actual license revenues. Third, the use of lead values also enables us to avoid the possibility of simultaneity between changes in some of our dependent variables and the observed growth in sales. Fourth, single year changes may represent an idiosyncratic change in performance that may not have much to do with the change in platform competition. Hence, to better understand the effect of platform competition, we show the effect with one-year and two-year leads alongside the baseline values. We use the corresponding values for our controls as well in our regressions.

4.3.4 Independent Variables

4.3.4.1 Oracle Market Share

Our key independent variable is platform competition measured as the market share of Oracle relative to the incumbent platform SAP. We define it as the ratio of Oracle's License Revenue to the sum of the License Revenue of Oracle and SAP in the enterprise software market in the US.[26] While limiting the license revenue of Oracle to applications enables us to get a more accurate proxy for competition with SAP, it is hard to rule out the spillover effects of Oracle's database capabilities on dominance in the ERP market. The

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[26] The License Revenues (in $ million) of SAP and Oracle as published in their annual reports are shown in the appendix.

relatively high proportion of SAP ERP installations with Oracle databases makes us believe that this is less of a concern. It may be noted that there is a gap between the date of announcement of merger and actual book merger of license revenues. To account for this, we bring all the license revenues back by two years to match with the time of announcement. This is consistent with our observation that SAP reacts to the announcement made by Oracle regarding its acquisition rather than wait until the book merger of license revenues.[27]

Relative market share has often been used as a proxy for competition (Hansen and Wernerfelt, 1989). Further, in the case of two-sided platform based ecosystems with cross-side network effects such as enterprise software in our case and others such as video games, PCs and mobiles, installed base of the hardware, the operating system, or the core software application have been used to proxy for the size of the network on one side that represents the potential size of demand for the other.

It may be noted that the relative market share of Oracle varies only over time and remains common across complementors. Technological factors such as architectural complexity could have an impact on the attractiveness of Oracle and SAP as ERP platforms and may not be accounted for even after we control for other factors that vary over time. Instead of license revenues, we use the *Acquisition Time Window (ATW)* as an alternative measure to capture the effect of the investment commitment from the platform owner (Oracle). The time window is defined as a dichotomous variable that starts with zero and

[27] Readers may refer to the appendix for more information on the actual sequence of events.

turns one during the time window (2004-2006) when Oracle made the stream of acquisitions.

4.3.4.2 Specialist Firm

Complementors that are above the 75th percentile on any one form of human capital but below this level on the other forms of human capital are referred to as specialist firms. We identify three different forms of human capital - Technical, Functional and Industry relevant to our setting. We describe the three human capital forms below.

4.3.4.3 Technical Human Capital

Measured as the log transformation of the aggregate technical skills possessed by complementor employees as of the year 2001, the starting year of our sample. Technical human capital is needed by the firm to develop an understanding of the technical architecture of a platform. The architecture of platforms can be quite complex (Kapoor and Agarwal, 2017) and hence the complementors may require technical consultants who demonstrate an understanding of the platform architecture as well as possess the ability to develop code that interacts with various built-in modules of the platform that are based on that architecture.

4.3.4.4 Functional Human Capital

Measured as the log transformation of the aggregate functional skills possessed by complementor employees as of the year 2001. ERP platform is aimed at automating the business process flows within and across companies. Hence, complementors that choose to develop products on an ERP platform need to have substantial understanding on the actual implementation of those flows within the ERP platform. Order-to-Cash is a typical example of a business process flow within an ERP ecosystem. It refers to the various steps involved in the ordering of a product or service and the collection of cash from the customer for it by the end user of the ERP solution. An end-to-end business process may involve several steps and may be carried out by individuals spread within/ across organizations. Further, the process often cuts across the modular boundaries within the ERP platform as well as encompasses solutions built by complementors. A functional consultant is expected to have an understanding of the flow involved in the implementation of a particular business process say order-to-cash on the ERP platform.

4.3.4.5 Industry Human Capital

Measured as the log transformation of the aggregate industry skills possessed by complementor employees as of the year 2001. Knowledge work often requires individuals to know, to some extent, the industry context in which their solutions are being implemented (Mayer, Somaya and Williamson, 2012; Chatterjee, 2017). Domain/ Industry consultants usually have prior experience in a certain industry or develop expertise in a given industry by working on multiple projects specific to that industry.

4.3.4.6 Multihoming

Multihoming has been treated as a dichotomous variable that takes either zero or one as its value. When a complementor enters into a partnership with SAP[28], the propensity is initialized to zero. Once the complementor enters into a partnership with Oracle, the value is changed to one and stays at one till the end of the sampling period. If the firm

[28] Note that our focus in this study is on complementors affiliated with the incumbent platform. The assumption made is that there are only a limited number of complementors affiliated with the entrant platform to start with.

never multihomes, the variable continues to remain at zero till the end of the sampling period.

4.3.5 Control Variables

4.3.5.1 Log Employees

Log transformation of number of employees of the complementor as of a given year. We use this variable as a proxy for firm size and use it as a control in our regressions.

In addition to firm level control for size, to capture industry level changes that could impact individual firm sales, we use two different control variables as defined below.

4.3.5.2 Industry Establishments

Total number of establishments in the SIC industry in a given year. This is the average value for a given year based on the Quarterly Census of Employment and Wages (QCEW).

4.3.5.3 Industry Employment

Total employment in the SIC industry in a given year. Again, this is the average value obtained from the Quarterly Census of Employment and Wages (QCEW).

4.3.6 Other Variables

We introduce certain other variables in our regressions to rule out potential alternative explanations for our results, which we discuss in detail later. They are defined here as below.

4.3.6.1 Partnership Duration

The partnership duration is measured based on the prior SAP partnership of the complementors in our setting. It is measured as the total duration of the complementor's partnership with SAP prior to the shock.

4.3.6.2 Age at Partnership

Firm age is captured as at the beginning of partnership with SAP. This definition enables us to separate the experience gained by the complementor through its partnership with SAP from prior internal experience of the complementor.

4.3.7 Estimation

We use a fixed effects panel data model to carry out the estimation. The fixed effects model helps us to control for time-invariant factors such as the innovative ability of the complementor and the type of partnership with the platform owner that are unobservable to the researcher. Our key independent variable, *Oracle Market Share*, varies only over time. *Specialist Firm* is defined as of the start of the sample and is fixed over time for any given firm. However, it is possible to estimate its interaction with platform competition in a fixed effects model.

4.4 Results

The basic summary statistics are shown in Table 4.1 while the correlations are reported in Table 4.2. Note that all the variables have been log transformed. This is to take care of the skewed nature of the distribution of the variables. The average share of Oracle in the combined license revenues of SAP and Oracle is 0.344 during the period. The relative share varies by as much as 17.5 percentage points between a low of 0.260 and a high of 0.435. It may be seen that around one-third of the complementors are specialized in terms of human capital. Multihoming, in general is quite low. In any given year, less than 3% of the firms are likely to multihome.

Table 4.1 Descriptive Statistics

	Variable	Description	Mean	Std. Dev.	Min	Max
(1)	Log Sales	Log Transformation of Sales Revenues	9.871	7.604	0	24.23
(2)	Log Employees	Log Transformation of Number of Employees	2.478	2.686	0	12.35
(3)	Acquisition Time Window	Dichotomous variable that equals 1 during the acquisition time window (2004-06) and stays 0 otherwise	0.596	0.491	0	1
(4)	Oracle Market Share	Relative Market Share of Oracle with respect to SAP based on License Revenues	0.344	0.063	0.260	0.435
(5)	Specialist Firm	Firms above the 75th percentile on only one of the three forms of Human Capital namely Technical, Functional or Industry	0.306	0.461	0	1
(6)	Technical HC	Firms above the 75th percentile on Technical HC	0.234	0.423	0	1
(7)	Industry HC	Firms above the 75th percentile on Industry HC	0.235	0.424	0	1
(8)	Functional HC	Firms above the 75th percentile on Functional HC	0.248	0.432	0	1
(9)	Multihoming	Dichotomous variable that equals 1 when the firm multihomes and stays 0 otherwise	0.143	0.350	0	1
(10)	Partnership Duration	Duration of Partnership with SAP (difference between the year 2004 and the start of partnership)	4.848	2.428	0	10
(11)	Age at Partnership	Firm age at the beginning of partnership with SAP	3.594	4.357	0	15
(12)	Industry Establishments	Number of establishments in the SIC industry in a given year (in thousands)	53.37	23.08	11	82.81
(13)	Industry Employment	Total Employment in the SIC industry in a given year (in thousands)	455.2	154.9	105.8	796.5

Number of Firms: 233; Number of Observations: 1155

Table 4.2 Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	1												
(2)	0.859*	1											
(3)	0.091*	0.068*	1										
(4)	0.088*	0.059*	0.879*	1									
(5)	-0.069*	-0.055	0.004	0.008	1								
(6)	-0.089*	-0.114*	0.017	0.013	0.094*	1							
(7)	-0.067*	-0.014	0.011	0.005	0.115*	0.259*	1						
(8)	-0.062*	-0.015	-0.03	-0.026	0.232*	0.157*	0.137*	1					
(9)	-0.026	-0.032	0.039	0.042	0.034	-0.138*	-0.121*	-0.028	1				
(10)	0.085*	0.109*	-0.285*	-0.241*	0.011	-0.139*	-0.098*	0.094*	0.33*	1			
(11)	0.596*	0.443*	0.044	0.037	-0.145*	-0.075*	-0.083*	-0.125*	0.024	-0.188*	1		
(12)	0.103*	0.023	0.132*	0.226*	-0.127*	0.001	0.046	-0.086*	-0.081*	-0.056	0.077*	1	
(13)	0.178*	0.081*	0.127*	0.263*	-0.159*	0.023	0.043	-0.103*	-0.107*	-0.043	0.134*	0.921*	1

* p-value <0.05

Table 4.3 shows the average effect of the change in market share of Oracle on sales. We find that when platform competition increases, it benefits the SAP complementors. To put this in perspective, a 4.98 percentage point increase in *Oracle Market Share* (which is the actual difference in the relative share between the years 2005 and 2006) leads to a 14.46 percentage point change in the sales of the complementor. Columns 2 and 3 correspond to 1-year and 2-year lead values of sales with corresponding controls. We find that the effect of platform competition persists across these lead values. Also, the economic significance of the effect on sales increases with time, reflecting the increase in response of complementors to actions taken by the incumbent platform over time.

Table 4.3 H1: Platform Competition and Complementor Performance

VARIABLES	(1) Log Sales	(2) Log Sales (1-year Lead)	(3) Log Sales (2-year Lead)
Oracle Market Share	2.713**	3.789***	4.443***
	(2.493)	(3.509)	(3.595)
Log Employees	2.710***		
	(16.320)		
Industry Establishments	0.000		
	(0.039)		
Industry Employment	-0.000		
	(-0.219)		
Log Employees (1-year Lead)		2.662***	
		(16.333)	
Industry Establishments (1-year Lead)		0.000	
		(0.060)	
Industry Employment (1-year Lead)		-0.000	
		(-0.024)	
Log Employees (2-year Lead)			2.550***
			(10.137)
Industry Establishments (2-year Lead)			0.000
			(0.306)
Industry Employment (2-year Lead)			-0.000
			(-0.219)
Constant	2.410***	2.080***	2.283***
	(5.015)	(3.379)	(2.825)
Firm FE	Y	Y	Y
Year FE	N	N	N
Observations	1,155	1,155	1,155
R-squared (with Fixed Effects)	0.969	0.962	0.953
Number of Firms	233	233	233
R-squared within	0.768	0.713	0.588
R-squared between	0.730	0.728	0.730

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

We show the differential effect of platform competition on complementor performance in Table 4.4. In line with our expectations, even though the average impact is positive, we find that generalists perform better than specialists when subject to the change in platform competition owing to the acquisitions. This reflects the dynamic and integrative capabilities of generalists that enables them to respond better to changes in the environment and to internalize the benefits of steering through higher sales.

Table 4.4 H2: Specialists and Generalists

VARIABLES	(1) Log Sales	(2) Log Sales (1-year Lead)	(3) Log Sales (2-year Lead)
Oracle Market Share	3.983***	5.595***	6.052***
	(2.867)	(4.049)	(3.848)
Specialist Firm X Oracle Market Share	-4.133*	-6.174**	-5.447*
	(-1.820)	(-2.275)	(-1.846)
Log Employees	2.709***		
	(16.36)		
Industry Establishments	0.000149		
	(0.00930)		
Industry Employment	-0.000462		
	(-0.209)		
Log Employees (1-year Lead)		2.670***	
		(16.70)	
Industry Establishments (1-year Lead)		-0.00570	
		(-0.255)	
Industry Employment (1-year Lead)		0.000812	
		(0.266)	
Log Employees (2-year Lead)			2.559***
			(10.41)
Industry Establishments (2-year Lead)			0.00595
			(0.172)
Industry Employment (2-year Lead)			-0.000469
			(-0.100)
Constant	2.427***	2.070***	2.281***
	(5.083)	(3.418)	(2.877)
Firm FE	Y	Y	Y
Year FE	N	N	N
Observations	1,155	1,155	1,155
R-squared (with Fixed Effects)	0.970	0.962	0.953
Number of Firms	233	233	233
R-squared within	0.770	0.717	0.591
R-squared between	0.731	0.728	0.732

Robust t-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

4.4.1 Robustness Checks

We already included alternative specifications with different lead values of the dependent variable as part of our main results to help readers compare these effects over time. Apart from this, we carried out a number of other robustness checks. Instead of using continuous changes in installed base, we defined a dichotomous variable that takes the value of 0 initially and 1 during the acquisition the time window (2004-2006). Our results were robust to the use of this alternative variable in our regressions.

Table 4.5 Robustness: H1 with Acquisition Time Window

VARIABLES	(1) Log Sales	(2) Log Sales (1-year Lead)	(3) Log Sales (2-year Lead)
ATW	0.227**	0.370***	0.508***
	(1.975)	(3.077)	(2.999)
Log Employees	2.725***		
	(16.21)		
Industry Establishments	-0.00677		
	(-0.440)		
Industry Employment	0.001000		
	(0.481)		
Log Employees (1-year Lead)		2.669***	
		(16.33)	
Industry Establishments (1-year Lead)		-0.0183	
		(-0.822)	
Industry Employment (1-year Lead)		0.00272	
		(0.912)	
Log Employees (2-year Lead)			2.557***
			(10.20)
Industry Establishments (2-year Lead)			0.0144
			(0.389)
Industry Employment (2-year Lead)			-0.00171
			(-0.337)
Constant	2.888***	2.932***	3.603***
	(6.868)	(6.204)	(5.160)
Firm FE	Y	Y	Y
Year FE	N	N	N
Observations	1,155	1,155	1,155
R-squared (with Fixed Effects)	0.969	0.961	0.952
Number of Firms	233	233	233
R-squared within	0.767	0.711	0.584
R-squared between	0.733	0.731	0.728

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1
ATW (Acquisition Time Window): 2004-2006

Table 4.6 Robustness: H2 with Acquisition Time Window

VARIABLES	(1) Log Sales	(2) Log Sales (1-year Lead)	(3) Log Sales (2-year Lead)
ATW	0.374**	0.621***	0.756***
	(2.364)	(3.610)	(3.651)
ATW X Specialist Firm	-0.473	-0.838***	-0.845**
	(-1.586)	(-2.654)	(-2.227)
Log Employees	2.723***		
	(16.21)		
Industry Establishments	-0.00725		
	(-0.471)		
Industry Employment	0.00103		
	(0.493)		
Log Employees (1-year Lead)		2.671***	
		(16.80)	
Industry Establishments (1-year Lead)		-0.0272	
		(-1.254)	
Industry Employment (1-year Lead)		0.00384	
		(1.318)	
Log Employees (2-year Lead)			2.567***
			(10.50)
Industry Establishments (2-year Lead)			0.00705
			(0.196)
Industry Employment (2-year Lead)			-0.000795
			(-0.161)
Constant	2.908***	2.902***	3.563***
	(6.927)	(6.257)	(5.237)
Firm FE	Y	Y	Y
Year FE	N	N	N
Observations	1,155	1,155	1,155
R-squared (with Fixed Effects)	0.969	0.962	0.953
Number of Firms	233	233	233
R-squared within	0.768	0.715	0.590
R-squared between	0.735	0.734	0.733

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1
ATW (Acquisition Time Window): 2004-2006

Table 4.5 shows the results corresponding to H1 and is comparable to Table 4.3. Similarly, Table 4.6 is comparable to Table 4.4 and is in support of H2.

We used time dummies in our regressions instead of the controls for industry growth. Note that *Oracle Market Share* varies only with time. Hence, it is not estimable separately. However, we are able to test H2 that uses its interaction with *Specialist Firm*. Again, we found our results to be robust to this alternative specification.

Table 4.7 Robustness: H2 with Time Dummies

VARIABLES	(1) Log Sales (1-year Lead)	(2) Log Sales (2-year Lead)	(3) Log Sales (3-year Lead)
Specialist Firm X Oracle Market Share	-4.106*	-6.175**	-5.515*
	(-1.808)	(-2.274)	(-1.862)
2002.y	-0.122	-0.0986	-0.110
	(-0.829)	(-0.871)	(-0.758)
2003.y	-0.158	-0.106	0.0157
	(-0.957)	(-0.625)	(0.0885)
2004.y	0.0350	0.265	0.310*
	(0.191)	(1.414)	(1.680)
2005.y	0.288	0.468**	0.706***
	(1.450)	(2.357)	(3.660)
2006.y	0.484**	0.899***	1.006***
	(2.187)	(4.014)	(4.206)
Log Employees	2.714***		
	(16.20)		
Log Employees (1-year Lead)		2.657***	
		(16.49)	
Log Employees (2-year Lead)			2.537***
			(10.35)
Constant	3.457***	3.791***	4.151***
	(7.256)	(7.312)	(5.218)
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	1,155	1,155	1,155
R-squared	0.730	0.612	0.540
Number of Firms	233	233	233
R-squared within	0.730	0.612	0.540
R-squared between	0.710	0.718	0.710

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.5 Alternative Explanations

4.5.1 Partnership Duration and Steering

It could be that our results in H2 are driven by the incumbent platform (SAP) favoring those partners with longer partnership duration. The fixed effect model that we employ controls for the time invariant characteristics of the partnership between the complementor and the platform owner. However, this does not account for the time varying component of the partnership. The platform partnership involves several repeated exchanges and the platform owner would be more willing to trust familiar partners (Gulati, 1995) with longer partnerships. Also, the duration of the partnership could influence the ability of complementors to absorb more knowledge and benefit from steering activities such as the SAP Developer Network (SDN) initiated by the platform owner. These in turn could end up in better sales for complementor with longer partnerships. We address this possibility by including the interaction between the entrant's market share and the partnership duration (as of the year 2004) to our baseline regression.

Table 4.8 Alternative Explanation: H2 with the Addition of Partnership Duration

VARIABLES	(1) Log Sales	(2) Log Sales (1-year Lead)	(3) Log Sales (2-year Lead)
Oracle Market Share	5.033	8.212**	9.658***
	(1.640)	(2.413)	(2.714)
Specialist Firm X Oracle Market Share	-4.101*	-6.087**	-5.308*
	(-1.799)	(-2.222)	(-1.791)
Oracle Market Share X Partnership Duration	-0.200	-0.511	-0.701
	(-0.352)	(-0.800)	(-1.193)
Log Employees	2.710***		
	(16.39)		
Industry Establishments	0.000423		
	(0.0267)		
Industry Employment	-0.000522		
	(-0.241)		
Log Employees (1-year Lead)		2.667***	
		(16.60)	
Industry Establishments (1-year Lead)		-0.00767	
		(-0.334)	
Industry Employment (1-year Lead)		0.00111	
		(0.353)	
Log Employees (2-year Lead)			2.547***
			(10.34)
Industry Establishments (2-year Lead)			0.00470
			(0.137)
Industry Employment (2-year Lead)			-0.000236
			(-0.0508)
Constant	2.399***	1.972***	2.161***
	(5.029)	(3.158)	(2.649)
Firm FE	Y	Y	Y
Year FE	N	N	N
Observations	1,155	1,155	1,155
R-squared (with Fixed Effects)	0.950	0.962	0.954
Number of Firms	233	233	233
R-squared within	0.770	0.717	0.593
R-squared between	0.731	0.727	0.729

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

We find that our results shown in Table 4.8 are robust to the addition of this interaction term to the initial specification found in Table 4.4, supporting our original theory.

4.5.2 Firm Age and Value Appropriation

While we addressed the possibility that firms could benefit from longer partnerships above, it could be that firms simply get better at developing software over time. This in turn could influence their productivity and help them achieve higher sales per employee over time. This could again provide an alternative explanation for the differential effects we observe in H2.

We address this issue by including the interaction between the entrant's market share and the age of the complementor at the time of forming the partnership with SAP. The assumption made is that the firm age measured as at the time of joining the partnership should proxy for internal firm learning. The results are shown in Table 4.9 and are comparable to the results found in Table 4.4. We find that the interaction effect between *Age at Partnership* and *Oracle Market Share* is actually negative and significant. However, we find that our initial results concerning the differential effects of performance based on human capital specialization are still supported.

Table 4.9 Alternative Explanation: H2 with the Addition of Firm Age at Partnership

VARIABLES	(1) Log Sales	(2) Log Sales (1-year Lead)	(3) Log Sales (2-year Lead)
Oracle Market Share	9.109***	11.43***	12.12***
	(4.857)	(5.795)	(5.335)
Specialist Firm X Oracle Market Share	-6.002***	-8.215***	-7.580***
	(-2.650)	(-3.102)	(-2.619)
Oracle Market Share X Age at Partnership	-6.002***	-8.215***	-7.580***
	(-2.650)	(-3.102)	(-2.619)
Log Employees	2.673***		
	(16.96)		
Industry Establishments	0.00484		
	(0.303)		
Industry Employment	-0.000747		
	(-0.342)		
Log Employees (1-year Lead)		2.633***	
		(17.38)	
Industry Establishments (1-year Lead)		-0.00479	
		(-0.213)	
Industry Employment (1-year Lead)		0.000733	
		(0.239)	
Log Employees (2-year Lead)			2.521***
			(10.61)
Industry Establishments (2-year Lead)			0.00504
			(0.154)
Industry Employment (2-year Lead)			-0.000401
			(-0.0904)
Constant	2.495***	2.192***	2.440***
	(5.638)	(3.982)	(3.356)
Firm FE	Y	Y	Y
Year FE	N	N	N
Observations	1,155	1,155	1,155
R-squared	0.971	0.964	0.956
Number of Firms	233	233	233
R-squared within	0.784	0.735	0.616
R-squared between	0.529	0.513	0.517

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.5.3 SAP Platform as a Stable Alternative

It is quite possible that our results in H1 are driven by the fact that the SAP platform was seen as a stable alternative by customers when the industry went through an uncertain phase during this consolidation initiated by Oracle's acquisitions. In particular, given that, once installed, ERP software stays in operation for several years, customers would be worried about ongoing support for the software that they install and may like to steer clear of uncertainties that may arise due to the merging of several different companies to form one common platform. Further, they may also be worried about the continued availability of complements on the platform. These uncertainties should result in an increase in SAP installed base as well as an increase in SAP complementor sales. Though it is difficult to rule out this effect completely, the relative change in the level of installed base of the two platforms and Oracle's ability to successfully catch up with the market leader SAP over this time period seems to suggest otherwise. The improvement in sales of SAP complementors in spite of the relative increase in Oracle's market share seems to be driven, instead, by SAP's initiatives aimed at steering the complementors away from the Oracle platform.

4.5.4 Multihoming and Specialization in Human Capital.

Our results on the performance premium for generalists in H2 could be a function of their superior ability to multihome. We do find that the propensity to multihome is far greater among generalists than specialists. However, conditional on multihoming, there is no significant differential effect on performance between specialists and generalists. We confirm this by including the triple interaction involving the *Oracle Market Share*, *Specialist Firm*, and *Multihoming* in our regressions (shown in Table 4.10) and checking the coefficient on it. We find the triple interaction to be statistically insignificant. While these results do not necessarily rule out the possible benefits from multihoming, they do not seem to explain the observed difference in performance between generalists and specialists.

Table 4.10 Oracle Market Share, Specialist Firm, and Multihoming

VARIABLES	(1) Log Sales	(1) Log Sales (1-year Lead)	(1) Log Sales (2-year Lead)
Oracle Market Share	4.210**	5.887***	5.772***
	(2.591)	(3.591)	(3.105)
Specialist Firm X Oracle Market Share	-3.633	-5.924*	-5.438
	(-1.373)	(-1.853)	(-1.600)
Multihoming	0.823	2.160	1.845**
	(0.733)	(1.608)	(2.065)
Oracle Market Share X Multihoming	-2.020	-4.635	-2.432
	(-0.663)	(-1.473)	(-0.887)
Specialist Firm X Multihoming	0.802	-0.969	1.250
	(0.513)	(-0.561)	(0.782)
Specialist Firm X Oracle Market Share X Multihoming	-2.356	1.553	2.570
	(-0.539)	(0.339)	(0.535)
Log Employees	2.707***		
	(16.32)		
Industry Establishments	-0.000646		
	(-0.0397)		
Industry Employment	-0.000383		
	(-0.170)		
Log Employees (1-year Lead)		2.661***	
		(16.74)	
Industry Establishments (1-year Lead)		-0.00403	
		(-0.180)	
Industry Employment (1-year Lead)		0.000588	
		(0.193)	
Log Employees (2-year Lead)			2.551***
			(10.52)
Industry Establishments (2-year Lead)			0.0188
			(0.550)
Industry Employment (2-year Lead)			-0.00221
			(-0.479)
Constant	2.291***	1.922***	2.252***
	(4.457)	(2.933)	(2.736)
Firm FE	Y	Y	Y
Year FE	N	N	N
Observations	1,155	1,155	1,155
Number of Firms	233	233	233
R-squared	0.970	0.962	0.954
R-squared within	0.770	0.718	0.596
R-squared between	0.731	0.728	0.719

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.6 Discussion and Conclusion

In this study, we use a sample from the ERP platform ecosystem and focus on the effect of platform level competition on complementor performance. Prior research on ecosystems that has often relied on network effects based explanations would predict that a change in installed base of an entrant relative to the incumbent on one side of the market should result in a decrease in performance of complementors associated with the incumbent platform. However, this does not take into account the possibility that the incumbent platform owner could engage in efforts to substitute efforts of the complementors and be more willing to share the value created in the ecosystem. Our results suggests that this is indeed a possibility and can lead to a counterintuitive result wherein the performance of complementors actually increases when the relative installed base of its partner, the incumbent platform owner, decreases.

Further, we explore whether these main results are affected by the heterogeneity among complementors in terms of their human capital. We find that generalists perform better than specialists when the relative installed base changes, which we attribute to their dynamic and integrative capabilities (Helfat and Raubitschek (2018). We also rule out a number of alternative explanations for the results that we observe. In particular, we find that these results continue to hold even after accounting for multihoming as a potential explanation for differential complementor performance.

The study has a number of limitations. First, it is based on a single industry setting, making it harder to generalize the implications of our findings. Second, we do not have additional information on the complementor's upstream and downstream capabilities. These could improve the complementor's bargaining power as well as affect their response to steering by the platform owner. Third, we do not have additional information on the demand side in terms of the nature and expectations of customers. This prevents us from disentangling the installed base effects further. We believe that addressing some of these limitations could lead to interesting avenues for future research. Even with these limitations, the paper makes some notable contributions to the literature.

Our paper joins a stream of the literature that has questioned the logic of interpreting network effects as purely a measure of size (Cennamo and Santalo, 2013; Rietveld and Eggers, 2018) and stressed the need to take into account the role of structure and conduct within the network (Afuah, 2013). In particular, our work shows that the structure of the ecosystem in terms of the human capital within and across complementors plays an important role in value creation and appropriation in the context of the ecosystem. It also highlights the role of signaling by entrants through acquisitions and the role of trust and reputation built by incumbents though steering activities.

Firm adaptation to change has been an important area of focus in the strategy literature. While the bulk of this stream of literature has paid attention to technological change, recent work has tried to draw our attention to demand side changes (Agarwal and Wu, 2014). Theories based on dynamic capabilities have often been used to explain differences in firm adaptation and performance in the face of environmental change. It is important to understand how these theories extend to the realm of ecosystems (Teece, 2010). Our paper is a small step in this direction. In particular we show how integrative capabilities of complementors that arise from their human capital can influence adaptation to change in complex digital ecosystems (Helfat and Raubitschek, 2018).

The paper is also relevant to practitioners. Traditional thinking has been that activities such as knowledge sharing and support to complementors are aimed at opening up and growing the ecosystem. However, managers in platform owner companies need to be aware that these activities can also be used strategically to steer the ecosystem by engaging and retaining complementors in the face of competition from rival platforms. The paper is also useful to managers of complementors thinking about sourcing and deploying human capital.

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4.8 Appendix

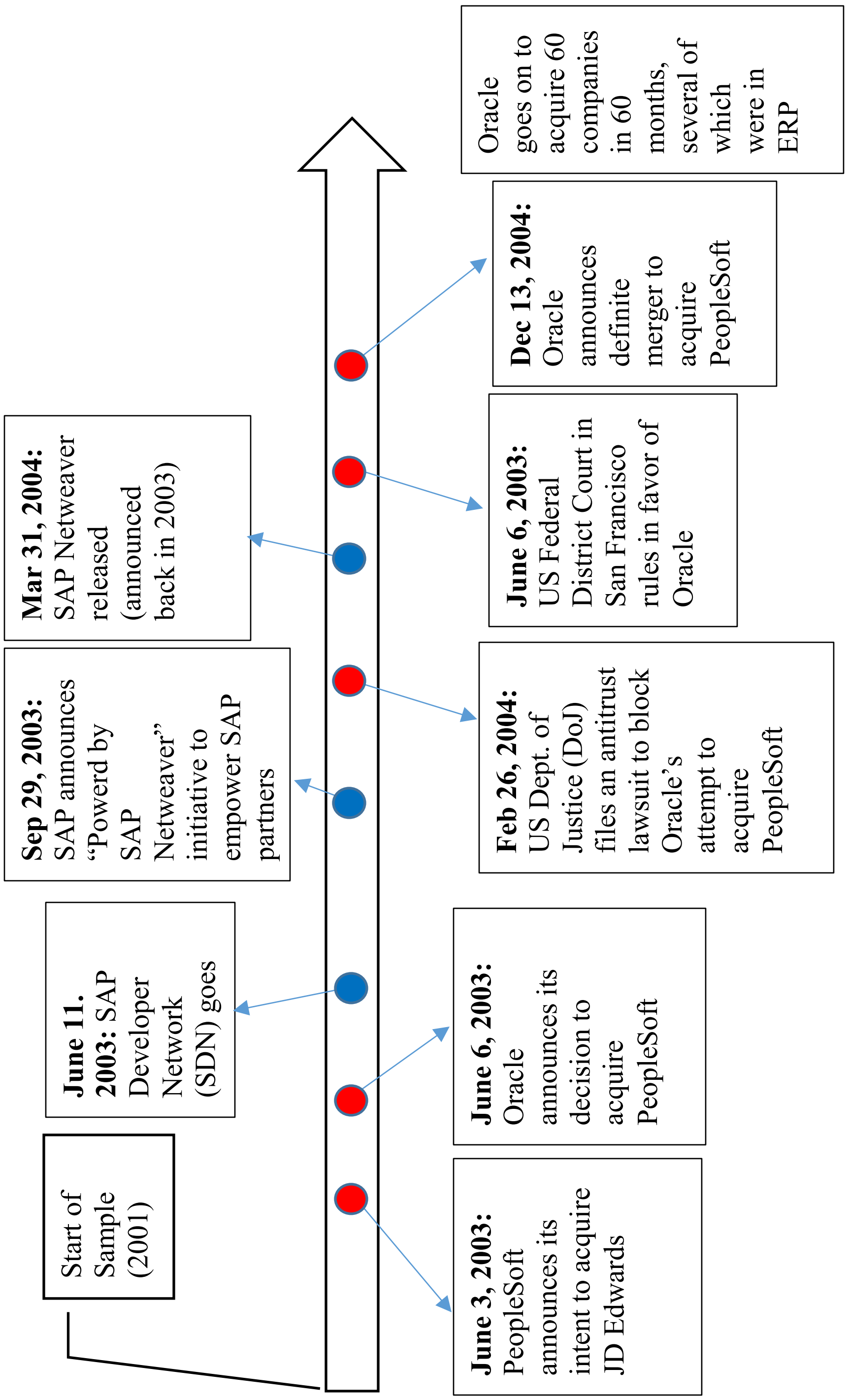

Figure 4.1 Sequence of Events

Table 4.11 Installed Base - License Revenues (in $ million)

Year	SAP	Oracle	Oracle Market Share Relative to SAP
2000	681.04	504.68	42.56%
2001	647.43	413.50	38.98%
2002	585.36	300.94	33.95%
2003	608.09	268.32	30.62%
2004	734.14	302.22	29.16%
2005	934.85	474.18	33.65%
2006	1081.02	680.37	38.63%
2007	1214.66	906.42	42.73%
2008	1326.26	936.67	41.39%
2009	909.06	896.24	49.64%

Note: These values are based on the revenues reported by Oracle and SAP in their annual reports and pertain to the US enterprise software market.

Figure 4.2 SAP Developer Network Web Announcement

Note: SAP Developer Network (SDN) Beta Site launched back in 2003. It was later renamed as SAP Community Network (SCN).

The graph below captures the level of participation in the network in the form of questions raised by members of the ecosystem in response to SAP's efforts to engage the community.

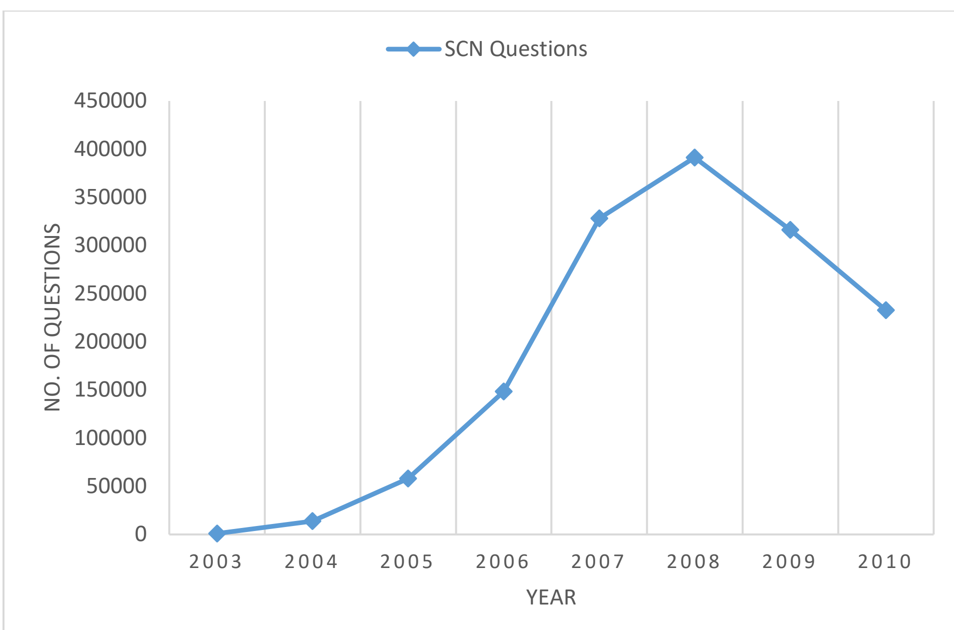

Figure 4.3 SAP Community Participation

Table 4.12 List of Keywords

Technical HC	Industry HC	Functional HC	Managerial HC
ABAP	Aerospace	SAP FICO	Management
Netweaver	Defense	SAP MM	Project Management
SAP BASIS	Automotive	SAP SD	PMP
Java	Banking	SAP PP	Project Management Professional
Javascript	Chemicals	SAP BI	Manage
HTML	Consumer Products	SAP SRM	Managed
SQL	Engineering	SAP CRM	Lead
Database	Construction	SAP HCM	Led
Code	Operations	SAP BW	Coordinate
Coding	Healthcare	SAP FI	Coordinated
Programming	Higher Education	SAP PS	Control
Technical	Research	SAP PM	Controlled
Architecture	High Tech	Financial Accounting	Delegate
C	Industrial Machinery	Materials Management	Delegated
C++	Insurance	Sales and Distribution	Direct
Websphere	Life Sciences	Production Planning	Directed
J2EE	Media	Business Intelligence	Supervise
	Mill Products	Supplier Relationship Management	Supervised
	Mining	Customer Relationship Management	
	Oil	Human Capital Management	
	Gas	Business Warehouse	
	Professional Services	Project System	
	Public Sector	Plant Maintenance	
	Retail	Functional	
	Sports		
	Entertainment		
	Telecommunications		
	Transportation		
	Logistics		
	Utilities		
	Wholesale Distribution		