Technological Competition and Strategic Alliances*

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Abstract

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Keywords: boundaries of the firm, innovation, patents, R&D, strategic alliances, technological competition

JEL classification: G34, O32

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Abstract

Using a novel measure of technological competition, we show that firms facing greater technological competition are more likely to form alliances. We further show that those alliances lead to more patents at both client and partner firms. Finally, we show that the number of related patents increase significantly at both client and partner firms, whereas the number of unrelated patents, R&D expenditures and efficiency, and inventor productivity increase significantly only at partner firms facing greater technological competition. Our results are robust to endogeneity concerns. We conclude that technological competition is an important impetus for redrawing firm boundaries to accelerate innovation.

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1. Introduction

Corporate innovation is a key factor in determining firm competitiveness, comparative advantages, and long-term productivity growth. The process of corporate innovation is characterized by a prolonged period of resource commitment and a high degree of uncertainty. Adopting an organizational form that can effectively address these unique features of corporate innovation is crucial for an innovative firm to survive and succeed in a technological race.

Strategic alliances are long-term contracts between legally distinct organizations that allow for costs and benefits sharing in mutually beneficial activities. Robinson (2008) notes that since the mid-1980's, the number of alliances surpassed that of mergers and acquisitions (M&As). While alliances frequently take place in a broad range of industries, they tend to cluster in risky, high-R&D settings (Robinson and Stuart, 2007). Despite the importance of alliances in facilitating corporate R&D, little is known about the role of technological competition in alliance formation and their joint effect on corporate innovation outcomes. This paper fills a void in the literature, providing a comprehensive investigation and new empirical evidence on the relations between technological competition, alliances, and corporate innovation.

The following example illustrates some key aspects of the relation between technological competition and alliances examined in this paper. Incyte Corporation is a biotech company developing inhibitors for JAK, a causative factor in the majority of myeloproliferative disorders that affect blood cell levels in the human body. Its JAK inhibitor (INCB18424) entered its phase III trial in July 2009. In October 2009, another biotech company, YM BioSciences, initiated a phase I/II trial of a new JAK inhibitor (CTYT387) that had a key potential advantage over INCB18424 in improving patients' anemia symptoms. In November 2009, Incyte formed an alliance with the pharmaceutical giant Novartis to jointly develop INCB18424. Under the terms of their alliance agreement, Novartis was responsible for developing the drug outside the US, while Incyte retained rights in the US. In exchange for these rights, Incyte received an upfront payment of \$150 million and was eligible for up to a \$60 million milestone payment in the future.

INCB18424 succeeded in its phase III trial and was approved by the US Food and Drug Administration (FDA) for the treatment of intermediate or high-risk myelofibrosis in November 2011.

The above example highlights one important consideration in firms' decisions to form alliances—the presence of intense technological competition faced by both the two small biotech companies and the large pharmaceutical company. In November 2009, when Incyte and Novartis formed an alliance, Incyte faced competition from YM BioSciences, Inc., in advancing INCB18424, the first JAK inhibitor that reached the pivotal phase III trial. In the meantime, many large pharmaceutical companies, including Novartis, faced fierce competition from biotech companies and the threat of “patent cliff”—a term signifying the sharp drop-off in revenues from blockbuster drugs that faced generic competition once their patents expired. By joining forces with the pharmaceutical giant Novartis, Incyte was able to accelerate its innovation capacity, and received the FDA approval much ahead of its competitor. This example illustrates that alliances are an important vehicle through which firms gain access to knowledge and capacities outside their own boundaries, thereby accelerating their innovation effort; most importantly, the alliance decision and its success hinge on technological threats and opportunities.

In this paper, we argue that alliances, as an organizational form fostering commitment to long-term risky investments (Robinson, 2008), naturally arise when firms face intense technological competition. At that point, the speed of innovation becomes crucial for firms to succeed in a technological race. Close collaboration via alliances facilitates the transfer of existing know-how and pooling specialized knowledge to generate new knowledge (Gomes-Casseres, Hagedoorn, and Jaffe, 2006). Further, the flexibility inherent in alliances facilitates experimentation with new ideas and new combinations of participants in the pursuit of new knowledge (Mody, 1993). Finally, the presence of intense technological competition serves as an effective disciplinary device to prevent participant firms from shirking and self-dealing, leading to better innovation outcomes than cases without such competitive pressure.

To examine the relation between technological competition and alliance formation, we first develop a new measure to capture competition in the technological space, and then provide large-sample analyses on the determinants of alliance formation and alliances' impact on corporate innovation outcomes. Our

empirical investigation addresses the following two questions: What is the role of technological competition in a firm's decision to join an alliance? How do alliances and technological competition change the innovation outcomes of alliance participants?

We capture technological competition faced by an innovative firm as a cosine similarity measure between its own patent output, measured by the number of patents across different technological classes, and the patent output of all other firms in the economy. This cosine measure builds on the firm-to-firm technological proximity measure of Jaffe (1986). The higher the cosine measure's value, the greater the overlap will be in technological innovation between a firm and all other firms in the economy. Intuitively, this measure captures two key aspects of technological competition: threats and opportunities. On the one hand, greater overlaps between a firm's patent portfolio and the aggregate patent portfolio of all other firms in the economy indicate that this firm's technologies are facing greater threats from other firms' similar technologies, and thus will have a higher obsolescence risk. On the other hand, greater overlaps with the aggregate innovative activity of the economy suggest that this firm's technologies will attract interest from other firms, and thus will have a higher upside potential. Our cosine similarity measure captures both threats and opportunities faced by a firm's technologies (i.e., a greater obsolescence risk as well as greater opportunity), which we call technological competition.

Using a large patent-alliance dataset over the period 1991-2004, we start by examining whether and how technological competition affects alliance formation. Using our new measure of technological competition and a panel dataset of innovative Compustat firms, we show that technological competition faced by a firm is positively associated with the likelihood of that firm joining an alliance. The effect of technological competition on alliance formation is economically significant; when increasing the measure of technological competition by one standard deviation, the number of alliances formed per year increases by 17%. Using either industry- and size-matched or randomly-drawn control firms, we again show that alliance participants are facing significantly greater technological competition than their peer firms. Our results suggest that the increasingly intense technological competition faced by firms nowadays might explain the rising popularity of alliances identified by Robinson (2008).

Next, we examine the roles of alliances and technological competition in post-alliance innovation outcomes. Following convention, we call the larger firm in a bilateral alliance a client and the smaller firm a partner. Using both the difference-in-differences specification and the treatment regression with an instrumental variable, we find that after alliance formation, the innovation output of alliance participants is significantly improved, especially when these firms face more intense technological competition.

Once we establish the positive effects of alliances and technological competition on post-alliance innovation outcomes, we explore possible underlying mechanisms through which these effects take place. We first find that after alliance formation, partner firms significantly increase their R&D expenditures and R&D efficiency when facing more intense technological competition, consistent with the typical practice in alliances, in which clients provide funding while partners focus on developing new technologies. We also find that after alliance formation, the number of related patents significantly increases at both client and partner firms when these firms face more intense technological competition, suggesting effective information flows between alliance participants. We note that the number of unrelated patents also significantly increases at partner firms (but not at client firms). Finally, using inventor-level data, we find that after alliance formation, the productivity of individual inventors improves significantly at partner firms facing more intense technological competition, consistent with the increased R&D efficiency results. In contrast, we do not observe any significant improvement in the productivity of individual inventors after alliance formation at client firms facing more intense technological competition.

In our additional investigation, we explore the role of technological competition in redrawing firm boundaries in other ways. We find that technological competition plays a similar role in corporate acquisition decisions: Firms facing greater technological competition are more likely to engage in acquisitions. Our findings are consistent with Bena and Li (2014) who show that M&As play a significant role in facilitating technological innovation. In contrast, we find that there is no significant association between technological competition facing a firm and its number of joint ventures (JVs).

We also compare our measure of technological competition with Hoberg, Phillips, and Prabhala's (2014) measure of product market threats and find that such threats also significantly affect firms' decisions

to form alliances. However, after alliance formation, the presence of intense technological competition is significantly associated with improved innovation outcomes, while the presence of intense product market threats is not, suggesting that technological competition is distinctly different from product market competition.

We conclude that technological competition is an important impetus for redrawing the boundaries of the firm—forming alliances—to accelerate corporate innovation, particularly for partner firms.

Our paper makes a number of important contributions to the literature. First, we develop a novel firm-level measure of technological competition that captures threats and opportunities facing innovative firms in the technological space. Given the crucial role of technology in our knowledge-based economy, our measure to quantify the amount of technological competition facing individual firms, complementing the well-established measure of product market competition (see Hoberg and Phillips, 2010; Hoberg, et al., 2014 for the latest development of this measure), is an important contribution. As we do with product market competition, we expect technological competition to have important implications for corporate policies.

Second, this paper contributes to the literature on organizational design and the boundaries of the firm (Grossman and Hart, 1986; Hart and Moore, 1990; Hart, 1995). A firm can be viewed as the nexus of contracts (Jensen and Meckling, 1976); alliances are part of the contracts that surround the firm and blur its boundaries. Although the importance of alliances in facilitating knowledge transfer and technological innovation has been well recognized (Mowery, Oxley, and Silverman, 1996; Chan, Kensinger, Keown, and Martin, 1997; Fulghieri and Sevilir, 2003; Gomes-Casseres et al., 2006), there is little large-sample evidence on the role of technological factors in the formation of alliances. Robinson (2008) finds that the risk of alliance activities outside a client firm is greater than the risk of activities conducted inside the firm. Bodnaruk, Massa, and Simonov (2013) show that firms with a higher quality of governance are more likely to form alliances and also are better able to reap their benefits. While alliances are a common phenomenon among technology firms, prior studies are silent on one important question: How does (technological)

competition affect firms' decisions to join alliances? Our paper fills a void in the literature by addressing this question.

Finally, this paper extends Coase's (1937) original insight that organizational forms have important implications for investment performance by focusing on the relation between alliances and corporate innovation. Prior studies including Allen and Phillips (2000), Lindsay (2008), Robinson (2008), Hoberg and Phillips (2010), Beshears (2013), Bodnaruk et al. (2013), Bena and Li (2014), and Seru (2014) have examined whether and how alliances, JVs, and M&As take place to address agency problems and information asymmetry, reallocate decision rights, and combine firms' capabilities to create synergies. A central issue in this strand of the literature is understanding the economic implications of these changes to firm boundaries. Our results suggest that alliances are crucial for firms to succeed in their innovation effort, especially in the presence of intense technological competition.

The rest of the paper proceeds as follows. Section 2 develops our hypotheses. Section 3 describes the sample and key variables used in this study. Section 4 examines whether and how technological competition affects alliance formation. Section 5 presents the innovation outcomes after alliance formation and examines the underlying mechanisms. Section 6 conducts additional investigation. Section 7 concludes.

2. Hypothesis Development

When firms face intense technological competition, they also face a greater threat of technology obsolescence as well as greater opportunity. The speed of innovation is thus crucial for firms to succeed in a technological race. Alliances provide an effective organizational form for otherwise independent firms to pool resources in accelerating the development of new technologies. Forging an alliance enables a firm to focus resources on its core competencies while acquiring other skills or capabilities from the market place. Chan et al. (1997) note that alliances are becoming increasingly important as competitive pressures force firms to adopt flexible and more focused organizational structures.

Alliances also offer an effective mechanism for firms to commit *ex ante* to technological innovation characterized by a low likelihood of success but potentially high payoffs ("long-shot projects" as modeled

in Robinson, 2008). Internal capital markets are prone to the practice of “winner-picking,” whereby headquarters have incentives to divert resources to short-term projects with a greater likelihood of success but low payoffs conditional on success. The possibility of reallocating resources *ex post* dis-incentivizes divisional managers from undertaking long-term risky investment *ex ante*. Robinson (2008) suggests that alliances as enforceable contracts between participant firms help resolve such an incentive problem because they mitigate winner-picking. Such commitment is critical when firms face intense technological competition, as the consequence of diverging resources from innovation can be dire, resulting in obsolete technologies and missed opportunities.

Jensen and Meckling (1992) refer to alliances as a network organization. They argue that such an organizational form can add value to participant firms by aligning decision authority with decision knowledge. In an alliance, such alignment is achieved when each participant has specific decision responsibility allocated according to its expertise and business objective. The benefits of forming an alliance are especially high for innovative firms, because innovation requires both highly specialized knowledge and decision authority allocated to experts equipped with such knowledge.

Further, a network organization provides participant firms with organizational flexibility, facilitating experimentation with new ideas and new combination of participants in the pursuit of new technologies (Mody, 1993; Chan et al., 1997) and allowing firms to divest *ex post* failed investments at relatively low costs. In contrast, Jensen (1993) argues that traditional corporate form destroys value because of its inability to divest assets. This *ex post* flexibility of alliances is particularly valuable when technological competition intensifies and the future is uncertain (e.g., Mody, 1993; Seth and Chi, 2005).

On the other hand, there are also costs associated with network organizations like alliances that do not apply in integrated firms or arm’s length transactions. These costs arise out of the potential for opportunistic behavior by participant firms (Klein, Crawford, and Alchian, 1978; Kranton, 1996). Because innovative projects call for specialized knowledge, monitoring and controlling participants’ opportunistic behavior can become difficult, if not impossible. The costs associated with opportunistic behavior are likely

to be high when alliances involve innovative projects. Ultimately, whether alliances enhance corporate innovation is an empirical question.

The above discussions lead to the following set of hypotheses:

Hypothesis 1: Technological competition increases the likelihood of alliance formation.

Hypothesis 2A: Alliances lead to improved post-alliance innovation outcomes.

One key advantage of forming an alliance is that participant firms can pool knowledge and resources in pursuit of a common goal. Gomes-Casseres et al. (2006) note that closer collaboration via alliances, as opposed to an arm's length market transaction, facilitates not only the transfer of existing know-how, but also pooling specialized knowledge to generate new knowledge. Thus, if an alliance does improve participant firms' post-alliance innovation outcomes, we would expect that some of the improved innovation outcomes would build on the shared expertise of participant firms. This conjecture leads to the following hypothesis:

Hypothesis 2B: Alliances lead to improved post-alliance innovation outcomes that build on participants' shared expertise.

To mitigate the costs associated with a network organization, Jensen and Meckling (1992) suggest establishing an internal control system to provide performance measurement, and a reward and punishment system to reduce opportunistic behavior. Parkhe (1993) recommends that alliance participants commit to relationship-specific investments that would be of little value outside the alliance.

We posit that technological competition provides an external solution to limiting alliance participants' opportunistic behavior, in the same way as product market competition does for alliances (Mody, 1993). The presence of fierce technological competition, through either the threats of lagging behind or the risks of missed opportunities, as our motivating example demonstrated, can serve as an effective disciplinary device to prevent alliance participants from shirking and self-dealing, and press for greater efficiency. Further, given that technological alliances typically have clients as capital providers and

partners as technology owners/developers, we expect that partners would likely benefit more than clients from the positive effect of alliances on their innovation outcomes.

The above discussions lead to our final hypothesis:

Hypothesis 3: Technological competition strengthens the positive effect of alliances on post-alliance innovation outcomes, especially for partners.

In our empirical investigation, we test the above hypotheses, and also attempt to control for several alternative explanations for why alliances take place. In the next section, we describe our sample, define key innovation variables, and present a sample overview.

3. Sample Formation and Variable Constructions

3.1. Our Sample

Our alliance sample comes from the Thomson Financial's SDC database on Joint Ventures and Strategic Alliances.¹ This database has been used in recent studies (e.g., Allen and Phillips, 2000; Fee, Hadlock, and Thomas, 2006; Lindsey, 2008; Boone and Ivanov, 2012; Bodnaruk et al., 2013) given its comprehensive coverage. We obtain data on Compustat firms' patenting activity from the National Bureau of Economics Research (NBER) Patent Citations Data File (Hall, Jaffe, and Trajtenberg, 2001).

Our sample period starts in 1991 because it is the first year when the data quality in the SDC database became reliable. Our sample period ends in 2004 because the year 2006 is the last year in which the patenting information from the NBER database was available. Due to the well-known patent approval lag between application and award, the data coverage of patents in 2004-2006 was poor; hence, we use patent data ending in 2003 (to predict alliances formed in 2004). For any bilateral alliance deal in our sample, following convention, we identify the participant with a larger (smaller) value of total assets as the client (partner).

¹ According to SDC, their data come from SEC filings and their international counterparts, trade publications, wires, and news sources.

Our alliance sample includes all deals in which the form of the deal is coded as a “strategic alliance” by the SDC. We require that: 1) the alliance involves at least one US public firm or a subsidiary to a US public firm as covered by Compustat/CRSP; and 2) the US public firm involved is not from the financial sector (SIC 6000-6999). These filters yield 29,008 alliances for our sample period 1991-2004.²

3.2. *Measuring Technological Competition*

Our central idea is that technological competition-driven alliances enhance corporate innovation output. The concept of technological competition is not new (see, for example, Schumpeter, 1943); however, there is no off-the-shelf measure for our purpose.

3.2.1. Definition

We capture technological competition faced by an innovative firm at a point in time as a cosine similarity measure between the firm’s own patent output, measured by the number of patents across different technological classes, and the similarly measured patent output of all other firms in the economy. Innovative firms are firms with at least one awarded patent over the period 1976-2006 by the US Patent and Trademark Office (USPTO).³

To construct the variable, we first measure the scope of innovation activity through patent output of firm i using the technology vector $S_{i,t} = (s_{i,1,t}, \dots, s_{i,K,t})$, and the scope of innovation activity through patent output of all other firms in the economy using the aggregate technology vector $S_{-i,t} = (s_{-i,1,t}, \dots, s_{-i,K,t})$. The subscript $k \in (1, K)$ is the technology class index.⁴ The scalar $s_{i,k,t}$ ($s_{-i,k,t}$) is the ratio of the number of awarded patents to firm i (all other firms in the economy excluding firm i) in technology class k with application

² Ideally, we would like to focus on alliances intended for developing the technological capacity of participant firms. However, the SDC data offer only a crude indication as to the purpose of each alliance. We therefore use our filter discussed later to try to limit our study to those alliances that are likely related to innovation. To the extent that the alliance sample is contaminated by deals motivated by other purposes, our measures of alliances’ effects on innovation outcomes will likely understate the magnitude of those effects.

³ About half of the Compustat firms over the period 1976-2006 are innovative based on our definition.

⁴ Whenever the USPTO changes its technology classification system, it retroactively changes the class assignments for all previous patents to maintain consistency at a particular point in time. Hence, our measures are unaffected by changes in the classification system. During our sample period, there are about 400 technology classes.

years from $t-2$ to t (application year t) to the total number of awarded patents to firm i (all other firms in the economy) applied over the same three-year period (the same year t).

Our technological competition measure is then computed as

$$Technological\ Competition_{i,t} = \left\langle \frac{S_{i,t}}{\|S_{i,t}\|}, \frac{S_{-i,t}}{\|S_{-i,t}\|} \right\rangle. \quad (1)$$

This cosine measure ranges from zero to one. The higher the value of this cosine measure, the more similar firm i 's innovation output will be to that of all other firms in the economy.

We believe that our measure is particularly suited to capturing technological competition, which, by construction, has two important components—threats and opportunities. On the one hand, a greater overlap with aggregate innovative activities in the economy potentially threatens the firm's existing patents, increasing their obsolescence risk. On the other hand, a firm with patents having a greater overlap with aggregate innovative activities is a firm possessing technologies of great interest to other firms, and hence has a higher upside potential. As such, our measure of technological competition captures both the threats and opportunities (i.e., greater downside risks as well as higher upside potentials) for the firm's technologies.

3.2.2. Technological Competition Over Time and Across Industries

Figure 1 plots the time series of our technological competition measure averaged across innovative firms in the agriculture and mining, manufacturing, and service sectors over the sample period 1980-2003. For the manufacturing and services sectors, we observe a gradual rise in the average value of technological competition until the burst of the Internet bubble, and a gradual decline thereafter. For the agriculture and mining sector, the average value of technological competition slowly decreases before the burst of the Internet bubble and experiences a reverse of the trend thereafter, consistent with the boom of the natural resources and commodities industries during the 2000s. The fact that the manufacturing sector has the highest level of technological competition is consistent with findings from the Business R&D and

Innovation Surveys by the National Science Foundation, which show that manufacturing industries are significantly more R&D intensive than non-manufacturing industries.⁵

Table 1 Panel A lists the top and bottom five industries (based on the two-digit SIC codes) facing the greatest technological competition in 1980, 1990, and 2000. We find that over time, firms facing the greatest technological competition shift from manufacturing and resources to IT and computers. Overall, the results suggest that our new measure captures both the heterogeneity and the dynamics in the race to develop new technologies.

3.2.3. Validation from 10-K Filings

Our measure for technological competition is based on the patent portfolio of a focal firm. Given that the measure is new, checking that it does capture the threats and opportunities in the technological space is important.

Firms are required to disclose potential risk factors that might adversely affect future performance in the Management Discussion & Analysis section (MD&A, typically item 7) or in the risk factor section (typically item 1 or item 1.A) of their 10-K filings. We examine whether firms facing intense technological competition based on our measure are also more likely to discuss this fact in their 10-K filings. We employ a machine-based algorithm to search the entire text of 10-K filings for the following keywords: technology competition, technological competition, technology competitiveness, technological competitiveness, technology risk, technological risk, technology risks, technological risks, technology threat, technological threat, technology threats, technological threats, technology uncertainty, technological uncertainty, technology change, technological change, technology changes, technological changes, and changes in technology. We record the number of times any of the above keywords show up in 10-K filings.⁶ As a robustness check, we also search for the above keywords within the MD&A section, the risk factors section,

⁵ For example, the 2005 survey reports that the manufacturing industries spent \$158,190 million on R&D, while the nonmanufacturing industries spent \$67,969 million on R&D.

⁶ The keywords with the most frequent occurrences are technological change and technological changes, while the keywords technology threat, technology threats, and technological threat receive zero counts.

and the combination of these two sections. To remove the file size effect, we normalize the number of keyword counts by the 10-K file size (Loughran and McDonald, 2014).

Table 1 Panels B-C provide summary statistics from the above exercise. We find that firms facing intense technological competition are more likely to discuss this fact in their 10-K filings, although such discussion is not limited to the MD&A section or the risk factors section. This exercise provides some validating evidence in support of our measure for technological competition.

To corroborate with the machine-based search results, we randomly pick 300 firms and ask a research assistant (without any prior knowledge of our measure for technological competition) to go over their 10-K filings and verify the machine-based counts of the 15 keywords. Further, we also ask the research assistant, based on her reading of 10-K filings, to assign a score of 0 (no technological competition), 1 (lowest competition) to 3 (highest competition) to each of these 300 firms. The correlation between the research assistant's scores and values of our technological competition measure is 0.47.

3.2.4. Validation Using IPO and Delisted Firms

As a final validation test, we examine how technological competition faced by a firm is related to its technological proximity to IPO firms, delisted firms, and the combination of these two groups of firms.⁷ To the extent that IPO firms tend to enter sectors with the greatest opportunities, while delisted firms tend to be in sectors faced with the greatest threats, these two groups of firms should have closer technological proximity to firms facing greater technological competition. We identify IPO firms and delisted firms according to the year they enter and leave the CRSP database, respectively. We then compute Jaffe's technological proximity between firm i 's patents and the patents of IPO firms (delisted firms, and the combination of IPO and delisted firms) over the same period.

Panel D examines the relation between technological competition faced by a firm and its technological proximity to IPO (delisted) firms. The dependent variable in columns (1), (2), and (3) is

⁷ Hoberg et al. (2014) employ a similar approach for the validation test of their product market fluidity measure. They use products of IPO firms and venture capital-backed firms to identify the threats a firm faces.

technological proximity to IPO firms, delisted firms, and the combination of IPO and delisted firms, respectively. The independent variables are technological competition, patent count, patent diversification, R&D, and product market competition (measured by the Herfindahl index of a two-digit SIC industry based on sales). We find that the coefficients on technological competition are all positive and significant at the 1% level, suggesting that our technological competition measure captures the opportunities and threats facing an innovative firm.

3.3. Summary Statistics

Table 2 presents the temporal distribution of alliances over our sample period 1991-2004. Panel A presents different samples without imposing the requirement that alliance participants have at least one patent in the NBER patent database. We show that the number of alliance deals peaks during the late 1990s and declines after the burst of the Internet bubble in the early 2000s. The evidence that alliances are most active around the Internet bubble is consistent with the view that technological innovation is a key driver. We further show that there are close to 30,000 alliances involving at least one US public firm. Over 90% of the alliances are bilateral arrangements involving at least one US public firm or a subsidiary to a US public firm. The sample size drastically drops when we require both alliance participants to be US public firms.

Panel B presents different samples used in our multivariate analysis after imposing the requirement that alliance participants have at least one patent over the period 1976-2006. This filter is applied because we would like to focus on alliances related to corporate innovation. Comparing column (1) across Panels A and B, we show that close to 80% of alliances involve innovative US public firms, and over 90% of these alliances are bilateral arrangements involving at least one innovative US public firm.⁸ When we require both alliance participants to be innovative US public firms (as shown in column (4)), only a fifth of the full sample (as shown in column (1)) meets the requirement. Alliances are clearly a common phenomenon

⁸ Among the 22,653 alliance deals between the period 1991-2004, we find only 63 deals involving equity stakes and 153 deals resulting in acquisitions.

among innovative firms that are either publicly listed or subsidiaries of publicly listed firms. Bilateral alliances with one client and one partner are the prevailing practice.

To capture innovation output as well as the strength of intellectual property rights, we use patent count, constructed as the year- and technology-class adjusted number of patents over the three-year period preceding the formation of an alliance. Patents grant assignees property rights and hence clearly delineate their contractual rights. Gans, Hsu, and Stern (2002) argue that the presence of patents reduces transaction costs associated with collaborative arrangements like alliances. Frésard, Hoberg, and Phillips (2014) highlight the distinction between unrealized innovation through R&D and realized innovation through patents in firms' decisions to be vertically integrated. To capture the diversity of a firm's patent portfolio, following Hirshleifer, Hsu, and Li (2014), we use patent diversification, computed as one minus the Herfindahl index of a firm's patent portfolio. Firms with more diversified patent portfolios might have less incentive to form alliances, as they already have a wide range of technologies to develop in-house. Detailed variable definitions and constructions can be found in Appendix 1.

Table 3 presents the summary statistics for the panel data sample that consists of innovative non-financial firms covered by Compustat/CRSP over the period 1990-2003. All continuous variables are winsorized at the 1st and 99th percentiles. All dollar values are measured in 2004 dollars.

In Panel A, we show that on average an innovative US public firm forms 0.61 alliances every year. Once we include alliances involving subsidiaries of a public firm, the average number of alliances increases to 0.80 per year. The mean (median) value of technological competition is 0.09 (0.05). The mean (median) number of patents in the three-year period preceding alliance formation is 25 (2.0). The mean (median) value of patent diversification is 0.32 (0). The remaining firm characteristics are typical of Compustat firms.

In Panel B, we present pairwise correlation coefficients. We show a positive and significant correlation between technological competition and the number of alliances. More general examination of

the correlation matrix suggests that there is little problem of multicollinearity.⁹ Since biases due to omitted variables in univariate correlations can mask true relations between the variables, we rely on multivariate analysis to examine the factors associated with alliance formation.

4. Technological Competition and Alliances

Our empirical investigation in this section helps answer the following question: What is the role of technological competition in a firm's decision to join an alliance?

4.1. Panel Data Evidence

To test our first hypothesis relating technological competition to alliance formation, we run the following Tobit regression using the panel data sample:

$$\begin{aligned} \text{Log}(1 + \# \text{ of alliances}_{i,t}) = & \alpha + \beta_1 \text{Tech Competition}_{i,t-1} + \beta_2 \text{Patent Count}_{i,t-1} \\ & + \beta_3 \text{Patent Diversification}_{i,t-1} + \beta_4 \text{R\&D}_{i,t-1} \\ & + \beta_5 \text{Other Firm Characteristics}_{i,t-1} + \text{Industry FE} + \text{Year FE} + e_{i,t}. \end{aligned} \quad (2)$$

The dependent variable is the logarithm of one plus the number of alliances a firm joins in year t . The set of firm innovation characteristics includes technological competition, patent count (in logarithms), patent diversification, and R&D spending. Other firm characteristics that explain alliance formation include firm size (the logarithm of total assets), leverage, ROA, cash holdings, Tobin's Q, sales growth, and capital expenditures (e.g., Gomes-Casseres et al., 2006; Boone and Ivanov, 2012; Bodnaruk et al., 2013). To control for industry- and time-clustering in alliances, we include both industry and year fixed effects. Table 4 presents the results.

We first show that firms facing greater technological competition are more likely to form alliances, consistent with our first hypothesis (H1). When a firm's technological capability is under threat, that firm

⁹ The correlation between patent count and patent diversification is 0.82. It is worth noting that our main findings regarding technological competition do not change if we exclude patent diversification from the regression specification (see Table 4).

is more likely to form alliances to fend off the threat and tap into a potential opportunity. We then show that innovative firms with more patents are more likely to form alliances, consistent with Gans et al. (2002) who argue that the strength of intellectual property rights is important for alliances. In contrast, we show that innovative firms with more diversified patent portfolios are less likely to form alliances, suggesting that diversified in-house technologies reduce firms' need for forming alliances to expand their R&D portfolios. We further show that firms with higher R&D spending are also more likely to form alliances.

In terms of the economic significance, when the measure of technological competition increases by one standard deviation, the number of alliances formed per year increases by 17%; when the number of patents increases by one standard deviation, the number of alliances formed per year increases by 24%; when the measure of patent diversification increases by one standard deviation, the number of alliance formed per year decreases by 16%; and when the R&D spending increases by one standard deviation, the number of alliances formed per year increases by 21% (based on column (1) estimates). The effects of these technological factors on alliance formation are economically significant.

Table 4 also provides other interesting results. We find that large firms with low leverage, high cash holdings, high Tobin's Q, and fast sales growth are more likely to form alliances. We conclude that alliance participants are characterized as large fast-growing innovative firms facing great technological competition.

4.2. Firm-Level Evidence

The advantage of using the panel data sample is that it provides large sample evidence on the importance of technological competition in the formation of alliances. The downside is that many firms included in the analysis are totally different from alliance participants, raising the hurdle to rejecting our hypotheses. For example, firms at different stages of their technological life cycle are included and compared. Further, the panel data analysis in Table 4 does not differentiate between alliance clients and partners.

To further examine whether and how technological competition affects a firm's likelihood of joining an alliance, we follow Bena and Li's (2014) methodology by employing matched control firms for participants in alliance deals. The alliance sample is limited to bilateral deals formed by US public firms with available financial information. For each participant of an alliance deal announced in year t , we find up to five control firms matched by industry and size. We move up to one-digit SIC industry if we cannot find three control firms in two-digit SIC industry. We require a control firm to satisfy the following conditions: 1) it is an innovative firm; 2) it shares at least one-digit SIC code with the alliance participant; 3) its total assets in year $t-1$ falls between 50% and 150% of the alliance participant's total assets; and 4) it is not an alliance participant in the seven-year period from year $t-3$ to year $t+3$. As noted by Bena and Li (2014), such matching creates a pool of potential alliance participants that captures clustering not only in time, but also by industry. Further, industry-matching controls for product market competition and size-matching partially controls for technological life cycles. In addition to using industry- and size-matching to obtain control firms for alliance participants, we also obtain control firms for each alliance participant by randomly drawing five firms that are not an alliance participant in the seven-year period centered at the alliance deal announcement year t .

Table 5 presents summary statistics for alliance participants and their control firms. Panel A compares alliance clients versus partners. We find that clients face significantly greater technological competition than alliance partners. In terms of innovative activities, clients have more patents and greater patent diversification, but lower R&D spending compared to their partners. Further, we find that clients are much larger than their partners, consistent with the pattern documented in Lerner and Merges (1998) and Robinson and Stuart (2007). Finally, clients employ higher leverage, are more profitable, have lower cash holdings, lower Tobin's Q, and much slower sales growth, and have higher capital expenditures than their partners.

Panel B compares clients with their industry- and size-matched peer firms. We find that clients face greater technological competition, exhibit greater patent diversification, and are significantly more innovative in terms of patent count and R&D spending than their peers. Panel C compares partners with

their industry- and size-matched peer firms. Again, we find that partners face greater technological competition, exhibit greater patent diversification, and are significantly more innovative in terms of patent count and R&D spending than their peers. The evidence strongly supports the view that technological factors are important considerations for firms to join alliances.

We run the following conditional logit regression:¹⁰

$$\begin{aligned} Event Firm_{im,t} = & \alpha + \beta_1 Tech Competition_{im,t-1} + \beta_2 Patent Count_{im,t-1} \\ & + \beta_3 Patent Diversification_{im,t-1} + \beta_4 R\&D_{im,t-1} \\ & + \beta_5 Other Firm Characteristics_{im,t-1} + Deal FE_m + e_{im,t}. \end{aligned} \quad (3)$$

The dependent variable, $Event Firm_{im,t}$, takes the value of one if firm i is the client (partner) in deal m , and zero otherwise. For each deal m , there is one observation for the client (partner), and multiple observations for the client (partner) control firms. $Deal FE_m$ is the fixed effect for each client (partner) and its control firms in deal m . The firm-level client (partner) sample contains alliance clients (partners) and their industry- and size-matched (or randomly-drawn) control firms. Table 6 Panel A presents the results.

Columns (1) and (2) report the results where the dependent variable is the alliance client indicator variable. We find that technological competition faced by a firm is positively associated with the likelihood of that firm becoming a client. We further find that firms with more patents and high R&D spending are more likely, while firms with greater patent diversification are less likely, to be clients.

Columns (3) and (4) report the results where the dependent variable is the alliance partner indicator variable. We again find that technological competition faced by a firm is positively associated with the likelihood of that firm becoming a partner. We further find that partners tend to possess characteristics similar to clients such as more patents and higher R&D spending.

¹⁰ See McFadden (1974) for an introduction to the conditional logit regression, and Bena and Li (2014) for a recent application in finance.

In summary, the firm-level results in Table 6 Panel A are largely consistent with the panel data evidence and provide strong support for our first hypothesis (H1), that technological competition is an important factor in firms' decisions to form alliances, regardless of their specific role in the alliance.

4.3. Pair-Level Evidence

So far, our multivariate analysis focuses on using (unilateral) firm characteristics to explain alliance formation, while prior work (see, for example, Mowery et al., 1996; Gomes-Casseres et al., 2006) has shown that firms with complementary technologies or in the same industry, are more likely to form alliances. To control for these known bilateral factors, we introduce three new pairwise measures. Technological proximity from Jaffe (1986) measures the correlation of alliance participants' patent portfolios. Same industry is an indicator variable that takes the value of one if alliance participants operate in the same industry, and zero otherwise. Same state is an indicator variable that takes the value of one if alliance participants are headquartered in the same state, and zero otherwise. The pair-level sample contains alliance pairs and their control pairs where for each alliance pair, the client is paired with up to five matches to the partner (by industry and size or randomly drawn), and the partner is paired with up to five matches to the client (by industry and size or randomly drawn).

Table 5 Panel D compares these pairwise measures between alliance pairs and their control pairs. We show that there are significant differences in all three measures—technological proximity, same industry, and same state: Alliance pairs have greater technological overlap, and are more likely to be in the same industry and to be headquartered in the same state compared to their control pairs.

We then run the following conditional logit regression using the pair-level sample:

$$\begin{aligned}
 Pair_{ijm,t} = & \alpha + \beta_1 Client\ Innovation\ Characteristics_{im,t-1} \\
 & + \beta_2 Partner\ Innovation\ Characteristics_{jm,t-1} \\
 & + \beta_3 Client\ Other\ Firm\ Characteristics_{im,t-1} \\
 & + \beta_4 Partner\ Other\ Firm\ Characteristics_{jm,t-1} \\
 & + \beta_5 Technological\ Proximity_{ijm,t-1} + \beta_6 Same\ Industry_{ijm} \\
 & + \beta_7 Same\ State_{ijm} + Deal\ FE_m + e_{ijm,t}.
 \end{aligned} \tag{4}$$

The dependent variable, $Pair_{ijm,t}$, takes the value of one if a pair is the alliance pair, and zero otherwise. For each deal m , there is one observation for the alliance pair, and multiple observations for the control pairs. $Deal FE_m$ is the fixed effect for each alliance pair and its control pairs in deal m . Table 6 Panel B presents the results.

We find that pair-level evidence is largely consistent with firm-level results. Moreover, we show that technological proximity between two firms is positively and significantly associated with their likelihood of forming an alliance, and that two firms from the same industry or in the same state are also more likely to form an alliance. Importantly, after controlling for these pairwise characteristics, we find that innovative firms facing greater technological competition are still significantly more likely to form alliances.¹¹

We conclude that technological competition prompts alliance formation, in support of our first hypothesis (H1). Next, we examine the innovation outcomes after alliance formation.

5. Alliances, Technological Competition, and Post-Alliance Innovation Outcomes

In this section we answer the question: How do alliances and technological competition change the innovation outcomes of alliance participants?¹² Due to the patent approval lag noted before and the requirement for measuring post-alliance innovation outcomes over a three-year period, for this investigation, we limit alliances to those formed before 2001.¹³

¹¹ In untabulated analyses, we examine the question of how to choose which firm to be an alliance partner (client). We find that a client (partner) is more likely to choose a firm as the partner (client) if that firm faces greater technological competition, shares similar technologies, is in the same industry, or locates in the same state.

¹² The extent to which corporate innovation improves operating performance and enhances firm value has been extensively studied in the literature (Pakes, 1985; Austin, 1993; Hall, Jaffe, and Trajtenberg, 2005; Nicholas, 2008; Kogan, Papanikolaou, Seru, and Stoffman, 2014). In untabulated analyses, we find that both clients and partners facing fierce technological competition experience an increase in Tobin's Q subsequent to alliance formation.

¹³ When measuring innovation outcomes, prior work has also used patent citation-based variables (see, for example, Fang, Tian, and Tice, 2014; Bena and Li, 2014; Seru, 2014). However, for our purposes, patent citations as a measure of corporate innovation have a number of limitations. First, in the presence of technological competition, winning the race and/or gaining exclusive access to new technology are the key. So it seems that patent count is a better measure of alliance outcomes than citations. Second, given that alliances on average last about five years (Chan et al., 1997), we would like to examine the short- and medium-run response of alliance participants to technological competition,

5.1. The Difference-in-Differences Approach

To test our second set of hypotheses, we run the following regression:

$$\begin{aligned} \text{Log}(1 + \text{Patent Count}_{it}) = & \alpha + \beta_1 \text{Sample}_i \times \text{After}_{it} + \beta_2 \text{Sample}_i + \beta_3 \text{After}_{it} \\ & + \beta_4 \text{Firm Innovation Characteristics}_{it} + \beta_5 \text{Other Firm Characteristics}_{it} \\ & + \beta_6 \text{Pairwise Characteristics}_{it} + \text{Deal FE}_m + e_{it}. \end{aligned} \quad (5)$$

The dependent variable is the logarithm of one plus the client's (partner's) patent count. *Sample_i* takes the value of one if firm *i* is a client (partner) in deal *m*, and zero otherwise. *After_{it}* takes the value of one in the years after alliance formation, and zero otherwise. *Sample_i × After_{it}* captures the difference in the change of innovation outcome after alliance formation between the alliance participant firm and its control firms. The difference-in-differences approach allows us to control for selection (to be in an alliance or not) based on time-invariant unobservable firm characteristics. The sample for estimation is a panel dataset of alliance participants and their industry- and size-matched control firms from three years before to three years after alliance formation.

Table 7 columns (1) and (3) presents the results. We show that the coefficients on the standalone term *Sample* are positive and significant, suggesting that clients (partners) are generating significantly more patents compared to their peers. We further show that the coefficients on the interaction term *Sample × After* are positive and significant, suggesting that alliance participants have significantly larger increases in patents after alliance formation than their peers. This is strong evidence in support of our second hypothesis (H2A) on the positive effect of alliances on post-alliance innovation outcomes.

To investigate the heterogeneity in the effect of an alliance on post-alliance innovation outcomes and test our third hypothesis, we employ the difference-in-difference-in-differences approach by estimating the following regression:

$$\text{Log}(1 + \text{Patent Count}_{it}) = \alpha + \beta_1 \text{Sample}_i \times \text{After}_{it} \times \text{Tech Competitoin}_{it}$$

while counting the number of future citations to each awarded patent after alliance formation requires information over many years that is not readily available from the NBER Patent Citations Data File.

$$\begin{aligned}
& + \beta_2 \text{Sample}_i \times \text{After}_{it} + \beta_3 \text{Sample}_i \times \text{Tech Competition}_{it} \\
& + \beta_4 \text{After}_{it} \times \text{Tech Competition}_{it} + \beta_5 \text{Sample}_i + \beta_6 \text{After}_{it} \\
& + \beta_7 \text{Tech Competition}_{it} + \beta_8 \text{Other Firm Innovation Characteristics}_{it} \\
& + \beta_9 \text{Other Firm Characteristics}_{it} + \beta_{10} \text{Pairwise Characteristics}_{it} \\
& + \text{Deal FE}_m + e_{it}.
\end{aligned} \tag{6}$$

Table 7 columns (2) and (4) present the results. In column (2), the dependent variable is the logarithm of one plus the client's patent count. We show that the coefficient on *After* is positive and significant, suggesting that client peer firms are generating more patents over time. Further, we show that the coefficient on the two-way interaction term *Sample* $\times$ *Tech competition* is positive and significant, suggesting that before alliance formation, clients facing more intense technological competition generate more patents than their peer firms, and that the coefficient on *After* $\times$ *Tech competition* is negative and significant, suggesting that client peers facing more intense technological competition generate fewer patents over time. This finding suggests that peer firms facing technological competition that do not form alliances actually have lower innovation output over time compared to clients. Importantly, we find that the increase in patent output is strengthened for clients facing more intense technological competition. The coefficient on the three-way interaction term *Sample* $\times$ *After* $\times$ *Tech Competition* is 0.986 and significant at the 1% level, suggesting that as technological competition increases by one standard deviation (= 0.123), clients' patent output will further increase by 12% after alliance formation. These findings offer strong support for our third hypothesis (H3), that greater technological competition enhances innovation output in alliance participants.

In column (4), the dependent variable is the logarithm of one plus the partner's patent count. We show that the coefficient on *Sample* is negative and significant, suggesting that partner firms are generating fewer patents than their peer firms, and that the coefficient on *After* is positive and significant, suggesting an increasing trend in patent output for partner peer firms. Further, we show that the coefficient on the two-way interaction term *Sample* $\times$ *After* is negative and significant, suggesting that partners have smaller

increases in patent output post-alliance formation than their peers. In contrast, we show that the coefficient on *Sample* $\times$ *Tech competition* is positive and significant, suggesting that before alliance formation, partners facing more intense technological competition generate more patents than their peer firms, and that the coefficient on *After* $\times$ *Tech Competition* is negative and significant, suggesting that partner peer firms facing more intense technological competition have fewer patents over time. Importantly, the coefficient on the three-way interaction term *Sample* $\times$ *After* $\times$ *Tech Competition* is 1.792 and significant at the 1% level, indicating that as technological competition increases by one standard deviation ($= 0.102$), partners' patent output will further increase by 18% after alliance formation. These findings offer strong support for our third hypothesis (H3), that greater technological competition enhances innovation output in alliance participants.

5.2. The Treatment Regression

So far, we have shown that firms facing greater technological competition are more likely to join alliances, which in turn enhances participant firms' innovation output. However, the above results are subject to reverse causality concerns, i.e., firms expected to improve innovation output choose to join alliances, so our findings may be driven by selection, instead of by the treatment effect of alliances on innovation output. To address this concern, we employ the treatment regression framework; for identification, we employ an instrumental variable that clearly affects alliance decisions but has nothing to do with innovation outcomes other than through the channel of joining alliances.¹⁴

For this purpose, we use a “natural experiment”—changes to US states requiring combined reporting of corporate income (Mazero, 2009) to help pin down the direction of causality (Bodnaruk et al., 2013). We consider situations where the opportunity costs of forming alliances differ due to exogenous reasons that are not firm specific, and examine how the differential reaction to this variation is related to patent outcome. To do so, we rely on the differences in corporate income reporting rules across US states.

¹⁴ See Li and Prabhala (2007) for an overview of dealing with selection issues versus treatment effects in corporate finance.

There are two types of corporate income reporting for the purpose of state-level taxation: separate reporting and combined reporting. Under separate reporting rules, a multi-state firm can reduce its taxable income by isolating highly profitable parts of its business in an affiliate that is not subject to state taxes. Combined reporting rules, however, require firms to report their overall income generated in the US and pay state corporate income tax on the proportion of income attributable to activity in each state in which these firms have business activities. Thus, combined reporting rules reduce the benefits of using non-arm's-length transactions between the subsidiaries of a firm located in different states—internal capital markets—to reduce the tax burden. This suggests that combined reporting reduces the opportunity costs of forming alliances to commit assets. We thus expect that firms form more alliances in states with combined reporting.

Our instrumental variable is a firm's combined reporting index, where a higher value of the index indicates that more of the firm's operations are located in states that require combined reporting. To construct the combined reporting index, data on the locations of the firm's subsidiaries is required. Bodnaruk et al. (2013) and their Appendix D provide the detailed information on the construction of the variable. We have data on the firm-level combined reporting index for 1998, 2000, 2002, and 2004. We use the 1998 data for alliances formed between 1991-1998; the 2000 data for alliances formed between 1999-2000; the 2002 data for alliances formed between 2001-2002; and finally the 2004 data for alliances formed between 2003-2004.

Table 8 presents the treatment regression results. The sample for columns (1)-(2) comprises both the clients and their industry- and size-matched control firms. The sample for columns (3)-(4) comprises both the partners and their industry- and size-matched control firms. Column (1) ((3)) presents the first-stage regression results where the dependent variable is the alliance client (partner) indicator variable in year t , and the instrumental variable is based on a firm's headquarters location. The variable of interest is the firm's combined reporting index. We show that indeed, when a firm has a higher value of the combined reporting index, that firm is more likely to join an alliance (either as a client or a partner). We also show that a firm facing greater technological competition is more likely to join an alliance.

Column (2) presents the second-stage regression results where the dependent variable is the logarithm of one plus the client's patent count from year $t+1$ to year $t+3$. Consistent with findings from the difference-in-difference analyses, the coefficient on the interaction term *Sample $\times$ Tech Competition* is positive and significant at the 1% level, suggesting that clients do generate significantly more patents when facing more intense technological competition, consistent with our third hypothesis (H3). Column (4) presents the second-stage regression results where the dependent variable is the logarithm of one plus the partner's patent count from year $t+1$ to year $t+3$. The coefficient on the interaction term *Sample $\times$ Tech Competition* is positive and significant at the 1% level, suggesting that partners do generate significantly more patents when facing more intense technological competition, consistent with our third hypothesis (H3).

Columns (5)-(8) repeat the analysis in columns (1)-(4), except that the instrumental variable—the combined reporting index for each firm—is based on location information of its headquarter and subsidiaries. It is worth noting that our main findings remain unchanged.

In summary, our results in Tables 7 and 8 suggest that alliances are associated with improved innovation output, especially for alliance participants facing more intense technological competition, consistent with our third hypothesis (H3).

5.3. *The Underlying Mechanisms*

In this section, we explore a number of possible underlying economic mechanisms through which innovation output improves at alliance participant firms.

5.3.1. R&D Expenditures and R&D Efficiency

We conjecture that one direct benefit of technological competition-driven alliances is improvement in R&D efficiency; the competitive pressure may also push alliance participants to increase R&D expenditures. We measure R&D expenditures using their dollar amount. We measure R&D efficiency as the ratio of the number of awarded patents applied for from year $t-2$ to year t to cumulative R&D

expenditures during the same period. We employ similar model specifications as the difference-in-differences models in Equations (5) and (6). Table 9 Panel A presents the results.

Columns (1)-(2) and (5)-(6) present the regression results where the dependent variable is the logarithm of one plus R&D expenditures. The coefficients on *After × Tech Competition* are negative and significant in columns (2) and (6), suggesting that alliance peer firms facing more intense technological competition cut their R&D expenditures over time. The coefficient on the three-way interaction term *Sample × After × Tech competition* is negative and significant in column (2), whereas it is positive and significant in column (6), suggesting that when facing more intense technological competition, clients will significantly reduce their R&D expenditures, whereas partners will significantly increase such expenditures after alliance formation.

Columns (3)-(4) and (7)-(8) present the regression results where the dependent variable is the logarithm of one plus R&D efficiency. The coefficients on *Sample × Tech Competition* are negative and significant in columns (4) and (8), suggesting that before alliance formation, alliance participants facing more intense technological competition have lower R&D efficiency. The coefficient on the three-way interaction term *Sample × After × Tech competition* is not significantly different from zero in column (4), suggesting that clients facing more intense technological competition will experience little change in their R&D efficiency, whereas it is positive and significant in column (8), suggesting that when facing more intense technological competition, partners will significantly improve R&D efficiency.

In a nutshell, the evidence in Panel A suggests that technological competition increases partners' R&D expenditures and their R&D efficiency after alliance formation, which is intuitive, considering that partners typically specialize in technology development in alliances.

5.3.2. Unrelated and Related Patents

Gomes-Casseres et al. (2006) find that one immediate impact of alliances is enhanced knowledge flows as proxied by patent citations (Jaffe and Trajtenberg, 2002) between participant firms, which can in turn lead to improved patent output. For a client (partner) in year t , we define related patents as those

awarded patents that are applied for in year t and cite patents of the partner (client) and unrelated patents as those awarded patents that are applied for in year t and do not cite patents of the partner (client).¹⁵ Table 9 Panel B presents the results.

Columns (1)-(2) ((3)-(4)) present the regression results where the dependent variable is the logarithm of one plus the client's number of unrelated (related) patents. The coefficients on *Sample* $\times$ *After* are positive and significant in columns (1) and (3), suggesting significant increases in the number of unrelated and related patents in client firms after alliance formation. The coefficient on the three-way interaction term *Sample* $\times$ *After* $\times$ *Tech competition* is not significantly different from zero in column (2), suggesting that clients facing more intense technological competition will experience little change in their number of unrelated patents, whereas it is positive and significant in column (4), suggesting that when facing more intense technological competition, clients do significantly increase their number of related patents, consistent with our second hypothesis (H2B). This finding is also consistent with our earlier observation that clients facing more intense technological competition generate significantly more patents; we show above that it is the enhanced knowledge flow via alliances that helps those clients to generate significantly more patents related to their partners.

Columns (5)-(6) ((7)-(8)) present the regression results where the dependent variable is the logarithm of one plus the partner's number of unrelated (related) patents. We find that there are significant increases in the partners' number of unrelated and related patents after alliance formation (columns (5) and (7)). Further, we find that these increases are significantly larger when partners facing more intense technological competition (columns (6) and (8)), thereby supporting our second hypothesis (H2B) that enhanced knowledge flow via alliances leads to improved innovation output.

5.3.3. Inventor-Level Evidence

¹⁵ There are a number of caveats to our measure of knowledge flow. First, a significant number of patent citations are added by the patent examiner, and hence may represent prior work of which the inventor was unaware (Jaffe and Trajtenberg, 2002). Second, not all inventions are patented, so there might be flows of knowledge between alliance participants that do not show up in a patent citation. Both caveats would bias against us finding any significant results.

Finally, we examine the productivity of individual investors associated with alliance participants. For this analysis, the sample consists of inventors working either at the alliance participants or their industry- and size-matched control firms. We obtain information about inventors from the Harvard Business School (HBS) Patent Inventor Database (Lai, D'Amour, Yu, Sun, Torvik, and Fleming, 2011; see Bradley, Kim, and Tian, 2013 for a recent application). For a particular firm, stayers are inventors who have at least one patent with the firm in the three-year period prior to, at least one patent with the same firm in the three-year period after alliance formation, and do not have any patents outside the firm over these two periods. For a particular firm, new hires are inventors who do not have any patents with the firm in the three-year period prior to, have at least one patent with the firm in the three-year period after alliance formation, and do not have any patents outside the firm over the post-alliance period. Table 9 Panel C presents the results.

The dependent variable is the logarithm of one plus the number of patents that an inventor has, taken at the end of the two three-year periods: year $t-3$ to $t-1$ and year $t+1$ to $t+3$ relative to the deal announcement year t . Firm characteristics are measured at the end of the respective three-year period. We find that both stayers and new hires at alliance participants exhibit significantly improved productivity after alliance formation (columns (1) and (3)). Importantly, such improvement is significantly greater for stayers and new hires at partner firms facing more intense technological competition (column (4)).¹⁶

In summary, we conclude that technological competition is positively associated with both the likelihood of firms joining alliances and the subsequent improved innovation output for alliance participants.

6. Additional Investigation

In this section we perform two additional tests to examine the relation between technological competition and other organizational forms and to compare technological competition with product market competition.

¹⁶ In untabulated analyses, we show that both stayers and new hires, respectively, exhibit significant improvement in productivity at partner firms facing fierce technological competition.

6.1. Technological Competition and Other Organizational Forms

Mowery et al. (1996) and Robinson and Stuart (2007) note that firms might also form JVs to conduct R&D. Bena and Li (2014) find that complementarity in technological innovation leads to full integration. These studies suggest that technological competition might also play a role in firms' choice of other organizational forms to accelerate innovation.

We obtain data on JV deals from the Thomson Financial's SDC database on Joint Ventures and Strategic Alliances and on M&A deals from the SDC Mergers and Acquisitions database.¹⁷ Table 10 presents the results using the Tobit regression in Equation (1).

In columns (1) and (2), the dependent variable is the logarithm of one plus the number of JV deals. We find that there is no significant association between technological competition facing a firm and its number of JV deals, while firms with more patents and less patent diversification are more likely to form JVs. Our finding highlights a key difference between alliances and JVs: The former is a flexible arrangement between distinct firms to develop new ideas, whereas the latter creates a new rigid legal entity to develop and market new products. Our finding suggests that when there is significant uncertainty associated with fierce technological competition, creating a new legal entity that requires a clear division of intellectual property rights could be prohibitively costly.

In columns (3) and (4), the dependent variable is the logarithm of one plus the number of M&A deals. We find that firms facing greater technological competition are more likely, while high R&D firms are less likely, to engage in M&As. These results are consistent with Hoberg and Phillips (2010) that product market competition triggers integration, and with Grossman and Hart (1986) and recent empirical evidence in Frésard et al. (2014) that firms avoid integration and remain independent to maintain *ex ante* incentives to invest in relationship-specific assets through R&D.

¹⁷ We impose the same filters as we did for alliances and end up with 7,120 JVs formed by innovative firms over the period 1991-2004. For M&A deals, we require that: 1) the deal is eventually completed; 2) the form of deal is coded by SDC as a merger, an acquisition of majority interest, or an acquisition of assets; and 3) the acquirer owns less than 50% of the target firm prior to the deal and is seeking to own more than 50% of the target firm. We end up with 42,251 M&A deals by innovative firms over the same period.

Taken together, we find that technological competition plays a significant role in firms' decision to form alliances or engage in M&As. What separates alliances from M&As in accelerating corporate innovation is beyond the scope of this study and will be an interesting area for future study.

6.2 Technological Competition and Product Market Competition

We expect that firms facing technological competition are likely to face similar threats from the product market; alliance decisions could thus also be affected by similar product market threats. To measure product market competition, we use Hoberg et al.'s (2014) product market fluidity measure that captures changes in rival firms' products relative to a firm's own products. The correlation between our technological competition measure and Hoberg et al.'s measure is 0.34.

In Table 11, we run a horse race between our measure of technological competition and Hoberg et al.'s measure of product market threats in explaining alliance formation and post-alliance innovation output. Panel A replicates the same specification as in Table 4, except that we add the product market fluidity variable. We find that similar to the role of technological competition, product market threats also play a significant role in firms' decisions to form alliances.

Panel B replicates the same treatment regression as in Table 8, except that we add the product market fluidity variable. We find that only the presence of intense technological competition is positively and significantly associated with improved innovation output for alliance participants.¹⁸ This is not surprising, given that controlling for the effect of technological competition, product market fluidity captures threats to firms in the product market space but not in the technological space and, thus, has no direct bearing on firms' new technology developments. Our findings in Table 11 are consistent with this interpretation and suggest that despite their positive correlation, our technological competition measure and the product market fluidity measure capture distinctly different aspects of the competition faced by firms.

7. Conclusions

¹⁸ In untabulated analyses, we obtain similar findings using the difference-in-differences approach (as in Table 7).

Alliances are an important organizational structure through which firms enhance their technological capacity, product market competitiveness, and long-term productivity growth. However, little is known about whether and how technological competition affects firms' decisions to form alliances, and their joint effects on the innovation outcomes of alliance participants. This paper fills a gap in the literature by first developing a novel measure of technological competition, and then relating it to alliance formation and subsequent innovation outcomes.

Using a large patent-alliance dataset over the period 1991-2004, we show that innovative firms facing greater technological competition are more likely to form alliances. Technological competition is captured by a cosine similarity measure between a firm's own patent output and the patent output of all other firms in the economy. We further show that alliances lead to more patents in participant firms, especially when these firms face greater technological competition. Finally, we show that the number of related patents increases significantly at participant firms, while the number of unrelated patents, R&D expenditures, R&D efficiency, and the productivity of individual inventors increase significantly only at partner firms facing greater technological competition. Our results are robust to endogeneity concerns. In our additional investigation, we find that firms facing greater technological competition are more likely to engage in M&As, while there is no significant association between technological competition and firms' JV decisions. We further find that firms facing greater product market threats are more likely to join alliances but there is no significant association between product market threats and post-alliance innovation outcomes. We conclude that technological competition is an important impetus for redrawing the boundaries of the firm in order to accelerate corporate innovation.

Given the increasing importance of technological innovation in developing new knowledge and serving as the catalyst to economic growth and increased productivity, gaining a better understanding of the important interactions between corporate innovation and the boundaries of the firm will be a fruitful area for future research.

Appendix 1: Variable definitions

Firm characteristics are measured as of the fiscal year end before the alliance deal announcement and are winsorized at the 1st and 99th percentiles.

<i>Technological competition</i>	<p>Technological competition is computed as a cosine similarity measure</p> $Technological\ Competition_{i,t} = \cos \left(\frac{S_{i,t}}{\ S_{i,t}\ }, \frac{S_{-i,t}}{\ S_{-i,t}\ } \right)$ <p>where the vector $S_{i,t} = (s_{i,1,t}, \dots, s_{i,k,t}, \dots, s_{i,K,t})$ captures the scope of innovation activity through patent output of firm i, and the vector $S_{-i,t} = (s_{-i,1,t}, \dots, s_{-i,k,t}, \dots, s_{-i,K,t})$ captures the scope of innovation activity through patent output of all other firms in the economy excluding firm i. The subscript k in (I, K) is the technology class index. The scalar $s_{i,k,t}$ ($s_{-i,k,t}$) is the ratio of the number of awarded patents to firm i (all other firms in the economy excluding firm i) in technology class k with application years from $t-2$ to t (application year t) to the total number of awarded patents to firm i (all other firms in the economy excluding firm i) applied over the same period. This scalar is set to zero if an innovative firm does not have any patent application over year $t-2$ to t.</p>
<i>Entire 10-K</i>	<p>For each firm-year with available 10-K filings, we employ a machine-based algorithm to search and count the number of times that the following keywords show up in the 10-K main text: “Technology competition, technological competition, technology competitiveness, technological competitiveness, technology risk, technological risk, technology risks, technological risks, technology threat, technological threat, technology threats, technological threats, technology uncertainty, technological uncertainty, technology change, technological change, technology changes, technological changes, changes in technology.” We normalize the number of word counts by the 10-K text file size (in mega bytes).</p>
<i>MD&A and risk factors</i>	<p>For each firm-year with available 10-K filings, we employ a machine-based algorithm to search and count the number of times that the above keywords show up in the 10-K MD&A section or risk factors section.</p>
<i>MD&A</i>	<p>For each firm-year with available 10-K filings, we employ a machine-based algorithm to search and count the number of times that the above keywords show up in the 10-K MD&A section.</p>
<i>Risk factors</i>	<p>For each firm-year with available 10-K filings, we employ a machine-based algorithm to search and count the number of times that the above keywords show up in the 10-K risk factors section.</p>
<i>Patent count</i>	<p>This variable is constructed in three steps. First, for each technology class k and patent application year t, we calculate the median value of the number of awarded patents in technology class k with application year t across all firms that were awarded at least one patent in technology class k with application year t. Second, we scale the number of awarded patents to firm i in technology class k with application year t by the corresponding (technology class and application year) median value from the first step. Finally, for firm i, we sum the scaled number of awarded patents from the second step across all technology classes and across application years from $t-2$ to t. Since firms’ patenting activities tend to cluster over technology classes and time, <i>patent count</i> thus measures a firm’s relative productivity in innovation by excluding those clustering effects. This variable is set to zero if an innovative firm does not have any patent application over year $t-2$ to t.</p>
<i>Patent diversification</i>	<p>Following Hirshleifer et al. (2014), patent diversification is constructed as</p>

$$Patent\ diversification_{i,t} = 1 - \sum_{k=1}^K \left(\frac{n_{i,k,t}}{\sum_{k=1}^K n_{i,k,t}} \right)^2,$$

where $n_{i,k,t}$ is the number of awarded patents to firm i in technology class k with application years from $t-2$ to t and K is the total number of patent classes.

<i>R&D</i>	R&D expenditures scaled by total assets.
<i>Total assets</i>	Book value of total assets in millions of 2004 constant dollars.
<i>Firm age</i>	The number of years since a firm is covered by CRSP
<i>HHI</i>	The Herfindahl index of a two-digit SIC industry based on sales.
<i>Leverage</i>	Total debt scaled by total assets, where total debt is the sum of short-term debt and long-term debt.
<i>ROA</i>	Earnings before interest, taxes, depreciation, and amortization scaled by total assets.
<i>Cash holdings</i>	Cash and short-term investment scaled by total assets.
<i>Tobin's Q</i>	Market value of total assets scaled by book value of total assets, where market value of total assets is computed as book value of total assets minus book value of common equity plus market value of common equity.
<i>Sales growth</i>	The ratio of sales in year t to sales in year $t-1$ minus one.
<i>Capex</i>	Capital expenditures scaled by total assets.
<i>Technological proximity</i>	<p>Following Jaffe (1986), technological proximity is computed as a correlation coefficient</p> $Technological\ Proximity_{i,j,t} = \frac{S_{i,t}S'_{j,t}}{\sqrt{S_{i,t}S'_{i,t}}\sqrt{S_{j,t}S'_{j,t}}},$ <p>where the vector $S_{i,t} = (s_{i,1,t}, \dots, s_{i,k,t}, \dots, s_{i,K,t})$ captures the scope of innovation activity through patent output of firm i, and the vector $S_{j,t} = (s_{j,1,t}, \dots, s_{j,k,t}, \dots, s_{j,K,t})$ captures the scope of innovation activity through patent output of firm j. The subscript k in (I,K) is the technology class index. The scalar $s_{i,k,t} (s_{j,k,t})$ is the ratio of the number of awarded patents to firm i (j) in technology class k with application years from $t-2$ to t to the total number of awarded patents to firm i (j) applied over the same period.</p>
<i>Same industry</i>	Equal to one if the client and the partner operate in the same two-digit SIC industry, and zero otherwise.
<i>Same state</i>	Equal to one if the client and the partner are incorporated in the same state, and zero otherwise.
<i>Sample</i>	Equal to one if it is an alliance participant, and zero otherwise.
<i>After</i>	Equal to one if it is after the alliance deal announcement, and zero otherwise.
<i>R&D expenditures</i>	R&D expenditures in millions of 2004 constant dollars over the three-year period $t-2$ to t .
<i>R&D efficiency</i>	The number of awarded patents with application years from $t-2$ to t scaled by the cumulative R&D expenditures during the same period.

<i>Unrelated patent</i>	For a client (partner), unrelated patents are its awarded patents with application year t that do not cite patents of its partner (client).
<i>Related patent</i>	For a client (partner), related patents are its awarded patents with application year t that cite patents of its partner (client).
<i>Combined reporting index (headquarters)</i>	Following Bodnaruk et al. (2013), the combined reporting indicator variable is set to one if a firm's headquarter is located in a state that imposes the combined reporting rule, and zero otherwise.
<i>Combined reporting index (headquarters and subsidiaries)</i>	Following Bodnaruk et al. (2013), for each subsidiary (including the headquarter) of a firm, the combined reporting indicator variable is set to one if the subsidiary (or the headquarter) is located in a state that imposes the combined reporting rule, and zero otherwise. The firm's combined reporting index is the average value of the combined reporting indicator variable across all of its subsidiaries (including the headquarter) when the information on subsidiary location is available, and the value of the combined reporting indicator variable based on headquarter location otherwise.
<i>Product market fluidity</i>	This variable captures the overlap between changes in rival firms' products and a firm's own products (see Hoberg et al. (2014) for more detailed discussion). We obtain the data from the Hoberg-Phillips Data Library at: http://alex2.umd.edu/industrydata/ .

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Figure 1: Technological competition over time

This figure shows the average level of technological competition over the period 1980-2003 across three major sectors: agriculture and mining (SIC 0000 – 1999), manufacturing (SIC 2000 – 3999), and services (SIC 4000 – 9999, excluding financial industries SIC 6000 – 6999). The sample includes innovative US public firms covered by Compustat/CRSP. Innovative firms are firms with at least one awarded patent over the period 1976-2006 by the USPTO.

Table 1
Measuring technological competition

This table summarizes a number of cross-validation exercises on our measure for technological competition. Panel A provides a list of top (bottom) five industries (based on two-digit SIC) with the highest (lowest) levels of technological competition in 1980, 1990, and 2000. Panel B presents summary statistics of our measure for technological competition and alternative measures based on 10-K keyword search that try to capture the competitive pressure faced by firms in the technological space. The sample is based on Compustat firms with non-zero value for our technological competition measure over the period 1996-2003. Panel C presents correlations between our measure for technological competition and alternative measures based on 10-K keyword search. p -values of the Pearson correlation coefficient are reported in parentheses. Panel D examines the relation between technological competition faced by a firm and the proximity of its patent portfolio to that of IPO (delisted) firms. The dependent variable is technological proximity between the firm's patent portfolio in year t covering awarded patents with application years from $t-2$ to t and that of IPO firms in column (1), and that of delisted firms in column (2), and that of both IPO and delisted firms in column (3). The IPO firms in year $t-3$ are obtained from the CRSP database and their patent portfolio includes awarded patents with application years from $t-2$ to t . The delisted firms in year $t+1$ are obtained from the CRSP database and their patent portfolio includes awarded patents with application years from $t-2$ to t . Definitions of the variables are provided in Appendix 1. Robust standard errors that allow for clustering at the firm level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Industries with the highest and lowest levels of technological competition in 1980, 1990, and 2000

Panel A: Industries with the highest and lowest levels of technological competition in 1980, 1990, and 2000								
1980			1990			2000		
Highest technological competition								
SIC	Industry	Tech Comp	SIC	Industry	Tech Comp	SIC	Industry	Tech Comp
29	Petroleum refining and related industries	0.264	28	Chemicals and allied products	0.225	48	Communications	0.226
28	Chemicals and allied products	0.238	37	Transportation equipment	0.193	28	Chemicals and allied products	0.193
48	Communications	0.210	2	Food and kindred products	0.180	36	Electronic and other electrical equipment and components, except computer equipment	0.189
37	Transportation equipment	0.167	26	Paper and allied products	0.157	73	Business services	0.174
32	Stone, clay, glass, and concrete products	0.164	21	Tobacco products	0.152	99	Nonclassifiable establishments	0.168
Lowest technological competition								
SIC	Industry	Tech Comp	SIC	Industry	Tech Comp	SIC	Industry	Tech Comp
54	Food stores	0.030	45	Transportation by air	0.021	10	Metal mining	0.013
25	Furniture and fixtures	0.030	53	General merchandise stores	0.017	72	Personal services	0.013
72	Personal services	0.007	79	Amusement and recreation services	0.015	31	Leather and leather products	0.010
79	Amusement and recreation services	0.007	31	Leather and leather products	0.009	44	Water transportation	0.004
42	Motor freight transportation and warehousing	0.006	12	Coal mining	0.009	17	Construction special trade contractor	0.003

Panel B: Summary statistics of technological competition and alternative measures based on 10-K search

	Mean	S.D.	Median
Technological competition	0.118	0.105	0.090
Entire 10-K	1.839	4.471	0.000
MD&A and risk factors	6.854	2.337	0.000
MD&A	4.777	1.929	0.000
Risk factors	2.076	1.294	0.000
Number of observations	17,210		

Panel C: Correlations between technological competition and alternative measures based on 10-K search

	(1)	(2)	(3)	(4)
(1) Technological competition				
(2) Entire 10-K	0.191 (0.00)			
(3) MD&A and risk factors	0.145 (0.00)	0.695 (0.00)		
(4) MD&A	0.121 (0.00)	0.605 (0.00)	0.833 (0.00)	
(5) Risk factors	0.082 (0.00)	0.352 (0.00)	0.565 (0.00)	0.013 (0.08)

Panel D: Technological competition and technological proximity to IPO and delisted firms

	IPO firms (1)	Delisted firms (2)	Both (3)
Technological competition	0.504*** (0.011)	0.247*** (0.009)	0.447*** (0.012)
Log (1 + patent count)	0.001 (0.001)	0.003*** (0.001)	-0.001 (0.001)
Patent diversification	0.002 (0.003)	0.002 (0.003)	-0.002 (0.003)
R&D	0.184*** (0.010)	0.133*** (0.009)	0.195*** (0.010)
Log (total assets)	0.002*** (0.000)	0.003*** (0.000)	0.004*** (0.000)
Log (firm age)	-0.010*** (0.001)	0.001** (0.001)	-0.006*** (0.001)
HHI	-0.073*** (0.014)	-0.099*** (0.014)	-0.144*** (0.018)
Intercept	0.024*** (0.003)	-0.005* (0.003)	0.007** (0.003)
Number of observations	37,154	37,154	37,154
Adjusted R-squared	0.32	0.13	0.24

Table 2
Strategic alliances over time, 1991–2004

This table reports the number of strategic alliances involving US public firms by the year of alliance deal announcement over the period 1991–2004. In Panel A, a deal enters the sample if at least one of the alliance participants or their parent firms is covered by Compustat/CRSP and the alliance participants (or their parent firms) are not financial firms (SIC 6000 – 6999). In Panel B, we further require that alliance participants (or their parent firms) be innovative. Innovative firms are firms with at least one awarded patent over the period 1976–2006 by the USPTO.

Panel A: Different forms of alliances over time

Year	Alliances involving at least one public firm	Bilateral alliances involving at least one public firm	Bilateral alliances between public firms or their subsidiaries	Bilateral alliances between public firms
	(1)	(2)	(3)	(4)
1991	1,783	1,671	402	275
1992	2,250	2,130	593	370
1993	2,349	2,149	559	369
1994	2,481	2,269	594	354
1995	2,209	2,041	593	368
1996	1,536	1,434	480	349
1997	2,180	1,998	670	472
1998	2,648	2,442	700	450
1999	3,065	2,832	890	633
2000	2,640	2,420	474	296
2001	1,690	1,593	340	195
2002	1,200	1,142	230	143
2003	1,622	1,554	302	184
2004	1,355	1,302	230	139
Total	29,008	26,977	7,057	4,597

Panel B: Alliances involving innovative firms

Year	Alliances involving at least one public firm	Bilateral alliances involving at least one public firm	Bilateral alliances between public firms or their subsidiaries	Bilateral alliances between public firms
	(1)	(2)	(3)	(4)
1991	1,562	1,467	390	270
1992	1,902	1,795	552	352
1993	2,001	1,824	524	348
1994	2,052	1,865	561	336
1995	1,748	1,620	545	342
1996	1,200	1,115	440	319
1997	1,669	1,518	611	443
1998	1,910	1,740	597	387
1999	2,212	2,030	753	540
2000	1,849	1,679	400	250
2001	1,320	1,239	303	177
2002	916	872	209	132
2003	1,269	1,216	270	165
2004	1,043	1,003	217	135
Total	22,653	20,983	6,372	4,196

Table 3
Descriptive statistics for the panel data sample

This table reports descriptive statistics of the panel data sample. The panel data sample includes non-financial innovative firms covered by Compustat/CRSP over the period 1991-2004. Firm characteristics are measured at the fiscal year end before the alliance announcement year. Definitions of the variables are provided in Appendix 1. The numbers in parentheses in Panel B are the p -value of Pearson correlation.

Panel A: Summary statistics for the panel data sample

	Mean	S.D.	Median
# of alliances, public firms only	0.612	2.662	0
# of alliances, including subsidiary deals	0.799	3.463	0
Technological competition	0.086	0.108	0.045
Patent count	25	153	2
Patent diversification	0.320	0.355	0
R&D	0.081	0.121	0.031
Total assets (2004 \$ million)	2,413	14,393	169
Leverage	0.203	0.202	0.160
ROA	0.037	0.259	0.110
Cash holdings	0.211	0.241	0.104
Tobin's Q	2.353	2.135	1.587
Sales growth	0.258	0.823	0.085
Capex	0.057	0.053	0.043
Number of observations	31,983		

Panel B: Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Log (1 + # of alliances, public firms only)												
(2) Log (1 + # of alliances, including subsidiary deals)	0.951 (0.00)											
(3) Technological competition	0.296 (0.00)	0.302 (0.00)										
(4) Log (1 + patent count)	0.293 (0.00)	0.320 (0.00)	0.651 (0.00)									
(5) Patent diversification	0.168 (0.00)	0.181 (0.00)	0.632 (0.00)	0.821 (0.00)								
(6) R&D	0.064 (0.00)	0.037 (0.00)	0.282 (0.00)	0.059 (0.00)	0.075 (0.00)							
(7) Log (total assets)	0.205 (0.00)	0.255 (0.00)	0.220 (0.00)	0.477 (0.00)	0.389 (0.00)	-0.388 (0.00)						
(8) Leverage	-0.056 (0.00)	-0.032 (0.00)	-0.120 (0.00)	-0.007 (0.22)	-0.018 (0.00)	-0.226 (0.00)	0.225 (0.00)					
(9) ROA	0.034 (0.00)	0.046 (0.00)	-0.097 (0.00)	0.089 (0.00)	0.066 (0.00)	-0.661 (0.00)	0.438 (0.00)	0.029 (0.00)				
(10) Cash holdings	0.063 (0.00)	0.029 (0.00)	0.229 (0.00)	-0.012 (0.03)	-0.007 (0.21)	0.508 (0.00)	-0.331 (0.00)	-0.442 (0.00)	-0.393 (0.00)			
(11) Tobin's Q	0.111 (0.00)	0.086 (0.00)	0.161 (0.00)	0.039 (0.00)	0.015 (0.01)	0.385 (0.00)	-0.215 (0.00)	-0.194 (0.00)	-0.290 (0.00)	0.419 (0.00)		
(12) Sales growth	0.043 (0.00)	0.028 (0.00)	0.053 (0.00)	-0.031 (0.00)	-0.039 (0.00)	0.134 (0.00)	-0.089 (0.00)	-0.096 (0.00)	-0.135 (0.00)	0.230 (0.00)	0.279 (0.00)	
(13) Capex	0.032 (0.00)	0.029 (0.00)	0.022 (0.00)	0.031 (0.00)	0.022 (0.00)	-0.030 (0.00)	0.102 (0.00)	0.044 (0.00)	0.068 (0.00)	-0.151 (0.00)	0.041 (0.00)	0.056 (0.00)

Table 4
Tobit regressions

This table reports coefficient estimates from Tobit models in Equation (2). The panel data sample includes non-financial innovative firms covered by Compustat/CRSP over the period 1991-2004. The dependent variable is the logarithm of one plus the number of alliance deals. In columns (1) and (2), alliance deals involve public firms only, whereas deals involving public firm subsidiaries are included in columns (3) and (4). Firm characteristics are measured at the fiscal year end before the alliance announcement year. Definitions of the variables are provided in Appendix 1. Robust standard errors that allow for clustering at the firm level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	<i>Log (1 + # of alliances, public firms only)</i>		<i>Log (1 + # of alliances, including subsidiary deals)</i>	
	(1)	(2)	(3)	(4)
Technological competition	1.571*** (0.171)	1.284*** (0.164)	1.397*** (0.164)	1.125*** (0.159)
Log (1 + patent count)	0.161*** (0.019)	0.097*** (0.015)	0.152*** (0.018)	0.091*** (0.015)
Patent diversification	-0.442*** (0.071)		-0.421*** (0.067)	
R&D	1.765*** (0.150)	1.750*** (0.151)	1.763*** (0.149)	1.752*** (0.150)
Log (total assets)	0.257*** (0.013)	0.260*** (0.013)	0.315*** (0.012)	0.318*** (0.012)
Leverage	-0.455*** (0.083)	-0.460*** (0.084)	-0.426*** (0.078)	-0.431*** (0.078)
ROA	-0.037 (0.070)	-0.046 (0.071)	-0.140** (0.069)	-0.148** (0.070)
Cash holdings	0.588*** (0.068)	0.608*** (0.069)	0.449*** (0.065)	0.468*** (0.066)
Tobin's Q	0.076*** (0.006)	0.078*** (0.006)	0.076*** (0.006)	0.078*** (0.006)
Sales growth	0.081*** (0.011)	0.084*** (0.011)	0.075*** (0.011)	0.077*** (0.011)
Capex	0.520** (0.259)	0.529** (0.263)	-0.021 (0.247)	-0.009 (0.251)
Intercept	-2.732*** (0.247)	-2.729*** (0.241)	-2.837*** (0.262)	-2.836*** (0.255)
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Number of observations	31,983	31,983	31,983	31,983
Pseudo R-squared	0.17	0.17	0.18	0.18

Table 5
Summary statistics for the firm-level and pair-level samples

This table reports summary statistics of the firm-level and pair-level samples over the period 1993-2004. A client (partner) in a bilateral deal is the firm with a higher (lower) value of total assets. The firm-level client (partner) sample contains innovative clients (partners) and their control firms. For each client (partner), we identify up to five control firms that satisfy the following conditions: 1) they are innovative; 2) they share at least one-digit SIC code with the alliance participant; 3) their total assets in year t falls between 50% and 150% of the alliance participant's total assets; and 4) they are not part of an alliance in the seven-year period from year $t-3$ to year $t+3$ centered at the alliance deal announcement year t . The pair-level sample contains alliance pairs and their control pairs where for each alliance pair, the client is paired with up to five industry- and size-matched control firms of the partner, and the partner is paired with up to five industry- and size-matched control firms of the client. Panels A, B, and C report summary statistics for the firm-level client (partner) sample. Panel D reports summary statistics of pairwise characteristics for the pair-level sample. Definitions of the variables are provided in Appendix 1. p -values of the t-test and Wilcoxon test are reported in the last two columns.

Panel A: Alliance clients versus partners

	Clients			Partners			t-test	Wilcoxon
	Mean	S.D.	Median	Mean	S.D.	Median		
Technological competition	0.220	0.161	0.208	0.150	0.128	0.148	(0.00)	(0.00)
Patent count	112	215	15	33	129	3	(0.00)	(0.00)
Patent diversification	0.592	0.347	0.733	0.410	0.357	0.5	(0.00)	(0.00)
R&D	0.109	0.101	0.098	0.160	0.142	0.126	(0.00)	(0.00)
Total assets (2004 \$ million)	3,527	4,809	1,399	914	2,227	162	(0.00)	(0.00)
Leverage	0.149	0.177	0.102	0.108	0.166	0.029	(0.00)	(0.00)
ROA	0.120	0.168	0.145	-0.012	0.286	0.068	(0.00)	(0.00)
Cash holdings	0.287	0.237	0.237	0.415	0.258	0.414	(0.00)	(0.00)
Tobin's Q	3.533	2.773	2.603	4.167	3.278	2.958	(0.00)	(0.00)
Sales growth	0.472	0.988	0.183	0.721	1.342	0.258	(0.00)	(0.00)
Capex	0.067	0.050	0.055	0.060	0.050	0.046	(0.00)	(0.00)
Number of observations	1,286			1,857				

Panel B: Alliance clients versus their industry- and size-matched firms

	Clients			Client controls			t-test	Wilcoxon
	Mean	S.D.	Median	Mean	S.D.	Median		
Technological competition	0.220	0.161	0.208	0.067	0.085	0.040	(0.00)	(0.00)
Patent count	112	215	15	22	71	2	(0.00)	(0.00)
Patent diversification	0.592	0.347	0.733	0.382	0.390	0.375	(0.00)	(0.00)
R&D	0.109	0.101	0.098	0.027	0.056	0.009	(0.00)	(0.00)

Total assets (2004 \$ million)	3,527	4,809	1,399	2,720	3,743	1,168	(0.00)	(0.00)
Leverage	0.149	0.177	0.102	0.275	0.199	0.267	(0.00)	(0.00)
ROA	0.120	0.168	0.145	0.127	0.109	0.130	(0.12)	(0.00)
Cash holdings	0.287	0.237	0.237	0.109	0.168	0.036	(0.00)	(0.00)
Tobin's Q	3.533	2.773	2.603	1.880	1.488	1.426	(0.00)	(0.00)
Sales growth	0.472	0.988	0.183	0.210	0.601	0.083	(0.00)	(0.00)
Capex	0.067	0.050	0.055	0.056	0.046	0.045	(0.00)	(0.00)

Number of observations 1,286 5,905

Panel C: Alliance partners versus their industry- and size-matched firms

	Partners			Partner controls			t-test	Wilcoxon
	Mean	S.D.	Median	Mean	S.D.	Median		
Technological competition	0.150	0.128	0.148	0.056	0.082	0.018	(0.00)	(0.00)
Patent count	33	129	3	8	36	1	(0.00)	(0.00)
Patent diversification	0.410	0.357	0.5	0.233	0.330	0	(0.00)	(0.00)
R&D	0.160	0.142	0.126	0.060	0.102	0.018	(0.00)	(0.00)
Total assets (2004 \$ million)	914	2,227	162	735	1,740	140	(0.00)	(0.01)
Leverage	0.108	0.166	0.029	0.205	0.214	0.139	(0.00)	(0.00)
ROA	-0.012	0.286	0.068	0.081	0.207	0.120	(0.00)	(0.00)
Cash holdings	0.415	0.258	0.414	0.204	0.243	0.095	(0.00)	(0.00)
Tobin's Q	4.167	3.278	2.958	2.293	1.945	1.573	(0.00)	(0.00)
Sales growth	0.721	1.342	0.258	0.311	0.837	0.109	(0.00)	(0.00)
Capex	0.060	0.050	0.046	0.056	0.054	0.039	(0.01)	(0.00)

Number of observations 1,857 8,768

Panel D: Alliance pairs versus their matching pairs

	Alliance pairs			Control pairs			t-test	Wilcoxon
	Mean	S.D.	Median	Mean	S.D.	Median		
Technological proximity	0.214	0.287	0.046	0.033	0.128	0.000	(0.00)	(0.00)
Same industry	0.498	0.500	0.000	0.426	0.494	0.000	(0.00)	(0.00)
Same state	0.269	0.444	0.000	0.085	0.229	0.000	(0.00)	(0.00)

Number of observations 869 8,142

Table 6
Firm- and Pair-level conditional logit regressions

This table reports coefficient estimates from conditional logit models in Equations (3) and (4). In Panel A, the dependent variable is an indicator variable that equals to one if a firm is the client (partner), and zero otherwise. Column (1) uses the firm-level client sample as described in Table 5 Panel B. Column (2) uses clients and their control firms where for each client, we obtain five randomly-drawn control firms that are not part of an alliance deal in the seven-year period centered at the alliance deal announcement year. Column (3) uses the firm-level partner sample as described in Table 5 Panel C. Column (4) uses partners and their control firms where for each partner, we obtain five randomly-drawn control firms that are not part of an alliance deal in the seven-year period centered at the alliance deal announcement year. In columns (2) and (4), we repeat the regression in Equation (3) 500 times by drawing with replacement at the deal cluster level to obtain standard errors of the coefficient estimates. In Panel B, the dependent variable is an indicator variable that equals to one if a pair is the alliance pair, and zero otherwise. Column (1) uses the pair-level sample as described in Table 5 Panel D. Column (2) uses alliance pairs and their control pairs where for each alliance pair, the client is paired with five randomly-drawn control firms of the partner that are not part of an alliance deal in the seven-year period centered at the alliance deal announcement year, and the partner is paired with five randomly-drawn control firms of the client that are not part of an alliance deal in the seven-year period centered at the alliance deal announcement year. In column (2), we repeat the regression in Equation (4) 500 times by drawing with replacement at the deal cluster level to obtain standard errors of the coefficient estimates. Robust standard errors that allow for clustering at the deal level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Firm-level conditional logit regressions

	<i>Client = 1, client control = 0</i>		<i>Partner = 1, partner control = 0</i>	
	Industry- and size-match	Random match	Industry- and size-match	Random match
	(1)	(2)	(3)	(4)
Technological competition	6.640*** (0.711)	5.040*** (0.699)	4.288*** (0.429)	5.166*** (0.461)
Log (1 + patent count)	0.367*** (0.063)	0.225*** (0.060)	0.265*** (0.049)	0.102** (0.044)
Patent diversification	-1.010*** (0.260)	-0.740*** (0.272)	-0.365** (0.173)	-0.701*** (0.166)
R&D	9.212*** (0.982)	7.876*** (0.784)	5.553*** (0.398)	6.447*** (0.394)
Other firm characteristics	Yes	Yes	Yes	Yes
Deal fixed effects	Yes	Yes	Yes	Yes
Number of observations	7,191	15,309	10,625	12,970
Pseudo <i>R</i> -squared	0.60	0.83	0.44	0.51

Panel B: Pair-level conditional logit regressions

	<i>Alliance pair = 1, control pair = 0</i>	
	Industry- and size-match	Random match
	(1)	(2)
Client technological competition	4.600*** (0.954)	3.099*** (0.994)
Partner technological competition	1.727** (0.715)	1.695*** (0.586)
Log (1 + client patent count)	0.271*** (0.098)	0.137 (0.086)
Log (1 + partner patent count)	0.262*** (0.083)	0.119** (0.051)
Client patent diversification	-0.574 (0.393)	-0.222 (0.352)
Partner patent diversification	-0.335 (0.275)	-0.518** (0.219)
Client R&D	7.186*** (1.134)	6.280*** (1.270)
Partner R&D	5.253*** (0.548)	6.235*** (0.534)
Technological proximity	2.931*** (0.260)	5.073*** (0.443)
Same industry	1.809*** (0.388)	1.921*** (0.115)
Same state	0.822*** (0.132)	0.753*** (0.130)
Other firm characteristics	Yes	Yes
Deal fixed effects	Yes	Yes
Number of observations	9,011	18,906
Pseudo <i>R</i> -squared	0.48	0.70

Table 7
Difference-in-differences regressions

This table reports the ex-post treatment effect of alliances on innovation output of clients and partners using a difference-in-differences approach. The sample is a panel dataset tracking clients (partners) and their industry- and size-matched control firms from three years prior to the alliance deal announcement (year $t-3$) to three years after the alliance deal announcement (year $t+3$). The sample period is 1994-2000. The dependent variable is client (partner) innovation output as measured by the logarithm of one plus patent count. Columns (1) and (3) present estimates from the difference-in-differences regressions in Equation (5). Columns (2) and (4) present estimates from the difference-in-difference-in-differences regressions in Equation (6). Definitions of the variables are provided in Appendix 1. Robust standard errors that allow for clustering at the deal level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	<i>Log (1 + patent count)</i>			
	Clients and their industry- and size-matched control firms		Partners and their industry- and size-matched control firms	
	(1)	(2)	(3)	(4)
Sample $\times$ After $\times$ Tech competition		0.986*** (0.18)		1.792*** (0.15)
Sample $\times$ After	0.169*** (0.03)	0.028 (0.04)	0.191*** (0.02)	-0.048** (0.02)
Sample $\times$ Tech competition		1.095*** (0.19)		1.025*** (0.16)
After $\times$ Tech competition		-0.634*** (0.13)		-0.956*** (0.09)
Sample	0.194*** (0.03)	0.031 (0.04)	0.089*** (0.02)	-0.044* (0.03)
After	0.020** (0.01)	0.062*** (0.01)	-0.011* (0.01)	0.053*** (0.01)
Technological competition	3.310*** (0.14)	2.719*** (0.21)	2.080*** (0.13)	1.775*** (0.13)
Patent diversification	2.518*** (0.04)	2.606*** (0.04)	2.087*** (0.03)	2.124*** (0.03)
R&D	1.341*** (0.16)	1.259*** (0.16)	0.581*** (0.07)	0.585*** (0.07)
Other firm characteristics	Yes	Yes	Yes	Yes
Three pairwise characteristics	Yes	Yes	Yes	Yes
Deal fixed effects	Yes	Yes	Yes	Yes
Number of observations	35,522	35,522	49,476	49,476
Pseudo <i>R</i> -squared	0.86	0.86	0.82	0.82

Table 8
Treatment regressions

This table reports the ex-post treatment effect of alliances on innovation output of clients and partners using the treatment regression with an instrumental variable. The sample includes clients (partners) and their industry- and size-matched control firms. The sample period is 1994-2000. In the first-stage regressions, the dependent variable is an indicator variable that equals to one if a firm is the client (partner), and zero otherwise. In the second-stage regressions, the dependent variable is the logarithm of one plus patent count over the three-year period (year $t+1$ to $t+3$, where year t is the alliance announcement year). We use the client (partner) combined reporting index as the instrumental variable in the first-stage regressions. The construction of this instrumental variable follows Bodnaruk et al. (2013). The combined reporting index is constructed either using location information on a firm's headquarter (columns (1) and (3)) or using location information on a firm's headquarter and its subsidiaries (columns (5) and (7)). The estimation of the two-stage regressions using Stata command *itreatreg* (Brown and Mergoupis, 2010) allows for consistent estimation of the interaction terms involving endogenous variables. Firm characteristics are measured at the fiscal year end before the alliance announcement year. Definitions of the variables are provided in Appendix 1. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Clients and their industry- and size-matched control firms		Partners and their industry- and size-matched control firms		Clients and their industry- and size-matched control firms		Partners and their industry- and size-matched control firms	
	1 st -stage	2 nd -stage	1 st -stage	2 nd -stage	1 st -stage	2 nd -stage	1 st -stage	2 nd -stage
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample × Tech competition		2.738*** (0.202)		2.244*** (0.158)		2.685*** (0.203)		2.230*** (0.158)
Sample		0.042 (0.087)		0.022 (0.052)		0.104 (0.087)		0.040 (0.052)
Combined reporting index (headquarters)	0.124** (0.053)		0.147*** (0.039)					
Combined reporting index (headquarters and subsidiaries)					0.380*** (0.064)		0.225*** (0.042)	
Technological competition	3.790*** (0.291)	-1.236*** (0.183)	2.866*** (0.240)	-1.326*** (0.123)	3.674*** (0.293)	-1.270*** (0.183)	2.824*** (0.241)	-1.334*** (0.123)
Log (1 + patent count)	-0.065*** (0.024)	0.285*** (0.010)	-0.022 (0.022)	0.313*** (0.008)	-0.059** (0.024)	0.286*** (0.010)	-0.020 (0.022)	0.313*** (0.008)
Patent diversification	0.163** (0.078)	3.325*** (0.033)	0.419*** (0.064)	2.778*** (0.025)	0.160** (0.078)	3.323*** (0.033)	0.415*** (0.064)	2.776*** (0.025)
R&D	4.315*** (0.394)	0.450** (0.203)	2.209*** (0.196)	0.289*** (0.084)	4.117*** (0.396)	0.392* (0.203)	2.187*** (0.196)	0.281*** (0.084)
Other firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Three pairwise characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	5,794		8,531		5,794		8,531	

Table 9
The underlying mechanisms

This table examines possible underlying mechanisms through which the improvement in innovation output as shown in Table 7 takes place. In Panel A, the dependent variables are the logarithm of one plus R&D expenditures (columns (1), (2), (5), and (6)) and the logarithm of one plus R&D efficiency (columns (3), (4), (7), and (8)). The sample is a panel dataset tracking alliance clients (partners) and their industry- and size-matched control firms from three years prior to the alliance deal announcement (year $t-3$) to three years after the alliance deal announcement (year $t+3$). The sample period is 1994-2000. Columns (1), (3), (5), and (7) present estimates from the difference-in-differences regressions in Equation (5). Columns (2), (4), (6), and (8) present estimates from the difference-in-difference-in-differences regressions in Equation (6). In Panel B, the dependent variables are the logarithm of one plus the number of unrelated patents (columns (1), (2), (5), and (6)) and the logarithm of one plus the number of related patents (columns (3), (4), (7), and (8)). In Panel C, the dependent variable is the logarithm of one plus the number of patents an inventor has in the three-year period (year $t-3$ to $t-1$) prior to or the three-year period (year $t+1$ to $t+3$) after alliance formation. The sample consists of inventors working either at the alliance participants or their industry- and size-matched control firms. For a particular firm, stayers are inventors who have at least one patent with the firm in the three-year period prior to, at least one patent with the same firm in the three-year period after alliance formation, and do not have any patents outside the firm over these two periods. For a particular firm, new hires are inventors who do not have any patents with the firm in the three-year period prior to, have at least one patent with the firm in the three-year period after alliance formation, and do not have any patents outside the firm over the post-alliance period. Firm characteristics are measured at the end of the three-year period before alliance formation and at the end of the three-year period after alliance formation. Definitions of the variables are provided in Appendix 1. Robust standard errors that allow for clustering at the deal level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: R&D expenditures and R&D efficiency

	<i>Log (1 + R&D expenditures)</i>		<i>Log (1 + R&D efficiency)</i>		<i>Log(1 + R&D expenditures)</i>		<i>Log (1 + R&D efficiency)</i>	
	Clients and their industry- and size-matched control firms				Partners and their industry- and size-matched control firms			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample $\times$ After $\times$ Tech competition		-0.545** (0.26)		-0.026 (0.05)		0.707** (0.29)		0.323*** (0.07)
Sample $\times$ After	0.015 (0.04)	0.201*** (0.06)	0.000 (0.01)	0.012 (0.01)	0.007 (0.03)	-0.080 (0.05)	0.024** (0.01)	0.003 (0.02)
Sample $\times$ Tech competition		0.544 (0.33)		-0.203*** (0.06)		0.097 (0.34)		-0.350*** (0.09)
After $\times$ Tech competition		-0.329* (0.19)		-0.032 (0.04)		-0.356* (0.19)		-0.329*** (0.05)
Sample	1.079*** (0.07)	0.947*** (0.10)	0.034*** (0.01)	0.065*** (0.02)	1.023*** (0.05)	1.004*** (0.08)	0.038*** (0.01)	0.072*** (0.02)
After	0.144*** (0.02)	0.166*** (0.02)	0.006* (0.00)	0.010** (0.00)	0.110*** (0.01)	0.132*** (0.02)	0.012** (0.00)	0.035*** (0.01)
Technological competition	2.811*** (0.19)	2.795*** (0.25)	0.534*** (0.04)	0.671*** (0.05)	2.893*** (0.17)	2.895*** (0.23)	0.542*** (0.04)	0.811*** (0.06)
Patent diversification	1.589*** (0.08)	1.601*** (0.08)	0.394*** (0.01)	0.380*** (0.01)	1.087*** (0.06)	1.097*** (0.07)	0.536*** (0.02)	0.528*** (0.02)

R&D expenditures			-0.128*** (0.01)	-0.127*** (0.01)			-0.176*** (0.01)	-0.176*** (0.01)
Other firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Three pairwise characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	33,014	33,014	23,502	23,502	43,588	43,588	30,647	30,647
Pseudo <i>R</i> -squared	0.70	0.70	0.43	0.43	0.66	0.66	0.42	0.42

Panel B: Unrelated versus related patents

	<i>Log(1 + # of unrelated patents)</i>		<i>Log (1 + # of related patents)</i>		<i>Log(1 + # of unrelated patents)</i>		<i>Log (1 + # of related patents)</i>	
	Clients and their industry- and size-matched control firms				Partners and their industry- and size-matched control firms			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample × After × Tech competition		0.210 (0.23)		0.482*** (0.13)		1.014*** (0.24)		0.634*** (0.18)
Sample × After	0.102*** (0.03)	0.075 (0.05)	0.155*** (0.02)	0.009 (0.03)	0.104*** (0.03)	-0.058* (0.03)	0.098*** (0.02)	-0.062*** (0.02)
Sample × Tech competition		1.522*** (0.22)		0.560*** (0.11)		1.504*** (0.24)		1.665*** (0.27)
After × Tech competition		-0.240 (0.15)		0.085** (0.04)		-0.421*** (0.13)		0.163*** (0.05)
Sample	0.282*** (0.04)	0.037 (0.05)	-0.011 (0.01)	-0.072*** (0.02)	0.114*** (0.03)	-0.046 (0.03)	0.082*** (0.01)	-0.076*** (0.02)
After	0.010 (0.01)	0.024* (0.01)	0.007*** (0.00)	-0.001 (0.00)	-0.006 (0.01)	0.027*** (0.01)	-0.001 (0.00)	-0.000 (0.00)
Technological competition	4.613*** (0.16)	3.800*** (0.23)	0.520*** (0.10)	0.036 (0.05)	1.990*** (0.17)	1.482*** (0.15)	0.628*** (0.15)	-0.160** (0.07)
Patent diversification	1.651*** (0.04)	1.748*** (0.05)	-0.132*** (0.02)	-0.080*** (0.01)	1.290*** (0.03)	1.310*** (0.03)	-0.060** (0.02)	-0.038** (0.02)
R&D	1.424*** (0.21)	1.313*** (0.20)	-0.100 (0.08)	-0.129* (0.08)	0.423*** (0.09)	0.437*** (0.09)	-0.070 (0.04)	-0.050 (0.04)
Other firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Three pairwise characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	23,348	23,348	23,348	23,348	22,966	22,966	22,966	22,966
Pseudo <i>R</i> -squared	0.80	0.80	0.32	0.34	0.68	0.68	0.32	0.39

Panel C: Stayers and new hires

	<i>Log (1 + # of patents)</i>			
	Clients and their industry- and size- matched control firms		Partners and their industry- and size- matched control firms	
	(1)	(2)	(3)	(4)
Sample × After × Tech competition		0.110 (0.10)		0.345** (0.15)
Sample × After	0.036* (0.02)	-0.013 (0.03)	0.055** (0.02)	-0.065* (0.04)
Sample × Tech competition		0.325** (0.15)		0.118 (0.21)
After × Tech competition		0.058 (0.06)		0.075 (0.07)
Sample	0.153*** (0.03)	0.079* (0.04)	0.103** (0.04)	0.091** (0.04)
After	0.017* (0.01)	0.005 (0.01)	0.009 (0.01)	-0.007 (0.01)
Technological competition	0.049 (0.11)	-0.165 (0.10)	0.215 (0.17)	0.002 (0.18)
Patent diversification	-0.277*** (0.04)	-0.259*** (0.04)	-0.141*** (0.05)	-0.110** (0.05)
R&D	0.498*** (0.18)	0.516*** (0.17)	0.378** (0.15)	0.411*** (0.15)
Other firm characteristics	Yes	Yes	Yes	Yes
Other pairwise characteristics	Yes	Yes	Yes	Yes
Deal fixed effects	Yes	Yes	Yes	Yes
Number of observations	77,849	77,849	52,653	52,653
Pseudo <i>R</i> -squared	0.06	0.06	0.08	0.08

Table 10
Technological competition and other forms of firm boundary changes

This table reports coefficient estimates from Tobit models in Equation (2) for joint ventures and mergers and acquisitions. The panel data sample includes non-financial innovative firms covered by Compustat/CRSP over the period 1991-2004. In columns (1) and (2), the dependent variable is the logarithm of one plus the number of JV deals. In column (1), JV deals involve public firms only, whereas deals involving public firm subsidiaries are included in column (2). In columns (3) and (4), the dependent variable is the logarithm of one plus the number of M&A deals in which the firm is either the acquirer or the target firm. In column (3), M&A deals involve public firms only, whereas deals involving public firm subsidiaries are included in column (4). Firm characteristics are measured at the fiscal year end before the deal announcement year. Definitions of the variables are provided in Appendix 1. Robust standard errors that allow for clustering at the deal level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	Joint Ventures		Mergers & Acquisitions	
	<i>Log (1 + # of JVs, public firms only)</i>	<i>Log (1 + # of JVs, including subsidiary deals)</i>	<i>Log (1 + # of M&As, public firms only)</i>	<i>Log (1 + # of M&As, including subsidiary deals)</i>
	(1)	(2)	(3)	(4)
Technological competition	0.108 (0.211)	0.267 (0.210)	0.346** (0.146)	0.366*** (0.127)
Patent count	0.141*** (0.023)	0.147*** (0.022)	-0.007 (0.015)	0.023* (0.014)
Patent diversification	-0.187** (0.088)	-0.200** (0.087)	0.056 (0.055)	0.029 (0.048)
R&D	-0.179 (0.240)	-0.128 (0.244)	-0.369*** (0.137)	-0.349*** (0.125)
Other firm characteristics	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Number of observations	31,983	31,983	31,983	31,983
Pseudo <i>R</i> -squared	0.22	0.20	0.06	0.10

Table 11
Product market fluidity

This table compares the roles of technological competition and product market fluidity in alliance formation and post-alliance innovation outcome. Panels A and B replicate Tables 4 and 8, respectively, while including product market fluidity as an additional explanatory variable. Product market fluidity is from Hoberg et al. (2014). Definitions of the variables are provided in Appendix 1. Robust standard errors that allow for clustering at the firm level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Tobit regressions

	<i>Log (1 + # of alliances, public firms only)</i>	<i>Log (1 + # of alliances, including subsidiary deals)</i>
	(1)	(2)
Technological competition	0.747*** (0.190)	0.990*** (0.204)
Product market fluidity	6.549*** (0.572)	7.153*** (0.626)
Log (1 + patent count)	0.139*** (0.019)	0.153*** (0.021)
Patent diversification	-0.291*** (0.073)	-0.342*** (0.080)
R&D	0.904*** (0.173)	0.919*** (0.173)
Other firm characteristics	Yes	Yes
Industry fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Number of observations	16,163	16,163
Pseudo <i>R</i> -squared	0.18	0.18

Panel B: Treatment regressions

	Clients and their industry- and size-matched control firms		Partners and their industry- and size-matched control firms	
	1 st -stage	2 nd -stage	1 st -stage	2 nd -stage
	(1)	(2)	(3)	(4)
Sample × Tech competition		4.782*** (0.331)		2.722*** (0.238)
Sample × Product market fluidity		1.466 (1.235)		-1.681** (0.821)
Sample		-0.575*** (0.190)		0.131 (0.120)
Combined reporting index (headquarters and subsidiaries)	0.197* (0.102)		0.136** (0.066)	
Technological competition	3.890*** (0.485)	-2.730*** (0.300)	2.585*** (0.357)	-1.613*** (0.182)
Product market fluidity	7.783*** (1.494)	-0.902 (0.646)	7.732*** (1.146)	-1.347*** (0.439)
Log (1 + patent count)	-0.091** (0.040)	0.326*** (0.016)	0.020 (0.032)	0.312*** (0.012)
Patent diversification	0.402*** (0.127)	3.335*** (0.051)	0.328*** (0.097)	2.811*** (0.037)
R&D	2.701*** (0.585)	0.765*** (0.274)	1.672*** (0.301)	0.214* (0.121)
Other firm characteristics	Yes	Yes	Yes	Yes
Three pairwise characteristics	Yes	Yes	Yes	Yes
Number of observations	2,168		3,573	