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RESEARCH ARTICLE

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How Does the Positioning of Information Technology Firms in Strategic Alliances Influence Returns to R&D Investments?

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Abstract

Because software is fungible, has low marginal replication costs, and requires relatively high levels of initial investment to develop, understanding how IT-producing firms protect and leverage value from their research and development (R&D) investments is important. We examine how the positioning of IT-producing firms within their networks of strategic alliances moderates profits from R&D investments. We posit that alliances with IT-consuming firms generate relation-specific rents that, in turn, protect the value of R&D investments by making software innovations difficult for rivals to appropriate. Among IT-producing firms, we make a distinction between software consulting and services firms and software package-product firms. Our analyses of 464 IT-producing firms for the 14-year period 1996-2009 suggest that IT-producing firms' returns on R&D investments increase with alliance ties to IT-consuming firms. We also find that alliances with IT-consuming firms have a more beneficial effect on R&D investment returns for software consulting and services firms than for software package-product firms. Our findings yield nuanced insights into how IT-producing firms should position themselves within a network of alliances with IT-consuming firms. We discuss implications for research and practice.

Keywords: Information Technology Firms, Software, Alliances, Innovation, Network, Returns on Research & Development, R&D Investments

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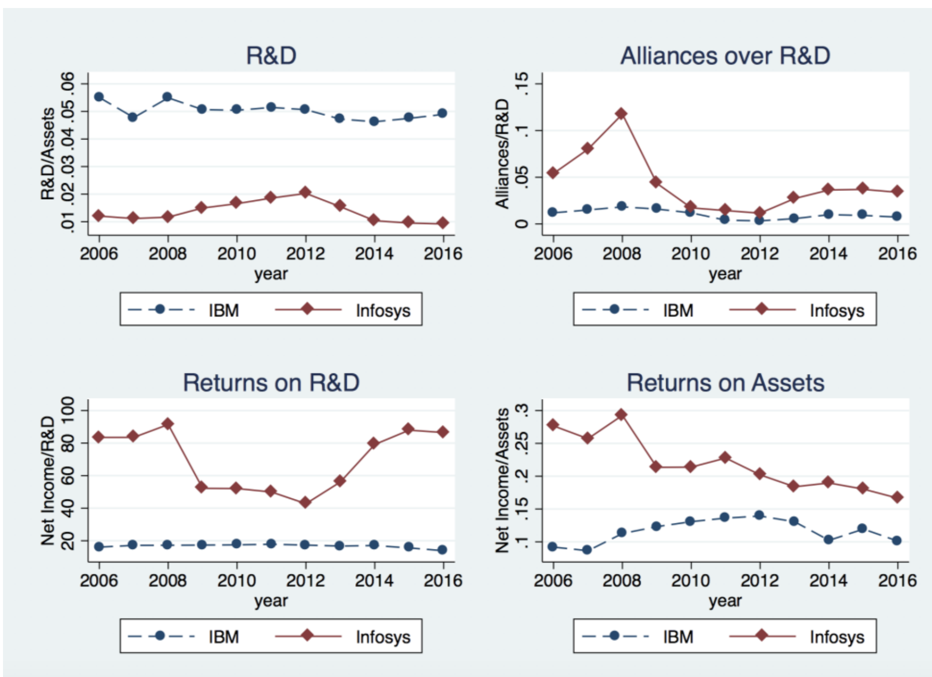
1 Introduction

Firms that produce information technology often struggle to profit from their innovations, particularly considering the risks and benefits of collaborating with other firms. As larger segments of economic goods become tradable in digital form, IT-producing firms face even greater challenges in protecting and leveraging value from their research and development (R&D) investments. On the one hand, innovation in IT industries occurs in a distributed manner through multifirm collaborations (Yoo et al., 2010). On the other hand, value appropriation hazards in IT industries are relatively high, causing unintended resource spillovers between alliance partners (Han et al., 2012; Lavie, 2007). This situation creates a unique challenge for firms in IT industries: they need to collaborate with other IT-producing and IT-consuming firms in order to co-create value, and, at the same time, such collaborations expose them to a variety of risks.

Among IT artifacts, software generates considerable variation in the value that firms derive from their investments in R&D. Software requires very high and fixed initial investments but has low marginal replication costs. In addition, software is fungible and modular, with different modules often developed through combining internal R&D with external sources of knowledge from partner or customer collaborations. Software development is a major part of IT production and requires leveraging complementary resources through interfirm alliances. Because software enables and integrates business processes that run through almost every industry, IT production involves not only the development of hardware or software products in isolation but also the integration and servicing of software and its accompanying processes in many aspects of business and society (Nagle, 2018; Pan, Huang, & Gopal, 2019; Saunders & Brynjolfsson, 2016).

Although alliances have benefits and hazards, their overall effect on the value that IT-producing firms derive from their R&D investments is not well understood. Protecting the intellectual property (IP) of digital innovations such as software has proved challenging, and whether alliance benefits outweigh the risks of opportunistic partners is unclear in this industry context. Software patents have historically been controversial, uncertain, and unreliable in the degree of protection they provide (Bessen & Hunt, 2007; Hurley, 2014). For example, some firms developed pioneering innovations for voice-recognition technologies but were unable to protect and sustain value from their R&D investments; competitors acquired related patents, replicated the underlying technology, claimed the IP rights through litigation, or used superior marketing resources to take control of the end market (Duhigg & Lohr, 2012).

One way that IT-producing firms protect and sustain value from their R&D investments is through interfirm partnerships. For example, Apple leans heavily on complementary resources from its alliance partners in order to maximize the value of its own R&D efforts. Accordingly, the company earned $267 billion in annual revenue in 2019 while spending only 7.9% of its revenue on R&D. Even in areas such as artificial intelligence (AI), in which Apple has traditionally followed a more conservative partnership strategy, the company has started collaborating with its competitors to enhance its gains from R&D investments (Tilley, 2017). By contrast, Google earned $161.19 billion in annual revenue in 2019 and spent as much as 16% of its revenue on R&D. Among other firms, Infosys spent a significantly lower portion of its annual assets on R&D and formed more partnerships for every dollar spent on R&D in comparison to IBM (see Figure 1).



Comparison of annual R&D over assets (top left), number of alliances per millions of dollars spent on R&D (top right), annual net income returns over R&D (bottom left), and annual net income returns over assets (ROA) (bottom right) for two software consulting-services firms: IBM and Infosys. While IBM has a higher R&D intensity compared to that of Infosys, Infosys has a more active alliancing strategy, accompanied by higher returns on R&D and returns on assets. (Data sources: Compustat and SDC Platinum)

Figure 1: IBM vs. Infosys Example

Comparing Infosys to IBM further reveals that Infosys generated higher rates of net income over assets and created more income from each dollar spent on R&D. Whether the examples of Apple and Infosys correspond with a more general pattern such that alliances enable firms to leverage value from their R&D investments is an important and understudied empirical question.

Against this backdrop, we examine how alliances made by IT-producing firms (i.e., those producing software, hardware, networking, and other IT services) moderate their returns on R&D investments.[1] We draw upon and explain how the relational view of the firm described by Dyer and Singh (1998) offers some insight into when alliances provide beneficial mechanisms for deriving value from R&D investments, especially in light of the challenges involved in protecting digital innovations, which require high and risky levels of initial investment and can be subsequently replicated by opportunistic partners with only a marginal investment. The relational view bridges the resource-based view (RBV) and transaction cost economics (TCE) to describe how alliances create sustainable value in ways that are not easily appropriated by potential competitors or rival partners, in particular through the relation-specificity of alliance activities.

To probe the role of these mechanisms, we consider alliances between IT-producing firms and IT-consuming firms (i.e., firms in all other industries except IT) and distinguish software consulting and services firms from software package-product firms. We consider a focal IT-producing firm's alliance positioning among IT-consuming firms, and posit that alliances with IT-consuming firms generate relation-specific rents. Since such investments do not transfer readily beyond the context of the relationship, they also leverage firm-specific and industry-specific processes that are difficult for competitors to replicate. In turn, these alliances protect the value of R&D investments for IT-producing firms by making their software innovations difficult for rivals to appropriate.

We use a panel of 464 firms in IT-producing industries, spanning the 14-year period from 1996 to 2009. We construct a network of alliances in which at least one participant is a firm in an IT-producing industry and examine the returns to R&D as IT-producing firms form alliances with other IT-producing firms and also with IT-consuming firms. Our findings yield insights into how IT-producing firms should position themselves within an ecosystem through alliances with potential clients (i.e., IT-consuming firms) operating in industries characterized by heterogeneous IT intensity. We find that alliances with IT-consuming firms have a more beneficial effect on R&D returns for software consulting and services firms than for software package-product firms. Finally, our findings suggest some implications for how IT-producing firms can protect their intellectual property (IP) and thereby generate positive economic returns on their R&D investments.

Our theoretical contribution builds on the relational view of the firm (Dyer & Singh, 1998) and creates a link between the information systems (IS) literatures on digital innovation and value co-creation in two specific ways. First, we contribute to the recent and growing literature on the economic value of IT investments and related strategic choices (Havakhor et al., 2019; Ravichandran et al., 2017; Steelman et al., 2019; Yoo et al., 2010) and to the IS literature on innovation (Fichman et al., 2014; Kleis et al., 2012; Saldanha et al., 2017) by showing how IT-producing firms can profit from their investments in fungible digital innovation. By establishing a complementary relationship between IT-producing firms' alliances with their customers and their R&D investments, our study posits that such alliances help IT-producing firms leverage value from and safeguard their investments in R&D. Second, our results contribute to the IS literature on coordination and architectural choices (Tafti et al., 2013; Tiwana, 2008) and to the IS literature on the co-creation of value from digital innovations (Foerderer et al., 2018; Han et al., 2012; Kim et al., 2016; Saldanha et al., 2017; Sarker et al., 2012) by underscoring the importance of collaborative interfirm relationships for safeguarding IT-producing firms' R&D investments.

2 Background and Theoretical Framework

2.1 Strategic Alliances in Software Industries

Our review of extant research in the strategy literature suggests that alliance networks are often viewed as proxies for flows of knowledge (Ahuja, 2000a; Schilling & Phelps, 2007). Prior strategy literature highlights the importance of positioning within a broader network for firms to benefit from indirect as well as direct alliance relationships (Gulati, 1999; Stuart, 1998). In addition, this literature also focuses on how firms can mitigate the risks of knowledge appropriation by alliance partners, such as by limiting the scope of alliances (Oxley, 1999; Oxley & Sampson, 2004). IS scholars have contributed to the literature by investigating the link between strategic

[1] Following prior literature, we adopt Gulati's (1998, p. 293) definition of strategic alliances: "voluntary arrangements between firms involving the exchange, sharing, or co-development of products, technologies, or services."

alliances and information systems from different perspectives (see Table A1). This body of research explores IT strategic alliances from transaction cost and resource-based perspectives (Chi et al., 2010; Lavie, 2007), the design and architecture of shared IT resources (Tafti et al., 2013; Tiwana, 2008), the role of IT in sharing knowledge between alliance partners (Liu & Ravichandran, 2015; Ravichandran & Giura, 2019), and the mechanisms that drive the co-creation of value in IT alliances (Han et al., 2012; Sarker et al., 2012). In the current study, we focus on alliance positioning of IT-producing firms, defined as firms that provide software, hardware, networking, and other IT services (Nagle, 2018; Pan et al., 2019; Saunders & Brynjolfsson, 2016).

The role of IT-related knowledge resources in creating relational rents in such alliances requires more attention for two specific reasons. First, software products are inherently networked products, developed and offered over a network of collaborating firms (Lee et al., 2010). Firms use alliances to implement different strategies to position themselves in networks of potential investors, clients, and rivals (Ahuja, 2000b). Positioning strategies can range from a broader strategy that fosters many alliance partnerships to a focused strategy that cultivates deeper collaborative relationships with fewer alliance partners. Prior research has considered the depth of collaborative activity in alliances (Anand & Khanna, 2000; Gulati & Singh, 1998; Tafti et al., 2013; Zollo, Reuer, & Singh, 2002).

An implication of the relational view of the firm is that IT-producing firms' returns to R&D increase with the depth of collaborative activities. Tafti et al. (2013) define collaborative alliances as those that involve: (1) sharing firm-specific and tacit knowledge, (2) recombining products, services, and processes across organizational boundaries, or (3) heavy coupling of interorganizational processes. These collaborative alliances are distinguished from arm's-length alliances, in which firms might share information or license rights to a product in activities that are loosely coupled, rather than in joint development, integration, or recombination of capabilities across industry boundaries. The literature shows that collaboration in joint research and development generally requires greater human co-specialization, process specificity, informal governance, and formation of trust—key elements of relational rents as described in Dyer and Singh (1998).

Building on RBV and TCE, the relational view suggests that some information assets may not necessarily be specific to a firm; rather, they are specific to a relationship or network of relationships that ties multiple firms together (Dyer & Singh, 1998). By definition, resources are relation-specific when they are more valuable within a firm's network of interfirm relationships than they would be in the absence of such relationships.

Second, although almost every innovation in IT involves the combined efforts of multiple firms, there are few mechanisms for IP protection. Contractual mechanisms are limited in their ability to quantify or delineate resources shared through IT alliances, and this creates higher levels of ambiguities for the exchange of resources in IT alliances, compared to other types of alliances (Anand & Khanna, 2000; Gulati & Singh, 1998; Saldanha et al., 2013). The knowledge shared through IT alliances—domain knowledge, design specifics, or the knowledge of developing or operationalizing a certain technology, for instance—is tacit and embodied in participating social structures, and thus not codifiable for structured transactions (Gans et al., 2008; Kim et al., 2018; Niculescu et al., 2018).

Three theories provide useful insights to understand how IT-producing firms can effectively generate value in alliances while safeguarding their intellectual assets: TCE, RBV, and the relational view of the firm, which bridges the two former perspectives. TCE describes the conditions under which firms are more likely to benefit from close interfirm collaboration and those under which firms should maintain interfirm relationships at arm's length (Parkhe, 1993). RBV holds that firms can sustain their competitive advantages by accumulating assets that are "rare, valuable, non-substitutable, and difficult to imitate" (Dyer & Singh, 1998, p. 660). Sampler (1998) describes how digital assets, such as software, can be knowledge-specific to some firms. In turn, such information assets would be costly to transfer and, thus, difficult for competitors to steal. A firm's knowledge base can make it uniquely capable of generating value from an information asset, particularly when the knowledge base itself is embedded in a specific business context or when the knowledge is tacit, unstructured, and embedded in a firm's idiosyncratic organizational culture and routines (Sampler, 1998).

We adopt a *relational view of the firm* perspective (Dyer & Singh, 1998) and argue that relation-specific resources in collaborative alliances enable IT-producing firms to derive greater value from their R&D investments, particularly when IP protection mechanisms are not strong. Among IT-producing firms, we make a distinction between software "consulting-services" firms, which are focused on building firm-specific and industry-specific knowledge, and software "package-product" firms that develop broad applications that work across multiple contexts. From a relational view of the firm, we expect resources shared through alliances between software consulting-services firms and their partners to be more specific to the scope of their partnerships.

2.2 Alliances with IT-Consuming Firms

Although prior research has typically described positioning for access to resources as a critical component of competitive strategy, the research also suggests that the nexus of such resources is not the firm itself but the industry ecosystem in which the firm operates and the concentration of fungible knowledge that resides within the industry (Adner & Kapoor, 2010; Powell et al., 1996). In this context, partnerships between firms that produce IT and firms that consume IT are becoming increasingly important in creating new products and services in the contemporary economy. For example, Microsoft partnered with many health care organizations to offer free internet-based personal health records in an initiative called HealthVault. Microsoft has also partnered with Ford to provide the software layer to manage the operation and charging of electric vehicles (Microsoft, 2010), extending existing partnerships for providing vehicle entertainment and communication systems. Such partnerships or alliances, at the interface between IT-producing and IT-consuming firms, involve the joint development or licensing of digital products or services, as well as the integration of knowledge among alliance partners (Tiwana, 2008).

Consider the example of the alliance between Microsoft and Ford (Microsoft, 2010). This alliance has its origins in Microsoft's first alliance in 1998 with Clarion Corporation, a provider of automotive entertainment electronics, to develop the "AutoPC," an in-car entertainment and information platform built on Windows CE (Microsoft, 1998). This initiative led to the "SYNC" service in Ford vehicles from 2007, which was intended to allow drivers to control their mobile phones or media players with the interface provided by the SYNC platform. Microsoft gained access to Ford's customers by gaining domain expertise from Clarion Corporation. Microsoft later developed similar services for Kia, Nissan, and Fiat (Archambault, 2013).

This example demonstrates how the domain-specific knowledge derived from collaborating with an IT-consuming firm enables an IT-producing firm to develop new domain-relevant products and services. Prior research suggests that firms can foster innovation through collaboration with potential clients (Saldanha et al., 2017). Moreover, these partnerships enable the joint development of products and services, extending the nexus of a firm's capabilities beyond its boundaries (Afuah, 2000) and ultimately leading to cross-industry spillovers and the generation of new knowledge and resources (Lavie, 2007).

We next present some testable implications of the relational view to consider how alliances with IT-consuming firms can enhance returns on R&D investments for IT-producing firms.

2.3 Hypotheses

2.3.1 Alliances Among IT-Producing and IT-Consuming Firms

Compared to alliances between two IT-producing firms, alliances between IT-producing and IT-consuming firms are subject to a qualitatively different form of transaction hazard (Hagedoorn, 1993). IT-consuming firms produce something other than IT hardware or software as their primary goods or services, though they may rely heavily on IT in many of their functional areas and production processes.[2] IT-consuming partners may be clients to focal IT-producing firms at the same time that they build their own IT capabilities, such as custom software applications (Qu et al., 2010). While IT-consuming partner firms do not necessarily pose a direct competitive threat, they may act opportunistically in appropriating the IP from their alliance partners in the software industry (Lavie, 2006). Some IT-consuming firms may also have high levels of absorptive capacity to learn and make use of technical knowledge and, in turn, develop industry-specific or domain-specific solutions (Lane & Lubatkin, 1998). For focal IT-producing firms, their alliance partners' high levels of industry-specific knowledge can put them in a vulnerable position; alliance partners can develop competing products or services for firms within their own industries, market to the clients of the focal IT-producing firms, and undermine their alliance partners' profits (Mowery et al., 1996). IT-consuming firms may also have alternative alliance partners that are competitors to a focal IT-producing firm, resulting in an indirect alliance-network link between the focal IT-producing firm and its competitors, which could be detrimental to the focal firm.

Despite the potential hazards, an IT-producing firm might benefit from alliances with IT-consuming firms. First, the process of co-invention could yield benefits for both IT-producing and IT-consuming firms' alliance partners. The process of co-invention is integral to the structure of the software industry (Bresnaham & Greenstein, 1997). New products are developed and introduced to IT-consuming firms through a collaborative process in which IT-consuming firms also reinvent and reorganize their own processes. For example, Oracle collaborated with major banks to build core banking systems (Palmer,

[2] IT-consuming firms may be in such industries as commercial banking, pharmaceuticals and healthcare, manufacturing, entertainment, hospitality, and transportation and logistics, to name a few among many other industries.

2013). Accenture and SAP jointly worked with petroleum and natural gas companies to develop hydrocarbon production accounting systems for managing gas and oil production data (Digital Energy Journal, 2014). In the process of such co-invention, IT-producing firms gain valuable firm-specific knowledge. The absorbed knowledge is firm-specific because it is only created through the relationship between the IT-producing firm and its specific IT-consuming customers. Meanwhile, the appropriated knowledge is valuable because it results from complex social interactions between groups of specialists from the IT-producing firm and its IT-consuming partners and is not easily imitable by its rivals. Because specialized expertise is hard for rivals to appropriate, IT-producing firms are better able to sustain and derive value from their R&D investments.

Another potential benefit from an IT-producing firm's alliances with IT-consuming firms involves the complexity of integration and depth of firm-specific knowledge tied to value chain activities that can help protect IP related to those activities (Dyer & Singh, 1998). For example, Dyer and Hatch (2006, p. 701) describe how specialized interorganizational routines and policies between automakers and suppliers acted as "barriers to knowledge transfer", preventing valuable capabilities from being redeployed to competitors or their networks. Hence, the co-invention process can foster relation-specific investments. Alliances with IT-consuming partners provide a way of safeguarding and deriving value from R&D investments. Thus, we hypothesize:

H1: IT-producing firms' returns to R&D investments increase as they form more alliances with other IT-consuming firms.

2.3.2 The Role of Relation-Specificity: Distinguishing among Alliances of Software Package-Product versus Software Consulting-Services Firms

We distinguish between two broad subclasses of firms in the software industry. The first category is software package-product firms, which produce encrypted software products and tend to rely on strong IP protections (e.g., patents, encryption, copyrights, etc.) because their software products are general purpose commodities used broadly in many industry contexts. Firms such as Microsoft exemplify this business model. The second category is software consulting-services firms, which develop software to enable industry-specific and firm-specific processes. Firms such as Accenture, Infosys, and Wipro exemplify this model as they focus on building highly specialized software for clients and, in turn, develop a depth of expertise in specific industries and firm processes.

Two major features distinguish software consulting-services firms from software package-product firms. First, the former firms focus on building firm-specific and industry-specific knowledge rather than broad applications that work across multiple contexts (Kim, Mithas, Whitaker, & Roy, 2014; Whitaker, Mithas, & Liu, 2019).

Second, consulting-services firms do not have strong encryption mechanisms built into their product delivery mechanisms. In addition, they deliver services according to specifications and contractual terms specified by their clients, and clients sometimes assume IP rights over the specific products these firms build. At the same time, consulting-services firms develop their own IP around specialized knowledge of vertical industries and firm-specific processes through the idiosyncratic knowledge gained from collaboration with IT-consuming firms. For example, Accenture developed an Air Cargo reservations software system through close collaboration with clients in the logistics and transportation industries (Logistics Business Review, 2014). Other software consulting-services firms focus on the idiosyncratic needs of their IT-consuming alliance partners, such as in CSC's long-term partnership with Zurich Insurance (Savvas, 2014) through which CSC provides specialized desktop software services. As consulting-services firms focus on more industry-specific and firm-specific collaboration in developing specialized software services, the idiosyncratic requirements of their IT-consuming partners serve to protect and sustain the value of their R&D investments.

Accordingly, we posit that compared to software package-product firms, software consulting-services firms depend more heavily on informal sources of IP protection, which in the alliance context means making relation-specific investments through close collaboration with IT-consuming firms. Thus, we hypothesize:

H2: Among IT-producing firms, alliances with IT-consuming firms have a more beneficial effect on R&D returns for software consulting-services firms than for software package-product firms.

3 Method

We model a network of IT-producing firms and their alliance partners in which nodes represent firms and undirected edges represent alliance relationships. This alliance network includes collaborative development projects, outsourcing and licensing contracts, joint ventures, and standards-based coalitions, among other cooperative initiatives that link IT-producing and IT-consuming firms. We initially obtained 16,432 alliance announcements from the SDC Platinum database (a product of Thomson-Reuters Corporation), resulting in 18,184 alliance pairs. Some alliance announcements include more than two firms; hence, such alliances result in more than one pair of linked firms.

The alliance announcements span the years 1996-2009 for the main analysis and 1991-2016 for a robustness test, and each alliance has at least one participant in IT-producing industries.[3] Consistent with similar usage in the existing literature (Nagle, 2018; Pan et al., 2019; Saunders & Brynjolfsson, 2016), our definition of IT-producing firms includes firms that provide software, hardware, networking, and other IT services. The focal firms in our study comprise a narrower sample of software consulting-services (NAICS codes 5415 and 518) and software package-product (NAICS codes 5112) firms.[4]

Our final sample comprises a total of 3,535 linked pairs forming a bipartite network that connects firms in the narrower sample (of software consulting-services and package-product firms) with firms in IT-consuming industries. In Section 4.3.3, we report results for firms in all IT-producing industries for an extended time period as a robustness check.

Following prior literature, we assume alliance formation dates to be the date of the alliance announcement (Schilling & Phelps, 2007). Since firms rarely announce the termination of an alliance, we set the lifetime of alliances to be three years, a span consistently used in previous studies with the same data source (Lavie, 2007); this approximation is conventional in alliance studies using the SDC Platinum database (e.g., Schilling & Phelps, 2007). For each firm in each year, we obtained measures pertaining to a firm's positioning within the network of IT-producing and IT-consuming firms. We calculated aggregate measures of network metrics, along with other quantitative firm metrics, across all IT-consuming partners of each IT-producing firm (the focal firms serving as the units of analysis). We then merged the alliance network data with the Compustat Industrial annual database for each combination of focal IT-producing firm and year.

The final data set is an unbalanced panel of firms in IT-producing industries, including industry-level IT investment figures from the Bureau of Economic Analysis (BEA), IT-producing firms' package and consulting sales from Compustat Segments, and firm performance metrics and controls from Compustat. We merged this data set with the set of assigned US patents available on the website of the NBER patent data project.[5] The final sample includes 464 firms and 1,311 firm-year observations. Table 1 presents a summary of variables. Table 2 shows summary statistics for IT-producing firms in the sample and correlations.

To operationalize the two hypothesized types of relationships, we develop two network measures: *OutNet* (alliances with IT-consuming firms)[6] and *IndirectNet* (indirect alliance links with IT-producing firms through alliances with common IT-consuming partners). The *OutNet* measure captures cross-industry alliances with IT-consuming partners. For each IT-producing firm, this is the number of alliances with IT-consuming firms. The *IndirectNet* measure captures indirect alliance links with IT-producing firms through alliances with common IT-consuming partners. For each IT-producing firm, this is the average number of its IT-consuming partners' alliances with other firms in IT-producing industries. Log values are used in all regressions. We also develop an *InNet* measure (direct alliances with other IT-producing firms) to control for alliances with other IT-producing firms.

Figure 2 illustrates the alliance network connecting IT producers and IT consumers in the year 2007, one of the years of our 14-year panel data set. We select and highlight a small subset of the overall network showing First Data Corp (a data services and payment processing provider) at the center of its subnetwork of alliances with firms in the financial industry. The alliance between First Data Corp (an IT-producing firm) and JPMorgan Chase (an IT-consuming firm) is thus counted as an *OutNet* alliance for First Data. Meanwhile, the indirect connection between First Data and Trading Technologies Intl Inc. through their common alliance with JPMorgan Chase is counted as an *IndirectNet* alliance.

[3] Broader IT-producing industries include NAICS codes 511-Information and Software Publishers; 517-Telecommunications; 519-Information Services; 334-Computer and Electronic Product Manufacturing; 518-Data Processing, Hosting, and Related Services; 333-Semiconductor Manufacturing; 335-Electrical Equipment, Appliance, and Component Manufacturing; and 423-Computer and Computer Peripheral Equipment and Software Merchant Wholesalers. Some firms with NAICS codes 561-Administrative and Support Services; 541-Professional, Scientific, and Technical Services; and 443-Elecronics and Appliances Stores also fit this classification to the extent that they provide software products or information systems consulting services.

[4] We identify software consulting-services firms as those with the following NAICS classifications: 5415-Computer Systems Design and Related Services and 518-Data Processing, Hosting, and Related Services.

[5] National Bureau of Economic Research (NBER) patent data project: https://sites.google.com/site/patentdataproject/

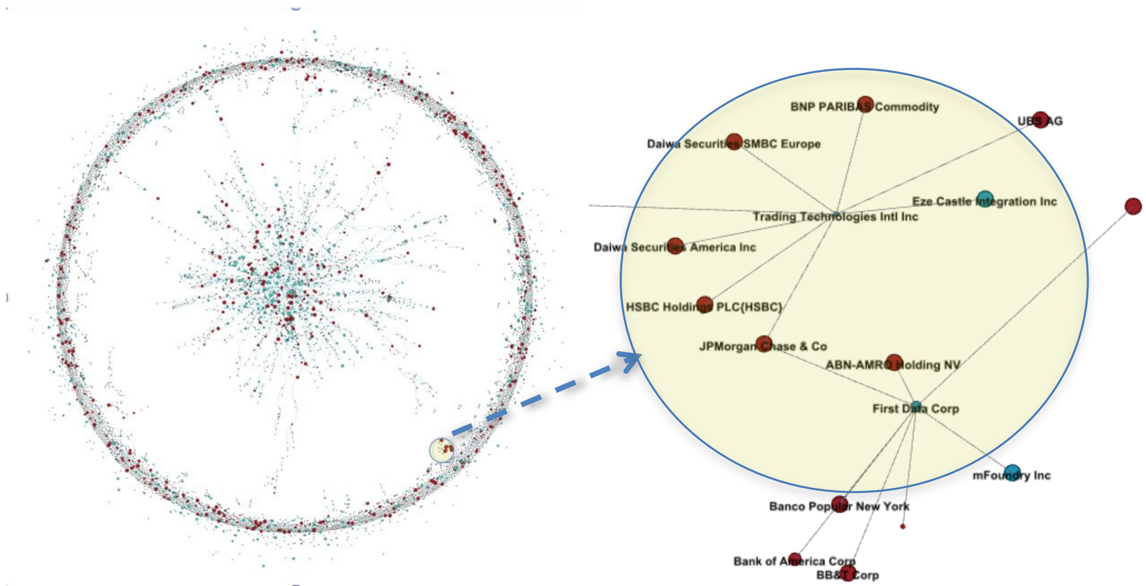
[6] We also constructed an alternative measure of *OutNet* by multiplying firms' number of alliances with IT-producing firms by the R&D intensity of those IT-producing partners. The results gained after using this alternative measure were consistent with our main results.

Table 1. Variable Definitions

Key variables	Definition	Source
Profits	Total net operating income, in millions of dollars.	Compustat
R&D investments (RD)	Research and development, in millions of dollars. In the regression models, we use the logarithm of R&D stock calculated using the perpetual inventory method, following the structural derivation given in Jaffe (1986).	Compustat
Alliances with IT-consuming firms (OutNet)	Cross-industry alliances with IT-consuming partners. For each IT-producing firm, this is the number of alliances with IT-consuming firms. Log values are used in all regressions.	SDC Platinum
Consultancy firm (Consult)	Binary indicator variable classifying the focal firm as a software consulting-services firm according to NAICS classifications 5415-Computer Systems Design and Related Services or 518- Data Processing, Hosting, and Related Services.	Compustat
Indirect alliance links with IT-Producing Firms (IndirectNet)	Indirect alliance links with IT-producing firms through alliances with common IT-consuming partners. For each IT-producing firm, this is the average number of alliances held by its IT-consuming partners with other firms in the IT-producing industries. Log values are used in all regressions.	SDC Platinum
Alliances with other IT-producing firms (InNet)	Direct alliances with other IT producers. Log values are used in all regressions.	SDC Platinum
Consultancy sales (Consult Sales)	Ratio of a firm's sales in NAICS classifications 5415-Computer Systems Design and Related Services and 518-Data Processing, Hosting, and Related Services to their total sales.	Compustat Segments
Packaged software sales (Package Sales)	Ratio of a firm's sales in NAICS classification 5112-Software Publishers to their total sales.	Compustat Segments
Software patents	Number of assigned US patents registered under the 7XX technology class in one year.	NBER
Patents	Number of assigned US patents in the preceding five years, expressed in logs.	NBER
Betweenness centrality	Betweenness centrality for node i is calculated as the sum of the ratio of the total number of shortest paths between every two nodes j and k in the network that pass through node i, σ_{jk}(i), over the total number of shortest paths between every two nodes j and k, σ_{jk} (Freeman, 1978).	SDC Platinum
Constraint	The constraint between two nodes i and j is measured as the sum of the intensity of the direct relationship between those two nodes, p_{ij}, as well as the intensity of every indirect path between those two nodes that goes at least through node q (Burt, 2009).	SDC Platinum
Degree centrality	Number of firms each firm is connected to.	SDC Platinum
JVs/total alliances	Ratio of a firm's joint ventures over their total number of alliances.	SDC Platinum
R&D/total alliances	Ratio of a firm's R&D alliances over their total number of alliances.	SDC Platinum
Tie multiplicity	Ratio of a firm's total alliance activities over their total number of alliances.	SDC Platinum

Table 2. Correlations and Summary Statistics

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Profits	1.000							
(2) Tobin's *q*	-0.014	1.000						
(3) Alliances with IT-Consuming Firms (OutNet)	0.346*	0.058	1.000					
(4) Alliances with IT-Producing Firms (InNet)	0.431*	0.051	0.268*	1.000				
(5) Indirect Alliances with IT-Producing Firms (IndirectNet)	0.083*	0.047	0.629*	0.019	1.000			
(6) Consultancy Firm (Consult)	0.086*	0.007	-0.138*	-0.020	-0.117*	1.000		
(7) R&D Stock	0.481*	-0.120*	0.348*	0.389*	0.160*	-0.048	1.000	
(8) Patents	0.429*	-0.049	0.306*	0.338*	0.165*	0.023	0.577*	1.000
(9) ITIndPartners	0.038	0.039	0.607*	-0.112*	0.567*	-0.138*	0.099*	0.107*
(10) Total Capital	0.513*	-0.072	0.302*	0.422*	0.116*	0.226*	0.776*	0.462*
(11) Market Share	0.450*	-0.132*	0.272*	0.411*	0.101*	0.115*	0.766*	0.450*
(12) HHI	0.117*	-0.030	-0.197*	0.003	-0.181*	0.753*	0.047	0.005
(13) RDPartners	0.067	0.001	0.246*	-0.025	0.188*	-0.044	-0.001	0.030
(14) Collab	0.490*	0.061	0.527*	0.545*	0.221*	-0.036	0.324*	0.408*
(15) Arm's-Length	0.347*	0.060	0.497*	0.406*	0.191*	-0.051	0.205*	0.293*
Obs	1311	1218	1311	1311	1311	1311	1311	1311
Mean	463.83	3.75	3.36	2.98	3.17	0.278	700.38	31.24
Std Dev	2373.3	8.90	15.52	7.98	8.74	0.448	3336.5	282.06
Min	-269.8	-0.5	0.0	0.0	0.0	0	0.0	0.0
Max	25877	189.8	248.0	115.0	74.0	1	38571	3652.0
Variables	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	
(9) ITIndPartners	1.000							
(10) Total Capital	0.030	1.000						
(11) Market Share	0.019	0.878*	1.000					
(12) HHI	-0.196*	0.257*	0.140*	1.000				
(13) RDPartners	0.271*	0.012	0.001	-0.072*	1.000			
(14) Collab	0.142*	0.317*	0.309*	-0.066	0.077*	1.000		
(15) Arm's-Length	0.156*	0.192*	0.206*	-0.104*	0.116*	0.675*	1.000	
Obs	1311	1311	1311	1311	1311	1311	1311	
Mean	25.26	406.99	0.01	0.06	1.05	2.687	1.416	
Std Dev	29.06	2520.6	0.03	0.03	3.41	7.105	3.551	
Min	0.0	0.0	0.0	0.0	0.0	0	0	
Max	87.7	39596	0.3	0.2	59.9	125	52	



IT-producing companies (blue nodes), such as First Data Corp, have direct ties to other IT-producing companies and IT-consuming firms (red nodes). Further, IT-producing firms have indirect ties to other IT-producing firms through common partners (i.e., the triad between First Data Corp, JP Morgan Chase, and Trading Technologies in the close-up in the bubble on the right).

Note: Largest connected component of firms with at least one degree of connection is presented with node size scaled by log(Sales). In the close-up of First Data's subnetwork on the right, node-size scaling range is reduced.

Figure 2: Year 2007 Snapshot of Alliance Network and Close-Up View of Selected Network Segment

Since both Trading Technologies International and Eze Castle Integration Inc. are IT-producing firms, their direct connection counts as an *InNet* alliance. We are interested in the moderating influence of *OutNet* on R&D investment returns. We also control for *IndirectNet*, indirect connections formed through an IT-consuming partner firms' alternative alliances with other IT-producing firms; *Arm's-Length*, the number of arm's-length alliance activities; and the interactions of these variables with R&D.

We construct a set of network and alliance-based measures using a network of strategic alliances: *network diversity*, *betweenness centrality*, *degree centrality*, *access to structural holes*, *joint ventures to total*, *R&D to total*, and *tie multiplicity*. *Network diversity* is measured as the Shannon entropy of the weights of its incident edges (Eagle et al., 2010). *Betweenness centrality* represents the portion of shortest paths that traverse a node (Freeman, 1978). The constraint measure represents the density of connections among a node's neighbors, and therefore is the inverse of *access to structural holes* (Burt, 2004). *Joint ventures to total* is constructed as the ratio of the number of joint ventures over the total number of firm alliances. *R&D to total* is constructed as the ratio of the number of R&D alliances over the total number of firm alliances. *Tie multiplicity* is constructed as the total number of alliance activities reported for all firm alliances over its total number of alliances. Including these structural measures controls for the potential confounding effects of a firm's network structure on both the existence and strength of a firm's ties with IT consumers and its R&D stock—and helps to isolate the hypothesized effects. At the same time, these measures mitigate potential concerns regarding the interdependencies between our main variables and network-related time-variant unobservable factors.

For our empirical analyses, we consider the following base model as a starting point:

$$\text{Profits} = \beta_1 \log(\text{OutNet}) \text{ X } \log(\text{RD}) + \beta_2 \log(\text{OutNet}) \text{ X } \log(\text{RD}) \text{ X Consult} + X_c B_c + \sum \beta_t \text{Year}_t + \sum \beta_i \text{Industry}_i + u_i + \varepsilon_{i,t} \quad (1)$$

To test the first hypothesis, we consider the coefficient β_1 of the interaction between *log(RD)* and *log(OutNet)*. To test the second hypothesis, we consider the coefficient β_2 of the three-way interaction between the terms *Consult* (consulting-services firms), *log(RD)*, and *log(OutNet)*. Our estimation model includes all of the main effects and two-way interactions implied by the three-way interaction model, which we subsume in the matrix X_c along with all other control variables to display Equation (1) succinctly. We control for *Patents* (patents awarded over the preceding five years) and the full model of two-way and three-way interactions involving *Patents, R&D*, and each of the three types of alliances.

As an alternative to the dichotomous classification between software consulting-services firms and software package-product firms and to allow for a continuous spectrum of firms' activities between these two types, we use the sales that firms report in both market segments. Using the Compustat Segments database, we construct the alternative measures *Consultancy Sales* and *Package Sales*, measured respectively as the ratios of firms' revenue from consultancy and packaged software sales over their total sales.

We use fixed-effect panel regression estimates to test our hypotheses. This method controls for all unobserved firm characteristics that change little over time.[7] We also use indicator variables for each year in the sample (excluding one reference year) in addition to accounting for the fixed effect of each firm; thus, we utilize a two-way fixed-effect panel model based on each firm-year combination. To facilitate interpretation of regression results, we mean-center the values of variables used in interaction terms, including R&D, patents, and alliance network variables for all regression models.

The profitability model is based on the basic model derived in Jaffe (1986), and we extend that empirical framework here.[8] We measure *Profits* as total annual net operating income, in millions of dollars. R&D in the profits model is calculated as a stock value using the perpetual inventory method. The matrix X_c represents a matrix of control variable data including the controls mentioned above as well as the logarithm of capital, logarithm of market share, and Herfindahl Index (*HHI*), which is a measure of industry concentration. In addition, we control for IT intensity of partner industries (*ITPartnerIndus*) and R&D intensity of partner industries (*RDPartnerIndus*). We further examine models with log(Tobin's *q*) as their dependent variable. In the Tobin's *q* models, we use advertising intensity and number of employees—commonly used controls for such models—in addition to the controls used in the profitability models.

Table 3 shows our estimates for the fixed-effect panel regression testing the first hypothesis. As shown in Table 3, we test H1 using the estimate of coefficient β_1 of the interaction between *OutNet* and *R&D*.

We test Hypothesis 2 (H2) in two ways. First, as shown in Model 1 of Table 4, we use coefficient β_2 of the three-way interaction term *Consult X RD X OutNet* in a regression test that includes all IT-producing firms, where *Consult* is a binary indicator for software consulting-services firms. In effect, this test compares the β_1 coefficient of the interaction term *RD X OutNet* between the two subclasses of the software industry in a single combined sample of all IT-producing firms. Second, as presented in Table 4, we conduct panel regressions for the subsample of software consulting-services firms in Model 2 and for the subsample of software package-product firms in Model 3. In this way, we further test H2 by comparing the coefficient estimate of the interaction term *RD X OutNet* across these two models. By using firm-level fixed effects in all panel regression models, we also account for variation in the fungibility of digital products and services among different industries.

4 Results

4.1 Main Results

We find support for H1, which predicts that alliances with IT-consuming firms are associated with greater returns to IT-producing firms' R&D investments, because the coefficient β_1 of the interaction term *RD* X *OutNet* in Model 1 of Table 3 is positive and statistically significant (β_1 = 131.3, and is statistically significant at a 1% level). Table 3 also shows the results of excluding different sets of control variables in Model 2 and Model 3. The consistency among the coefficient estimates for H1 in these three models shows that the results are not attributable to confounding influences from any group of control variables.

Model 1 in Table 3 shows the coefficient estimates of patenting interactions terms with *OutNet* (*Patent* X *OutNet*) and with *InNet* (*Patent* X *InNet*) in addition to the interactions between R&D stock and the same set of variables. The results show a positive moderating effect of R&D but a potentially hindering effect of patenting activities for firms involved in strategic alliances. Thus, these findings suggest that patenting activities, which are formal IP protection mechanisms, may not contribute much to annual firm profits in the context of strategic alliances. This is consistent with the theory underlying our hypotheses: tacit/relational mechanisms are more effective than formal protection mechanisms in safeguarding IP in the context of interfirm alliances.

[7] The average variance inflation factor (VIF) of time-varying terms in the model is 5.5, well below the threshold of concern for multicollinearity. Added variable plots indicate no visual evidence of influential outliers.

[8] As a robustness step, we also estimate our hypothesized relationships using the Cobb-Douglas production function, which provides consistent results.

Table 3. Moderating Influence of Alliances on Effect of R&D on Firm Profits: Test of H1

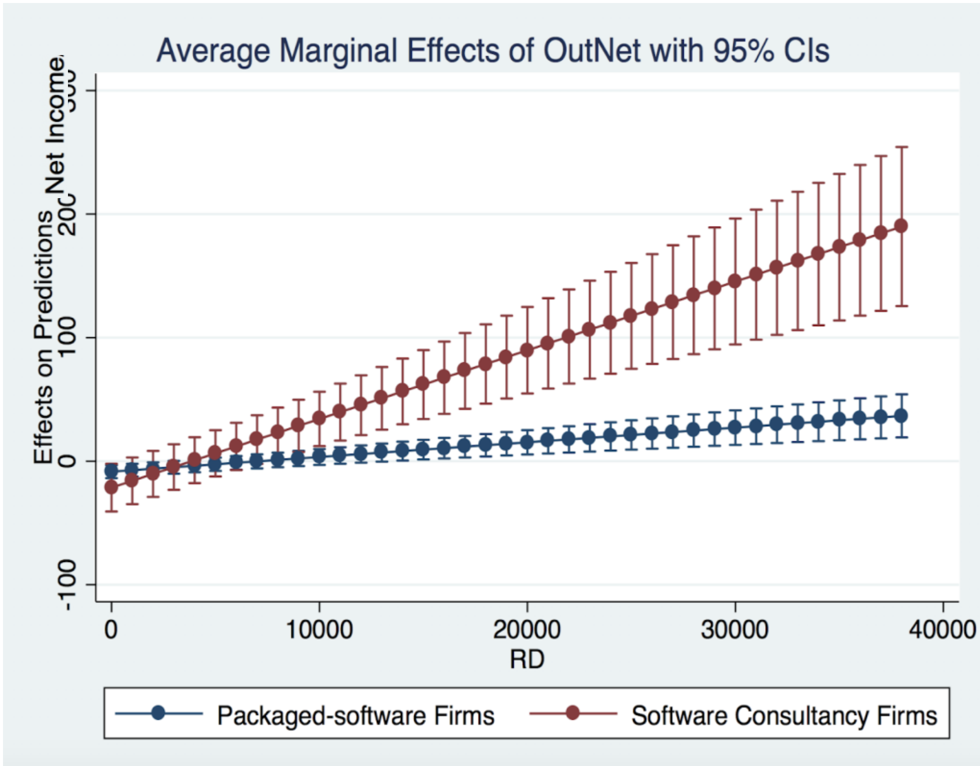
VARIABLES	(1) Profits	(2) Profits	(3) Profits
H1: RD X OutNet (Alliances with IT-consuming firms)	131.3*** (22.42)	44.11*** (14.92)	90.33*** (17.31)
RD X InNet (Alliances with IT-producers)	141.1*** (19.97)		
RD X IndirectNet (Indirect Links to IT-producers)	-31.33 (20.21)		
Patent X OutNet	-159.8*** (21.11)		
Patent X InNet	-89.40*** (19.59)		
Patent X IndirectNet	87.01*** (20.90)		
IndirectNet	-20.01 (34.91)	9.811 (32.44)	
InNet	21.72 (44.45)	209.7*** (40.18)	
Patent	-170.9*** (42.65)	-60.42 (45.57)	
ITPartnerIndus	-0.000267 (1.004)	0.422 (1.109)	
log(Capital)	50.60 (51.29)	82.81 (56.38)	
log(Marketshare)	62.99 (57.47)	48.19 (63.48)	
HHI	-214.5 (1,552)	1,496 (1,704)	
Collab	-33.39*** (4.639)	-49.76*** (4.875)	
Arm's-Length	-98.96*** (8.654)	-117.5*** (9.154)	
RD	29.22 (49.50)	9.785 (54.54)	83.33 (58.16)
RD X Patent	35.24*** (10.80)	-42.98*** (9.108)	-66.89*** (6.422)
OutNet	74.04 (57.98)	112.3* (60.76)	-167.9*** (51.90)
Constant	962.6* (523.7)	773.9 (577.4)	156.4 (113.4)
Observations	1,311	1,311	1,315
Number of Unique Firms	464	464	467
F stat	42.03***	35.13***	15.88***
R-squared	0.615	0.527	0.245

Note: Fixed-effect panel regression. Dependent variables are annual profit.
Significant at 10%, ** significant at 5%, *** significant at 1%. Fixed-effect panel regression, with standard errors in parentheses. The model includes indicator variables for each year, as well as firm-level fixed effects. The research and development (RD) variable is the logarithm of R&D stock calculated using the perpetual inventory method. Logarithm values of InNet, OutNet, and IndirectNet are also used.

Table 4: Comparison of Software Consulting-Services Firms and Software Package-Product Firms in the Moderating Influence of Cross-Industry Alliances on R&D Returns: Test of H2

VARIABLES	(1) Profits	(2) Profits (consulting-services firms)	(3) Profits (package-product firms)
H2: RD X Consult (Consultancy) X Alliances with IT-consuming firms (OutNet)	107.9*** (29.26)		
H1: RD X Alliances with IT-consuming firms (OutNet)	90.44*** (25.32)	138.4*** (26.87)	87.54*** (29.57)
RD X Indirect Links to IT-producers (IndirectNet)	137.6*** (19.81)	96.74*** (22.01)	129.4*** (26.43)
RD X Alliances with IT-producers (InNet)	-28.67 (20.02)	-41.84 (26.01)	-19.08 (24.64)
Patent X OutNet	-182.2*** (21.55)	-110.8*** (26.20)	-198.7*** (28.13)
Patent X InNet	-88.48*** (19.43)	86.96*** (22.20)	-142.5*** (26.46)
Patent X IndirectNet	85.46*** (20.70)	75.44*** (24.75)	77.36*** (26.43)
RD X Consult	128.5 (79.88)	83.29 (52.42)	
Consult X OutNet	-26.30 (83.41)	20.52 (63.17)	
Consult	-154.1 (664.4)		
RD X Patent	53.44*** (11.52)	-63.94*** (15.07)	90.04*** (15.68)
OutNet	124.8* (65.93)		147.3* (77.22)
IndirectNet	-23.22 (34.60)	-33.60 (45.54)	-33.91 (42.74)
InNet	23.43 (44.08)	-70.97 (58.40)	36.43 (54.20)
RD	-3.373 (56.83)		-45.61 (66.20)
Patent	-196.3*** (42.64)	89.55 (60.30)	-244.1*** (51.10)
ITPartnerIndus	-0.249 (1.000)	-1.095 (1.447)	-0.0793 (1.190)
log(Capital)	50.33 (50.84)	78.94 (75.69)	19.27 (60.50)
log(Marketshare)	63.70 (57.11)	-16.57 (83.84)	117.8* (69.00)
HHI	2,613 (2,155)	-5,763* (3,431)	9,144** (4,035)
Collab	-29.04*** (4.712)	40.40*** (10.89)	-25.35*** (5.423)
Arm's-Length	-105.1*** (8.803)	-114.1*** (16.79)	-107.2*** (10.11)
Constant	875.3 (548.4)	1,413 (1,063)	1,125* (603.7)
Observations	1,311	365	946
R-squared	0.625	0.831	0.621
Number of Unique Firms	464	150	315
F stat	38.59***	29.15***	32.89***

Note: Fixed-effect panel regression. Dependent variable is annual profits.
*Significant at 10%, ** significant at 5%, *** significant at 1%. Fixed-effect panel regressions, with standard errors in parentheses. All models include indicator variables for each year and indicator variables for each NAICS industry at the three-digit level. The research and development (RD) variable is the logarithm of R&D stock calculated using the perpetual inventory method. Logarithm values of InNet, OutNet, and IndirectNet are also used.



This figure presents the marginal effects of *OutNet* for Model 2 and Model 3 in Table 4. For both samples of software package-product and software consulting-services firms, as firms invest more in their R&D, the predicted effect of their alliances with IT-consuming firms on their profits increases. However, except for firms with R&D stock lower than $10 billion, the estimated effect of *OutNet* is significantly higher for consulting-services firms compared to the estimated effect of *OutNet* for package-product firms. Both X and Y axes are in millions of dollars.

Note: For better visualization, we have replaced the two logarithm-transferred and mean-centered variables of R&D and *OutNet* with their original values: R&D stock and number of alliances with IT-consuming firms.

Figure 3: Marginal Effects of Alliances with IT-Consuming Firms (*OutNet*) on Net Income in Millions of Dollars

Table 4 presents the results of testing H2, which predicts that alliances with IT consumers are associated with a more beneficial effect on R&D returns for software consulting-services firms than for software package-product firms. A parsimonious and formal way of testing this comparison involves a regression test that includes all IT-producing firms, testing the three-way interaction term *RD X Consult X Alliances with IT-consuming firms (OutNet)*. This model also includes all of the implied two-way interactions (*RD X OutNet*, *RD X Consult*, and *Consult X OutNet*). As seen in Model 1 of Table 4, the estimate of the three-way interaction term *RD* X *Consult X OutNet* is positive and statistically significant (β_2 = 107.9, and is statistically significant at a 1% level) in support of H2. While software packaging (and the copyright protections associated with software packaging) and patenting may be seen as means of protecting IP, our results support the view that the tacit and relational mechanisms at work in collaborative relationships, such as in interfirm consulting practices, appear to be a more effective way to reap benefits from R&D investments through alliance partnerships. Model 2 and Model 3 in Table 4 provide further support for H2 as the estimated β_1 (=138.4) in Model 2 is statistically significant at a 1% level and is higher than it is in Model 3 (β_1 = 87.54).

Figure 3 presents the marginal effect on net income of IT-producing firms' alliances with IT-consuming firms as an increasing function of their R&D stock, comparing this effect between the two samples of package-product and consulting-services firms. This figure is based on estimates from Model 2 and Model 3 in Table 4 for the consulting-services and package-product firms, respectively. To calculate the marginal effects of *OutNet* in Figure 3, we fix R&D stock at $1 billion increments between our sample's minimum and maximum values. For each value of R&D stock in this range, we calculate and present the marginal effect of one more alliance with IT-consumers on the firm's net income. This figure shows that for both software package-product and consulting-services firms, as firms invest more in their R&D the predicted profitability effect of their alliances with IT-consuming firms increases. For example, a consulting-services firm with $30 billion in R&D stock should be able to extract an extra $100 million to $200 million for each alliance with an IT-consuming firm. By contrast, a package-product firm with $30 billion in R&D stock would be able to extract no more than $40 million for each alliance with an IT-consuming firm. Figure 3 shows that except for firms with R&D stock lower than $10 billion, the estimated effect of *OutNet* is significantly higher for consulting-services firms than for package-product firms.

We further explored our models using alternative measures for our theoretical constructs. Table 5 presents the results of using the alternative measures of *Consultancy Sales* and *Package Sales* instead of the binary measure of *Consult*. This table's results show a positive and significant moderating influence of *Consultancy Sales* (in proportion to total sales) on the effect of the interaction between *RD* and *OutNet* (see the coefficient estimate for the three-way interaction *RD X Consultancy Sales X OutNet*) on firm profits. Although not directly hypothesized, the negative and significant moderating influence of package software sales (in proportion to total sales), *Package Sales*, on the effect of the interaction between *RD* and *OutNet* (see the three-way interaction *RD X Package Sales X OutNet*) on firm profits provides further empirical evidence for theoretical arguments supporting H2. Table A6 presents the results of using the following alternative R&D measures: log(R&D investments) as the logarithm of annual R&D investments in Model 1 and Model 2, and R&D intensity, measured as the ratio of annual R&D investments over revenue, in Model 3 and Model 4. The results of using these alternative measures, presented in Table A6, are, by and large, supportive of the main results.

Table 6 presents the results of using the number of firms' software patents as an alternative dependent variable that captures firms' innovation output. Showing the effect of alliances on firms' innovative output provides further empirical evidence supporting our theoretical arguments.

Finally, Table 7 includes a number of important network structure and alliance characteristics measures to ensure the robustness of our results to such time-variant factors. In Table 7, Model 1 and Model 2 include control variables for *network diversity*, *betweenness centrality*, *degree centrality*, and *access to structural holes*. In addition, Model 1 in this table controls for the ratio of joint ventures and R&D agreements to total alliances, as well as the measure of *tie multiplicity*, calculated as the total number of alliance activities that a firm reports for its alliances over the total number of alliances that a firm has, as in Lavie (2007). The stability of the hypothesized relationships across Tables 5, 6, and 7 provides a further robustness check for our main results.

4.2 Complementarities Between Alliances with Other IT-Producing Firms and R&D Investments

The results in Table 3 show a positive and significant interaction between alliances with other IT-producing firms and R&D investments, *RD X InNet*. Alliances with other IT-producing firms can enable IT-producing firms to generate greater value from their R&D investments and pursue an R&D program that keeps pace with peers. As the relational view suggests, alliance network positioning is an inimitable firm resource that helps firms maintain a competitive advantage (Gulati et al. 2000). Powell et al. (1996, p. 119-120) argue that innovation arises from learning networks of firms, rather than from individual firms; as a consequence, "firms must learn how to transfer knowledge across alliances and locate themselves in those network positions that enable them to keep pace with the most promising scientific or technological developments."

We further compare the moderating effect of alliances with other IT-producing firms (*InNet*) and R&D in the two samples of software consulting-services and package-product firms. The results, presented in Table 4, show a higher coefficient estimate for package-product firms compared to the coefficient estimate for consulting-services firms (seen by comparing the coefficients of the interaction term *InNet* X *RD* between Model 2 and Model 3), which is in the opposite direction of H2. Potential IT-producing partners will have strong technical capabilities; thus, while they may be complementary in some ways, these partners also will directly compete with the focal IT-producing firm, thereby creating a source of risk of partnering with such firms. Prior studies have viewed alliance networks as structural conduits through which firms gain access to flows of knowledge and information. Knowledge-spillovers occur through both formal and informal channels (Owen-Smith & Powell, 2004). Since IT-producing industries involve highly fungible IP that has diverse applications, a positioning strategy may have specific consequences for knowledge creation and value appropriation (Lavie, 2007; Schilling & Phelps, 2007). As discussed earlier, knowledge in consulting-services firms is perceived to have higher levels of fungibility, and the higher coefficient estimate for software package-product firms might be attributed to the ability of the latter firms to better protect their IP.

Table 5: Using Alternative Measures for Consulting-Services and Package-Product Firms

VARIABLES	(1) FE: profits	(2) FE: profits
H1: RD X Alliances with IT-consuming firms (OutNet)	111.2*** (26.36)	217.1*** (29.94)
H2: RD X Consultancy Sales X Alliances with IT-consuming firms (OutNet)	70.39* (38.07)	
H2: RD X Package Sales X Alliances with IT-consuming firms (OutNet)		-135.6*** (30.88)
RD X Consultancy Sales	-84.14 (63.82)	
OutNet X Consultancy Sales	-21.09 (92.65)	
RD X Patent	41.70*** (11.91)	53.43*** (11.58)
RD X Package Sales		50.65 (64.46)
OutNet X Package Sales		59.45 (87.26)
Package Sales		176.3 (185.5)
Consultancy Sales	-25.53 (196.9)	
OutNet	99.59 (70.11)	75.99 (80.93)
RD	61.86 (53.38)	24.53 (64.68)
Observations	1,267	1,267
R-squared	0.620	0.629
Number of unique firms	448	448
F stat	35.46***	36.80***

Note: Fixed-effect panel regression. Dependent variable is annual profits.
*Significant at 10%, ** significant at 5%, *** significant at 1%. Fixed-effect panel regressions, with standard errors in parentheses. All models include every control variable, removed from the table in the interest of space.

Table 6: Software Patents as Dependent Variable

VARIABLES	(1) Same year software patents	(2) 1 yr. future software patents	(3) 2 yr. future software patents
H1: RD X Alliances with IT-consuming firms (OutNet)	6.399*** (2.292)	8.660*** (2.323)	10.74*** (3.225)
H2: RD X Consultancy (Consult) X Alliances with IT-consuming firms (OutNet)	20.49*** (2.701)	15.85*** (2.717)	19.69*** (3.505)
RD	-4.175 (5.219)	-1.071 (5.264)	1.732 (6.940)
Consult	-0.0831 (61.93)	16.20 (59.02)	46.15 (85.37)
RD X Consult	1.505 (7.410)	-1.186 (7.495)	-6.127 (10.76)
OutNet	20.99*** (5.981)	15.49** (6.264)	17.47** (8.026)
Consult X OutNet	-3.626 (7.654)	2.042 (7.745)	-0.287 (9.905)
Observations	1,279	1,109	926
R-squared	0.669	0.706	0.638
Number of unique firms	450	398	341
F stat	44.51***	46.47***	28.61***

Note: Fixed-effect panel regression. Dependent variable is software patents instead of annual profits.
*Significant at 10%, ** significant at 5%, *** significant at 1%. Fixed-effect panel regressions, with standard errors in parentheses. All models include every control variable, removed from the table in the interest of space.

Table 7: Controlling for Alliance Network Measures and Alliance-Related Factors

VARIABLES	(1) FE: profits	(2) FE: profits	(3) FE: profits
H1: RD X Alliances with IT-consuming firms (OutNet)	75.69** (32.63)	78.56** (32.66)	94.36*** (25.83)
H2: RD X Consultancy (Consult) X Alliances with IT-consuming firms (OutNet)	134.1*** (37.66)	131.2*** (37.58)	110.2*** (30.40)
RD X Indirect Links to IT-producers (IndirectNet)	145.8*** (26.85)	146.4*** (26.93)	134.6*** (21.41)
RD X Alliances with IT-producers (InNet)	-39.48 (26.79)	-35.92 (26.84)	-30.45 (20.39)
Patent X OutNet	-193.2*** (26.54)	-191.1*** (26.51)	-187.8*** (22.39)
Patent X InNet	-88.86*** (24.33)	-93.25*** (24.31)	-85.94*** (20.43)
Patent X IndirectNet	97.31*** (25.51)	95.04*** (25.56)	87.80*** (21.20)
RD	-9.739 (73.02)	-1.740 (73.12)	1.816 (58.94)
Consult	-176.8 (828.3)	-66.10 (829.9)	-146.9 (697.5)
RD X Consult	109.4 (106.4)	118.5 (105.9)	121.7 (84.46)
OutNet	170.5* (88.56)	156.6* (88.70)	120.9* (67.46)
Consult X OutNet	-36.71 (110.9)	-43.83 (110.7)	-4.764 (86.23)
Network Diversity	54.33 (117.1)	-32.40 (107.2)	
log(Network Constraint)	-70.73 (88.66)	-0.735 (83.67)	
log(Betweenness Centrality)	-1.840 (11.54)	-0.492 (11.53)	
Joint Ventures / Total Alliances	-340.4 (261.0)		
R&D Alliances / Total Alliances	-290.4 (190.9)		
Tie Multiplicity	159.6** (80.38)		
Constant	1,413* (783.5)	1,376* (771.8)	832.2 (559.1)
Observations	999	999	1,272
R-squared	0.643	0.639	0.626
Number of unique firms	350	350	449
F stat	26.08	27.70	36.62

Note: Fixed-effect panel regression. Dependent variable is annual profits.
*Significant at 10%, ** significant at 5%, *** significant at 1%. Fixed-effect panel regression, with standard errors in parentheses. The model includes indicator variables for each year, as well as firm-level fixed effects. The research and development (RD) variable is the logarithm of R&D stock calculated using the perpetual inventory method. All models include all of the control variables in Table 3, some removed from the table in the interest of space.

4.3 Econometric Considerations and Robustness Tests

We consider here several econometric issues and how we address them: reverse causality, unobserved heterogeneity, sample selection, and multicollinearity.

4.3.1 Reverse Causality

To rule out reverse causality, we consider whether profits jointly drive alliances and R&D—and, more specifically, whether the joint effects are a result of reverse causality among individual variables in the model. Firms might adjust their R&D and alliance practices in response to windfalls in operating profits, and this would create a spurious interaction effect. Thus, we consider whether lag effects are present in the direction of causality suggested by the model, wherein joint interaction effects are present not just for the current year but also for the subsequent year**.** Table A2 in the Appendix shows the difference in results when we consider the dependent variable as operating profits not just for the current year but also for three and four years in the past and up to three years into the future. We observe the separation in the sign and magnitude of main coefficient estimates to provide some insight into the direction of causality among the variables of interest. In particular, we see that the interaction between R&D investment and alliance types *OutNet* and *InNet* have no significant relationship with past values of operating profits, but they do have a positive and significant association with the same year profits as well as with profits in the third and fourth year into the future. Overall, our supplementary regressions do not suggest that firms attract more alliances as a result of more profits or more R&D.

Further, we examine whether profits and R&D might influence alliancing activity, reporting the results in Table A3 of the Appendix. Addressing this concern is important because firms with high levels of R&D or profitability might attract more alliances. Thus, if reverse causality were a problem, we would detect a reverse effect in which alliance activity exhibits a positive sensitivity to firm-specific shocks in R&D or profits. In Table A3, we see that one-year lags of R&D (*1 yr. past RD)* have no effect on *IndirectNet*, with a statistically insignificant coefficient of -0.0987 in Model 1, or on *InNet*, with a statistically insignificant coefficient of -0.0901 in Model 3. We also see in Model 2 that after a year, one-year lags of R&D (*1 yr. past RD)* are associated instead with *lower* levels of *OutNet*. Coefficient effects of profits (*1 yr. past Profits*) on future *IndirectNet* in Model 1 and Model 7, as well as on future *OutNet* in Model 2 and Model 8, are statistically insignificant. Table A3 also shows a negative association between profits (*1 yr. past Profits*) and *InNet* after three years in Model 9. If reverse causality were present, it would make our coefficient estimates more conservative. Overall, we do not see lagged effects of three years in the relationship between profits and alliance activity that are positive; rather, some effects are actually negative, which further alleviates concerns about reverse causality as an underlying driver of our hypothesis tests.

4.3.2 Unobserved Heterogeneity

Even in the absence of reverse causality, unobserved variables might still bias the coefficient estimates. To some extent, the results in Tables A2 and A3 also reduce concerns about the simultaneous effects of potentially missing variables because most sources of reverse causality stem from unobserved factors that jointly influence the variables of interest. To address this further, we exploit the fact that a large set of unobserved factors tend not to change over short time periods: for instance, corporate culture (i.e., the external orientation of the firm culture which could lead to a tendency to form alliances), leadership strategy, R&D culture, and organizational structure. Although these relatively innate firm features sometimes change over long periods of time, they tend not to change very quickly. Firm-fixed effects over a relatively short panel already control for such factors by design, and these are already incorporated in our main empirical models. Therefore, it is useful to compare our empirical models with and without fixed effects to assess the sensitivity of the model estimates to such time-invariant firm characteristics. If ordinary least squares (OLS) and fixed-effect (FE) panel model estimates are similar, this would suggest that unobserved firm-specific factors are not systematically related to our main variables of interest. Arguably, if our model variables are generally uncorrelated with the comprehensive set of time-invariant firm characteristics (i.e., firm-fixed effects), this would suggest that the model variables are also unrelated to other unobserved characteristics that might change more frequently in time. Including fixed effects for each year, as well as market share, physical capital, industry competitiveness, and alliance partner R&D investments, reduces the likelihood that residual time-varying unobservables might bias our model estimates. We report OLS results in Table A4, and they suggest that our results are, by and large, insensitive to firm-fixed effects.

In order to further explore the potential of unobserved heterogeneity, we test Arellano-Bond (AB) and random-effect models and report the results in Table A4 alongside OLS and FE results. In the AB model, we have included two lags of the dependent variables and instrumented our main interaction terms and the direct effects of variables in them using one lag. The Hausman test statistic to compare the results of AB, RE, and OLS models with the FE models was significant, a finding that can be attributed to different assumptions in these models. The hypothesized relationship, however, has been largely stable in the models. Since FE models are known to have lower bias and greater stability in the presence of firm-level unobserved heterogeneity, we rely upon the FE model for tests of our main hypotheses. Yet, the consistency of the results under vastly different model assumptions suggests that our results are robust to unobserved heterogeneity.

In Table A7, we show the result of using Garen's correction technique, as well as an extension of Garen's model that has been used in prior research (Luan & Sudhir, 2010). We separately regress *OutNet*, *IndirectNet*, and *R&D stock* on factors likely to impact them. For *OutNet* and *IndirectNet*, we use partners' IT investments, and for *R&D stock*, we use industry R&D intensity as an exclusion restriction to help with model identification. We store the residuals and include them, as well as their interaction with potentially endogenous variables, in the main model. The hypothesis test results (coefficient estimates of the interaction terms *RD X OutNet* and *RD X Consult X OutNet* in Table 7) remain robust under this correction technique.

4.3.3 Sample Selection

Our unpaired *t*-tests (with unequal variances) suggest that compared with the broader population of publicly listed US firms, firms in our final sample have slightly lower R&D investment, less physical capital, lower market value, higher sales, higher ROA, higher market size, higher operating income, and higher competition. Generally, this means that our findings may not extend as well to very small or unprofitable firms or to those in less competitive industries. A second potential concern is that the sample selection could skew the hypothesis test results under certain conditions, such as if idiosyncratic factors determining sample selection were systematically related to the main variables in the study. To alleviate these concerns, we make use of the unbalanced nature of the panel and exploit the fact that sample selection in a fixed-effect context is only a problem when it is related to time-varying idiosyncratic errors; hence, "any test for selection bias should test only this assumption" (Wooldridge, 2002, p. 581). We conduct the Nijman-Verbeek test adapted to the fixed-effect panel context and test for the significance of the lagged and forward selection indicators in our main models (Wooldridge, 2002). These selection indicators are statistically insignificant in our models, suggesting that there is no selection bias because of idiosyncratic errors. In summary, our statistical tests show no evidence of a selection mechanism that would positively bias our hypothesis test results; rather, our results appear to become more conservative when sample selection is accounted for.

In Table A8, we present a test of our hypotheses for the time period of 1991 to 2016. The time frame of our original model, presented in Table 3, is limited by the lack of available patent data for the years after 2009. In the models that we present in Table A8, we have excluded the patent-related variables to extend the time frame. Table A8 also presents the results of testing our hypothesized relationships on samples of software and hardware firms in Model 1, broader IT-producing industries in Model 2, and IT-consuming industries in Model 3. Model 1 in this table shows consistent estimations for both hypotheses (H1 and H2), addressing concerns regarding potential biases introduced by our sample choice. Model 2, testing our main model on a sample of broader IT-producing industries, shows consistency in the magnitude and significance of the coefficient estimates of our hypothesized relationship. In addition, Model 3, presenting the results of testing our model on a sample of non-IT-producing firms, reveals a negative coefficient estimate for the interaction term of *RD X OutNet*, which is in the opposite direction of the hypothesized relationship. Comparing Model 1 and Model 2 with Model 3 shows that the hypothesized relationships are unique to IT-producing industries.

4.3.4 Multicollinearity

Our results do not suffer from multicollinearity because the mean variance inflation factor (VIF) in our main regression model is approximately four, which is well below the recommended threshold. As shown in Table A5, we estimated different versions of the main model with different subsets of variables in hierarchical style. The signs and magnitudes for the main variables of interest are quite stable as different subsets of control variables are included in the model specification. Overall, we do not find that the coefficient estimates suffer from instability caused by severe collinearity among the variables.

5 Discussion

5.1 Main Findings

Our goal in this study is to examine whether positioning in an alliance network affects the value firms appropriate from investments in R&D in an industry setting characterized by the high fungibility of knowledge. We begin with the premise that alliances provide opportunities to generate new value, enhancing the value of R&D investments. We test that premise and then further explore the alliance features that help protect R&D investments from appropriation by opportunistic partners, building on the relational perspective of the firm.

Our findings suggest that central positioning in an alliance network in a complex industry ecosystem, such as in the interface between IT-producing and IT-consuming firms, has positive implications for profitability and returns to R&D investments. In the absence of strong formal mechanisms to protect IP, we argue that firms rely on informal barriers to serve as the underlying drivers of relational rents, as discussed by Dyer and Singh (1998). These drivers may include human co-specialization, process specificity, informal governance, and formation of trust in collaborative alliance activities. We propose and test direct implications of this theory: Alliances with IT-consuming firms have a more beneficial effect on R&D returns for software consulting-services firms than for software package-product firms.

In particular, our findings suggest that IT-producing firms' returns to R&D investments increase with alliance ties to IT-consuming firms. Our models rule out a number of alternative explanations. In addition, we control for indirect ties of IT-producing firms to other IT producers (their potential rivals) by way of alliances with IT-consuming firms; the results hold after controlling for firm-fixed effects, which account for many unobserved characteristics that can be reasonably assumed as stable or constant over multiple years, such as organizational culture, subindustry (microchips vs. software), and many relatively stable organizational capabilities.

5.2 Research Implications

Our findings underscore the importance of positioning within the alliance networks of IT consumers and have major implications for at least two streams of IS research. First, our results contribute to the literature on the co-creation of digital innovations (Han et al., 2012) in two ways. The extant literature considers alliances between IT-producing firms (Han et al., 2012; Sarker et al., 2012), and our study extends this literature by exploring alliances between IT-producing firms and IT-consuming firms. While the existing literature on this topic explores the co-creation of value between IT-producing firms, our paper posits a similar phenomenon in the partnerships between IT-producing and IT-consuming firms. Our findings underscore that alliances with IT-consuming firms, similar to those with other IT-producing firms, provide both formal and informal channels through which firms gain access to information and knowledge (Owen-Smith & Powell, 2004).

In addition, we extend the existing literature by adopting a relational view of the firm and distinguish two broad groups of IT-producing firms based on the extent to which their resources and capabilities might be considered relation-specific: software consulting-services versus software package-product firms. IT-producing firms benefit more from alliances with IT-consuming firms when firms develop industry-specific and firm-specific expertise that address the idiosyncratic needs of their alliance partners, which is generally the business model for software consulting-services firms. From a research perspective, our findings suggest the need to consider how the idiosyncratic requirements of IT-consuming partners serve to protect and sustain the value of R&D investments and how these considerations may be different for different types of IT-producing firms that seek partnerships with IT-consuming firms.

Second, our results contribute to the IS innovation literature (Kleis et al., 2012) in two ways. In line with the digital innovation literature on the distributed nature of digital innovations (Yoo et al., 2010), we posit an interaction effect between IT-producing firms' partnerships with their corporate customers and their R&D investments. By showing that IT-producing firms may benefit from alliances with IT-consuming firms to derive greater profits from their R&D investments, our results expand research focused on the complementarities between returns on R&D and other strategic investments and resource-based factors (Havakhor et al., 2019; Ravichandran et al., 2017; Steelman et al., 2019). Ultimately, we posit a novel relation-based factor to add to existing resource-based factors (Havakhor et al., 2019).

In addition, the costs and risks to IT-producing firms associated with collaborating with IT-consuming firms may be worth considering. Our findings suggest that the relational mechanism is effective in allowing firms to enhance their R&D output and safeguard their R&D returns by co-developing innovative resources and capabilities with IT-consuming firms. Alliances with customers and suppliers can help generate knowledge that can enhance innovation. For IT-producing firms, the value of these alliances overall seems to outweigh their potential hazards. In the IT industry context in which intellectual capital is highly fungible, our empirical results suggest that such risks do not negate the benefits of collaborating closely with alliance partners from other industries. This is a surprising and significant finding, considering the extent to which prior work has served to caution firms against such appropriation risks (Lavie, 2007).

By using the relational view of the firm, we create a theoretical link between two streams of IS literature, namely co-creation of IT business value (Han et al., 2012) and digital innovation (Kleis et al., 2012; Yoo et al., 2010). Accordingly, we extend our knowledge of relation-specific characteristics that contribute to the co-creation of digital innovations and provide an intradisciplinary contribution to the field of IS (Tarafdar & Davison, 2018).

We also contribute to the extant literature on the performance of software alliances by investigating the fungibility of a firm's resources in the context of its local network structure, rather than focusing on the firm's choice of resource architecture. Our findings are supported by anecdotal evidence in the IT industry where alliances are the norm in many areas even as companies compete vigorously for the same customers or technologies. The business press suggests that superior returns on R&D for Apple may in part be because of the company's ability to leverage the R&D efforts of its suppliers, the scale of business it provides to them, and the complementary investments that Apple makes in its marketing activities (Satariano, 2015). Further research on how alliances help leverage value from other types of investments, such as those in marketing, may shed light on the relative importance of various types of information and knowledge supported by such partnerships.

5.3 Managerial Implications

Our findings provide potentially generalizable insights because software is not altogether different from the digital products and services developed in many industries—entertainment, news, and publishing, for instance. Most digital and intangible innovations tend to be fungible with many alternative applications, low marginal replication costs, and high initial development costs. This characteristic makes investment in digital innovations risky and sustaining value from innovation potentially hazardous in the context of alliance relationships. Our findings suggest that interfirm relationships, in particular the joint development of digital innovations with firms' customers, can help firms sustain and generate value from their investments in R&D. In this way, our findings highlight the value of partnerships that entail collaboration with consumers.

In line with the theoretical perspective of the relational view, managers should consider whether their counterparts in an alliance relationship are sufficiently invested by virtue of the relation-specificity of their investments and whether they will be perceived to be likewise invested by their alliance partners. Such noncontractible factors help enhance trust and commitment to generate and sustain R&D investment value through interfirm alliances (Mithas et al., 2008), especially when contracts are insufficient to manage the hazards of exposing valuable intellectual property. Such noncontractible investments are particularly important in the context of digital innovation, where initial development costs are high but replication costs are low, factors that make these investments vulnerable to ex post opportunism.

5.4 Limitations and Suggestions for Further Work

This study has several limitations that can be addressed in future work. First, because of data limitations, we use industry-level approximations for the control variables of partner firms' IT and R&D investments. Future studies might use firm-level measures of IT investments and IT applications to gain additional insights into the role of IT capabilities (Ravichandran et al., 2017; Saldanha et al., 2017; Saldanha et al., 2020).

Second, this study does not examine factors that influence the R&D returns of IT-consuming firms; doing so in addition to studying the performance of their IT-producing partners will lead to more detailed conclusions regarding who benefits more from such cross-industry alliances. Finally, it would be useful to conduct similar studies in emerging economies and for alliances among IT-consuming firms to support further generalizability. Researchers can further explore how alliances help firms improve the pace and inimitability of their innovation efforts and the governance mechanisms that firms use to manage alliance partners.

Future research might examine how the same theoretical mechanisms for leveraging and safeguarding innovation apply in other multifirm innovation contexts. For example, there has been a growing interest in the open innovation context, which sometimes involves networks of corporate alliances (Boudreau & Lakhani, 2009; Jarvenpaa, 2014). Many products and services developed in open innovation contexts are digital in form; hence, the same mechanisms for safeguarding and leveraging value in the face of acute transaction hazards can apply in open innovation settings, as well.

To conclude, our analyses of a panel of 464 IT-producing firms spanning the 14-year period from 1996 to 2009 provide new insights regarding how such firms protect and leverage value from their R&D investments according to their positioning in networks of alliances with IT-consuming firms. Overall, our findings suggest that firms need to position themselves in alliance ecosystems to maximize their ability to generate innovations and derive value from them. We find evidence that IT-producing firms can enhance their returns to R&D by forming alliances with IT-consuming firms. For IT-producing firms, returns to R&D increase with alliance ties to IT-consuming firms, and alliances with IT-consuming firms have a more beneficial effect on R&D returns for software consulting-services firms than for software package-product firms. The relation-specific resources that are shared in alliances help consulting-services firms to limit appropriation hazards and safeguard their R&D because they gain unique domain knowledge while co-creating value with their corporate partners. Together, these findings have implications for how firms should develop their strategic posture for alliances in terms of the types of partners and depth of collaborative activities they pursue. Such an ecosystem perspective is becoming more relevant as a theoretical lens, as technological innovations are increasingly interdependent across firm and industry boundaries and increasing digitization serves to make such innovations at once more dynamic and fungible.

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Appendix

Table A1: Selected Studies

Theme	Information systems contributions	Underlying theory	Dataset	Summary of the results	Focus on cross-industry alliances	Distinction between types of alliances
Transaction cost, RBV, and network resources	Lavie (2007)	Resource-based view (Barney, 1991)	Alliances from 1985-2001	Firms with higher bargaining powers and under higher market competition appropriate a larger share of the value generated through the alliance.	No. Focused on alliances between IT-producing firms.	No
	Chi et al. (2010)	Alliance network structure (Gulati et al., 2000)	Alliances from 1988-2003	Network structures and IT capabilities enhance firms' ability to reach and exploit network resources.	No. Focused on automobile industries.	No
Coordination, control, and modularity	Tiwana (2008)	Coordination and control (Kirsch, Sambamurthy et al., 2002)	Survey data	Software modularity, and process and outcome control have a positive effect on alliance performance.	Not mentioned.	Yes. Based on governance structures.
	Tafti et al. (2013)	Knowledge sharing (Anand & Khanna, 2000; Zollo et al., 2002)	Alliances, IT architecture from 2000-2006	Flexibility of firms' IT is associated with the formation and value of different alliance types.	No. Alliances from different industries but not focused on cross- industry alliances.	Yes. Based on the nature of activities.
Knowledge sharing	Liu & Ravichandran (2015)	Organizational learning (Hoang & Rothaermel, 2005)	Alliances, IT tools 1990-2001	Knowledge integration IT capabilities have a positive moderating effect on the effects of both relatedness and diversity on ex ante value gains	No. Alliances from different industries.	No
	Ravichandran & Giura (2019)	Alliances as flows of knowledge (Gomes-Casseres et al., 2006)	Alliances, IT investment, and patent data 1991-2001	Partners' IT intensity positively moderates knowledge flows within alliances.	No. Alliances between high-tech industries but not focused on cross-industry alliances.	No
Cocreation of value	Sarker et al. (2012)	Resource-based view (Barney, 1991)	Case study	Mechanisms underlying value co-creation in B2B alliances.	No. Only alliances between IT-producing firms.	No

	Han et al. (2012)	Open innovation (Chesbrough, 2003)	Open innovation alliances 2000 - 2009	Participation in OIA alliances enhances focal firms' and their rivals' market value.	No. Alliances between firms from the same industries.	No
Innovation productivity	***This paper***	*Relational view (Dyer & Singh, 1998)*	*Alliances from 1996-2009 (and as a robustness test 1991-2016)*	*Alliances with IT-consuming firms can help IT-producing firms leverage greater value from their R&D. The effect is greater for software consulting-services firms than it is for software package-product firms. As consulting-services firms focus on more industry-specific and firm-specific collaboration in developing specialized software services, the idiosyncratic requirements of their IT-consuming partners serve to protect and sustain the value of their R&D investments.*	*Yes. Alliances between IT-producing firms and IT-consuming firms.*	*Yes. Based on the nature of shared resources.*

Note: This table is not meant to show an exhaustive list of relevant studies.

Table A2: Fixed-Effect Panel Regressions: Past and Future Profit

VARIABLES	**(1) L4. Profits**	**(2) L3. Profits**	**(5) Profits**	**(6) F1. Profits**	**(7) F2. Profits**	**(8) F3. Profits**
RD X Alliances with IT-consuming firms (OutNet)	-29.22 (30.26)	-0.840 (26.36)	90.44*** (25.32)	142.3*** (25.67)	135.0*** (35.40)	47.95 (39.63)
RD X Alliances with IT-producers (InNet)	-12.48 (22.19)	4.769 (20.65)	137.6*** (19.81)	175.6*** (21.07)	164.1*** (28.81)	43.00 (35.97)
RD X Indirect Links to IT-Producers (IndirectNet)	2.511 (23.24)	10.27 (21.07)	-28.67 (20.02)	-65.33*** (20.56)	-68.49** (29.66)	-46.07 (33.93)
Observations	631	767	1,311	1,141	950	770
Number of Unique Firms	225	265	464	406	345	255
F stat	26.70***	32.04***	38.59***	36.63***	16.26***	16.01***
R-squared	0.688	0.686	0.625	0.640	0.484	0.506

Note: * Significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors in parentheses. L[N] represents N years in the past, and F[N] represents N years in the future for the dependent variable firm profits. All models include indicator variables for each year, in addition to firm-fixed effects. Also included in these models are all the control variables from the Table 3 models (not shown for brevity). The research and development (RD) variable is the logarithm of R&D stock calculated using the perpetual inventory method.

Table A3: Reverse Causality Tests: Fixed-Effect Panel Regressions

VARIABLES	(1) Present IndirectNet	(2) Present OutNet	(3) Present InNet	(4) 1 yr. future IndirectNet	(5) 1 yr. future OutNet	(6) 1 yr. future InNet	(7) 2 yrs. future IndirectNet	(8) 2 yrs. future OutNet	(9) 2 yrs. future InNet
1 Yr. Past Profits	1.99e-05 (4.47e-05)	1.32e-05 (3.30e-05)	-1.60e-05 (2.98e-05)				0.000159 (0.000485)	-0.000243 (0.000358)	-0.000782** (0.000321)
1 Yr. Past RD	-0.0987 (0.126)	-0.179* (0.0933)	-0.0901 (0.0843)				-0.101 (0.127)	-0.176* (0.0935)	-0.0787 (0.0839)
1 Yr. Past ITPartnerInd	-0.00381* (0.00196)	-0.00104 (0.00145)	0.00280** (0.00131)				-0.00379* (0.00196)	-0.00108 (0.00145)	0.00270** (0.00130)
1 Yr. Past RDPartnerInd	-0.00560 (0.0270)	0.0349* (0.0200)	0.0226 (0.0180)				-0.00527 (0.0271)	0.0343* (0.0200)	0.0208 (0.0179)
1 Yr. Past log(Capital)	0.280** (0.130)	0.230** (0.0963)	-0.0631 (0.0870)				0.279** (0.131)	0.232** (0.0964)	-0.0573 (0.0865)
1 Yr. Past log(MarketShare)	6.99e-05 (0.156)	-0.0729 (0.115)	0.185* (0.104)		0.0707 (0.155)		-0.00768 (0.159)	-0.0586 (0.117)	0.227** (0.105)
1 Yr. Past HHI	-5.892 (3.980)	-7.654*** (2.939)	2.285 (2.655)	-3.543 (5.255)	-10.82** (4.270)	5.227 (3.633)	-5.917 (3.986)	-7.607** (2.942)	2.425 (2.639)
2 Yrs. Past Profits				1.68e-05 (5.58e-05)	-1.03e-05 (4.58e-05)	-4.61e-05 (3.86e-05)			
2 Yrs. Past log(RD)				-0.240 (0.148)	-0.252** (0.114)	-0.161 (0.102)			
1 Yr. Past ITPartnerInd				-0.00219 (0.00227)	-0.000613 (0.00186)	0.00419*** (0.00157)			
1 Yr. Past RDPartnerInd				-0.0311 (0.0299)	0.0195 (0.0246)	0.0286 (0.0207)			
2 Yrs. Past log(Capital)				0.0215 (0.149)	0.0510 (0.114)	0.0785 (0.103)			
2 Yrs. Past log(Marketshare)				0.134 (0.192)		0.00128 (0.133)			
1 Yr. Past RD X Profit							-1.26e-05 (4.38e-05)	2.32e-05 (3.23e-05)	6.94e-05** (2.90e-05)
Constant	-0.181 (1.383)	-0.700 (1.021)	1.461 (0.923)	1.337 (1.618)	1.397 (1.271)	-0.168 (1.118)	-0.247 (1.403)	-0.580 (1.036)	1.820* (0.929)
Observations (Firms)	620 (237)	620 (237)	620 (237)	459 (169)	459 (169)	459 (169)	620 (237)	620 (237)	620 (237)
R-squared	0.098	0.183	0.090	0.100	0.196	0.107	0.098	0.184	0.104
F stat	2.085	4.292	1.893	1.674	3.694	1.812	1.980	4.098	2.109
F test	0.00517	1.20e-08	0.0137	0.0437	1.31e-06	0.0238	0.00768	2.09e-08	0.00387

Note: * Significant at 10%, ** significant at 5%, *** significant at 1%. Fixed-effect panel regression coefficients, with standard errors in parentheses. All models include indicator variables for each year (not shown for brevity).

Table A4: Comparison of Fixed Effects, OLS, Random Effects, and Arellano-Bond Tests of H1: Moderating Influence of Alliances on Effect of R&D on Firm Profits

VARIABLES	(1) FE: Profits	(2) AB: Profits	(3) OLS: Profits	(4) RE: Profits
H1: RD X Alliances with IT-consuming firms (OutNet)	131.5*** (22.43)	74.34* (41.53)	385.5*** (23.72)	534.4*** (128.5)
RD X Alliances with IT-producers (InNet)	140.5*** (19.99)	87.17** (36.97)	328.9*** (21.19)	365.3*** (82.30)
RD X Indirect Links to IT-producers (IndirectNet)	-31.41 (20.21)	-1.214 (34.17)	-149.3*** (23.04)	-284.8*** (86.86)
Patent X OutNet	-160.4*** (21.12)	-94.48*** (30.26)	-302.1*** (24.76)	-437.9*** (136.7)
Patent X InNet	-89.47*** (19.59)	24.41 (31.75)	-144.2*** (23.45)	-116.3* (69.17)
Patent X IndirectNet	87.44*** (20.91)	40.26 (29.06)	138.8*** (25.86)	221.5** (101.8)
1st Lag Profit		0.421*** (0.0686)		
2nd Lag Profit		0.328*** (0.0826)		
1st Lag RD X OutNet		-44.71* (24.87)		
1st Lag RD		93.16 (225.7)		
OutNet	69.37 (58.21)	-85.38 (126.4)	-230.4*** (63.25)	-388.3*** (138.9)
1st OutNet		3.133 (85.76)		
RD X Patent	35.95*** (10.83)	-27.11 (21.57)	174.6*** (10.61)	251.3*** (52.00)
IndirectNet	-20.81 (34.93)	-38.18 (73.56)	41.69 (38.71)	93.17 (66.42)
InNet	24.06 (44.53)	-164.7* (98.66)	-190.5*** (48.98)	-288.9*** (99.90)
RD	28.36 (49.51)	-100.9 (274.2)	185.9*** (28.27)	117.0** (48.99)
Patent	-173.1*** (42.72)	18.71 (97.68)	-434.8*** (41.37)	-608.2*** (136.4)
ITPartnerIndus	-0.116 (1.012)	1.803 (2.008)	0.138 (1.197)	0.515 (1.158)
log(Capital)	53.01 (51.37)	76.97 (164.7)	127.6*** (38.21)	104.8* (57.80)
log(Marketshare)	61.26 (57.51)	46.66 (220.6)	16.68 (30.93)	37.62 (38.37)
HHI	-230.1 (1,552)	-4,452 (5,633)	-108.2 (1,099)	-214.3 (1,514)
RDPartnerIndus	8.765 (9.631)	-24.74 (19.65)	6.281 (7.627)	7.505 (9.296)
Collab	-33.33*** (4.640)	14.59* (7.464)	-11.43* (6.065)	14.01 (18.06)
Arm's-Length	-99.08*** (8.656)	-34.98 (22.12)	-19.78* (10.18)	15.70 (28.65)
Observations	1,311	283	1,311	1,311
R-squared	0.615			0.801
Number of unique firms	464	100	464	
F stat	40.73***			
Chi sqr		1177		

Note: Fixed-effects, random-effects, and Arellano-Bond panel regressions and ordinary least-squares model regression. Dependent variable is annual profits.

*Significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors in parentheses. The models include indicator variables for each year, as well as firm-level or industry-level fixed effects. The research and development (RD) variable is the logarithm of R&D stock calculated using the perpetual inventory method. Logarithm values of InNet, OutNet, and IndirectNet are also used.

Table A5: Hierarchical Models for Robustness: Fixed-Effect Panel Regressions

VARIABLES	(1) FE: Profits	(2) FE: Profits	(3) FE: Profits	(4) FE: Profits
H1: RD X Alliances with IT-consuming firms (OutNet)	90.44*** (25.32)	135.0*** (22.41)	81.93*** (25.70)	
H2: RD X Consultancy (Consult) X Alliances with IT-consuming firms (OutNet)	107.9*** (29.26)		69.23* (36.59)	
RD X Consult	128.5 (79.88)	119.2 (80.46)	-84.39 (84.14)	103.8 (82.14)
Consult X OutNet	-26.30 (83.41)	153.4** (68.22)	188.0 (118.9)	131.0* (69.58)
RD X Alliances with IT-producers (InNet)	137.6*** (19.81)	140.1*** (19.96)		178.2*** (19.33)
RD X Indirect Links to IT-producers (IndirectNet)	-28.67 (20.02)	-31.48 (20.16)		48.31*** (15.53)
Patent X OutNet	-182.2*** (21.55)	-165.1*** (21.21)		-86.67*** (17.11)
Patent X InNet	-88.48*** (19.43)	-87.49*** (19.58)		-117.8*** (19.33)
Patent X IndirectNet	85.46*** (20.70)	85.58*** (20.86)		39.42** (19.82)
Consult	-154.1 (664.4)	-132.4 (669.5)	410.2 (956.7)	-135.3 (683.9)
RD X Patent	53.44*** (11.52)	38.66*** (10.88)		16.38 (10.45)
OutNet	124.8* (65.93)	29.94 (61.18)	-223.8*** (65.73)	210.4*** (54.48)
IndirectNet	-23.22 (34.60)	-17.58 (34.84)		-83.01** (33.81)
InNet	23.43 (44.08)	17.13 (44.38)		15.62 (45.33)
RD	-3.373 (56.83)	-11.33 (57.23)	94.67 (66.83)	-12.35 (58.45)
Patent	-196.3*** (42.64)	-176.4*** (42.62)		-135.2*** (42.97)
ITPartnerIndus	-0.249 (1.000)	0.0571 (1.004)		-0.493 (1.021)
log(Capital)	50.33 (50.84)	51.41 (51.23)		52.88 (52.33)
log(Marketshare)	63.70 (57.11)	71.62 (57.51)		54.98 (58.67)
HHI	2,613 (2,155)	2,126 (2,167)		1,443 (2,211)
Collab	-29.04*** (4.712)	-32.81*** (4.636)		-33.82*** (4.732)
Arm's-Length	-105.1*** (8.803)	-98.05*** (8.656)		-111.2*** (8.557)
Constant	875.3 (548.4)	914.6* (552.6)	-19.31 (297.7)	906.2 (564.4)
Observations	1,311	1,311	1,315	1,311
Number of Unique Firms	464	464	467	464
F stat	38.59***	38.72***	8.028***	37.19***
R-squared	0.625	0.618	0.162	0.601

Note: Fixed-effects panel regression. Dependent variable is annual profits.
* Significant at 10%, ** significant at 5%, *** significant at 1%. Standard errors in parentheses. All models include indicator variables for each year. Model 1 reports our main results. Model 2 reports the test of only H2. Model 3 tests H1 and H2 when not including any control variables. Model 4 reports the results of including only the control variables in Model 1. Comparing Model 1 and Model 4 shows that both the R-squared and the F statistic increase when adding the hypothesized relationships to the models.

Table A6: Alternative R&D and Dependent Measures

VARIABLES	(1) Tobin's *q*	(2) Tobin's *q*	(3) Profits	(4) Profits
H1: RD X Alliances with IT-consuming firms (OutNet)	0.639 (0.784)	1.611** (0.647)	47.58* (27.83)	100.1*** (23.58)
H2: RD X Consultancy (Consult) X Alliances with IT-consuming firms (OutNet)	1.752** (0.808)		114.0*** (32.65)	
RD X Alliances with IT-producers (InNet)	-0.428 (0.481)	-0.660 (0.472)	114.8*** (23.11)	121.7*** (23.19)
RD X Indirect Links to IT-producers (IndirectNet)	-1.688*** (0.631)	-2.241*** (0.581)	-0.400 (21.87)	-9.353 (21.88)
RD X Consult	1.578 (0.963)	0.0656 (0.667)	51.99 (105.5)	53.20 (106.3)
Patent X OutNet	0.0256 (0.0242)	0.0190 (0.0242)	-146.5*** (21.05)	-137.7*** (21.05)
Patent X InNet	-0.0461* (0.0259)	-0.0395 (0.0259)	-51.66*** (19.57)	-59.78*** (19.58)
Patent X IndirectNet	-0.0299 (0.0260)	-0.0322 (0.0262)	69.81*** (21.39)	75.71*** (21.48)
Consult X OutNet	-0.122 (0.175)	0.144 (0.126)	-330.2** (153.3)	137.2* (75.26)
RD	-1.240* (0.649)	-0.658 (0.595)	9.054 (69.74)	11.04 (70.25)
Consult	-0.0745 (0.775)	0.242 (0.766)	-310.4 (802.5)	-274.4 (808.4)
InNet	0.220* (0.115)	0.248** (0.115)	-243.9*** (91.79)	-269.7*** (92.17)
IndirectNet	0.404*** (0.141)	0.496*** (0.136)	-49.37 (77.32)	-19.78 (77.43)
OutNet	-0.241 (0.159)	-0.391*** (0.144)	59.66 (124.3)	-165.4 (107.1)
RD X Patent	0.0379* (0.0194)	0.0380* (0.0196)		
Patent	-0.204** (0.0809)	-0.199** (0.0814)	-43.76 (31.93)	-68.65** (31.35)
Advertising Intensity	2.033 (1.653)	2.126 (1.663)		
Employees	0.00877 (0.00743)	0.00944 (0.00747)		
ITPartnerIndus	0.000540 (0.00181)	0.000521 (0.00182)	-0.00872 (1.100)	0.190 (1.107)
log(Capital)	-0.0439 (0.115)	-0.0422 (0.115)	18.64 (62.70)	15.84 (63.16)
log(Marketshare)	-0.181 (0.154)	-0.144 (0.154)	64.78 (66.09)	80.85 (66.42)
HHI	2.171 (3.565)	3.572 (3.528)	2,551 (2,418)	1,620 (2,421)
RDPartnerIndus	-0.00403 (0.0171)	-0.00580 (0.0172)	2.474 (10.28)	5.254 (10.32)
Collab	0.00817 (0.00794)	0.00632 (0.00795)	-33.57*** (4.965)	-36.90*** (4.909)
Arm's-Length	-0.0138 (0.0133)	-0.0100 (0.0133)	-122.5*** (9.104)	-116.1*** (8.985)
Observations	527	527	1,197	1,197
R-squared	0.490	0.481	0.610	0.604
Number of unique firms	206	206	412	412
F stat	7.154***	7.128***	33.53***	33.66***

Note: Fixed-effects panel regression. Dependent variables are Tobin's *q* and annual profits.
*Significant at 10%, ** significant at 5%, *** significant at 1%. Fixed-effect panel regression, with standard errors in parentheses. The models include indicator variables for each year, as well as firm-level fixed effects. The research and development (RD) variable in Model 1 and Model 2 is the logarithm of annual R&D investments; in Model 3 and Model 4, RD is R&D intensity, defined as R&D/sales. In the Tobin's *q* models, advertising intensity and the number of employees are used as control variables. Logarithm values of InNet, OutNet, and IndirectNet are also used.

Table A7: Using Garen's Correction Technique to Test for Potential Endogeneity in the Main Variables

VARIABLES	(1) Profits	(2) Profits	(3) Profits
H1: RD X Alliances with IT-consuming firms (OutNet)	85.08*** (26.00)	83.47*** (25.34)	92.63*** (26.02)
H2: RD X Consultancu (Consult) X Alliances with IT-consuming firms (OutNet)	105.0*** (30.03)	105.4*** (29.97)	106.0*** (29.39)
RD X Alliances with IT-producers (InNet)	135.9*** (19.96)	135.0*** (19.94)	138.2*** (19.86)
RD X Indirect Links to IT-producers (IndirectNet)	-25.06 (20.54)	-23.56 (19.98)	-30.33 (20.60)
Patent X OutNet	-170.7*** (21.84)	-171.5*** (21.69)	-181.4*** (21.72)
Patent X InNet	-86.72*** (20.10)	-87.12*** (19.88)	-87.87*** (19.69)
Patent X IndirectNet	79.15*** (20.76)	78.99*** (20.75)	86.10*** (20.73)
RD	-125.8 (779.7)	-141.7 (778.9)	-1.455 (56.94)
Yc_RD	146.0 (785.4)	158.8 (784.7)	
RD X Yc_RD	92.55*** (19.12)	91.51*** (19.09)	
OutNet	301.4* (169.0)	116.8* (66.46)	280.3* (167.3)
Yc_OutNet	-175.8 (157.0)		-149.4 (154.8)
OutNet X Yc_OutNet	-15.03 (39.58)		-15.37 (39.70)
RD X Consult	253.7*** (90.23)	255.3*** (90.19)	124.3 (80.03)
Consult X OutNet	-68.17 (85.29)	-68.55 (85.22)	-26.34 (83.52)
RD X OutNet	49.22*** (11.93)	48.56*** (11.81)	54.04*** (11.65)
Consult	-449.2 (672.0)	-511.1 (669.5)	-105.7 (667.6)
Observations (unique firms)	1,269 (440)	1,269 (440)	1,311 (464)
R-squared	0.637	0.636	0.625
F stat	34.60	36.41	35.52

Note: Fixed-effects panel regression. Dependent variable is annual profits.
*Significant at 10%, ** significant at 5%, *** significant at 1%. Fixed-effect panel regression, with standard errors in parentheses. The models include indicator variables for each year, as well as firm-level fixed effects. The research and development (RD) variable is the logarithm of R&D stock calculated using the perpetual inventory method. Logarithm values of InNet, OutNet, and IndirectNet are also used. Yc_OutNet and Yc_RD are predicted residuals of regressing OutNet and R&D on industry average RD and advertising intensity, patents, physical capital, market share, HHI, Partners RD, InNet, and IndirectNet variables. All models also include the direct effects of IndirectNet, InNet, Patent, ITPartnerIndus, log(Capital), log(Marketshare), HHI, RDPartnerIndus, Collab, and Arm's-Length (not shown for brevity).

Table A8: Testing H1 and H2 for the Time Period of 1991-2016 and Comparing Results for IT-Producing and IT-Consuming Firms

VARIABLES	(1) Profits: software & hardware	(2) Profits: broader IT-producing industries	(3) Profits: IT-consuming industries
H1: RD X Alliances with IT-consuming firms (OutNet)	96.94*** (16.13)	117.2*** (14.42)	-58.33*** (18.74)
H2: RD X Consultancy (Consult) X Alliances with IT-consuming firms (OutNet)	175.0*** (51.79)	157.5*** (51.59)	
RD X Alliances with IT-producers (InNet)	-96.68*** (18.92)	-85.00*** (17.37)	71.71 (67.96)
RD X Indirect Links to IT-producers (IndirectNet)	-57.79*** (9.810)	-61.31*** (9.329)	-111.1*** (21.73)
RD	207.6*** (31.49)	179.6*** (27.99)	158.4*** (41.47)
OutNet	-206.9*** (69.68)	-253.7*** (63.19)	43.36 (85.07)
RD X Consult	-296.7*** (89.28)	-270.8*** (88.86)	
OutNet X Consult	-292.6 (265.0)	-259.2 (264.3)	
IndirectNet	157.6*** (39.42)	166.7*** (37.69)	289.3** (118.0)
InNet	275.0*** (91.37)	241.1*** (84.87)	37.06 (445.8)
Ind. Avg. Profitability	30.62 (34.02)	61.25** (30.46)	173.8*** (42.20)
Collab	-16.47*** (4.120)	-16.45*** (3.843)	29.13** (14.80)
Arm's-Length	-60.39*** (4.451)	-57.37*** (4.243)	-2.119 (9.842)
Diversification	70.14 (89.53)	41.76 (80.70)	-32.65 (133.6)
HHI	315.9* (165.3)	199.6 (148.4)	-157.8 (190.1)
Weighted Market Share	4,994*** (293.6)	3,982*** (261.4)	932.2*** (257.7)
Constant	-306.7 (283.7)	-268.2 (254.9)	-750.7** (381.5)
Observations	6,901	8,044	7,700
Number of unique firms	1,513	1,770	1,586
F stat	43.56***	41.30***	9.094***
R-squared	0.250	0.218	0.0552

Note: Fixed-effects panel regression. Dependent variable is annual profits.
*Significant at 10%, ** significant at 5%, *** significant at 1%. Fixed-effect panel regression, with standard errors in parentheses. The models include indicator variables for each year, as well as firm-level fixed effects. Model 1 includes firms in industries with NAICS codes 5112, 5145, 518, and 334. Model 2 includes firms in industries with NAICS codes 511, 514, 517, 518, 519, 334, 335, and 423. Model 3 includes firms that are not in Model 2 industries.

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