Multihoming within Platform Ecosystems: The Strategic Role of Human Capital

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Abstract

Platform ecosystems characterized by a few platform owners and numerous other complementor firms that partner with them have become quite common across industries. Even though there has been considerable research on platform ecosystems, attention has mostly been on the platform owners and their strategies. In this paper, we focus on the complementor firms and try to understand the phenomenon of multihoming, a strategy in which a complementor firm chooses to join multiple platforms rather than one. We build a micro-foundational capability framework based on human capital and test it on a novel dataset from the ERP platform ecosystem. The study has implications for our understanding of platform growth and innovation and contributes toward the literature on platform ecosystems as well as strategic human capital.

Keywords

Platform Ecosystems; Complementor; Multihoming; Enterprise Software; Capabilities

INTRODUCTION

The structure of an industry and the value creation and appropriation opportunities within it are inextricably linked. Across industries such as gaming, mobile, business software, e-commerce and credit cards, the nature of competition has shifted from product-based competition involving a few firms alone 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 an intricately networked innovation ecosystem composed of a few firms that own the core product and complementors that contribute toward building a platform around it through their product/service offerings (Gawer and Cusumano, 2002; Adner and Kapoor, 2010; Gawer, 2014).[1]

This paper is aimed at exploring complementor strategies within platform ecosystems. Specifically, we investigate complementor decisions to develop products and services for competing platforms at the same time, known as multihoming. Understanding where and when firms multihome is important because it influences market-level outcomes such as the likelihood whether will tip and become a winner-take-all market (e.g., Corts and Lederman, 2009; Landsman and Stremersch, 2011). In part because of its importance for understanding market structure, a small body of empirical work has sought to understand multi-homing behavior (Corts and Lederman, 2009; Landsman and Stremersch, 2011; Rysman, 2004; Bresnahan, Orsini, and Yin, 2015), focusing mostly on market-level outcomes in markets for video games and mobile applications. Despite this progress, at present we know relatively little about what factors shape

[1] 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 are a vehicle for market exchange (Gawer 2014).

individual firm decisions to multihome.[2] This is a significant gap in understanding. Platforms often display winner-take-all characteristics in some markets but not others.[3] These differences may be shaped in part by the propensity of firms in each market to multi-home.

To investigate the factors shaping individual firm decisions to multi-home, we investigate the multihoming decisions of complementors in the enterprise software industry. We take as our starting point the perspective that the architecture of a platform—including such things as the distance from the technological frontier (Anderson, Parker, and Tan, 2013; Claussen, Essling, and Kretschmer, 2015) and the extent of connectedness between the platform and its components (Kapoor and Agarwal, 2017)—influences the costs of platform affiliation. The interdependencies between the core product and the complementary products/services within a platform in terms of technical design creates interdependencies in the underlying task structure (Baldwin and Clark, 2000: p.360). In the case of enterprise software, 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 (Lazear, 2009; Chatterjee, 2017), leading to interdependencies in the corresponding task structure. The limited literature on this topic has focused on how characteristics of the platform influence the costs of affiliation. We instead focus our attention on the complementor firms themselves and their profile in term of human capital that may influence the cost of affiliation and their decision to multihome. This focus on enterprise software and the characteristics of complementors is valuable for several reasons. First, enterprise software platforms are economically important—one recent estimate put

[2] One notable exception is Cennamo, Ozlap, and Kretschmer (2017), who study factors shaping individual firm decisions to multihome in the US video game industry. We discuss their paper further below.
[3] For example, in the mobile platform ecosystem, the US market hasn't tipped toward Android or iOS, while Android has been dominant in emerging markets (Bresnahan, Orsini and Yin, 2017). In the case of enterprise software, both Oracle and SAP continue to remain strong players in the overall market.

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).

In response to this environment, firms choose heterogeneous strategies on what types of human capital to invest. Some complementors tend to specialize in only one form of human capital and rely on the broader ecosystem to deploy their software. Other complementors invest in multiple types of human capital related to the technology of the application as well as the industry and task structure in which it is embedded. We argue that the nature of human capital possessed by a complementor affects not only its decision to affiliate with a platform, but also its ability to respond to a demand shock that increases the size and value of affiliating with a new platform.[4] Specifically, complementors who specialize in one form of human capital cannot adjust quickly to take advantage of the new opportunity. As a result, complementors are heterogeneously positioned to take advantage of new opportunities that arise within the ecosystem.

We also argue that the duration of the partnership between platform owner and complementor affects multihoming, both directly as well as through the effect of human capital on multi-homing. First, longer partnerships lead to increased likelihood of multihoming. Repeated interactions with clients have been shown to improve firm capabilities in the software industry (Ethiraj et. al., 2005). We extend this to the platform setting and argue that such interactions facilitate learning and help firms develop the capability to multihome. Second, the impact of partnership duration is moderated by the firm's human capital. Specialist and generalist firms have different learning curves and this

[4] For a related effort that examines the ability of firms to respond to a demand shock in the defense industry, see Aggarwal and Wu (2014).

affects the capabilities they can build over time. In particular, generalist firms are capable of acquiring knowledge at the interface of multiple dimensions of human capital and this makes them better equipped to multihome when compared to specialist firms.

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.[5] We study the decisions of small SAP complementors as a response to this shock.[6] We take advantage of employee level data from LinkedIn to create a unique measure of human capital specialization and assemble a data set from a variety of sources. In sum, we construct an unbalanced panel composed of 244 complementors corresponding to 1038 observations spread across the years 2001-2006.

We use this data set to investigate whether firms who are more specialized in human capital are less likely to multihome. We find that firms specialized in any one form of human capital are 7.1% 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 routine. We find that these results are robust to the addition of firm sales and size as controls; alternative definitions of specialization; and differences in the length of time over which we define the demand shock. We next investigate the relationship between human capital specialization, duration of relationship with the existing platform, and the decision to multihome. We find that the longer the duration of prior partnership, the more likely a complementor will multihome. We argue that this is because

5 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 tech-based industries.

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

of better understanding and trust among the different forms of human capital (Reagans, Argote, and Brooks, 2005) that, in turn, promotes associative learning. However, longer duration of prior partnership tends to make it even more difficult for firms specialized in terms of human capital to multihome. This reflects the differences in the learning curve between specialist and generalist firms and is consistent with the idea of a 'survivor's paradox' where the very fit of a firm's activities to a certain environment makes it harder for the firm to react to changes within that environment (Aggarwal and Wu, 2014)

Our paper contributes to the literature on platform ecosystems in a number of ways. First, platform ecosystem researchers have often focused on platform owners and studied various platform owner strategies such as platform openness (Boudreau, 2010), standard setting (Rysman and Simcoe, 2008), ecosystem governance (Boudreau and Hagiu, 2011) and entry into complementor markets (Gawer and Henderson, 2007). However, less is known about complementors and their strategies. This paper joins a relatively small set of papers (Huang et. al., 2013; Kapoor and Agarwal, 2017; Cennamo, Ozlap, and Kretschmer, 2017) that are trying to explore complementor strategies within platform ecosystems. Second, our research also contributes to a body of work on multihoming. Prior research on multihoming has focused on demand side explanations for multihoming. The adoption of a platform by end users influences the willingness of complementors to partner with the platform (Rochet and Tirole, 2003). The availability of complementor applications, in turn, influences more customers to adopt the platform, resulting in a positive feedback loop (Rysman, 2007). Thus, increase in the relative market share of a platform influences the decision of a marginal complementor to multihome. It relies on the assumption that complementors can readily respond to changes in demand within the ecosystem. But, even when induced to multihome, not all complementors may be able to respond quickly and seize the opportunity (Teece, 2007). Prior literature has paid less attention to supply side considerations with regard to multihoming as we do. Last, the structural feature of a platform in terms of technological complexity has been shown to affect complementor performance (Kapoor and Agarwal, 2017) and the quality of multihoming complements (Cennamo, Ozlap, and Kretschmer, 2017). Our paper complements prior work by looking at the sources of heterogeneity in complementor capabilities, rather than among platforms, that lead to differences in complementor multihoming strategy.

THEORY AND HYPOTHESES

Complementors may decide to partner with multiple platforms for a variety of reasons. First, there may be significant benefits from serving the added network of users on another platform. Second, multihoming may help complementors to mitigate uncertainty related to future technological and competitive threats. For example, complementors may perceive risks that the platform will bundle its product or service into the platform (e.g., Davis et al., 2002; Eisenmann et al., 2011; Huang et al., 2013), or even that the platform owner may be able to 'squeeze' complementors who affiliate with only one platform (Farrell and Katz 2000). For example, Electronic Arts has used multi-homing to lower the risks that Microsoft might place strong demands on it when affiliating with its Xbox platform (Hagiu and Yoffie 2009). Further, when there is a platform war, complementors may be uncertain about who will win ultimately and so will affiliate with multiple platforms. Samsung, Motorola, and other OEMs for mobile phones have used this approach (Hagiu and Yoffie 2009). Despite these potential benefits, many complementors choose not to multihome because they may lack the required capabilities. In this paper, we contend that, in knowledge intensive settings such as platform software development, the source of such capabilities lie in the complementor's human capital. Further, given that software development is often a team development activity, we also explore the role of prior partnership experience in improving mutual trust among different human capital and promoting learning over time, thus enhancing the ability to multihome. Finally, we look at how the effect of partnership duration on multihoming is moderated by the nature of human capital endowments of the complementor.

Strategic Human Capital

Our theory used to explain multihoming is based on a micro-foundational approach toward firm capabilities. In particular, we focus on the nature of the firm's human capital (Castanias and Helfat, 1991 & 2001; Mayer, Somaya, and Williamson, 2012) and how employees with different skills interact in carrying out various organizational routines (Nelson and Winter, 1982). To keep things simple, we consider routines as multilevel, multi-person skills (Winter, 2012: p.177-180). This approach lets us take into account 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 (Nelson and Winter, 1982). 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 organizational routine.

To understand the issue better, let us consider the following motivating example. Company XYZ is a typical complementor within the ERP ecosystem. Let us suppose that it decides to develop an accounting solution for the retail industry on an ERP platform. The organizational routine involved in creating the solution involves several components. First, there is a need to understand the retail industry. Each industry has a unique set of business processes and is important that the final accounting solution captures these nuances while recording transactions. While the ERP platform in itself may support a basic set of processes, end customers within the retail industry (in our example) might want to invest in additional applications that enhance the value of the accounting functionalities provided in the basic product. Hence, it is important for XYZ to possess the necessary knowledge on the retail industry in order to be able to serve the needs of customers within that industry.

Second, accounting functionalities are implemented in particular ways within an ERP platform. To develop a solution that can seamlessly integrate with the basic functionalities provided in the ERP platform, it is important that XYZ has the necessary skills to understand the functionalities in the underlying platform as well as translate the retail industry needs into functional components of XYZ's own solution.

Third, the platforms, in themselves, may vary considerably in terms of complexity: the number of products with which complementary products need to interact and the associated implications for decisions related to product design (Kapoor and Agarwal, 2017). Hence, development of complementary products and services for a platform would require individuals who have significant knowledge about the technical complexity of the underlying platform.

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. First, domain expertise in retail industry is needed. Next, skills are needed to understand the particular implementation of the accounting functionalities on the platform as well as the solution. Lastly, technical human capital to develop code fragments that enable the solution to function smoothly on the platform. To develop the capability to create the needed solution for the retail industry, all the three forms of human capital discussed are needed.

< Inset Figure 1 about here >

As we have seen in our motivating example, the multi-dimensional nature of human capital needed to create products/ solutions in this setting would make it harder for some firms that do not possess such human capital to multihome. Technological skills may be necessary but not sufficient to build capabilities in software development within platform ecosystems (Chatterjee, 2017). Knowledge on the way business processes are implemented as application functionalities as well awareness of the industry context in which the solution is being implemented also becomes quite important. The marginal impact of a certain form of human capital on the performance of the overall routine is likely to be improved by an increase in any of the other forms of human capital involved in the routine. Also, given the nature of interdependencies among elements of the multihoming routine, complementors may find it hard to contract for these skills in the labor market within a short period of time[7]. To summarize, the multi-dimensional nature of human capital needed to create products/ solutions in this setting would make it harder for some firms that do not possess such human capital to multihome.

Therefore, we have the following hypothesis,

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

Duration of Partnership

So far, we have seen how an organization's prior human capital investment considerations create a tradeoff between specialization and multihoming. Now, we build on this idea further and explore the conditions under which multi-dimensional human capital can be brought together more effectively, thereby affecting the propensity to multihome. To be specific, we consider the impact of partnership duration on a complementor's multihoming decision, and its interaction with specialization based on human capital.

[7] The possibility of contracting for human capital as an alternative explanation is discussed in more detail in a subsequent section.

Experience within a partnership not only enhances performance within the focal partnership but also enhances the capability to enter into new partnerships. Prior literature on partnerships has explored the role of learning within partnerships over time (Anand and Khanna, 2000). Also, scholars have looked at the relationship between partnering experience and the success of inter-firm alliances (Kale, Dyer and Singh, 2002; Zollo, Reuer and Singh, 2002; Hoang and Rothaermel, 2005). Routinization processes get continuously refined at the partnering firm level and the accumulated experience enhances the capability of the firm to redeploy its routines. Here, we extend some of these broad ideas to the realm of platform ecosystems, in particular focusing on the relationship between partnership duration and the previous discussion on human capital dimensions.

Repeated interaction in prior engagements leads to better team learning (Reagans, Argote and Brooks, 2005). In the platform ecosystem setting, this learning may be thought of as composed of three interrelated parts. First, there is the solidification of roles and responsibilities within a complementor team. Over time, members within a team develop a sense of familiarity with regard to both division of tasks and the coordination among those tasks. Such familiarity enables the team to arrive at an optimal division of labor that facilitates the smooth performance of the overall routine. Also, teams tend to codify collective knowledge enhancing the performance of repetitive tasks (Zollo and Winter, 2002).

Second, experience creates a sense of trust (Uzzi, 1996) which promotes the sharing of knowledge. Familiarity among individuals with different forms of human capital working within a complementor team leads to more willingness to share knowledge within the team. This, in turn helps in better exchange of information among individuals engaged in the performance of the organizational routine. Within platform ecosystems, trust not only play a role in enhancing knowledge sharing within the complementor team but also helps in building relationships between platform owners and complementors and in sustaining innovation (Gawer and Henderson, 2007). Here, we contend that the duration of platform partnership improves the trust between the platform owner and complementor, which enables complementors to learn better. Also, similar to the alliances context, platform owners may be more willing to share relatively general knowledge rather than very specific knowledge regarding the development of products and services on the platform. While this enables platform owners to protect their platform from imitation, it also enables complementors to gain more general knowledge that are applicable across platforms, facilitating multihoming. For example, SAP may be more willing to share general software development best practices to help complementors improve their products and services. But, they may be reluctant to share critical SAP component know-how. Again, the general software development best practices may lead to a capability that can be more easily redeployed in another platform.

Third, partnership duration enhances team level learning at the complementor firm. Such learning obtained through one alliance gradually results in an alliance capability that can be leveraged in other alliances. This is made possible by internal sharing of prior alliance management experience (Kale and Singh, 2007). Also, knowledge stock in one platform creates an absorptive capacity (Cohen and Levinthal, 1990) in firms to learn new platforms through a process of associative learning. There are several aspects that are common across platforms. This is analogous to similarities between programming languages that are used to build software platforms. But, in reality, platform learning is not only about learning the technical aspects. There could be similarities in the way in which software projects across the two platforms are carried out. Often referred to as the software development lifecycle, these are a specific form of organizational routines in the context of software firms. An organization that has experience in greater number of project lifecycles may be more proficient in transferring those capabilities to the new platform. It may be noted here that a majority of the complementors across ecosystems are relatively small and inexperienced as compared to the platform owner. So, the initial platform partnership provides them with an ability to not only learn the specific platform but also develop different capabilities concerning the production of products and services, in general. It is this aspect of the partnership that is most important to multihoming.

To summarize, individuals endowed with different forms of human capital learn to work together when the partnership duration increases. Increase in partnership duration results in better identification of tasks and roles. Trust promotes the sharing of information among the different roles and facilitates learning. Finally, learning enables firms to develop the capabilities required to multihome. Beyond these mechanisms, we acknowledge that partnership duration may be associated with higher transaction costs and a reduction in the probability of multihoming. Transactions costs would imply that relationship specific investment in a prior partnership, which would increase for longer partnerships with a platform, can actually hold back the complementor from multihoming. We discuss this possibility along with other alternative mechanisms that may explain multihoming in the discussion section. To summarize, we 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.

The Interaction between Partnership Duration and Human Capital

We argue that the impact of partnership duration will not be the same across all firms. In particular, we hypothesize that specialized firms are less likely to benefit from longer partnerships when it comes to multihoming. Specialist and generalist firms have different learning curves. The breadth of prior knowledge stock possessed by generalist firms is broader and this makes them more capable of absorbing new knowledge in a related domain. Even though partnership duration is likely to improve learning within specialized firms as well, they may not be useful in gaining knowledge that are at the boundaries of the different forms of human capital. Experience with a platform involves not only the accumulation of modular technical, functional or industry knowledge. It is also involves the understanding of elements that lie at the intersection of these different aspects. As a result, specialized firms continue to be at a disadvantage even though the duration of partnership increases.

Cost differences among various possible forms of human capital mix that can be built leads to early choices concerning whether to specialize (or not), which in turn leads to path dependencies. However, as we have seen, multiple forms of human capital are required to engage in multihoming. Hence, while specialization may enable the firm to compete effectively in the existing platform, it also makes it harder for it to readjust to changes in the demand environment by pursuing a multihoming strategy. This may be thought of as a survivor's paradox (Aggarwal and Wu, 2014) wherein the very decisions that helped a complementor to adapt to its initial environment makes it harder for it to respond to changes in the environment.

Hence, we predict that, even though ability to multihome improves with duration, on average, firms specialized in one form of human capital would be unable to take advantage of this and, therefore, find it harder to multihome.

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.

DATA AND METHODOLOGY

Empirical Setting

We choose the ERP platform ecosystem setting to test our theories for several reasons. One, the ecosystem has evolved over many years and the human capital specializations within it have become well defined over time. Two, the presence of an incumbent platform owner SAP and a relatively new platform owner Oracle that was trying to improve its market share at the time makes it an interesting setting for studying the phenomenon of multihoming. Three, the ERP 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.

The origins of ERP software may be traced back to preliminary tools for managing inventory in predominantly manufacturing-based organizations. Over the years, the ERP software expanded in scope to include modules pertaining to accounting, human capital management, sales, and distribution. Within the ERP ecosystem, SAP and Oracle are the principal platform owners that develop and license the core ERP product to end customers operating across a wide range of industries. Even though there are other ERP vendors operating in the industry, SAP and Oracle are the dominant ones. Just as app developers come up with 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, it may be noted that products and services on the ERP platform can be considerably more complex and may hence require substantial investment in human capital to develop the needed expertise. Also, software development within ERP complementors is invariably carried out in complex teams composed of individuals specialized in functional, technical and industry human capital. Another dimension on which the ERP ecosystem is complex is with regard to the nature of partnering. While app developers can easily partner with platforms and start developing apps without incurring much cost, partnering in the ERP ecosystem required considerable investment related to partner membership fee; testing and certification of products; and endorsement of services.

Sample

We have built a comprehensive dataset on the ERP platform ecosystem based on several secondary data sources. More importantly, the dataset covers the years 2001-2006[8] that marked the rise of Oracle as an ERP platform owner and the subsequent intense rivalry between SAP and Oracle to dominate the ERP market. 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 snapshot of SAP's partner website is likely to induce a selection bias. Hence, we augmented the list of firms by adding exhibitors from past SAP annual meetings. SAP complementors enlist themselves as exhibitors at these meetings and set up booths at the conference venue to showcase their products and services. Since these meetings are well attended by existing and potential end customers, it is especially important for complementors to be present in order to take advantage of the opportunity and advertise themselves. While the data from the partner website was readily available, data for the SAP SAPPHIRE and SAP Insider annual meetings were collected by hand from the internet archive of various SAP related web pages.

[8] We use additional data from years 1999-2000 for evaluating the effect of the dot-com bubble and years 2007-2008 to check the robustness of the acquisition time window.

We decided to focus on US based complementors in order to ensure that all firms within the sample are comparable. In order to build a panel dataset, we also need to know the exact year in which each of the partners joined the SAP platform. Hence, we used press releases data from Factiva to accurately identify the year of partnership formation with SAP. We relied on keyword based search 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 press releases based approach was used for obtaining the year of multihoming (joining Oracle).

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. Though CVs have been used to study start-up founders and top management teams, they have rarely been used to analyze firm strategies (Tambe and Hitt, 2013). 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 the NETS database and ended up with 1,012 headquarter DUNS numbers which corresponded to as many as

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.

Dependent Variable

Multihoming: The dependent variable is multihoming which may be conceptualized as a dichotomous variable that 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 as well. If the firm never multihomes, the variable remains at zero until the end of the sample period.

Independent Variables

We seek to investigate how firms ex ante endowments of human capital and the extent to which they are specialized allow them to take advantage of new opportunities for multi-homing. Specialization in the context of the ERP ecosystem may be classified broadly into three types namely functional, technical and industry. For the purpose of our analysis, we construct separate variables corresponding to each of these three types of human capital specialization. Here we provide an overview of our approach; please see the Appendix for a specific illustration.

First, we identify a set of keywords that are associated with a specific form of human capital. In order to make the identification of keywords systematic and free of any sort of biases, we collect the keywords to be used for the different forms of human capital from resources that are made publicly available on SAP's own support website. For example, SAP architecture related terms such as ABAP and Netweaver and coding languages such as Java and C++ correspond to technical skills employed in this platform; 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 (please refer to the Appendix for the list of keywords).

Second, we search within the employee CV data for the keywords identified above and count all relevant instances of appearance of the keywords. The search process in itself involves a number of steps. As the first step, we identify the individuals employed with the company in a given year and present in the sample. While some CVs list the dates of employment at the monthly level, others do so at the yearly level. As stated earlier, we construct the sample at the firm-year level. And, once again, in order to maintain uniformity, we convert the employment duration as well to the yearly level. After identifying the relevant set of individuals, as the next step, we take a particular CV and search for each of the keywords (identified earlier) within it. We make a note of the exact count of keyword matches obtained in this way. 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. It may be noted that the summary section of an individual's CV is common across jobs while the job description section is common across all the years spent on a particular job. But, 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. So, we allocate only the fraction of the skills corresponding to the five years prior to 2001. In the following step, we repeat the search, match and count 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 level 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. Even though we acknowledge that more complex ways of aggregation are possible, this simple form of aggregation is consistent with the micro-foundational view of firm strategy (Barney and Felin, 2013). We use this procedure to create three types of human capital: technical human capital, industry human capital, and functional human capital.

Technical Human Capital: This measures the technical form of human capital in the firms partnered with SAP and is measured as the stock value as of the year 2001. 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. Technical human capital may be thought of as the typical skills acquired by individuals who fit into the job profile of a Technical Consultant in the ERP ecosystem. A Technical Consultant may be expected to have a clear understanding of SAP's ABAP (Advanced Business Application Programming) architecture and develop code that interacts with various built-in ERP modules that are based on that architecture.

Functional Human Capital: It is the functional form of human capital in the partner firms measured as of 2001. Functional human capital is essential to grasp the business process flows build into an ERP platform. Procure-to-pay is an example of a business process flow within an ERP ecosystem. It refers to the various steps involved in the procurement of a product or service and the payment to the supplier for it by the end user of the ERP solution. 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. Functional human capital corresponds to the skills associated with the job profile of a Functional Consultant in the ERP ecosystem.

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. The third of our human capital measures captures the industry knowledge of the firm as of the year 2001. Industry human capital may simply be thought of as the skills possessed by individuals who play Domain/ Industry Consulting roles within the ERP ecosystem.

Specialized Firm: We designate those firms that are above a certain percentile on any one of the human capital measures described above as specialized. We start with a cut-off of 75 percentile and show later that our results are robust to other percentile based cut-offs. We use the pre-shock human capital values as of the year 2001 to determine these cut-offs.

Acquisition Time Window (ATW): In order to capture the effect of announcements regarding platform level acquisitions by Oracle, we use a dichotomous variable that turns one during the acquisition time window (which is defined as three years immediately following the first acquisition related announcement) and stays zero otherwise. More details on the Oracle's acquisitions are contained in the identification section below.

Duration of Partnership (Duration): The duration of partnership is based on the number of years spent with the SAP platform as of the start of the acquisition time window. We use a dichotomous variable to differentiate between high duration and low duration partnerships and classify the complementors into two distinct groups. 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. This is primarily for ease of interpretation and the results continue to hold when the variable is redefined as a continuous measure.

Control Variables

Multihoming strategy could be correlated with a number of variables that are unobservable to the econometrician. We use a *fixed effects* model that controls for all time-invariant firm-level unobservables and *time dummies* that control for events that are common across firms in any given year. One might argue that there could still be time varying firm-level unobservables that could bias the results (please refer to the next section on identification for more details). In particular, we control for two major sources of such variation namely firm employees and firm sales. It has been shown in the literature that a firm's *Employees* and *Sales* control for a vast array of firm capabilities and, hence, have considerable potential to influence firm strategies. In particular, in the platform ecosystem setting, we can think of firm sales as a proxy for the quality of the complementor product as well.

Identification

A major potential challenge 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. The level of multihoming could be low because the cost of building a mix of human capital that can be deployed across platforms is high or the benefits from partnering with another platform are quite low or both. We make use of an exogenous shock within the ERP platform ecosystem that suddenly increased the benefits of joining the Oracle platform. Starting in 2004 with the acquisition of PeopleSoft, Oracle made a series of application platform acquisitions to inorganically improve its market share within a short period of time. As a Bloomberg article[9] noted, Oracle made a series of successful acquisitions over a relatively short period while SAP did not adopt a similar strategy.

Oracle's hostile bid to acquire PeopleSoft was met with stiff resistance initially. Also, the

[9] SAP Sheds M&A Shyness as Oracle Rivalry Moves to the Cloud Source: Bloomberg Business (2011)

acquisition size was huge. It 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. Oracle's acquisition spree transformed the entire platform ecosystem and had a profound impact on complementor firms. For them, joining Oracle suddenly meant the opening up of a significant opportunity to sell complementary products and services to a wider network of customers. However, most complementor firms realized that it wasn't going to be easy to adapt to the new platform.

We make use of heterogeneity across firms in human capital to identify how different pre-acquisitions firm characteristics related to human capital influence a change in the propensity to multihome within-firm in a post-acquisitions versus pre-acquisitions environment. 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. As explained in the next section, we control for any firm characteristic that does not vary over time only exploiting within-firm time variation in our key variables and interactions with pre-shock human capital characteristics. This is important as, by so doing, we will be also controlling for the type of partnership between SAP and complementors and the type of product and services of the focal complementor. Firms within our ecosystem may differ in their partnerships in terms of nature and scope of activities in terms of products and services, geography of operations, level of partnership as designated by the platform owner (SAP) and so on. Even though we control for firm size and sales, we also eliminate large complementor firms from the sample to reduce the extent of unobserved heterogeneity within the sample. We use pre-shock values of HC measured as of the year 2001 for our analysis. It 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 alone because it takes time for teams to learn to work together. 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.

Estimation Methodology

We use a panel-data linear probability model with time-invariant unobserved fixed effects (Wooldridge 2001) for estimation. The observation unit used for analysis is firm-year. 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 consisting of 1038 firm-year observations corresponding to 244 firms.

In our regression model, the interaction between level of human capital specialization pre-acquisitions and the acquisition time window (ATW) enables us to measure the response in multihoming of different type of firms before and after the acquisitions by Oracle. Even though the linear probability model has some inherent disadvantages such as allowing for probabilities that are outside of (0, 1), the model allows us to control for panel level unobservables. Also, our identification strategy relies on interaction terms, which are difficult to interpret in non-linear models (Ai and Norton, 2003). We use both firm and year fixed effects in our model and obtain robust standard errors for our estimates. We used the random effect LPM model as an alternative and found the results to be similar. However, the Hausman test clearly showed us that the fixed effects model is more appropriate for our analysis.

RESULTS

Table 1 shows the basic summary statistics while Table 2 reports the correlation among the different forms of human capital and the employee count. All variables are log transformed to account for the skewness of their distributions. The normalized HC measures do not vary much with firm size or sales. Specialized firms (defined by being above the 75th percentile on any one form of human capital) constitute just above 52% of our sample. Again, just above 50% of the observations correspond to firms that had partnered with SAP for five or more years as of the start of the ATW.

< Insert Tables 1 and 2 about here>

Our shock is relevant. In Figure 2, we show graphically that the acquisition time window 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 year dummies in the sample as independent variables. To ensure that the results are not based on underlying time trends alone, we interact the *specialized firm* variable with every year in the sample. We clearly find that (1) there is an increase in multihoming during the time window and (2) the coefficients for *specialized firms* x *year dummy* is lower than those of *other firms* x *year dummy* during the window. Also, consistent with what one would expect in a competitive environment, firms with the right human capital mix tend to take advantage by moving in early and partnering with Oracle, resulting in a sudden spike starting in the year 2004.

< Insert Figure 2 and Table 3 about here>

As stated earlier, firms that are above the 75th percentile in terms of any one of the three forms of human capital are denoted as specialized. This variable is then interacted with the ATW. The results based on the linear probability model (refer to Table 3) show that specialized firms have a lower propensity to multihome after the ATW shock by about 7 percentage points, which is in line with hypothesis 1a. Column 1 shows the results without the controls while column 2 includes the controls for firm size in terms of both employee count and sales. The coefficient on *Specialized Firm X ATW* is -0.071 with a p-value of 0.009 in column 1, and it is -0.072 with a p-value of 0.009 in column 2. This demonstrates that our hypothesis is supported and is robust to the addition of controls. As one might expect, the correlation between the logged values of employee count and sales is quite high. As further robustness, we run two separate regressions, one with log sales alone as a control and the other with log employees alone and find our results to be robust to these alternative specifications. The explanatory power of the linear probability model appears to be low when the mean deviated fixed effects model is used, which is in line with prior work (Agarwal and Goldfarb, 2008; Forman and van Zeebroeck, 2012). However, it may be seen that there is a substantial increase in the overall R-squared when the explanatory power of the firm fixed effects is incorporated into the R-squared calculation. For example, in column 2, the R-squared value increase from 0.080 to 0.622.

The unique nature of our data enables us to explore more about the nature of skills possessed by the firms and how they contribute toward multihoming. In particular, we are interested in the pairwise complementarities among the different types of skills employed by the firms. Table 4 captures the interaction effects among the different forms of human capital. Columns 1-3 show the interactions involving the different pairs of skill measures and the ATW. We interpret the coefficient on the triple interaction after controlling for the corresponding double interactions.[10]

[10] 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.

< Insert Tables 4 about here>

We find that all three types of interaction namely technical-industry, technical-functional and industry-functional have a positive effect on multihoming (we discuss the magnitude of the marginal effects of ATW at low and high values of the three forms of HC in the Appendix). This suggests that multihoming increases as a consequence of the shock when there is some form of complementarity between the different forms of human capital. This is consistent with the views of an industry expert that we interviewed (quoted below) and reiterates the point that a specific form of HC in itself is not valuable to multihoming but becomes more valuable when combined with other forms of HC. 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)"

< Insert Table 5 about here>

Now, we analyze the results corresponding to hypothesis 2 concerning the impact of partnership duration on multihoming. As noted earlier, the duration of partnership is captured as a dichotomous variable with 0 and 1 corresponding to low and high duration respectively. The interaction term between ATW and duration is found to be positive and significant (column 1 of Table 5). We computed the predicted probability of multihoming for the two groups of firms before and during the ATW. The change in predicted probability of multihoming as a result of the shock is very little for firms with short term partnerships (0.6 percentage points) while the change is comparatively high for firms with long term partnerships (7.7 percentage points), which is exactly what we would expect based on hypothesis 2.

The second column in Table 5 includes the interaction between duration and specialization when subject to the shock. We find that the marginal effect of partnership duration on the likelihood of multihoming is lower for specialized firms, which is in line with the prediction from Hypothesis 3. As a result of the demand shock, the predicted probability of multihoming increases by 1.4 percentage points for specialist complementors with short term partnership and by 2.0 percentage points for specialist firms with long term partnerships. In contrast, however, as a result of the demand shock the predicted probability of multihoming actually declines by 0.3 percentage points for generalist complements with short term partnerships but actually increases by a sizeable13.4 percentage points for generalist complementors with long term partnerships.

Robustness Checks and Investigation of Alternative Explanations

We carried out a number of robustness checks to ensure that our results are not sensitive to the particular ways in which we measure our variables or carry out our analysis. Detailed results are included in the Appendix.

*Longer and shorter ATW***.** Since the ATW window is arbitrary by nature, we check whether our results are sensitive to changes in length of the ATW. We find that our results continue to hold when the ATW is either shortened or lengthened.

Alternative cut-off to measure specialization. We use the 75th percentile as the cut-off for specialization for ease of interpretation. Some might argue that the term 'specialized' is applicable only to firms that are relatively very high on a given form of human capital or there could be non-linearities in the relationship. To address this concern, we use the 90th and 95th percentiles of the human capital distribution to identify highly specialized firms and repeat our analysis. We find that the initial results are robust to these alternative definitions.

*Shorter partnership duration***.** We initially made an assumption that firms that have partnered with SAP for five or more years as of the start of the ATW are said to be in high duration partnerships.

We relaxed this assumption and carried out the analysis for more stringent/ shorter partnership duration cut-offs, namely four and three years. Our initial results continued to hold.

Dot-com bubble. Even though it is quite clear from prior literature that the dot-com bubble had a very different impact on firms when they were known to adopt risky strategies (Scheinkman and Xiong, 2003), we decided to carry out a falsification exercise to formally test these assumptions using our sample. As expected, unlike the demand shock, the bubble does not have any significant differential impact on firms grouped by different levels of specialization.

*Investigation of Alternative Explanation: Transaction Costs***.** A theory based on transaction costs may provide an alternative explanation to our findings. Heterogeneous firm capabilities may induce firms to enter into partnerships in the first place. Over time, the repeated partnerships of the firm would influence its capabilities. For example, in a software development context such as ours, it has been shown that firms develop both relationship-specific capabilities and general capabilities through repeated partnerships (Ethiraj, Kale, Krishnan and Singh, 2005). It is hard to disentangle completely between capabilities and TCE since the two are often intertwined (Argyres and Zenger, 2012). Though we do not rule out the presence of transaction costs in our setting, transaction cost considerations seem to matter less when it comes to multihoming. We draw this conclusion based on the following arguments. First, if transaction cost theory was the dominant framework at work, duration of partnership would have a negative effect on multihoming. But, instead, we find the effect of partnership duration to be positive after the ATW (e.g. holdup does not limit multihoming after the shock) , which is in line with the idea that coordination costs decrease over time as individuals involved in a routine learn to coordinate. Second, we would expect industry human capital, a more general form of human capital by construction, to favor multihoming after the shock. Again, we find the opposite to be true (results shown in the

Appendix). Actually, none of the three forms of human capital favor multihoming when the firms are subject to the benefits shock orchestrated by Oracle.

DISCUSSION

In this paper, we try to develop an understanding of the phenomenon of multihoming within platform ecosystems by adopting a micro-foundational approach toward firm capabilities. Taken together, our results seem to suggest that a mechanism based on coordination costs is likely to be the most plausible explanation for what we find. The mechanism also seems to be consistent with the views from industry experts in the ERP platform ecosystem. In what follows, we discuss the coordination cost mechanism more fully.

Organizations face a constant tradeoff between specialization and coordination (Kogut and Zander, 1996). The degree of specialization within an organization is limited to a large extent by the cost of combining individuals with different forms of specialization (Becker and Murphy, 1994; Bolton and Dewatripont, 1994). To get to the actual mechanism by which coordination costs affect firm strategies, it is important to understand both the nature and location of interdependencies and how they vary across organizations (Thompson, 1967).

Our central argument is that firms with employees who are relatively diverse in terms of human capital are expected to experience higher costs of coordination. This has three implications. First, communication costs increase when members are specialized in different forms of human capital. 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. Hence, the coordination costs among technical consultants tends to be relatively low. However, when technical consultants and functional consultants try to interact, communication becomes more difficult. This in turn affects the performance of the overall software development routine.

Second, lack of expertise in the other field impairs the ability to track performance. This could lead to principal-agency problems that get manifested in the form of shirking and free-riding. 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 task. Again, this may be seen as an increase in the coordination costs.

Third, if a firm specializes in any one of technical or functional design, it may be harder for them to hire professionals specialized in the other group and integrate them into their team. This is partly to do with difficulties in the design of an incentive structure that is agreeable to both groups. A detailed case study on Accenture in Kaplan and Henderson (2005) illustrates that this problem exists even in large organizations. This forms the third element of the coordination cost faced by the organization. As a senior executive at an SAP complementor noted (quoted below), coordination costs tend to be higher in many respects in diverse teams involving different forms of human capital when compared to teams composed of similar human capital.

"There are definitely sometimes delays happening or, you know, arguments, or, you know, people are not on the same page at the same time all the time or points of view may be different."

However, such diversity of human capital is required to multi-home. As a consequence, firms where human capital is narrowly specialized will be less likely to multihome because they lack the capabilities to grasp all elements of the new platform, namely technology, functionality and industry context and embed these elements in their organizational routine required to multihome. To summarize, there is a tradeoff between specializing in one form of human capital, thereby keeping coordination costs low, and strategically investing in multiple forms of human capital to enable multihoming. The coordination cost mechanism is also consistent with our findings on partnership duration. Team level coordination costs tend to go down with time. This makes the environment more suitable for collective learning and enhances the capability to multihome. Further, the presence of coordination costs also prevent specialist firms from responding quickly to demand shocks in the environment.

CONCLUSION

Increasingly, traditional business models are being challenged across industries and being replaced with platform based ecosystems. This has been made possible by the tremendous improvements in information and communication technologies (ICT) over the last decade. In the coming years, we expect platform ecosystems to grow more in terms of reach and influence. A parallel trend is that platform owners increasingly count on external complementors for growth and innovation (Adner and Kapoor, 2010; Boudreau, 2012). Hence, it becomes important for them to pay attention to heterogeneity in complementor capabilities and strategies. Demand side considerations may matter more for multihoming in certain ecosystems such as credit cards where merchants may be able to adopt a different platform with relative ease. However, in settings such as enterprise software development or video game development where complementors not only use the platform as an intermediary but actively engage in creating value added products or services by making considerable investments in human capital, supply side considerations may be very relevant.

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 also 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 really 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 potential implications for the broader field of strategic management. Capability-based theories have long been used to explain differences in firm growth and performance and address the problem concerning firm boundaries (Penrose, 1959). Capabilities have often been thought of as a firm level concept and their origins have been traced at different points to firm level resources, structure, routines and/ or culture. But, more recently, this view has been challenged and researchers increasingly feel the need to look at the micro-foundations of firm capabilities (Felin and Foss, 2005). And, it is increasingly being recognized that heterogeneity at the micro-foundational level in terms of the nature of human capital plays a key role in shaping firm capabilities (Coff and Kryscynski, 2011; Campbell, Coff and Kryscynski, 2012) and fostering knowledge creation and innovation (Grigoriou and Rothaermel, 2014; Grigoriou and Rothaermel, 2015). In our study, we present empirical evidence on the micro-foundational nature of firm capabilities. Our study also provides plausible empirical evidence on a recent debate within this literature stream. Researchers have long held that the micro-foundational elements of a firm's strategy are embedded in its organizational routines (Nelson and Winter, 1982). More recently, a somewhat different perspective concerning the micro-foundations of firm strategies has gained traction. Scholars who support this perspective have tried to conceptualize organizations as a group of individuals and have argued that individual human capital and social capital form the basis for all firm strategies (Felin and Foss, 2005). Our results help reconcile these seemingly opposing perspectives.

Our approach shows that differences in human capital do lead to capability differences which, in turn, affect firm strategies. However, results related to our partnership duration hypothesis indicate that a firm's organizational routines are relatively stable and have an independent and positive effect on the firm's strategy of multihoming. Taken together, these results reiterate the importance of organizational routines as micro-foundations of firm strategies while acknowledging the role played by individual members of the organization (Winter, 2013). Future research could look at variation in human capital across firms and over time and how it affects firm strategies in different settings.

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TABLES AND FIGURES

Figure 1. Coordination among Routine Components

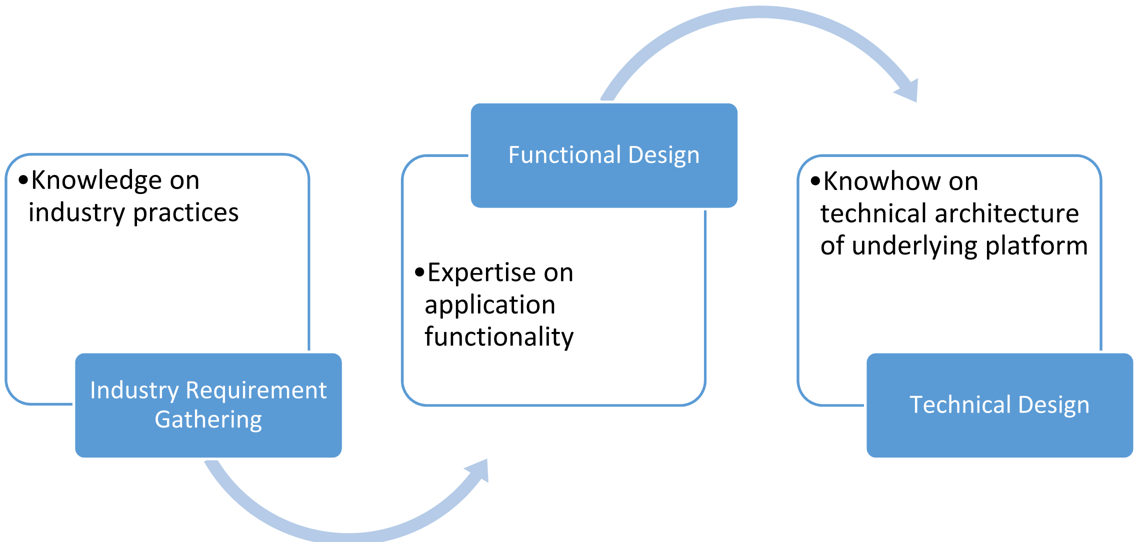
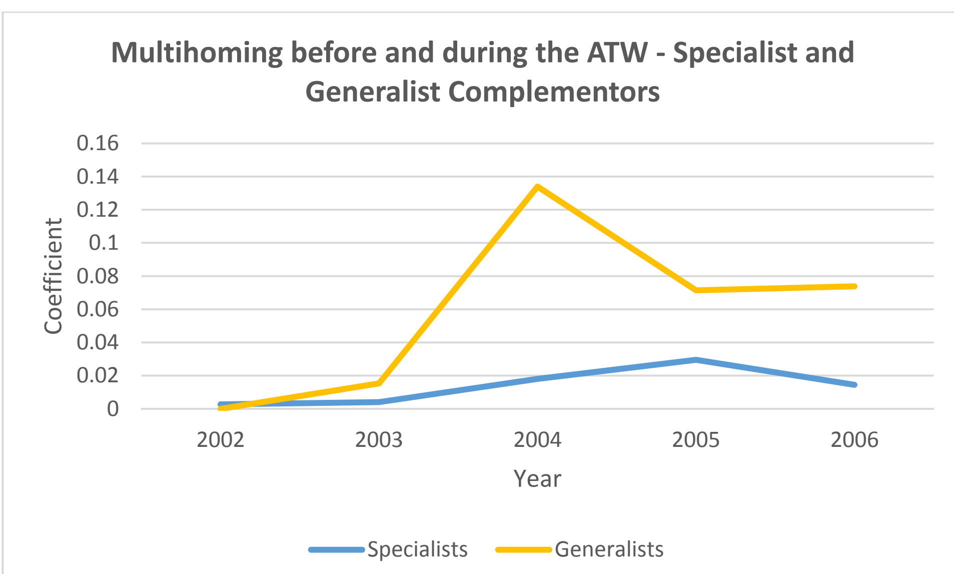


Figure 2. Effect of the Acquisition Time Window on Multihoming



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 2002 for generalist complementors.

Table 1. Descriptive Statistics

Variable Name	Description	Means (std. dev.)
Multihoming	Dichotomous variable (equals 1 when the firm multihomes and stays 0 otherwise)	0.0289
		(0.168)
Log Employees	Log Transformation of Number of Employees	2.521
		(2.748)
Log Sales	Log Transformation of Sales Revenues	9.99
		(7.625)
Partnership Duration	Dummy variable to denote high and low duration of SAP partnership (Cut-off of 5 years)	0.512
		(0.5)
Technical HC	Log Transformation of Technical Human Capital as of 2001	-5.455
		(3.629)
Industry HC	Log Transformation of Industry Human Capital as of 2001	-8.013
		(3.197)
Functional HC	Log Transformation of Functional Human Capital as of 2001	-8.848
		(2.873)
Specialist Firm	Firms that are above the 75^{th} percentile on any one of the three forms of Human Capital namely Technical, Functional and Industry	0.520
		(0.500)
Observations		1038

mean coefficients; sd in parentheses

Table 2. Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Multihoming	1							
(2) Log Employees	-0.02	1						
(3) Log Sales	-0.01	0.85	1					
(4) Partnership Duration	0.13	0.13	0.16	1				
(5) Technical HC	-0.14	0.09	0	-0.11	1			
(6) Industry HC	-0.11	-0.01	-0.05	-0.02	0.78	1		
(7) Functional HC	-0.11	0.14	0.05	-0.05	0.7	0.63	1	
(9) Specialized Firm	-0.01	0.05	0.02	-0.06	0.48	0.47	0.5	1

Table 3. H1: Increased human capital specialization is associated with a lower likelihood of multihoming

Dependent Variable: Multihoming	(1) Specialized Firm	(2) With controls
Log Employees		0.005
		(0.006)
		[0.413]
Log Sales		-0.003
		(0.002)
		[0.099]
Specialized Firm X ATW	-0.071	-0.072
	(0.027)	(0.027)
	[0.009]	[0.009]
Constant	-0.013	0.005
	(0.010)	(0.009)
	[0.206]	[0.614]
Firm FE	Y	Y
Year FE	Y	Y
Observations	1,038	1,038
No. of Firms	244	244
R-squared	0.077	0.080
R-squared (includes fixed effects)	0.620	0.622

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 4. H1: The interaction effect between different forms of multihoming is positive

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	0.007
	(0.005)	(0.005)	(0.005)
	[0.125]	[0.125]	[0.138]
Log Sales	-0.004	-0.004	-0.004
	(0.002)	(0.002)	(0.002)
	[0.058]	[0.043]	[0.060]
ATW X Technical HC	0.009		0.004
	(0.009)		(0.031)
	[0.302]		[0.887]
ATW X Functional HC	0.009	0.022	
	(0.011)	(0.014)	
	[0.420]	[0.126]	
ATW X Technical HC X Functional HC	0.003		
	(0.001)		
	[0.031]		
ATW X Industry HC		0.028	0.010
		(0.011)	(0.009)
		[0.016]	[0.262]
ATW X Industry HC X Functional HC		0.004	
		(0.002)	
		[0.007]	
ATW X Technical HC X Industry HC			0.002
			(0.002)
			[0.311]
Constant	0.002	0.006	0.002
	(0.012)	(0.011)	(0.011)
	[0.873]	[0.598]	[0.849]
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	1,038	1,038	1,038
No. of Firms	244	244	244
R-squared	0.235	0.205	0.225
R-squared (includes fixed effects)	0.685	0.673	0.681

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 5. H2 & H3: Partnership duration has a positive effect but it turns negative when duration is interacted with specialization

Dependent Variable: Multihoming	(1) Duration	(2) Duration-Specialization Interaction
Log Employees	0.003	0.004
	(0.006)	(0.006)
	[0.660]	[0.509]
Log Sales	-0.003	-0.004
	(0.002)	(0.002)
	[0.153]	[0.113]
Specialized Firm X ATW		0.016
		(0.016)
		[0.312]
Partnership Duration X ATW	0.067	0.133
	(0.023)	(0.037)
	[0.003]	[0.000]
Specialized Firm X Partnership Duration X ATW		-0.131
		(0.042)
		[0.002]
Constant	0.020	0.023
	(0.008)	(0.009)
	[0.019]	[0.011]
Firm FE	Y	Y
Year FE	Y	Y
Observations	1,038	1,038
No. of Firms	244	244
R-squared	0.076	0.110
R-squared (includes fixed effects)	0.620	0.634

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

APPENDIX A1 – ROBUSTNESS CHECKS

Table A1.1. Robustness: Longer ATW - Five Years (2004-2008)

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	0.005	0.007	0.008	0.007
	(0.006)	(0.005)	(0.005)	(0.005)
	[0.413]	[0.125]	[0.125]	[0.138]
Log Sales	-0.003	-0.004	-0.004	-0.004
	(0.002)	(0.002)	(0.002)	(0.002)
	[0.099]	[0.058]	[0.043]	[0.060]
Longer ATW X Technical HC		0.009		0.004
		(0.009)		(0.031)
		[0.302]		[0.887]
Longer ATW X Functional HC		0.009	0.022	
		(0.011)	(0.014)	
		[0.420]	[0.126]	
Longer ATW X Technical HC X Functional HC		0.003		
		(0.001)		
		[0.031]		
Specialized Firm X Longer ATW	-0.072			
	(0.027)			
	[0.009]			
Longer ATW X Industry HC			0.028	0.010
			(0.011)	(0.009)
			[0.016]	[0.262]
Longer ATW X Industry HC X Functional HC			0.004	
			(0.002)	
			[0.007]	
Longer ATW X Technical HC X Industry HC				0.002
				(0.002)
				[0.311]
Constant	0.005	0.002	0.006	0.002
	(0.009)	(0.012)	(0.011)	(0.011)
	[0.614]	[0.873]	[0.598]	[0.849]
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	1,038	1,038	1,038	1,038
Number of Firms	244	244	244	244
R-squared	0.080	0.235	0.205	0.225
R-squared (includes fixed effects)	0.622	0.685	0.673	0.681

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 A1.2. Robustness: 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	0.005	0.004	0.005	0.004
	(0.006)	(0.005)	(0.005)	(0.005)
	[0.367]	[0.406]	[0.314]	[0.417]
Log Sales	-0.003	-0.003	-0.003	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)
	[0.089]	[0.146]	[0.089]	[0.147]
Shorter ATW X Technical HC		0.006		0.001
		(0.008)		(0.022)
		[0.468]		[0.973]
Shorter ATW X Functional HC		0.006	0.015	
		(0.009)	(0.012)	
		[0.532]	[0.221]	
Shorter ATW X Technical HC X Functional HC		0.002		
		(0.001)		
		[0.072]		
Specialized Firm X Shorter ATW	-0.055			
	(0.024)			
	[0.021]			
Shorter ATW X Industry HC			0.019	0.006
			(0.009)	(0.007)
			[0.037]	[0.338]
Shorter ATW X Industry HC X Functional HC			0.003	
			(0.001)	
			[0.019]	
Shorter ATW X Technical HC X Industry HC				0.002
				(0.002)
				[0.363]
Constant	0.004	0.001	0.004	0.001
	(0.009)	(0.010)	(0.009)	(0.009)
	[0.619]	[0.894]	[0.669]	[0.880]
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	1,038	1,038	1,038	1,038
Number of Firms	244	244	244	244
R-squared	0.073	0.174	0.155	0.169
R-squared (includes fixed effects)	0.619	0.660	0.652	0.658

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 A1.3. Robustness: Specialized Firm - 90th and 95th Percentile

Dependent Variable: Multihoming	(1) Specialized - 90th	(2) Specialized - 95th
Log Employees	0.004	0.003
	(0.006)	(0.006)
	[0.530]	[0.550]
Log Sales	-0.004	-0.003
	(0.002)	(0.002)
	[0.080]	[0.098]
Specialized Firm (90th) X ATW	-0.060	
	(0.021)	
	[0.005]	
Specialized Firm (95th) X ATW		-0.064
		(0.016)
		[0.000]
Constant	0.007	0.006
	(0.008)	(0.008)
	[0.374]	[0.454]
Firm FE	Y	Y
Year FE	Y	Y
Observations	1,038	1,038
Number of Firms	244	244
R-squared	0.070	0.067
R-squared (includes fixed effects)	0.618	0.616

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.
Specialized Firm (90th): Firms are specialized when they are above the 90th percentile on any one form of HC
Specialized Firm (95th): Firms are specialized when they are above the 95th percentile on any one form of HC

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

Table A1.4. Robustness: Partnership Duration - Three and Four Year Cut-offs

Dependent Variable: Multihoming	(1) Duration – 3yr	(2) Duration – 4yr
Log Employees	0.003	0.002
	(0.006)	(0.006)
	[0.546]	[0.715]
Log Sales	-0.003	-0.003
	(0.002)	(0.002)
	[0.153]	[0.187]
Partnership Duration (3y) X ATW	0.051	
	(0.013)	
	[0.000]	
Partnership Duration (4y) X ATW		0.063
		(0.017)
		[0.000]
Constant	0.014	0.021
	(0.007)	(0.007)
	[0.063]	[0.004]
Firm FE	Y	Y
Year FE	Y	Y
Observations	1,038	1,038
Number of Firms	244	244
R-squared	0.061	0.069
R-squared (includes fixed effects)	0.614	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.
Partnership Duration (3y): Three-year cut-off for determining shorter and longer partnerships.
Partnership Duration (4y): Four-year cut-off for determining shorter and longer partnerships.

Here, we use more stringent four-year and three-year cut-offs instead of the initial five-year cut-off to determine shorter and longer partnership durations. We find that our results are largely unaffected by the change in cut-offs.

Table A1.5. Robustness: Dot-Com Bubble and Multihoming

	(1)
Dependent Variable: Multihoming	
Log Employees	-0.011
	(0.016)
	[0.465]
Log Sales	-0.004
	(0.005)
	[0.380]
Specialized Firm X Dot-com Bubble	0.013
	(0.069)
	[0.854]
Constant	0.028
	(0.018)
	[0.128]
Firm FE	Y
Year FE	Y
Observations	310
Number of Firms	130
R-squared	0.132
R-squared (includes fixed effects)	0.514

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.

As a falsification exercise, we define an alternative time window surrounding the dot com bubble (2001) and checked whether firms with different forms of human capital are affected differently by the bubble. As expected, we find that the bubble does not have any significant differential impact on firms characterized by different form of specialization based on human capital.

Table A1.6. Transaction Costs - Impact of the Different HCs on Multihoming

Dependent Variable: Multihoming	(1) Technical HC	(2) Functional HC	(3) Industry HC
Log Employees	0.008	0.008	0.004
	(0.005)	(0.005)	(0.005)
	[0.122]	[0.149]	[0.409]
Log Sales	-0.004	-0.004	-0.003
	(0.002)	(0.002)	(0.002)
	[0.060]	[0.058]	[0.149]
ATW X Technical HC	-0.028		
	(0.008)		
	[0.000]		
ATW X Functional HC		-0.028	
		(0.008)	
		[0.000]	
ATW X Industry HC			-0.024
			(0.007)
			[0.000]
Constant	0.001	0.003	-0.001
	(0.011)	(0.010)	(0.011)
	[0.902]	[0.800]	[0.953]
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Observations	1,038	1,038	1,038
No. of Firms	244	244	244
R-squared	0.223	0.162	0.158
R-squared (includes fixed effects)	0.680	0.655	0.653

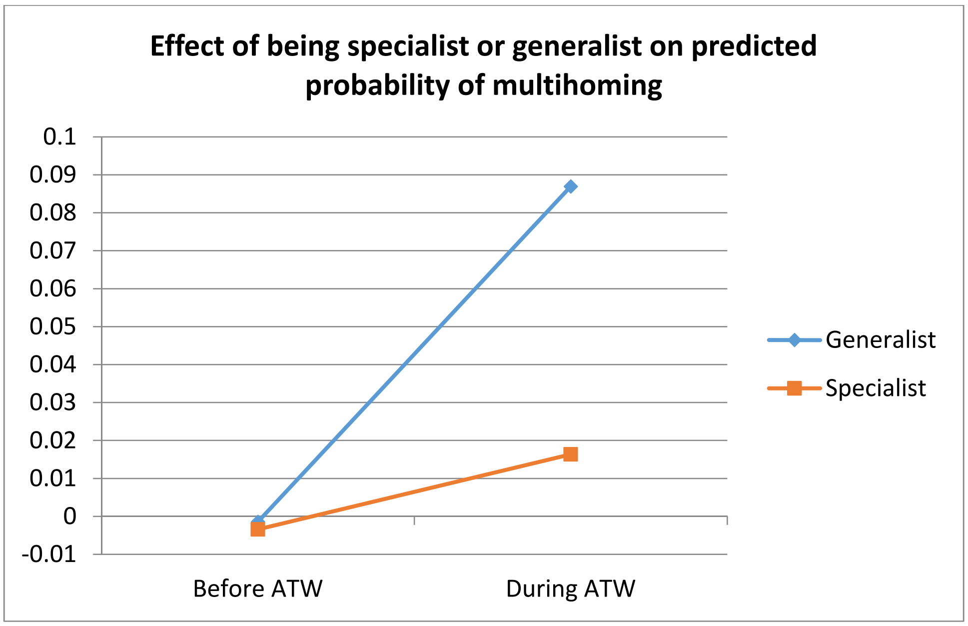
Robust standard errors clustered by firm in parentheses; p-values in brackets.
ATW: Acquisition time window (2004-2006). Estimates based on the linear probability model.

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.

APPENDIX A2 – INTERPRETATION OF RESULTS

Figure A2.1. Specialization and Multihoming

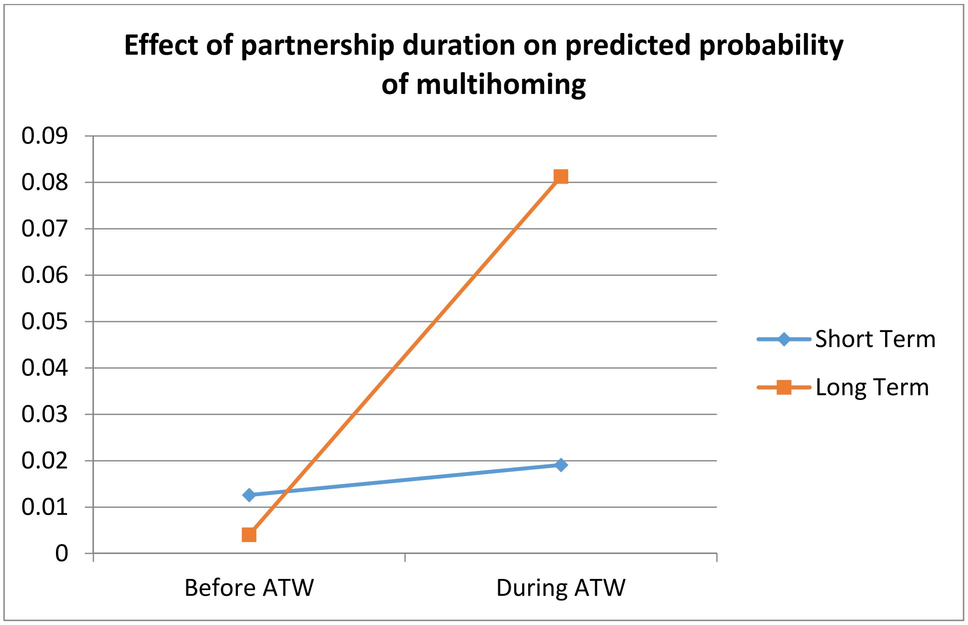
MH Propensity	Type of Complementor	
	Generalist	Specialist
Time Period		
Before ATW (2001-03)	-0.001	-0.003
During ATW (2004-06)	0.087	0.016



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.

Figure A2.2. Partnership Duration and Multihoming

MH Propensity	Partnership Duration	
	Short Term	Long Term
Time Period		
Before ATW (2001-03)	0.013	0.004
During ATW (2004-06)	0.019	0.081



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. 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 partners, long term partners are much more likely to respond to the shock.

Figure A2.3. Partnership Duration and Multihoming – Role of Specialization

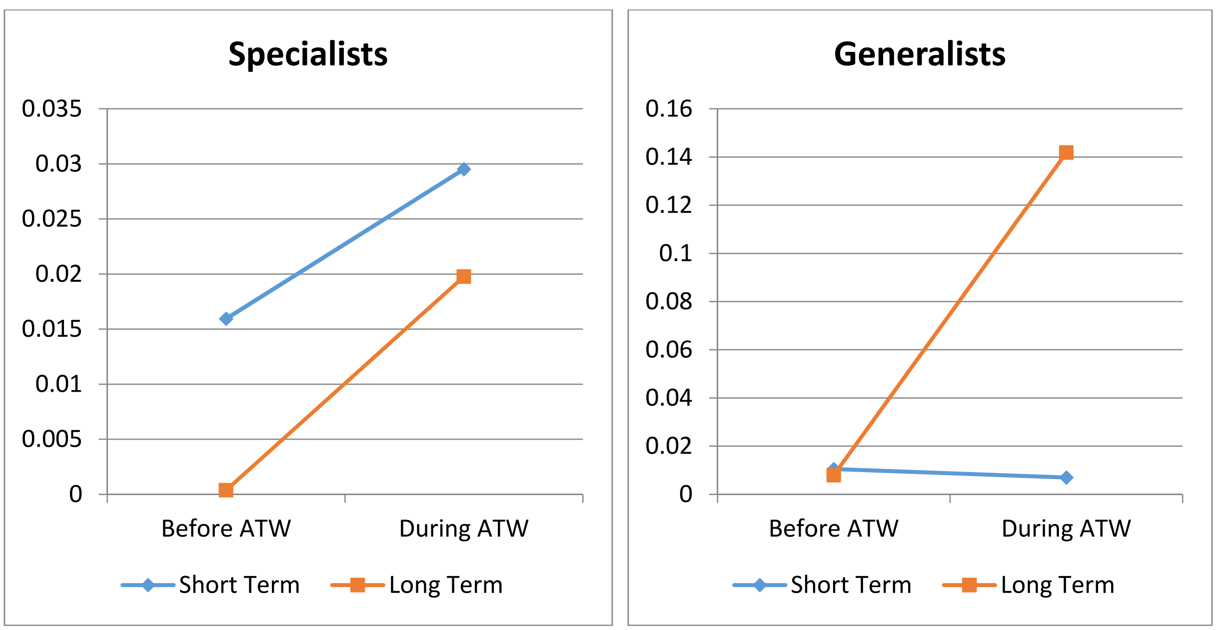
Specialist Complementors

MH Propensity	**Partnership Duration**	
	Short Term	Long Term
Time Period		
Before ATW (2001-03)	0.016	0.0004
During ATW (2004-06)	0.030	0.020

Generalist Complementors

MH Propensity	**Partnership Duration**	
	Short Term	Long Term
Time Period		
Before ATW (2001-03)	0.010	0.008
During ATW (2004-06)	0.007	0.142

Effect of partnership duration on predicted probability of multihoming



The left panel in the figure corresponds to the 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 (0.142) while specialists with long term prior partnership are the least likely to do so (0.02).

Table A2.4. Marginal Effect of ATW at Different Levels of Human Capital

Marginal Effect of ATW	**Functional HC**		
	Low	High	Difference
Technical HC			
Low	0.033	-0.010	-0.043
High	-0.026	-0.029	-0.003
Difference	-0.059	-0.019	

Marginal Effect of ATW	**Industry HC**		
	Low	High	Difference
Functional HC			
Low	0.112	-0.131	-0.243
High	-0.141	-0.145	-0.004
Difference	-0.253	-0.013	

Marginal Effect of ATW	**Industry HC**		
	Low	High	Difference
Technical HC			
Low	0.024	-0.004	-0.028
High	-0.035	-0.023	0.012
Difference	-0.059	-0.019	

Note: Since it is an LPM model, some probabilities tend to be below zero.

To help understand the size of the interaction effects shown in Table 4, we show the marginal effect of the ATW on firms endowed with different levels of HC here. Note that we evaluate the marginal effect at the 20th percentile for low value of HC and at the 80th percentile for high value of HC. The results suggest that the ATW tends to have a relatively higher impact when a particular value goes from low to high when the other HC value is high when compared to the situation when the other HC values is kept low. To illustrate, when the functional HC is at the 80th percentile (high), the difference in the marginal effect when going from 20th percentile of technical HC (low) to the 80th percentile of technical HC (high) is -0.019. Whereas, the difference in the marginal effect when going from low to high value of technical HC while keeping the functional HC at the 20th percentile (low) is -0.059. The difference between the two marginal effects is found to be positive (i.e. -0.019 – (-0.059) = 0.040). In other words, when firms tend to specialize in one form of HC, the impact is negative and this impact becomes gets reduced when an increase in one form of HC is accompanied by an increase in another form of HC, making the two forms of HC complementary.

APPENDIX A3 – COMPUTATION OF HUMAN CAPITAL

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 A3.1. Measurement of Human Capital

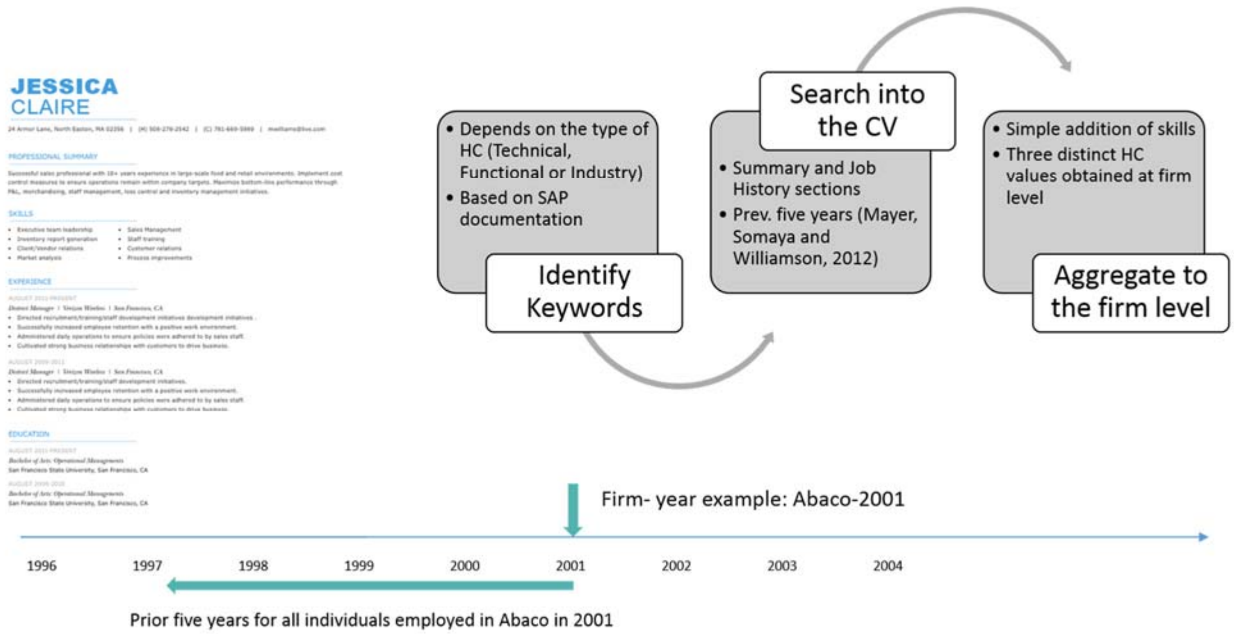


TABLE A3.1. LIST OF STOPWORDS

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 A3.2. 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	