Innovation beyond Firm Boundaries: Common Blockholders, Strategic Alliances, and Corporate Innovation

Thomas Chemmanur* Yao Shen† Jing Xie‡

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Abstract

We analyze the role of common equity blockholders in fostering the formation of strategic alliances, establish a positive causal effect of strategic alliances on corporate innovation, and analyze the channels through which strategic alliances foster innovation. Our findings may be summarized as follows. First, there is a positive and causal relation between the fraction of a firm's industry peers with which it shares common blockholders and the number of strategic alliances that it enters into. Second, there is a positive relation between the R&D-related alliances formed by a firm and its subsequent innovation outcomes, as measured by the quantity and quality of patents filed, especially for alliances backed by common blockholders. Third, we document, for the first time in the literature, a unique method that firms use to share patent rights with their alliance partners, namely, "co-patenting". Fourth, we establish a positive causal relation between the formation of strategic alliances and innovation: first, by comparing the innovation of firms that fail to form alliances to those of firms that are able to successfully form strategic alliances; and second, by using an instrumental variables approach. Fifth, we establish that an important channel through which strategic alliances foster greater innovation is through the more efficient redeployment of human capital (inventors) across alliance partners.

Keywords: Corporate Innovation; Strategic Alliances; Common Blockholders
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* Professor of Finance and Hillenbrand Distinguished Fellow, Carroll School of Management, Boston College, 440 Fulton Hall, 140 Commonwealth Avenue, Chestnut Hill, MA 02467. E-mail: chemmanu@bc.edu. Phone: (617) 552-3980. Fax: (617) 552-0431.

† Assistant Professor in Finance, Zicklin School of Business, Baruch College, CUNY, One Bernard Baruch Way, B10-225, New York, NY 10010. Email: yao.shen@baruch.cuny.edu

‡ Assistant Professor in Finance, School of Accounting and Finance, Hong Kong Polytechnic University. Li Ka Shing Tower, Hung Hom, Hong Kong. E-mail: jingxie@polyu.edu.hk.

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1 Introduction

It is well known that innovation is an important driver of the growth of firms and even the long-run economic growth of nations (Solow, 1957). However, much of the existing literature that analyzes the determinants of corporate innovation has focused on organizational and financial factors that affect a firm in isolation rather than on its relationships with other firms in its industry. In this paper, we study a potentially equally important factor that may drive corporate innovation, namely, the contractual relationships that a firm may develop with other firms in its industry. In particular, we focus on the formation of strategic alliances by a firm and their effect on corporate innovation. We first analyze the determinants of the formation of strategic alliances and provide evidence that having common equity blockholders with other firms in its industry facilitates the formation of strategic alliances by a firm. We then establish a positive causal relation between the formation of a particular form of strategic alliance, namely, an R&D-related strategic alliance, and an enhanced quality and quantity of corporate innovation. We also document the sharing of rights to innovations by alliance partners in the form of "co-patenting". Finally, we show that an important mechanism through which strategic alliances enhance innovation is by allowing better redeployment of human capital (movement of inventors) among the firms forming a strategic alliance.

There has been some debate in the academic as well as practitioner literature on the determinants of strategic alliance formation and the effect of such alliance formation on innovation. On the one hand, the formation of strategic alliances may confer obvious benefits to the firms forming the alliance since each firm can receive some ingredients required for innovation from outside their firm boundaries, thus supplementing the resources available within the firm. On the other hand, lack of trust between the two firms involved may impede the formation of strategic alliances despite the above advantage from such alliance formation. In particular, some firms may be reluctant to form strategic alliances because of the fear that their alliance partners, often competitors, may steal valuable intellectual property or other information. In this context, third parties that have economic links to both the competing firms may play a crucial role in initiating strategic alliances between them by removing informational and organizational barriers. We argue that blockholders, with significant shareholdings in both firms, may help to build trust, align interests, and foster strategic alliances between two competing firms. We then show that the presence of common equity blockholdings by institutions across firms in an industry promotes the formation of strategic alliances among these firms.

The above results on the effect of common blockholders on the propensity to form strategic alliances are unlikely to be driven by reverse causality. To demonstrate this, we exploit the annual Russell 1000/2000 index reconstitutions that bring exogenous shocks to the investor base of firms that switch index membership by a small margin. We find that firms that become more (less) connected with industry peers, after the annual index reconstitutions, form more (less) alliances than before. This evidence shows that our results are not driven by institutions accumulating blocks in the firms forming a strategic alliance because they anticipate the future formation of an alliance between these firms.

After analyzing the determinants of the formation of strategic alliances, we turn to our analysis of the effect of strategic alliances on corporate innovation. We focus on a specific type of alliance devoted to innovation, namely, an R&D-related strategic alliance, in our empirical analysis.[1] Theoretical models offer conflicting views about how the strategic alliance activities of firms affect their innovation output. For instance, D'Aspremont and Jacquemin (1988) ar-

[1] In the rest of this paper, we focus only on a specific form of strategic alliances devoted to innovation which we refer to as an "R&D-related strategic alliance" or sometimes simply as "R&D-related alliance". The other common forms of strategic alliances are marketing, manufacturing, and licence alliances.

gue that R&D cooperation help to improve firm innovation outcomes when spillovers are high enough. Robinson (2008) argues that strategic alliances help overcome incentive problems that arise when headquarters cannot pre-commit to a certain level of capital allocation. The above papers imply that R&D strategic alliances contribute positively to innovation through better aligned incentives and more efficient capital allocation. López and Vives (2016) suggest that, when knowledge-spillovers are high enough, firms may free-ride on the innovation efforts of their rivals and lower their investment in innovation. Therefore, in the presence of such knowledge-spillovers, R&D cooperation allows firms to internalize externalities, thereby preserving their incentives to invest in R&D. This paper implies that R&D-related strategic alliances contribute positively to innovation through limiting free riding among rivals.[2] In contrast to the above theories that predict a positive relation between R&D-related strategic alliances and innovation outcomes, a large body of research on the theory of moral hazard in teams predicts that alliance formation will distort innovation incentives and affect innovation outcomes negatively. For instance, Bonatti and Hörner (2011) suggest that free-riding between collaborating partners leads not only to a reduction in effort, but also to procrastination. Further, Campbell, Ederer, and Spinnewijn (2014) argue that, in addition to free-riding, lack of communication in teams may also lead to delays.

Motivated by the above theoretical papers, we hypothesize that, while strategic alliances may enhance the quantity and quality of innovation by alliance partners, their positive influence on corporate innovation may be driven primarily by alliances between firms that have common equity blockholdings. Blockholders in a firms' equity are likely to have produced detailed in-

[2]There are also many examples from the practitioner orientated literature consistent with the prediction that strategic alliances may have a positive effect on innovation. For example, Bill Gates, founder and former CEO of Microsoft, is quoted as saying: "The collaboration between Microsoft and Toshiba has consistently led to innovation (Toshiba) has also been our lead partner in developing Windows Vista for portable PCsI am sure our companies will continue to introduce break-through innovations for years to come." (2005 Annual Report of Toshiba Corporation)

formation about the strategy and the progress made by firms that they have invested in. At the same time, by virtue of their significant equity holdings in a firm, blockholders are also able to communicate directly with top firm management. Finally, these blockholders may also have the ability to influence firms' corporate behavior, for example, they can threaten to "exit" these firms, i.e., to sell their blockholdings. The above implies that blockholders common to partnering firms in a strategic alliance have the ability to enhance communication and coordination among alliance partners as well to monitor the behavior of alliance partners. This, in turn, may mitigate the costs arising from strategic alliances while enhancing their benefits.

The results of our empirical analysis support the above hypothesis. In our baseline results, we find a strong positive relation between the number of R&D-related strategic alliances formed by a firm and the quantity (number of new patents obtained) and the quality (total citations or citations per patent) of innovation output by the firm after the formation of these alliances. We also find that firms that have more R&D-related strategic alliances have higher innovation efficiency, as measured by either the number of new patents or the total citations for new patents scaled by R&D spending (Hirshleifer, Low, and Teoh, 2012). In addition, we find that R&D-related strategic alliances generate more favourable innovation output when the partnering firms are of higher quality (measured by their past innovation productivity). Moreover, the positive effect of R&D-related strategic alliances on innovation is primarily driven by alliances backed by common blockholders although the average effect of R&D-related strategic alliances on innovation is positive. Finally, we document the sharing of rights to innovations by alliance partners in the form of co-patenting. "Co-patenting patents" refer to patents with multiple assignees, which we view as direct evidence of research output arising from R&D collaboration between multiple firms. We find a strong positive relation between the number of R&D-related

strategic alliances formed by a firm and the number of new co-patenting patents that the firm obtains subsequent to the formation of these alliances.

While our baseline results are consistent with the hypothesis of a positive effect of strategic alliances on innovation, an important concern is that the formation of strategic alliances is potentially endogenous. For example, firms with higher innovation potential may attract more alliance partners. Moreover, unobservable firm characteristics may also affect both alliance formation and innovation outcomes. Therefore, to establish causality, we use three different identification strategies.

Our first identification strategy is to examine pre-existing trends in innovation (following Bertrand and Mullainathan (2003)) making use of a matched sample. For each firm that form a successful alliance, we find a matching firm that does not form alliances using a propensity score matching approach. We analyze the change in corporate innovation for both groups of firms using a difference-in-difference approach. We find that firms that form alliances experience an increase in both the quantity and quality of innovation outcomes after alliance formation. Moreover, we find that R&D-related strategic alliances have no impact on innovation one year before the announcement of the formation of the alliance. Most of the change in innovation occurs two or three years after the announcement of the alliance, indicating a causal effect of strategic alliances on innovation.

Our second identification strategy relies on the fact that firms that announce a strategic alliance but fail to complete it would serve as a comparable counterfactual to firms that form alliances successfully. This approach is somewhat similar to the failed M&A approach adopted by Savor and Lu (2009), though it differs from their analysis in that we conduct this test in the context of failed strategic alliances. We compare the innovation output of firms with announced but failed R&D-related alliance deals to the innovation output of firms with announced and successfully completed R&D-related alliance deals. We find that firms with failed R&D-related strategic alliance deals generate fewer patents and fewer total citations for their new patents obtained after the announcement. It is unlikely that there is a systematic relation between the innovation potential of a firm and the probability that the firm's announced R&D-related alliances fail, so that this identification strategy helps us to establish a causal effect of a firms strategic alliances on its subsequent innovation outcomes.

Our third identification strategy is to conduct an instrumental variable (IV) analysis where our instrument for the formation of a strategic alliance is the fraction of industry peers within driving distance (250KM) from the firms headquarters.[3] The results of our IV analysis confirm the positive effect of R&D-related strategic alliances on innovation. Overall, our identification tests suggest that R&D-related strategic alliances have a positive causal effect on the innovation of alliance partners.

In the final part of our paper, we uncover one mechanism through which strategic alliances may help to increase the innovation output and innovation productivity of firms. In particular, we investigate the effect of R&D-related strategic alliances on human capital redeployment between alliance partners. We provide three pieces of evidence in this regard. First, we find a strong positive relation between the number of R&D-related strategic alliances formed by a firm and the number of inventors, who have past work experience with one of the firms alliance partners (alliance-connected inventors), currently employed by this firm. Second, we find a positive relation between the number of R&D-related strategic alliances formed by a firm and the number of new patents (and the number of total citations for the new patents) contributed

[3]Prior studies suggest that the likelihood of alliance formation is negatively related to geographic distance, even within clusters: see, e.g., Reuer and Lahiri (2014) or Phene and Tallman (2014).

by alliance-connected inventors. Finally, we find that, the higher the number and the higher the quality of alliance-connected inventors employed by a firm involved in an R&D-related strategic alliance (as measured by the number of patents granted to alliance-connected inventors employed by the firm and the citations to these patents), the higher the quantity and quality of the total innovation achieved by that firm. Overall, we show that an important channel through which strategic alliances positively affect corporate innovation is by the redeployment of human capital (inventors) across alliance partners (as appropriate).

The rest of this paper is organized as follows. Section 2 discusses how our paper is related to the existing literature and our contribution to this literature. Section 3 describes our sample selection procedures. Section 4 analyzes the determinants of strategic alliances and in particular the relation between common equity blockholders and the formation of strategic alliances. Section 5 presents our baseline results on the effect of R&D-related strategic alliances on corporate innovation. Section 6 presents three different empirical methodologies through which we establish causality between the formation of R&D-related strategic alliances and innovation. Section 7 shows that one mechanism through which R&D-related strategic alliances enhance innovation is by facilitating the redeployment of human capital across alliance partners. Section 8 concludes.

2 Relation to the Existing Literature and Contribution

Our paper contributes to three different strands in the existing literature. The first literature our paper contributes to is the large literature on the effects of firm organization form and firm boundaries on corporate innovation. Seru (2014) argues that the conglomerate form negatively affects corporate innovation. Other papers in this literature show that firm boundaries shaped by strategic alliances have positive effects on firm growth. For instance, D'Aspremont and Jacquemin (1988) argue that R&D cooperation help to improve firm innovation outcome when spillovers are high enough. Chan, Kensinger, Keown, and Martin (1997) suggest that the formation of strategic alliances is associated with a positive stock market reaction and better long-run operating performance. They find that, for alliances within the same industry, more value is created when the alliance involves the transfer or pooling of technical knowledge compared to cases of nontechnical alliances. The above paper implies that technical alliances, such as R&D-related strategic alliances, create more value for the firms involved. Robinson (2008) pushes this argument further by introducing managerial effort into a model of internal capital markets. He argues that strategic alliances resolve contracting problems that surround resource allocations made in internal capital markets by facilitating the abandonment of winner-picking when it is ex ante inefficient.[4]

However, the existing literature has documented that there are large variations in the effect of strategic alliances on firm growth. For example, Lerner, Shane, and Tsai (2003) show that alliance agreements that are signed during periods of limited external equity financing are significantly less successful than other alliances. The empirical evidence in Lerner, Shane, and Tsai (2003) is consistent with the theoretical arguments that have been made about the costs arising from strategic alliances. For example, Bonatti and Horner (2011) argue that free-riding between collaborating partners leads not only to a reduction in effort, but also to procrastination. Campbell, Ederer, and Spinnewijn (2014) argue that, in addition to free-riding, lack of communication in teams may also lead to delays. Our paper contributes to this literature by analyzing how

[4]Bodnaruk, Massa, and Simonov (2013) find that role of alliances as a commitment technology is particularly important when the commitment problems are more acute, such as for significantly risky/long-horizon projects. Other papers also examine the interplay between strategic alliance partners and other participates, such as venture capital: see, e.g., Lindsey (2008) and Ozmel, Robinson, and Stuart (2013).

extending firm boundaries through the formation of R&D-related strategic alliances affects the outcomes of cooperative research endeavors between partnering firms. In addition, we explore the effect of R&D-related strategic alliances backed by common blockholders, since the presence of common blockholders may help to limit the costs arising from alliance formation while enhancing the benefits from such alliances. Moreover, we establish a positive causal relation between the formation of strategic alliances and subsequent corporate innovation output using three different empirical methodologies, and document a potential mechanism through which strategic alliances enhance corporate innovation.[5]

A contemporaneous paper that explores the formation and effects of strategic alliances is Li, Qiu, and Wang (2015), who argue that competition spurs the formation of alliances, and that strategic alliances promote corporate innovation. Our paper differs from the above paper in several important ways, though some of the evidence we present here may be viewed as being complementary to evidence presented by Li, Qiu, and Wang (2015). First, we show, for the first time in the literature, that the existence of common equity blockholders, after controlling for competition, fosters the formation of strategic alliances. Second, we adopt a different and arguably cleaner identification strategy to establish a causal relation between R&D-related strategic alliances and innovation outcomes. Further, we show that the positive effect of R&D-related alliances on corporate innovation is primarily driven by alliances backed by common equity blockholders. Third, we document a unique manifestation of the outcome of R&D-related strategic alliances, namely, co-patenting between alliance partners. Fourth, we establish that an important channel through which strategic alliances promote innovation is

[5]Our paper also contributes to the related literature that studies some other implications of strategic alliances. For example, Allen and Phillips (2000) document that strategic alliances create value for the target in an equity ownership transaction; Gomes-Casseres, Hagedoorn, and Jaffe (2006) study whether alliances affect information flow between alliance partners; Mathews (2006) analyzes how alliances motivate interfirm equity sales between alliance partners; and Robinson and Stuart (2006) find that past alliance relationships serve as a governance mechanism in interfirm transactions.

through more efficient human capital redeployment (inventors switching jobs between the two firms that previously formed a strategic alliance).

The second literature that our paper contributes to is the broader literature on the determinants of corporate innovation. The existing empirical evidence shows that various market-level and firm-specific factors affect managerial incentives to invest in innovation. Specifically, better access to bank credit (Cornaggia, Mao, Tian, and Wolfe, 2015), larger institutional ownership (Aghion, Van Reenen, and Zingales, 2013), less short-term pressures exerted by the financial markets (Tian and Wang, 2014; He and Tian, 2013), more non-executive employee stock options (Chang, Fu, Low, and Zhang, 2015), greater board independence (Balsmeier, Fleming, Manso, 2016), higher CEO overconfidence (Hirshleifer, Low, and Teoh, 2012), backing by corporate rather than independent venture capital firms (Chemmanur, Loutskina, and Tian, 2014) have all been shown to help to nurture greater corporate innovation. However, existing studies have largely ignored research inputs from outside the firm boundary: noteworthy exceptions are papers on acquiring innovation through M&A (Phillips and Zhdanov, 2012; Bena and Li, 2014; Sevilir and Tian, 2012), and learning from economically-linked customers (Chu, Tian, and Wang, 2015). Our paper contributes to this latter line of research by offering direct evidence that R&D-related strategic alliances are an effective channel for a firm to obtain important ingredients for innovation from outside the firm, and that they causally enhance corporate innovation.

Finally, our paper contributes to the debate about the role of financial institutions, particularly institutions that are blockholders, in influencing corporate behavior. We focus on the role of institutional blockholders in facilitating the formation of strategic alliances that may possibly nurture corporate innovation. Edmans (2009) argues that blockholders benefit firms by exerting implicit governance power, through "voting with their feet", and discipline myopic managerial behavior (such as underinvestment in intangible assets); see also Edmans and Manso (2011). Applying this theoretical framework to corporate innovation, blockholders may spur corporate innovation by reducing underinvestment in R&D. In contrast, Aghion, Van Reenen, and Zingales (2013) argue that institutional shareholders increase innovation incentives through reducing the career risk of managers and find a positive relation between institutional ownership and corporate innovation. In addition to these channels through which institutional shareholders may affect corporate innovation, we show, for the first time in literature, that the presence of common equity blockholdings by institutions across firms in an industry promotes the formation of strategic alliances and thereby enhance in-house innovation with resources from outside firm boundaries. Our paper enriches recent discussions about the effect of common ownership among firms on corporate actions. For example, Appel, Gormley, and Keim (2015) argue that quasi-indexers as shareholders play a key role in influencing firms' corporate governance choices. In a similar vein, Anton, Ederer, Gine, Schmalz (2016) find that executives are paid less for their own firm's performance and more for their rivals' performance if firms in an industry are commonly owned by the same set of investors. Finally, Azar, Schmalz, Tecu (2016) find that common ownership increases market concentration and hence increases ticket prices in the airline industry.

3 Data and Sample Selection

This section describes our data and sample used in our analysis, and provides summary statistics of the main variables.

3.1 Sample Selection

The sample includes US listed firms during the period from 1993 to 2003. We collect firm-year patent and citation information from the latest version of the National Bureau of Economic Research (NBER). To calculate the control variables, we collect information about strategic alliances from the Thomson Financial SDC Platinum database, financial statement items from Compustat, institutiaonal holdings data from Thomson's CDA/Spectrum database (13F), and stock price information from the Center for Research in Security Prices (CRSP). We also collect information about inventors from the Harvard Patent Network (Li, Lai, D'Amour, Doolin, Sun, Torvik, Yu, and Lee, 2014). The sample selection process ends up with 36,046 firm-year observations used in our baseline regressions.

3.2 Variable Measurement

3.2.1 Measuring Innovation

Data for patent counts and patent citations are constructed using the latest edition of the NBER patent database (Hall, Jaffe, and Trajtenberg, 2001). This covers over 3.2 million patent grants and 23.6 million patent citations from 1976 to 2006. Our first measure of innovation is the number of patent applications by a firm during the year.

Patents are included in the database only if they are eventually granted. Furthermore, there is, on average, a 2-year lag between patent application and patent grant. Since some patents applied in 2004-2006 may not appear in the database, as suggested by Hall, Jaffe, and Trajtenberg (2001) and Hirshleifer, Low, and Teoh (2012), we end our sample period in 2003 and include year fixed effects in our regressions to address potential time truncation issues.

Since patented innovations vary widely in their technological and economic importance, we use the total number of citations ultimately received by the patents applied for during the given year as our second measure. This measure takes into account both the number of patents and the number of citations per patent.

Patents created near the ending year of the sample have less time to accumulate citations because citations are received for many years after a patent is created. Following the existing innovation literature, see, e.g., Hall, Jaffe, and Trajtenberg (2001, 2005), we adjust the citation measure to mitigate the truncation bias in citation counts.

We also use four additional measures about the innovation productivity of a firm: citations per patent (the average quality of a patent), patent generality (the breadth of citations this patent has received), patent efficiency (total number of new patents per million of R&D expenses), citations efficiency (total number of new citations per million of R&D expenses).

In the final part of our empirical tests, we also measure the number and total citation of co-patenting patents (patents with multiple assignees). For each of the joint assignees, the ownership of the patent is equal to one divided by the total number of joint assignees for this patent. After we obtain the ownership of each firm in each co-patenting patent, we use the firm-level average as our dependent variable.

3.2.2 Measuring R&D-Related Strategic Alliances and other Control Variables

We obtain strategic alliance information from the SDC Platinum database. We count the number of R&D-related strategic alliances formed by a firm in the past five years.[6] Since R&D-related strategic alliances are very scarce before 1989, we start our sample period in 1993. We retain the R&D-related strategic alliances that involve at least one US listed firm. We then take the

[6]We also use alternative period length to count the number of past R&D-related alliances, such as three years or ten years. The results are qualitatively similar.

natural logarithm of (one plus) this raw measure to construct our main explanatory variable (*Log(1+#RDA)*). We focus on R&D-related strategic alliances in our main tests (other alliance types include, but are not restricted to: marketing alliance, manufacturing alliance, and licencing alliance).

Following the innovation literature, we control for firm characteristics that may affect a firm's future innovation output. We compute all variables for firm i over its fiscal year t (one year prior to the period when the dependent variable is measured). The control variables include firm size (the nature logarithm of book assets), firm age (the number of years since the initial public offering (IPO) date), investments in intangible assets (R&D expenditures over total assets), profitability (return on assets (ROA)), tangible assets (net property, plant, and equipment (PPE) scaled by total assets), leverage, capital expenditures, growth opportunities (Tobin's Q), financial constraints (the Kaplan and Zingales (1997) five-variable KZ index), industry concentration (the Herfindahl index based on sales), institutional ownership, and stock illiquidity (the natural logarithm of relative effective spreads), and market share (sales of a firm scaled by the sum of sales for firms in the same industry).

3.3 Summary Statistics

Table 1 provides summary statistics of the main variables based on the sample for our baseline analysis. Our main dependent (explanatory) variables are taken from a sample period from 1994 through 2004 (1993-2003). Due to the right-skewed distributions of patent counts and citations, we follow the literature to measure the dependent variables as the natural logarithm of one plus the number of patents or citation counts (we add one to the actual values when calculating the natural logarithm in order to avoid losing firm-year observations with zero patents or citations). On average, a firm in our final sample has a log total number of 0.703 patents and 1.372 total citations per year, among which an average of 0.037 patents are filed as co-patents (according to our characterization) generating 0.104 citations from co-patents per year. For each firm year, we also identify the inventors (from the HBS inventor database) that apply for a patent from this company. An inventor is treated as a strategic alliance (SA) related inventor if he/she has worked before in at least one of the firms involved in an R&D-related strategic alliance. On average, we identify 0.042 SA related inventors who contribute 0.053 patents and 0.091 citations per year. In addition to patent and citation count measures, we also track the average number of citations per patent, patent generality (measured as one minus the Herfindahl index of the three-digit technology class distribution of all patents that cite a given patent by a firm, averaged across all patents generated by that firm in a given year) as well as patent and citation efficiency (equal to the log of one plus the number of total patents or citations, respectively, in year t+1 divided by the R&D expense of a firm in year t).

An average firm in our sample has a log total number of 0.141 R&D-related strategic alliances established in from year t-4 to t. Following the innovation literature, we control for a vector of firm and industry characteristics that may have an impact on firms' future innovation productivity. These variables include size, R&D expenditure, capital expenditure, ROA, firm age, tangibility, leverage, Tobin's Q, stock illiquidity, institutional ownership, KZ index, Herfindahl index, and market share. In our sample, an average firm has total assets of $5.123 billion, ROA of 3.3%, PPE ratio of 24.4%, leverage of 15.1%, Tobin's Q of 2.3, and has a log firm age of 2.174 years since its IPO date.

4 Determinants of Strategic Alliances: Common Blockholders and Formation of Strategic Alliances

4.1 Connections with Industry Peers through Common Blockholders (Baseline Results)

To assess whether the existence of common blockholders increases the formation of strategic alliances, we first identify blockholders in each firm as those institutions that hold at least five percent of the shares outstanding in that firm. Then we determine whether two firms are cross-held by the same blockholder. If at least one institution holds a block in both firms, then we refer to the two firms as being connected. The variable we are interested in is the fraction of industry peers that are connected to this firm by a common blockholder, which we call *% of Peers Connected*. The underlying rationale for this is that most alliances are formed between firms in the same industry.

The dependent variables in this analysis measure number of different types of strategic alliances (in log) in year $t+1$. In this test, we use information about R&D-related alliances as well as other forms of strategic alliances. For example, $\#SAJV$ refers to the total number of all kinds of strategic alliances formed in year $t+1$, $\#RDA$ refers to the total number of R&D-related strategic alliances formed in year $t+1$, $\#LIC$ refers to the total number of licencing-related strategic alliances formed in year $t+1$, $\#MKT$ refers to the total number of marketing-related strategic alliances formed in year $t+1$, $\#MNF$ refers to total number of manufacturing-related strategic alliances formed in year $t+1$. All control variables are measured in year t.

In Table 2 panel A, we find evidence of a significant relation between the fraction of industry peers that are connected to a firm (through common blockholders) and the number of strategic alliances the firm forms in the subsequent year. This effect shows up when we look at the aggregate number of all forms of alliances. When we do a breakdown based on the types of strategic alliances, we find that this result holds for alliances that involve exchange of technological information or sensitive marketing information (i.e., R&D alliances, licencing alliances and marketing alliances), but not for manufacturing alliances. We use two-digit SIC code as industry classification, but we repeat our tests using one-digit or three-digit SIC code and observe similar results (please refer to the table in our Internet appendix).

4.2 Connections with Industry Peers through Common Blockholders of Different Types

We further extend our analysis to differentiate the effects of three types of institutions in connecting the firm and its industry peers: quasi-indexer, transient investors, and dedicated investors. We follow the classification of institutional investors proposed by Bushee and Noe (2000). Appel, Gormley, and Keim (2015) argue that quasi-indexers are passive investors, not passive owners, and provide evidence that quasi-indexers play a key role in influencing firms' corporate governance choices. Similarly, quasi-indexers are also influencing other corporate policies like payouts, investment, the composition of CEO pay, management disclosure, and acquisitions (Boone and White, 2015; Crane, Michenaud, and Weston, 2016; Lu, 2014).

Consistent with the active role of quasi-indexers in existing literature, in Table 2 panel B, we find that quasi-indexers play an important role in facilitating R&D-related alliances through their cross-holding in firms in the same industry. This evidence supplements recent discussions regarding the influence of these passive investors on corporate policy. We also find evidence that equity cross-holding by transient investors contributes to formation of alliances. It suggests that investors with relative shorter investment horizon have incentives to speed up the technology development through co-operation between firms. However, due to the nature of the short horizon of these investors , transient investors are also likely to help to form alliances and exit after capturing the short-term gain once the alliance is formed.[7] In contrast, we find that dedicated investors do not help the formation of R&D-related alliance. One possible reason for this may be that the presence of dedicated investors, with longer investment horizon, and presumably higher tolerance for R&D failures, allows the firm to take more risk by carrying out its R&D alone, rather than sharing the benefits of its R&D efforts with other research partners.

Anton, Ederer, Gine, Schmalz (2016) argue theoretically and document emprically that compensation schemes (and therefore managerial objectives) in firms with blockholdings seem to be such that managers take the effect of common blockholdings into account when making various corporate decisions. Therefore, although it is unlikely that passive investors such as index funds go into every firm that is part of their index portfolios and help them form strategic alliances, firm managers with significant commonblockholdings may themselves implicitly change their objective functions in such a way that they are more likely to form strategic alliances.

4.3 Connections with Industry Peers: Difference-in-Difference Analysis using Russell 1000/2000 Index Reconstitution

The positive relation that we document above between having common blockholders and the formation of strategic alliances may reflect either the active role of institutional blockholders in shaping corporate policy or the anticipation effect by these institutional investors. The anticipation effect explanation is that institutional investors anticipate the formation of strategic

[7]Chan, Kensinger, Keown, and Martin (1997) documented that the announcement effect upon the formation of strategic alliances is positive.

alliances in the future and therefore accumulate a block in the firms before they form an alliance. To differentiate between these two possible explanations, we use an exogenous shock to the investor base caused by the annual Russell index reconstitution. In May of each year, the Russell Company assigns the largest 1000 companies, based on firm market capitalization at the end of May, into the Russell 1000 index and the next 2000 companies into the Russell 2000 index. For firms that just pass the index reconstitution threshold and move from one index to the other index, the change of investor base is primarily due to reasons unrelated to firm fundamentals. The event of index reconstitution reflects an exogenous shock to the investor holdings in the switchers, and therefore a shock to the presence of common blockholders in these stocks. We therefore use index reconstitution in the Russell Index to distinguish between the above two alternative explanations.

To accomplish the above, we identify firms that switch index membership during two consecutive years but just cross the index reconstitution threshold. In particular, we retain firms that belong to the Russell 1000 (2000) index in year t -1, but switch to Russell 2000 (1000) index in year t . In addition, we require that the firms' ranks in year t, after switching indexes, fall in the range from 1001st to 1200th for the Russell 2000 index (801st to 1000th for the Russell 1000 index). In other words, we require that the distance of the retained index switchers to the reconstitution threshold be less than 200 following the existing literature that also explores the same event, such as Boone and White (2015).

For each of these index switchers in year t , we calculate the fraction of industry peers taht it connects via common blockholders as of the June of year t -1 and the June of year t , separately. We then calculate the change in the fraction of industry peers it connects from year t -1 to t . Within each year, we sort firms into three groups based on the change of the fraction of industry peers it connects. Firms in the top (bottom) group experience the largest increase (decrease) in the industry peers that they are connected with. We use firms in the top group as the treatment group and, as a comparison, use firms in the bottom group as the control group.

We measure the number of R&D-related strategic alliances and all other types of alliances formed by each firm in the twelve months starting from the July of year t (immediately after the index reconstitution). We compare it with the number of alliances formed in the twelve months immediately before the index reconstitution. We report the difference in the number of alliances formed during the twelve months after to the twelve months before. Table 3 presents the results using a difference-in-difference analysis. Panel A presents the results of univariate analysis. We find that firms in the treatment group form more alliances after the index reconstitution, while firms in the control group form fewer alliances in this period. The results hold for the aggregated number of R&D-related strategic alliances as well as all strategic alliances formed. Panel B presents the results of multivariate analysis. The dependent variable is the change in the natural logarithm of (one plus) the aggregated number of R&D-related strategic alliances (all strategic alliances) formed around the index reconstitutions in the first (second) column. We control for a set of control variables that are related to formation of strategic alliances. We confirm findings in the univariate test that firms in the treatment group form significantly more R&D-related strategic alliances as well as all strategic alliances after index reconstitutions than control firms. The results above suggest that there is a positive and causal relation between the fraction of a firm's industry peers with which it shares common blockholders and the number of strategic alliances that it enters into.

Overall, we find that firms that become more (less) connected with industry peers, after the annual index reconstitutions, form more (less) alliances than before. This evidence shows that our results are not driven by institutions accumulating blocks in various firms forming strategic alliances because they anticipate the future formation of alliances between these firms.

5 Effect of R&D-Related Strategic Alliances on Innovation: Baseline Empirical Results

5.1 Effect of R&D-Related Strategic Alliances on the Quantity and Quality of Innovation Output

To assess whether R&D-related strategic alliances enhance or impede corporate innovation, we first estimate the following model:

$$LOG(1+\#PAT)_{i,t+1} = \beta_0 + \beta_1 LOG(1+\#RDA)_{i,(t-4,t)} + \beta_2 X_{i,t} + \alpha_i + \gamma_t + \varepsilon_{i,t}, \qquad (1)$$

Our main explanatory variable is R&D-related strategic alliance (*Log(1+#RDA)*) measured as the logarithm of one plus the total number of R&D-related strategic alliances that a firm established in the past five years [*t*-4, *t*]. We are interested in the effect of alliances formed on the firm's innovation outcome, *Log(1+#Pat)* and *Log(1+#Cite)* in year t+1. Table 4 reports our baseline results for the effect of R&D-related strategic alliances on innovation. We include a large set of control variables that are found to be predictors of innovation output. We also control for unobserved firm and year effects on innovation with fixed effects specifications. The coefficient estimate of *Log(1+#RDA)* is positive and economically and statistically significant. A one unit increase in the log number of R&D-related strategic alliances formed in the past five years *(1+#RDA)* is associated with a 11.4% increase in the log number of patents filed in year t+1 and a 37.3% increase in the log total citations of patents filed in year t+1.

After observing a strong positive relation between R&D-related strategic alliance formation of a firm and the number of new patents (citations) the firm obtains after alliance formation, we conduct a similar analysis for alternative innovation outcome variables. Specifically, we replace the previous outcome variable in our baseline regression model with two types of variables measuring innovation quality (Cite/patent and Generality) and research efficiency (Patent/RD and Citation/RD). Table 5 reports the regression output with alternative corporate innovation outcome variables. The coefficient estimate of *Log(1+ #RDA)* is positive and economically and statistically significant in all specifications. A one unit increase in the log number of R&D-related strategic alliances formed in the past five years is associated with a 22.4% increase in the number of citations per patent, a 1.7% increase in patent generality, and a 3.5% (21.5%) increase in patent (citation) efficiency associated with the patents filed in year t+1.

5.2 Effect of R&D-Related Strategic Alliances on Innovation: Quality of Alliance Partners

The analysis in the previous sections provide evidence that strategic alliances foster innovation with an emphasis on the number of alliances formed, which measures the extensive margin of strategic cooperation between firms. Alternatively, we could argue that whatever consequence of strategic alliances on a firm should ultimately be coming from its alliance partners. In fact, strategic alliances may well be viewed as a form of interaction between peer firms. We thus conjecture that a positive spill-over effect arises from alliance partners: if the firm's alliance partners have performed well in innovation (i.e. being productive in generating new patents), we should expect to see an improvement in the firm's innovation output as a response. To further shed light on this, we adopt a measure to capture how the firm's strategic partners have performed in the innovation. We use the total number of patents filed by firm i's partner firms who formed R&D-related strategic alliances with firm i from year t-2 to year t as a measure of peer firms' innovation output. Table 6 presents the analysis of the effects of peer firms (formed via R&D strategic alliances) on innovation. The dependent variables are innovation outcomes of firm i in year t+1 (or in the period [t+1, t+3] or in the period [t+1, t+5]). As expected, the coefficient on the main explanatory variable, *Log(1+#PeerPat)*, is positive and highly significant in all specifications with various innovation outcome variables as dependent variables. For example, column 1, where the outcome is measured for year t+1, a one unit increase in the log number of alliance partners' patents filed in the past three years is associated with a 14.4% (2.4%) increase in the number of patents (co-patents) filed by the firm itself and a 22.2% increase in the number of citations per patent. [8]

5.3 Event Study Finding: Innovation Output after Strategic Alliances Backed by Common Blockholders

We conduct an event study around the formation of each R&D-related strategic alliance. We separate R&D-related strategic alliances by whether they are backed by common blockholders or not, i.e., whether or not there is at least one blockholder common to the two partnering firms. We then conduct a difference-in-difference analysis comparing firms involved in these two types of R&D-related strategic alliances. For each firm that forms an R&D-related strategic alliance in year t, we keep the firm-year observation in seven years centering on the formation year, i.e., from year t-3 to t+3. We run the following OLS regression with firm and year fixed effects to estimate the quantity of the innovation output of firms surrounding the formation of the two

[8]Because the quality of a firm's alliance partners is relatively stable across years, we focus on the cross-sectional differences in quality of alliance partners. Therefore, we use industry and year fixed effects in Table 6. In unreported tables, we find qualitatively similar although weaker results using firm and year fixed effects.

types of R&D-related strategic alliances:

$$LOGPAT = \beta_0 + \beta_1 Dummy(Common\,Blockholders\,Backed) \times POST$$
$$+ \beta_2 POST + \beta_3 Dummy(Common\,Blockholders\,Backed) + \alpha_i + \gamma_t + \varepsilon, \quad (2)$$

where *POST* is a dummy variable that equals to one if the observation is in the years t+1 to t+3 (i.e., after the formation of alliance), and equals to zero otherwise. We run a similar regression to analyze the quality of this innovation output, with the difference that *LOGPAT* is replaced by *LOGCITE* as the dependent variable. *Dummy(Common Blockholdesr Backed)* is a dummy variable that equals to one if there is at least one common blockholder that holds blocks (5% of shares outstanding) in both alliance partners, it otherwise equals zero. The dependent variable is either *LOGPAT*, firm *i*'s log number of patents in a given year, or *LOGCITE*, firm *i*'s log total citations for patents filed in a given year. We find positive and statistically significant coefficient estimates of β_1, which suggests that firms with common blockholder-backed R&D-related strategic alliances experience increases in innovation output (larger number of patents and more citations) after R&D-related strategic alliance formation. We also confirm our previous finding in our baseline results (in section 5.1) that the average effect of R&D-related strategic alliance formation on corporate innovation is positive, since the sum of the coefficient of the interaction term and the coefficient of *POST* dummy is positive (i.e., $\beta_1 + \beta_2 > 0$).

5.4 Effect of R&D-Related Strategic Alliances on Innovation: Sharing Rights to Innovations Through Co-patenting

In this section, we document the sharing of rights to innovation by alliance partners in the form of co-patenting. "Co-patenting patents" refer to patents with multiple assignees and is direct evidence of research output arising from R&D collaboration between multiple firms. We measure the quantity and quality of co-patenting patents and analyze how they are affected by past R&D-related alliance activities. In our multivariate analyses of co-patenting, *#Co-Pat* and *#Co-Cite* refers to total number of co-patents filed in year t+1, total citation for co-patents filed in t+1. We use logged variable as our dependent variables: *Log(1+#Co-Pat)* and *Log(1+#Co-Cite)*. #RDA refers to number of R&D-related strategic alliance each firm has established in the past five years [t-4, t]. We use *Log(1+#RDA)* as the main independent (test) variable. Other control variables are measured in year t. In Table 8, we report inter-firm co-patenting between R&D-related strategic alliance partners. For regressions of both *Log(1+#Co-Pat)* and *Log(1+#Co-Cite)*, the coefficient estimate of *Log(1+#RDA)* is positive and significant at the 1% level, suggesting that firms with more R&D-related strategic alliances have a larger number of co-patented patents.

6 Effect of R&D-Related Strategic Alliances on Innovation: Identification

While our baseline results show a strong positive relation between the number of R&D-related strategic alliances formed by a firm and the number of new patents (and citations) the firm generates after alliance formation, we need to establish that this effect is causal. The concern is that the formation of strategic alliance may be endogenous. In particular, it may be the case that firms with greater innovation potential may attract more alliances. Moreover, unobservable firm characteristics may affect both alliance formation and innovation outcomes. We attempt to address the above concerns using three different identification strategies, thus establishing causality.

6.1 Effect of R&D-Related Alliances on Innovation: Difference-in-Difference Analysis comparing Firms with Alliances to Firms without Alliances

Our first identification strategy is to examine pre-existing trends in innovation following Bertrand and Mullainathan (2003). For example, one argument against our results being causal is reverse causality: firms that experience an increase in the number of patents immediately respond by forming alliances for whatever reason. If this were the case, there would be a trend of increasing innovation even before an alliance are announced. We adopt a difference-in-difference (hereafter, DID) approach to compare the innovation output of a sample of treatment firms that have formed a R&D-related strategic alliance to that of control firms that have no R&D-related strategic alliance. Our treatment group consists of firms that have a completed R&D-related strategic alliance from 1992 to 2002. For each treatment firm, we find a control firm in the same year using a propensity score matching approach based on two requirements: first, the firm does not form R&D-related strategic alliance in the same year as the treatment firm; and second, it has the same likelihood (if not the same, the closest with less than 10% deviation) of forming a strategic alliance based on the first stage regression model predictions.

Table 9 panel A presents parameter estimates from the probit model used for estimating the propensity scores of the treatment and control group. The dependent variable is one if the firm-year belongs to the treatment group and zero otherwise. The result in column (1) shows that the specification captures a significant amount of variation in the dependent variable, as indicated by a pseudo-R^2 of 34.8% and a p-value from the Chi-square test of the overall model fitness well below 0.001. We then use the predicted probabilities from column (1) and perform a nearest-neighbour propensity score matching procedure. We end up with 1,079 unique pairs of matched firms. We apply diagnostic tests to verify that the parallel trends assumption is met. As shown in column (2) of Table 9 panel A, none of the explanatory variables is statistically significant. In particular, the coefficient estimates of the pre-shock innovation growth are not statistically significant, suggesting that there is no observable difference in the innovation outcomes between the two groups of firms pre-treatment event. We report the univariate comparisons between the treatment and control firm characteristics with their corresponding t-statistics in panel B. It is clear from Table 9, Panel B that the observed differences between the treatment and control firm characteristics are not statistically significant. These diagnostic tests suggest that the propensity score matching method has controlled for meaningful observable differences between the treatment and control group.

Table 9 panel C reports the DID estimators. *PAT3* is the sum of firm *i*'s number of patents in the three-year window before or after R&D-related strategic alliance formation (we take the log of the raw number plus one). *CITE3* is the sum of firm *i*'s total citations for patents filed in the three-year window before or after R&D-related strategic alliance formation (we take the log of the raw number plus one). We compute the average change in *LOGPAT3* and *LOGCITE3* for the treatment and control groups and report the DID estimators and the corresponding two-tailed t-statistics testing the null hypothesis that the DID estimators are equal to zero. We find that both the treatment group (successful alliance) and control group (no alliance) experience a significant increase in the number of patents and that the increase is larger for the treatment group than for the control group as the DID estimator of *LOGPAT3* is positive and statistically significant at the 1% level. The number of citations of the treatment (control) group goes up (down) significantly after the alliance formation. As a result, the DID estimator of *LOGCITE3* is positive and statistically significant at the 1% level.

In Table 9 panel D, we show our DID results in a regression framework to estimate the innovation dynamics of the treatment and control firms surrounding R&D-related strategic alliance formation. We estimate the following model:

$$
\begin{aligned}
LOGPAT\,(\,or\,LOGCITE) = \quad & \beta_0 + \beta_1 TREAT \times AFTER_{2\&3} + \beta_2 TREAT \times AFTER_1 \\
& + \beta_3 TREAT \times CONCURRENT + \beta_4 TREAT \times BEFORE_1 \\
& + \beta_5 AFTER_{2\&3} + \beta_6 AFTER_1 + \beta_7 CONCURRENT \\
& + \beta_8 BEFORE_1 + \alpha_i + \varepsilon. \qquad (3)
\end{aligned}
$$

The dependent variable is either $LOGPAT$, firm is log number of patents in a given year, or $LOGCITE$, firm i's log total citations for patents filed in a given year. TREAT is a dummy that equals one for treatment firms and zero for control firms. $BEFORE_1$ is a dummy that equals one if a firm-year observation is from the year before R&D-related strategic alliance (year -1) and zero otherwise. $CURRENT$ is a dummy that equals one if a firm-year observation is from the R&D-related strategic alliance year (year 0) and zero otherwise. $AFTER_1$ is a dummy that equals one if a firm-year observation is from the year immediately after R&D-related strategic alliance (year 1) and zero otherwise. $AFTER_{2\&3}$ is a dummy that equals one if a firm-year observation is from two or three years after R&D-related strategic alliance (year 2 and 3) and zero otherwise. We also control for firm fixed effects, α_i. Regression results of $LOGPAT$ are reported in columns 1 and 2 and ($LOGCITE$) in columns 3 and 4. In both columns 2 and 4, we observe statistically insignificant coefficient estimates of $BEFORE_1$, suggesting that the parallel trend assumption of the DID approach is not violated. We find positive and statistically significant coefficient estimates of β_1 and β_2, which suggests that compared to control firms, the treatment firms generate a larger number of patents and citations in the years following R&D-related strategic alliance formation.

In sum, this analysis shows that strategic alliances have no impact on innovation one year before the announcement and that the change in innovation occurs mostly at two or three years after the announcement of the strategic alliance, indicating a causal effect of strategic alliances on innovation.

6.2 Effect of R&D-Related Strategic Alliances on Innovation: Difference-in-Difference Analysis using Failed Attempts to Form Alliances

Our second identification strategy is built on the intuition that firms that announce a strategic alliance deal but fail to complete it would serve as a comparable counterfactual to firms that form alliances successfully. We adopt a difference-in-difference approach to examine the effect of an R&D-related strategic alliance on firm innovation by comparing the innovation output of firms with announced but failed to complete R&D-related strategic alliances to the innovation output of firms with announced and successfully completed R&D-related strategic alliances. To identify firms with failed alliances, we first obtain data on R&D-related strategic alliances with type “Pending” or “Intent” from SDC. Then we manually search via Google, Factiva, company website, 10K, 8K, and 10Q filings through SEC EDGAR about the outcome for each of these deals. Most of these deals eventually complete and are excluded from the sample, we retain “Pending” or “Intent” deals that are withdrawn. Firms with these failed alliance attempts serve as counterfactual group for firms with successfully completed alliance deals. We try to find out the reason for withdrawing the alliance deal and exclude deals withdrawn due to reasons about innovation ability. However, there is not enough disclosure regarding the reason why firms withdraw from the alliance. To mitigate the concern that these failed alliance deals are driven by deteriorating innovation ability of either alliance partner, we conduct a propensity score matching to control for observable differences in innovation ability and other firm characteristics.

In Table 10, we report the results of our DID analysis using failed alliances versus successfully completed alliances. The treatment group in this test consists of firms that have at least one failed R&D-related strategic alliance (we require these treatment firms not to have any other successful alliance in the same year). For each treatment firm, we find five control firms in the same year and in the same industry (one-digit SIC code) using propensity score matching. The controlling firm meets two requirements: first, it has at least one completed R&D-related strategic alliance in the same year as the treatment firm and is from the same industry; and second, it has the same likelihood of completing a strategic alliance(if not the same, the closest with less than 1% deviation) based on predictions from the first stage regression model. Panel A describes the procedure to collect the information about failed alliances starting with the R&D-related strategic alliance announcement in the SDC Platinum database. Failed alliance refers to alliances that a firm initiates or is in the "pending" stage, but eventually fails to arrive at a final deal. We were able to find 24 failed R&D-related strategic alliances and match them to 61 successful R&D-related strategic alliances.

In Table 10 panel B, we confirm that there is no significant difference between the observable characteristics of treatment and control firms on most dimensions. Panel C presents the DID test results. As shown, the DID estimators for both *LOGPAT* and *LOGCITE* are negative and statistically significant at the 5% level, indicating that firms experience a decrease in the number of patents and citations following failed alliances as compared to successful alliances. This result is consistent with the positive effect of completed R&D-related strategic alliances on innovation shown in Table 9 panel D.

To the extent that there is no systematic relation between the innovation potential of a firm and the probability that the firm's announced R&D-related strategic alliances fail, this identification strategy helps to establish a causal effect of a firm's alliance activity on its subsequent innovation outcomes.

6.3 Effect of R&D-Related Strategic Alliances on Innovation: An Instrumental Variable (IV) Analysis

Our third identification strategy is an instrumental variable approach. To instrument for R&D-related strategic alliance formation, we use the fraction of industry peers within a driving distance of 250 KM away from the firm's headquarters. The selection of this instrumental variable is motivated by prior studies showing that the likelihood of alliance formation is negatively related to geographical distance, even within clusters: see Reuer and Lahiri (2014) or Phene and Tallman (2014). Our instrumental variable is potentially confounded by an industry-clustering effect. For example, high-tech firms are clustered in the Silicon Valley, so that the instrumental variable is larger for high-tech firms in Silicon Valley than for high-tech firms elsewhere. Regional characteristics that affect both innovation and industry-clustering would therefore invalidate the exclusion restriction required for this instrumental variable. To tease out the distance effect not driven by industry-clustering, we include state fixed effects in both stages of our regressions to absorb time-invariant local economic, social, and cultural factors.

Table 11 panel A presents our instrumental variable analysis of the effect of R&D-related strategic alliances on innovation using a two-stage least square panel regression. We instrument *Log(1+#RDA)* with the fraction of same-industry firms that are located within 250 miles of the firm's headquarter, *Within250*. Column 1 reports our first-stage results, which generate the fitted (instrumented) value of *Log(1+#RDA)* for use in our second-stage regressions. The coefficient estimate of the instrument in our first stage is positive and significant at the 1% level, consistent with the intuition that firms that are geographically closer are more likely to form a strategic alliance. To address the concern of a weak instrument, we report F-statistics for the test of significance of the instrument. The value of the F-statistics is large, i.e., 36.2, which is greater than the critical values of the Stock-Yogo weak instrument test. Thus, we reject the null hypothesis that our instrument is weak. Columns 2 and 3 report the results from our second-stage regressions. The dependent variables in the second stage of our 2SLS regressions are log value of 1 plus each of following two variables: total number of patents filed in year t+1 and total citations for patents filed in t+1. It can be seen that the coefficient estimate on the instrumented value of *Log(1+#RDA)* in our second stage regression is positive and significant at the 5% (1%) level for the number of patents (citations). Thus, our two-stage least squares regression (2SLS) results confirm the positive effect of R&D-related strategic alliances on innovation.

Overall, our identification tests reported in this section suggest that there is a positive causal effect of R&D-related strategic alliances on firm innovation.

7 How R&D-Related Strategic Alliances Enhance Innovation: One Possible Mechanism

In this section, our objective is to show that an important mechanism through which strategic alliances enhances innovation is by allowing the redeployment of human capital (movement of inventors) among alliance partners. For each firm in each year, we identify the inventors (from the HBS inventor database) that apply for a patent for that company. An inventor is treated as an inventor related to strategic alliances entered into by a firm if he/she has worked before in at least one of the firm's R&D strategic alliance (SA) partners. We count the total number of SA-related inventors in each year (SA_INVT), total number of patents contributed by these SA-related inventors (SA_PAT), and total number of citations received by patents contributed by these SA-related inventors (*SA_CITE*). We conduct two different analyses: first, the effect of R&D-related strategic alliances on human capital redeployment between alliance partners (reported in Table 12); second, the effect of human capital redeployment among alliance partners on corporate innovation (reported in Table 13).

Table 12 presents our results of our analysis on the effect of R&D-related strategic alliances on human capital redeployment between alliance partners. We find that firms with more R&D-related strategic alliances have more inventors working for them who were previously employees of their alliance partners: we will refer to these investors as "alliance-related inventors". We also find that such firms also have more patents (and more citations of patents) contributed by these alliance-related inventors. This evidence suggests that one possible mechanism that R&D-related strategic alliances enhance corporate innovation is by facilitating the exchange of inventors between alliance partners.

We then dig deeper by analyzing the relation between alliance-related inventors and the extent of corporate innovation (quantity and quality) achieved by the firm as a whole. This analysis produces two interesting results, presented in Table 13. First, this analysis confirms that more human capital redeployment among alliance partners (i.e., the larger number of SA-related inventors employed by the firm), greater the quantity and quality of corporate innovation outcomes of the firm as a whole, after controlling for the number of alliances formed by the firm in the past (*Log(1+#RDA)*). Second, we find that the quality of SA-related inventors, as measured by the prior patenting as well as the citation record of these alliance-related inventors (captured by the respective variables *Log(1+#SA_PAT)* and *Log(1+#SA_CITE)*) is positively related to the quantity and quality of the corporate innovation outcomes achieved by the firm as a whole, as measured by the variables *Log(1+#PAT)* and *Log(1+#CITE)*, respectively. This second result suggests that, in addition to contributing their own innovations to the total achieved by the firm, higher quality SA-related inventors may contribute to improving the productivity of the other inventors working for the firm as well.

8 Conclusion

In this paper, we analyze the role of common equity blockholders in fostering the formation of strategic alliances, establish a positive causal effect of strategic alliances on corporate innovation, and analyze the channels through which strategic alliances foster innovation. Our findings may be summarized as follows. First, there is a positive relation between the fraction of a firm's industry peers with which it shares common blockholders and the number of strategic alliances that it enters into. Second, there is a positive relation between the R&D-related alliances formed by a firm and its subsequent innovation outcomes, as measured by the quantity and quality of patents filed, especially for alliances backed by common blockholders. Third, we document, for the first time in the literature, a unique method that firms use to share patent rights with their alliance partners, namely, "co-patenting". Fourth, we establish a positive causal relation between the formation of strategic alliances and innovation: first, by comparing the innovation of firms that fail to form alliances to those of firms that are able to successfully form strategic alliances; and second, by using an instrumental variables approach. Fifth, we establish that an important channel through which strategic alliances foster greater innovation is through the more efficient redeployment of human capital (inventors) across alliance partners.

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Table 1: Summary Statistics

This table summarizes the variables used in the analysis of innovation output. We measure innovation outcome in each year for each firm: *#Pat*, *#Cite*, *#Co-Pat*, and *#Co-Cite* denote the total number of patents filed in year *t*, the total citations for patents filed by a firm in *t*, the total number of co-patenting patents filed in year *t*, and the total citations for co-patenting patents filed in *t*, respectively. Co-patenting patents refer to patents with multiple assignees. For each firm in each year, we identify inventors (from HBS inventor database) that apply for patents for this company. An inventor is treated as an inventor related to strategic alliances (SA) if he/she had worked before in at least one of the firm's R&D partners before he/she joined current company. In each year, we count the total number of SA-related inventors (*#SA_INVT*), the total number of patents contributed by these SA-related inventors (*#SA_PAT*), and the total number of citations received by patents contributed by these SA-related inventors (*#SA_CITE*). We report the natural logarithm of one plus the original value measured in each year. *Cite/patent* is measured as Log(1+average number of citations per patent for patents filed in year *t*+1). *Generality* is measured as one minus the Herfindahl-Hirschman index of the three-digit technology class distribution of all the patents that cite a firm's given patent. We then take the average for all patents generated by the firm in year *t*+1. *Patent/RD* and *Citation/RD* are equal to *Log(1+#Total Patents/RD)* and *Log(1+# Total Citations/RD)* for all patents filed in year *t*+1 to year *t*+3 by each firm, respectively. *RD* denotes R&D expenses firms spent in year *t*. We use these two variables to measure the efficiency of research activity, similar to Hirshleifer, Hsu, and Li (2013). Our sample period spans from 1993 to 2003.

Variable	N	Mean	Std Dev	Min	Median	Max
Dependent variables						
Log(1+#Pat)	36,046	0.703	1.222	0	0	8.367
Log(1+# Cite)	36,046	1.372	2.219	0	0	11.553
Log(1+#Co-Pat)	36,046	0.037	0.204	0	0	3.71
Log(1+#Co-Cite)	36,046	0.104	0.567	0	0	6.886
Log(1+#SA_PAT)	36,046	0.053	0.409	0	0	7.34
Log(1+#SA_CITE)	36,046	0.091	0.678	0	0	9.188
Log(1+#SA_INVT)	36,046	0.042	0.327	0	0	6.292
Cite/Patent	36,046	0.838	1.3	0	0	5.839
Generality	36,046	0.124	0.216	0	0	0.693
Patent/RD	36,046	0.309	0.598	0	0	7.314
Citation/RD	36,046	0.849	1.468	0	0	10.929
Explanatory variables						
Log(1+#RDA)	36,046	0.141	0.426	0	0	4.511
Illiquidity	36,046	0.027	0.073	0	0.001	0.679
Log(Asset)	36,046	5.123	2.083	0.649	4.908	11.673
RD/AT	36,046	0.269	1.043	0	0.014	11.086
Institutional Ownership	36,046	34.433	25.15	0	30.656	95.907
Log(Firm Age)	36,046	2.174	1.048	0	2.303	3.807
ROA	36,046	0.033	0.256	-1.524	0.103	0.423
Tangible Asset	36,046	0.244	0.202	0	0.189	0.921
Leverage	36,046	0.151	0.18	0	0.083	0.907
Capex/TA	36,046	0.058	0.059	0	0.042	0.446
Tobin's Q	36,046	2.304	2.483	0.419	1.515	34.046
KZ_Index	36,046	-8.687	31.4	-356.71	-1.029	65.482
H_Index	36,046	0.215	0.164	0.016	0.17	1
Mkt Share	36,046	0.064	0.141	0	0.009	1

Table 2: Determinants of Strategic Alliances

This table reports the coefficients and t-statistics obtained from OLS estimation of the formation of strategic alliances. Dependent variables are the number of different types of strategic alliances (in log) formed by a firm in year *t*+1. *#ALL* refers to the total number of all types of strategic alliances formed in year *t*+1, *#RDA* refers to the total number of research and development (R&D)-related alliances formed in year *t*+1, *#LIC* refers to the total number of licencing related alliances formed in year *t*+1, *#MKT* refers to the total number of marketing related alliances formed in year *t*+1, and *#MNF* refers to the total number of manufacturing related alliances formed in year *t*+1. *% of Peers Connected* refers to the fraction of a firm's industry (2-digits SIC code) peers that are connected to this firm through a common block shareholder (i.e., if there is at least one shareholder that holds a block larger than 5% of shares outstanding in both firms, then the two firms are treated as connected). In panel B, we calculate *% of Peers Connected* separately using different types of institutional blockholders as classified by Bushee (2000): Quasi-Indexer, Transient Investor, and Dedicated Investor. *%Peers Conn (Quasi-Indexer) / (Transient)/ (Dedicated)* refers to the fraction of industry peers that are connected to a firm by a common blockholder that is a quasi-indexer/transient investor/dedicated investor. All control variables are measured in year *t*. The t-statistics based on robust standard errors clustered at firm level are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Percentage of peers connected through common blockholders as main explanatory variable

Dep. Var. =	Log(1+#ALL)	Log (1+# RDA)	Log (1+# LIC)	Log (1+# MKT)	Log (1+# MNF)
	(1)	(2)	(3)	(4)	(5)
% of Peers Connected	0.073***	0.045***	0.069***	0.037**	0.021
	(3.29)	(3.17)	(4.94)	(2.38)	(1.63)
Illiquidity	-0.052**	-0.052***	-0.032**	-0.079***	-0.025**
	(-2.32)	(-4.20)	(-2.54)	(-5.36)	(-2.42)
Log(Asset)	0.005	-0.007	-0.008**	-0.007*	0.001
	(0.91)	(-1.56)	(-2.56)	(-1.79)	(0.53)
RD/AT	0.004	-0.001	0.005**	0.002	0.000
	(1.30)	(-0.57)	(2.38)	(1.24)	(0.24)
Institutional Ownership	0.000	0.000	0.000	0.000	-0.000
	(0.17)	(1.45)	(0.14)	(1.31)	(-0.50)
Log(Firm Age)	0.008	0.007	0.009*	0.015***	0.019***
	(1.09)	(1.42)	(1.90)	(2.95)	(5.17)
ROA	0.035***	0.010	0.021**	0.006	-0.004
	(2.80)	(1.39)	(2.56)	(0.73)	(-0.89)
Tangible Asset	0.095***	0.045***	0.053***	0.064***	0.033***
	(3.71)	(2.96)	(3.19)	(3.80)	(2.65)
Leverage	-0.024	0.004	-0.002	0.001	-0.019***
	(-1.51)	(0.39)	(-0.24)	(0.10)	(-2.59)
Capex/TA	-0.007	0.023	0.023	0.012	0.028
	(-0.19)	(1.10)	(1.04)	(0.52)	(1.55)
Tobin's Q	0.006***	-0.001	0.000	-0.000	-0.001*
	(4.42)	(-1.16)	(0.06)	(-0.57)	(-1.87)
KZ_Index	-0.000	-0.000	-0.000	-0.000***	-0.000
	(-0.31)	(-0.36)	(-1.54)	(-3.16)	(-1.39)
H_Index	0.033	0.022**	-0.005	0.014	0.019
	(1.62)	(2.02)	(-0.37)	(1.09)	(1.60)
Mkt Share	0.004	-0.041	0.014	-0.016	-0.032
	(0.09)	(-1.59)	(0.61)	(-0.61)	(-1.20)
Constant	0.126***	0.090***	0.073***	0.112***	0.016
	(4.75)	(4.64)	(4.77)	(6.08)	(1.42)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Observations	36,046	36,046	36,046	36,046	36,046
R-squared	0.04	0.04	0.03	0.05	0.02
Number of Firms	5,967	5,967	5,967	5,967	5,967

Panel B: Percentage of peers connected by different types of institutions as explanatory variables

Dep. Var. =	Log(1+#ALL)	Log (1+# RDA)	Log (1+# LIC)	Log (1+# MKT)	Log (1+# MNF)
	(1)	(2)	(3)	(4)	(5)
%Peers Conn(Quasi-Indexer)	0.225***	0.089***	0.126***	0.113***	0.068***
	(8.65)	(6.61)	(8.26)	(6.85)	(4.83)
%Peers Conn(Transient)	0.139***	0.106***	0.110***	0.066***	0.049***
	(4.23)	(5.77)	(6.03)	(3.40)	(2.91)
%Peers Conn(Dedicated)	-0.055*	-0.014	0.010	-0.032*	-0.027*
	(-1.94)	(-0.81)	(0.57)	(-1.65)	(-1.78)
Illiquidity	-0.057**	-0.054***	-0.034***	-0.082***	-0.027***
	(-2.55)	(-4.32)	(-2.71)	(-5.52)	(-2.58)
Log(Asset)	0.007	-0.006	-0.008**	-0.006	0.002
	(1.25)	(-1.40)	(-2.32)	(-1.54)	(0.80)
RD/AT	0.004	-0.001	0.005**	0.002	0.000
	(1.31)	(-0.57)	(2.39)	(1.24)	(0.24)
Institutional Ownership	0.000	0.000*	0.000	0.000*	-0.000
	(0.61)	(1.66)	(0.41)	(1.65)	(-0.14)
Log(Firm Age)	0.009	0.007	0.009**	0.016***	0.020***
	(1.31)	(1.52)	(2.04)	(3.10)	(5.27)
ROA	0.035***	0.010	0.021**	0.006	-0.004
	(2.76)	(1.39)	(2.54)	(0.70)	(-0.91)
Tangible Asset	0.094***	0.045***	0.053***	0.063***	0.033***
	(3.68)	(2.95)	(3.17)	(3.77)	(2.63)
Leverage	-0.025	0.003	-0.003	0.001	-0.020***
	(-1.58)	(0.33)	(-0.30)	(0.05)	(-2.64)
Capex/TA	-0.004	0.024	0.024	0.013	0.029
	(-0.10)	(1.14)	(1.09)	(0.58)	(1.59)
Tobin's Q	0.006***	-0.001	0.000	-0.000	-0.001*
	(4.53)	(-1.03)	(0.14)	(-0.49)	(-1.74)
KZ_Index	-0.000	-0.000	-0.000	-0.000***	-0.000
	(-0.25)	(-0.29)	(-1.49)	(-3.10)	(-1.33)
H_Index	0.032	0.022**	-0.005	0.014	0.018
	(1.59)	(2.02)	(-0.39)	(1.07)	(1.59)
Mkt Share	-0.000	-0.043*	0.012	-0.018	-0.033
	(-0.01)	(-1.66)	(0.53)	(-0.69)	(-1.25)
Constant	0.119***	0.088***	0.070***	0.108***	0.013
	(4.47)	(4.50)	(4.58)	(5.85)	(1.21)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Observations	36,046	36,046	36,046	36,046	36,046
R-squared	0.04	0.04	0.03	0.05	0.02
Number of Firms	5,967	5,967	5,967	5,967	5,967

Table 3: Determinants of Strategic Alliances: Difference-in-Difference Analysis using Russell 1000/2000 Index Reconstitution

This table presents the difference-in-difference analysis using Russell 1000/2000 index reconstitutions as exogenous shocks to firms' connections with their industry peers through common equity blockholders. Annual Russell 1000/2000 index reconstitutions bring exogenous investor turnover around the reconstitution date. We identify firms that switch index membership (move up to Russell 1000 index or move down to Russell 2000 index), and calculate the resulting changes of their connections with their industry peers due to these exogenous investor turnovers. We rank these firms by changes in *% of Peers Connected* into three groups each year and analyze consequent formation of strategic alliances. *% of Peers Connected* refers to the fraction of a firm's industry peers (sic 2 digits) that are connected to this firm through a common block shareholder (with at least 5% shares outstanding in each firm). Treatment (Control) group consists of firms that rank in the top (bottom) group that experience the largest increase (decrease) of connections with industry peers after the index reconstitutions. Panel A presents univariate analysis. We report the number of strategic alliances formed in the year immediately after the Russell index reconstitution, and compare it with the number of strategic alliances formed one year before the reconstitution. We report the natural log of one plus number of R&D-related strategic alliances and the number of all types of strategic alliances in the first two columns. We report the difference-in-difference results in the last column. Panel B presents the multivariate analysis. The dependent variable is the natural log difference of number of strategic alliances formed in the year immediately after the Russell index reconstitution and the year before the reconstitution. T-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Univariate Analysis

	Mean Treatment Difference (After - Before)	Mean Control Difference (After - Before)	Mean DID Estimator (Treatment - Control)
Log(1+# RD Alliances)	0.006	-0.011**	0.017**
	(1.05)	(-2.02)	(2.11)
Log(1+# All Alliances)	0.01	-0.028**	0.038**
	(0.75)	(-2.19)	(2.04)

Panel B: Multivariate Analysis

Dep. Var. =	Change in Log(1+#RDA)	Change in Log(1+#ALL)
	(1)	(2)
Treatment Dummy	0.020**	0.048**
	(2.06)	(2.15)
Illiquidity	0.068	4.846
	(0.02)	(1.48)
Log (Asset)	0.022**	-0.005
	(2.40)	(-0.30)
RD/AT	0.021	0.010
	(1.05)	(0.48)
Institutional Ownership	0.000	-0.000
	(0.92)	(-0.54)
Log (Firm Age)	0.001	0.006
	(0.19)	(0.44)
ROA	0.208**	-0.016
	(2.06)	(-0.13)
Tangible Asset	-0.038	-0.198***
	(-1.19)	(-2.82)
Leverage	0.007	0.004
	(0.22)	(0.07)
Capex/TA	0.081	0.523*
	(0.61)	(1.77)
Tobin's Q	0.002	0.006
	(0.43)	(0.60)
KZ_Index	0.000	0.000
	(1.31)	(1.03)
H_Index	0.002	-0.119*
	(0.06)	(-1.75)
Mkt Share	-0.002	0.059
	(-0.07)	(0.82)
Constant	-0.186**	0.058
	(-2.38)	(0.40)
Year Dummies	Yes	Yes
Observations	824	824
R-squared	0.07	0.06

Table 4: Effect of R&D-Related Strategic Alliances on Innovation: Baseline Results

This table reports the coefficients and t-statistics obtained from OLS regressions of corporate innovation outcomes. Dependent variables are innovation outcomes in year *t*+1: *#Pat and #Cite* denote the total number of patents a firm applies in year *t*+1 and the total citations for patents a firm applies in *t*+1. We use the natural logarithm of one plus these measures as our dependent variables: *Log(1+#Pat, Log(1+#Cite)*. *#RDA* refers to the number of R&D-related strategic alliances that a firm has formed in past five years [*t*-4, *t*]. Other control variables are measured in year *t*. T-statistics based on robust standard errors clustered at firm level are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dep. Var. =	Log(1+#Pat)	Log(1+# Citation)
	(1)	(2)
Log(1+#RDA)	0.114***	0.373***
	(3.62)	(6.65)
Illiquidity	0.220***	0.351**
	(4.05)	(2.42)
Log(Asset)	0.162***	0.212***
	(11.06)	(7.60)
RD/AT	0.007	0.037**
	(0.99)	(2.23)
Institutional Ownership	-0.000	-0.003**
	(-0.27)	(-2.44)
Log(Firm Age)	-0.029*	-0.066*
	(-1.78)	(-1.82)
ROA	-0.030	0.080
	(-1.10)	(1.23)
Tangible Asset	0.067	0.136
	(1.17)	(1.04)
Leverage	-0.144***	-0.374***
	(-3.60)	(-4.18)
Capex/TA	0.155*	0.314
	(1.94)	(1.57)
Tobin's Q	0.018***	0.034***
	(8.69)	(6.92)
KZ_Index	0.000	0.000
	(1.17)	(0.32)
H_Index	0.068	0.177*
	(1.43)	(1.73)
Mkt Share	-0.027	0.102
	(-0.35)	(0.70)
Constant	-0.109	0.631***
	(-1.50)	(4.41)
Firm Fixed Effects	Yes	Yes
Year Dummies	Yes	Yes
Observations	36,046	36,046
R-squared	0.03	0.09
# of Firms	5,967	5,967

Table 5: Effect of R&D-Related Strategic Alliances on Innovation: Alternative Innovation Outcomes

This table reports the coefficients and t-statistics obtained from OLS regressions of the corporate innovation outcomes using alternative innovation measures. *Citation/Patent* is measured as *Log*(1+average number of citations per patent for patents filed in year *t*+1). *Generality* is measured as one minus the Herfindahl-Hirschman index of the three-digit technology class distribution of all the patents that cite a firm's given patent. We then take the average for all patents generated by the firm in year *t*+1. *Patent/RD* and *Citation/RD* measure the efficiency of research activity. They are equal to *Log(1+#Total Patent/RD expenses)* and *Log(1+# Total Citations/RD expenses)* for all patents filed in year *t*+1 to year *t*+3 by each firm, respectively. *RD* is the R&D expenses of a firm in year *t*. These two variables are constructed in a similar way as in Hirshleifer, Hsu, and Li (2013). We take the log of the original ratio *(#Total Patent/RD* and *# Total Citations/RD)*. *#RDA* refers to the number of R&D-related strategic alliances that a firm has formed in past five years [*t*-4, *t*]. Other control variables are measured in year *t*. T-statistics based on robust standard errors clustered at firm level are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dep. Var. =	Citation/patent	Generality	Patent/RD	Citation/RD
	(1)	(2)	(3)	(4)
Log(1+#RDA)	0.224***	0.017***	0.035**	0.215***
	(6.62)	(3.13)	(2.15)	(5.28)
Illiquidity	0.058	0.017	-0.006	-0.058
	(0.49)	(0.83)	(-0.06)	(-0.31)
Log(Asset)	0.077***	0.018***	-0.062***	-0.101***
	(3.93)	(6.18)	(-5.94)	(-4.09)
RD/AT	0.030**	0.001	-0.006	0.018
	(2.55)	(0.28)	(-1.03)	(1.34)
Institutional Ownership	-0.002***	-0.000***	-0.000	-0.001
	(-2.73)	(-3.35)	(-0.28)	(-1.04)
Log(Firm Age)	-0.060**	-0.000	-0.071***	-0.211***
	(-2.29)	(-0.07)	(-5.12)	(-6.32)
ROA	0.122**	0.018**	0.145***	0.303***
	(2.43)	(2.37)	(5.13)	(4.57)
Tangible Asset	0.016	0.010	-0.085	-0.105
	(0.17)	(0.56)	(-1.52)	(-0.80)
Leverage	-0.200***	-0.035***	-0.060*	-0.114
	(-3.15)	(-3.18)	(-1.80)	(-1.44)
Capex/TA	0.162	0.013	0.029	0.125
	(1.03)	(0.51)	(0.37)	(0.70)
Tobin's Q	0.017***	0.002***	0.004**	0.008**
	(4.81)	(4.11)	(2.18)	(2.14)
KZ_Index	-0.000	0.000	-0.000***	-0.001***
	(-0.14)	(1.02)	(-2.82)	(-2.85)
H_Index	0.123	0.027**	0.026	0.072
	(1.64)	(2.10)	(0.57)	(0.69)
Mkt Share	0.058	-0.004	0.024	0.201*
	(0.60)	(-0.22)	(0.52)	(1.67)
Constant	0.814***	0.083***	0.863***	2.165***
	(8.03)	(5.39)	(15.81)	(16.82)
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Observations	36,114	36,114	36,114	36,114
R-squared	0.09	0.07	0.09	0.20
# of Firms	5,967	5,967	5,967	5,967

Table 6: Effect of R&D-Related Strategic Alliances on Innovation: Quality of Alliance Partners

This table shows how the quality of a firm's alliance partners affects corporate innovation of the firm. Dependent variables are innovation outcomes of firm *i* in year *t*+1 (or in the period [*t*+1, *t*+3] or [*t*+1, *t*+5]). *#Peer Pat* refers to the total number of patents filed by firm *i*'s alliance partners that formed R&D alliances with firm *i* during year *t*-2 to year *t*. Other control variables are measured in year *t*. T-statistics are computed based on robust standard errors clustered at firm level are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	Log(1+#Patent)			Log(1+#Citation)		
	Log(Pat_{t+1})	Log(Pat_{t+3})	Log(Pat_{t+5})	Log($Cite_{t+1}$)	Log($Cite_{t+3}$)	Log($Cite_{t+5}$)
	(1)	(2)	(3)	(4)	(5)	(6)
Log(1+#Peer Pat)	0.144***	0.169***	0.176***	0.024***	0.043***	0.052***
	(14.76)	(15.55)	(15.59)	(7.64)	(9.09)	(9.64)
Other firm characteristics, industry and year fixed effects are also controlled for						
Observations	35,967	35,967	35,967	35,967	35,967	35,967
R-squared	0.42	0.43	0.44	0.19	0.25	0.27

Table 7: Innovation Output after R&D-Related Alliances Backed by Common Blockholders

This table presents the difference-in-difference analysis comparing firms forming R&D-related strategic alliances that are backed by common blockholders to firms forming R&D-related strategic alliances that are not backed by common blockholder-backed. For each firm that forms a R&D-related strategic alliance in year *t*, we keep firm-year observations in the three years before and three years after the formation year, i.e., from year *t*-3 to *t*+3. *POST* is a dummy variable that equals one if the observation is in the years *t*+1 to *t*+3 (i.e., after the formation of alliance), and it equals zero otherwise. *Dummy(Common blockholders Backed)* is a dummy variable that equals one if there is a common blockholder that holds a block (5% of shares outstanding) in both alliance partners, and zero otherwise. We run an OLS regression with firm and year fixed effects. T-statistics based on robust standard errors clustered at firm level are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dep. Var.=	Log(1+#Pat)	Log(1+#Citation)
Dummy(Common Blockholders Backed) * POST	0.344***	0.400***
	(3.58)	(2.65)
Dummy(Common Blockholders Backed)	-0.077	-0.017
	(-1.54)	(-0.18)
POST	-0.100***	-0.027
	(-3.20)	(-0.48)
Constant	0.923***	3.883***
	(31.30)	(88.45)
Firm and Year Fixed Effects	Y	Y
Observations	8,126	8,126
R-squared	0.17	0.14
# of firms	662	662

Table 8: R&D-Related Strategic Alliances and Inter-firm Co-patenting of Patents

This table reports the coefficients and t-statistics obtained from OLS regressions of the sharing of patent rights in the form of co-patenting. Co-patenting patents refer to patents with multiple assignees. *#Co-Pat* and *#Co-Cite* refer to the total number of co-patents filed in year *t+1* and the total citations of co-patents filed in *t*+1. We use the natural logarithm of one plus these measures as our dependent variables: *Log(1+#Co-Pat)* and *Log(1+#Co-Cite)*. *#RDA* refers to number of R&D-related strategic alliances that a firm has formed in past five years [*t*-4, *t*]. We use *Log(1+#RDA)* as main independent variable. Other control variables are measured in year *t*. T-statistics based on robust standard errors clustered at firm level are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dep. Var. =	Log(1+#Co-pat)	Log(1+# Co-Cite)
	(1)	(2)
Log(1+#RDA)	0.029***	0.195***
	(2.66)	(5.22)
Illiquidity	0.044***	0.092***
	(4.89)	(3.71)
Log(Asset)	0.009***	0.008
	(2.83)	(0.91)
RD/AT	0.001	0.000
	(0.57)	(0.08)
Institutional Ownership	-0.000*	-0.000
	(-1.91)	(-1.14)
Log(Firm Age)	-0.012***	-0.019*
	(-3.54)	(-1.76)
ROA	0.000	-0.002
	(0.06)	(-0.15)
Tangible Asset	0.002	0.026
	(0.23)	(0.69)
Leverage	-0.003	-0.023
	(-0.33)	(-0.78)
Capex/TA	0.004	0.011
	(0.30)	(0.23)
Tobin's Q	0.001*	-0.002
	(1.68)	(-1.33)
KZ_Index	0.000	0.000
	(1.18)	(1.16)
H_Index	-0.002	0.037
	(-0.23)	(1.25)
Mkt Share	0.010	-0.019
	(0.56)	(-0.35)
Constant	0.004	0.078*
	(0.30)	(1.86)
Firm Fixed Effects	Yes	Yes
Year Dummies	Yes	Yes
Observations	36,046	36,046
R-squared	0.01	0.02
# of Firms	5,967	5,967

Table 9: Effect of R&D-Related Strategic Alliances on Innovation: Difference-in-Difference Analysis comparing Firms with Successful Alliances to Firms with No Alliances

This table reports innovation outcomes of firms that successfully complete R&D-related strategic alliances using a difference-in-difference analysis. Treatment group consists of firms that have a completed R&D-related strategic alliance in 1992~2002. For each treatment firm, we find a control firm in the same year using propensity score matching. The control firm needs to meet two requirements: first, it does not have a completed R&D alliance in the same year as the treatment firm; and second, it has the same likelihood of completing a R&D-related strategic alliance (if not the same, we use the firm with the closest propensity score that has less than 10% deviation) based on predictions from our first stage regression model. Panel A presents parameter estimates from the probit model used in estimating the propensity scores for the treatment and control groups. The dependent variable is equal to one if the firm-year belongs to the treatment group and is zero otherwise. The "Pre-Match" column contains the parameter estimates of the probit model estimated using the sample prior to matching. These estimates are then used to generate the propensity scores for matching. The "Post-Match" column contains the parameter estimates of the probit model estimated using the subsample of matched treatment-control pairs after matching. Fama-French 48 industry fixed effects are included in both columns of Panel A but the coefficients are not reported. Coefficient estimates are shown in bold and their robust t-statistics clustered at firm levels are displayed in parentheses below. Panel B reports the univariate comparisons between the treatment and control firms' characteristics and their corresponding t-statistics. Panel C presents the DID test results. *PAT3* is the sum of firm *i*'s number of patents in the three-year window before or after R&D alliance formation (we take the natural logarithm of the raw number plus one). *CITE3* is the sum of firm *i*'s total citations for patents filed in the three-year window before or after R&D alliance formation (we take the natural logarithm of the raw number plus one). Panel D reports the regression results from estimating the innovation dynamics of treatment and control firms surrounding R&D alliance formation. We estimate the following model:

$$\begin{aligned}\mathrm{LOGPAT(LOGCITE)} = &\\ \beta_0 + \beta_1\mathrm{TREAT} * \mathrm{AFTER}_{2\&3} + \beta_2\mathrm{TREAT} * \mathrm{AFTER}_1 + \beta_3\mathrm{TREAT} * &\\ \mathrm{CONCURRENT} + \beta_4\mathrm{TREAT} * \mathrm{BEFORE}_1 + \beta_5\mathrm{AFTER}_{2\&3} + \beta_6\mathrm{AFTER}_1 + &\\ \beta_7\mathrm{CONCURRENT} + \beta_8\mathrm{BEFORE}_1 + \mathrm{FIRM\ FE}_i + e_{i,t}, \qquad (3)\end{aligned}$$

where the dependent variable is either LOGPAT, firm *i*'s log number of patents in a given year, or LOGCITE, firm *i*'s log total citations for patents filed in a given year. TREAT is a dummy that equals one for treatment firms and zero for control firms. BEFORE_1 is a dummy that equals one if a firm-year observation is from the year before R&D alliance (year -1) and zero otherwise. CURRENT is a dummy that equals one if a firm-year observation is from the R&D alliance year (year 0) and zero otherwise. AFTER_1 is a dummy that equals one if a firm-year observation is from the year immediately after R&D alliance (year 1) and zero otherwise. $\mathrm{AFTER}_{2\&3}$ is a dummy that equals one if a firm-year observation is from two or three years after R&D alliance (year 2 and 3) and zero otherwise. Coefficient estimates are shown in bold and robust t-statistics are displayed in parentheses below.

Panel A: Pre-match Propensity Score Regression and Post-match Diagnostic Regression

	(1)	(2)
	Pre-Match	Post-Match
Dep. Var. =	Dummy=1 if in treatment group (Success Alliance); 0 if in control group (No Alliance)	
Log(Asset)	0.253***	-0.019
	(14.74)	(-0.62)
RD/AT	1.734***	-0.192
	(9.42)	(-0.65)
ROA	-0.170*	0.141
	(-1.73)	(0.92)
Tangible Asset	-0.658***	-0.136
	(-4.10)	(-0.49)
Leverage	-0.424***	-0.257
	(-3.25)	(-1.18)
Capex/TA	0.979**	-0.339
	(2.33)	(-0.50)
H_Index	-0.294**	0.247
	(-2.06)	(1.00)
Tobin's Q	0.040***	0.014
	(6.17)	(1.25)
KZ_Index	-0.000	0.001
	(-0.58)	(1.14)
Log(Firm Age)	-0.073***	-0.048
	(-3.36)	(-1.24)
Institutional Ownership	-0.002**	0.002
	(-2.42)	(1.04)
Amihud Illiquidity	-1.150**	-0.498
	(-2.13)	(-0.45)
Log(1+#Pat)$_{t-1}$	0.214***	0.082
	(5.91)	(1.39)
Log(1+#Total Citations)$_{t-1}$	0.014	-0.028
	(0.71)	(-0.85)
Pat_Growth$_{t-3,t-1}$	-0.141***	-0.043
	(-3.22)	(-0.63)
Cite_Growth$_{t-3,t-1}$	0.033*	0.012
	(1.66)	(0.37)
Mkt Share	-0.355**	-0.297
	(-2.45)	(-1.17)
Constant	-2.577***	0.169
	(-6.77)	(0.18)
Industry and Year Fixed Effects	Yes	Yes
Observations	28245	2158
Prob > Chi2	0.000	1.000
Pseudo R2	0.348	0.0048

Panel B: Differences in Observables

	Treatment (#=1079)	Control (#=1079)	Treatment - Control	t-value
Log(Asset)	5.825	5.819	0.006	0.05
RD/AT	0.14	0.145	-0.005	-0.66
ROA	0.031	0.016	0.015	1.23
Tangible Asset	0.221	0.227	-0.006	-0.82
Leverage	0.11	0.12	-0.01	-1.56
Capex/TA	0.063	0.064	-0.001	-0.48
H_Index	0.186	0.184	0.002	0.21
Tobin's Q	3.281	3.128	0.153	1.22
KZ_Index	-9.797	-9.949	0.152	0.13
Log(Firm Age)	2.139	2.181	-0.042	-0.86
Institutional Ownership	41.317	40.528	0.789	0.79
Amihud Illiquidity	0.006	0.007	-0.001	-0.63
Mkt Share	0.085	0.09	-0.005	-0.74
$Log(1+\#Pat)_{t-1}$	1.957	1.905	0.052	0.67
$Log(1+\#Total\ Citations)_{t-1}$	3.871	3.808	0.063	0.51
$Pat\_Growth_{t-3,t-1}$	0.375	0.363	0.012	0.32
$Cite\_Growth_{t-3,t-1}$	0.747	0.721	0.026	0.29

Panel C: Difference-in-Difference Test (T-statistics are in bracket, Treatment=Firms with successful R&D-related alliances, Control = Firms without successful R&D-related alliances)

	Mean Treatment (Successful Alliance) Difference (After - Before)	Mean Control (No Alliance) Difference (After - Before)	Mean DID estimator (Treatment - control)
LOGPAT3	0.388***	0.131***	0.257***
	(10.910)	(3.780)	(5.172)
LOGCITE3	0.286***	-0.204***	0.498***
	(4.272)	(-3.262)	(5.347)

Panel D: Difference-in-Difference Analysis for Innovation Dynamics

	(1)	(2)	(3)	(4)
Dep. Var.=	LOGPAT		LOGCITE	
TREAT*AFTER	0.177***		0.358***	
	(4.00)		(4.64)	
AFTER	-0.192***		-0.285***	
	(-4.90)		(-4.42)	
TREAT*AFTER$_{2,3}$		0.221***		0.424***
		(3.61)		(3.97)
TREAT*AFTER$_{1}$		0.122**		0.254***
		(2.52)		(2.77)
TREAT*CONCURRENT		0.060*		0.120
		(1.65)		(1.54)
TREAT*BEFORE$_{1}$		-0.028		-0.105
		(-0.96)		(-1.53)
AFTER$_{2,3}$		-0.270***		-0.343***
		(-4.67)		(-3.68)
AFTER$_{1}$		-0.109**		-0.096
		(-2.42)		(-1.25)
CONCURRENT		-0.052		-0.018
		(-1.64)		(-0.31)
BEFORE$_{1}$		0.027		0.151***
		(1.13)		(2.92)
TREAT	-0.161***	-0.169***	-0.257***	-0.263***
	(-4.03)	(-3.71)	(-4.08)	(-3.43)
Constant	0.928***	0.935***	3.018***	3.023***
	(46.93)	(38.14)	(7.41)	(7.37)
Firm Fixed Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
Observations	16,215	16,215	16,215	16,215
R-squared	0.12	0.12	0.12	0.12

Table 10: Effect of R&D Strategic Alliances on Innovation: Difference-in-Difference Analysis using Firms with Failed Attempts to Form Alliances

This table reports the innovation outcome of firms that fail to form R&D-related strategic alliances using difference-in-difference analysis. Treatment group consists of firms that have at least one failed attempt to form R&D-related strategic alliances (We require that the treatment firms do not have other successful alliances in the same year). For each treatment firm, we identify five control firms in the same year and in the same industry (one-digit SIC code) using a propensity score matching approach. The control firm must meet two requirements: first, it has at least one completed R&D alliance in the same year as the treatment firm and is from the same industry; and second, it has the same likelihood of failing to form R&D-related strategic alliances (if not the same, we use the control firm with the closest propensity score that has less than 1% deviation) based on the predictions from our first stage regression model. Panel A describe the procedure to collect information about failed alliances starting with R&D alliance announcements in the SDC database. Failed alliances refer to the alliances that a firm initiate or in is the pending stage, but eventually fail to arrive at a final deal. Panel B reports the univariate comparisons between the treatment and control firms' characteristics and their corresponding t-statistics. Panel C gives the DID test results. *PAT3* is the sum of firm *i*'s number of patents in the three-year window before or after R&D alliance formation (we take log of the raw number plus one). *CITE3* is the sum of firm i's total citations for patents filed in the three-year window before or after R&D alliance formation (we take natural log of the raw number plus one).

Panel A: Procedure to Collect Firms Involving Failed Attempts to Initiate an R&D alliance

# of sample	Description
475	R&D alliance announcement in the category of "Intent" or "Pending" involving at least one U.S. firm formed during [1990, 2003] from SDC database
69	Firm-year observations that are associated with a failed alliance
48	Failed alliance observation with valid firm characteristics
34	After excluding firms with at least a successful alliance in the same year as the failed one
24	After excluding firms with any successful alliance in the same year as their failed alliance
61	Match each failed alliance to five control firms with successful alliances from the same industry in the same year, requiring that the difference in the propensity score between failed alliance firm and control firms is less than 1%
Total	85=24(Treatment)+61(Control)

Panel B: Differences in Observables

	Treatment (#=24)	Control (#=61)	Treatment - Control	t-value
Log(Asset)	7.672	8.805	-1.134	1.85
RD/AT	0.089	0.086	0.003	-0.16
ROA	0.109	0.105	0.004	-0.09
Tangible Asset	0.262	0.322	-0.059	1.49
Leverage	0.153	0.126	0.027	-0.88
Capex/TA	0.066	0.074	-0.008	0.69
Tobin's Q	2.690	2.624	0.066	-0.12
Log(Firm Age)	2.423	2.738	-0.316	1.22
Institutional Ownership	35.992	31.167	4.825	-0.71
Amihud Illiquidity	0.007	0.003	0.004	-0.73
Mkt Share	0.155	0.134	0.022	-0.48
Log(1+#Pat)$_{t-1}$	3.489	3.167	0.322	-0.55
Log(1+#Total Citations)$_{t-1}$	5.584	5.026	0.558	-0.70

Panel C: Difference-in-Difference Test (T-statistics are in bracket, Treatment=Firms that failed in their attempts to initiate an R&D alliance, Control = Firms that have successfully formed R&D alliances)

	Mean Treatment Difference (After - Before)	Mean Control Difference (After - Before)	Mean DID estimator (Treatment - control)
LOGPAT3	-0.694*	0.057	-0.750**
	(-1.95)	(0.332)	(-2.148)
LOGCITE3	-1.849***	-0.513*	-1.849**
	(-3.891)	(-1.93)	(2.579)

Table 11: Effect of R&D-Related Strategic Alliances on Innovation: An Instrumental Variable (IV) Analysis

This table reports the two-stage least square panel regression analyses examining the effect of R&D-related strategic alliance on firms' innovation outcomes. *#RDA* refers to the number of R&D alliance each firm established in the past five years [*t*-4, *t*]. We instrument *Log(1+#RDA)* with the fraction of industry peers that are located within 250 miles of the firm's headquarter, *Within250*. The first column reports the first-stage results, which generate the fitted (instrumented) value of *Log(1+#RDA)* for use in the second-stage regressions. Columns 2~ 3 report the results from the second-stage regressions. The dependent variables in the second stage of 2SLS are the log value of one plus each of the following two variables: the total number of patents filed in year *t*+1 (*Log(1+#Pat)*) and the total citations for patents filed in *t+1* (*Log(1+#Cite)*). Other control variables are measured at the end of year *t*. Since R^2 is not meaningful in the second stage of 2SLS, we report root MSE instead. Industry classification is based on Fama-French 48 industry classification. First-stage *F*-test refers to the Anderson-Rubin Wald test for weak-instrument-robust inference of the first-stage in IV estimation. T-statistics based on robust standard errors clustered at firm level are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

	1st Stage	2nd Stage (Y measured in *t*+1)	
Dep. Var. =	Log(1+#RDA)	Log(1+#Pat)	Log(1+#Cite)
	(1)	(2)	(3)
Log(1+#RDA) (Instrumented)		2.195**	3.603**
		(2.45)	(2.37)
Within 250	0.426***		
	(3.07)		
Illiquidity	0.286***	0.334	-0.206
	(5.64)	(1.21)	(-0.44)
Log(Asset)	0.089***	0.128	0.164
	(10.99)	(1.57)	(1.19)
RD/AT	0.001	0.052***	0.087***
	(0.29)	(4.82)	(4.48)
Institutional Ownership	-0.001***	0.002	0.005**
	(-3.43)	(1.43)	(2.50)
Log(Firm Age)	0.037***	-0.057	-0.114*
	(9.13)	(-1.64)	(-1.91)
ROA	-0.125***	0.218*	0.424**
	(-6.69)	(1.80)	(2.04)
Tangible Asset	-0.065**	0.048	-0.070
	(-2.32)	(0.53)	(-0.44)
Leverage	-0.219***	-0.196	-0.354
	(-8.73)	(-0.95)	(-1.00)
Capex/TA	0.353***	0.411	0.980
	(5.13)	(1.20)	(1.62)
Tobin's Q	0.011***	0.034***	0.065***
	(5.52)	(3.08)	(3.40)
KZ_Index	0.000***	-0.000	-0.000
	(5.77)	(-0.52)	(-0.44)
H_Index	-0.052**	0.095	0.182
	(-2.22)	(1.10)	(1.19)
Mkt Share	0.018	0.501***	0.726***
	(0.39)	(3.84)	(3.29)
Constant	-0.033	-0.384	-1.266**
	(-0.17)	(-1.03)	(-2.02)
Year & Industry Fixed Effects	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes
Observations	35,211	35,211	35,211
Root MSE	0.372	1.025	1.921
First-stage F-test	36.2		

Table 12: R&D-Related Strategic Alliances and Human Capital Redeployment

This table reports the coefficients and t-statistics obtained from OLS estimation of the human capital redeployment. For each firm-year observation, we identify inventors (from HBS inventor database) that apply for a patent for this company. An inventor is treated as an inventor related to strategic alliances (SA) if he/she had worked before in at least one of the firm's R&D partners before he/she joined current company. In each year, we count the total number of SA-related inventors (*#SA_INVT*), the total number of patents contributed by these SA-related inventors (*#SA_PAT*), and the total number of citations received by patents contributed by these SA-related inventors (*#SA_CITE*). We use the log of one plus the original value measured in year *t*+1 as dependent variable. *#RDA* measures the total # of R&D alliance one firm forms in the past five years. Other control variables are measured in year *t*. T-statistics based on robust standard errors clustered at firm level are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dep. Var. =	Log(1+# SA_INVT)	Log(1+# SA_PAT)	Log(1+# SA_CITE)
	(1)	(2)	(3)
Log(1+#RDA)	0.179***	0.225***	0.337***
	(6.78)	(6.56)	(6.55)
Illiquidity	0.067***	0.083***	0.126***
	(4.98)	(4.88)	(4.51)
Log(Asset)	0.026***	0.032***	0.046***
	(3.63)	(3.56)	(3.37)
RD/AT	0.004**	0.006**	0.006*
	(1.98)	(2.16)	(1.80)
Institutional Ownership	-0.001***	-0.001***	-0.001**
	(-3.42)	(-3.32)	(-2.32)
Log(Firm Age)	-0.028***	-0.035***	-0.023**
	(-4.71)	(-4.76)	(-2.31)
ROA	-0.017**	-0.021*	-0.035**
	(-2.01)	(-1.84)	(-2.10)
Tangible Asset	-0.033*	-0.043*	-0.006
	(-1.78)	(-1.67)	(-0.16)
Leverage	-0.004	-0.002	-0.033
	(-0.38)	(-0.16)	(-1.48)
Capex/TA	-0.004	-0.012	0.009
	(-0.23)	(-0.44)	(0.19)
Tobin's Q	0.003***	0.004***	0.006***
	(4.53)	(4.18)	(3.16)
KZ_Index	0.000**	0.000*	0.000**
	(2.22)	(1.96)	(2.28)
H_Index	-0.009	-0.008	0.015
	(-0.66)	(-0.44)	(0.53)
Mkt Share	0.051	0.044	0.061
	(1.32)	(0.97)	(0.97)
Constant	-0.069**	-0.082**	-0.170***
	(-2.14)	(-2.04)	(-2.72)
Firm Fixed Effects	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Observations	36,046	36,046	36,046
R-squared	0.06	0.06	0.03
# of Firms	5,967	5,967	5,967

Table 13: Effect of Human Capital Redeployment on Corporate Innovation

This table reports the coefficients and t-statistics obtained from OLS estimation of the effect of human capital redeployment on corporate innovation. Dependent variables measure innovation outcome in year *t*+1. *#Pat and #Cite* refers to total number of patents filed in year *t*+1 and total citations for patents filed in *t*+1. We use the log of one plus the original value measured in year *t*+1 as dependent variables: *Log(1+#Pat)* and *Log(1+#Cite). SA_INV, SA_PAT* and *SA_CITE* are defined in Table 12. Control variables are measured in year *t*. T-statistics based on robust standard errors clustered at firm level are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dep. Var. =	Log(1+#Pat)			Log(1+# Cite)		
	(1)	(2)	(3)	(4)	(5)	(6)
Log(1+# SA_INVT)	0.305***			0.079		
	(3.00)			(0.65)		
Log(1+# SA_PAT)		0.273***			0.116	
		(3.99)			(1.35)	
Log(1+# SA_CITE)			0.167***			0.164***
			(5.45)			(3.82)
Log(1+#RDA)	0.131***	0.133***	0.103***	0.377***	0.380***	0.361***
	(4.36)	(4.41)	(3.30)	(6.80)	(6.87)	(6.45)
Illiquidity	0.197***	0.194***	0.195***	0.345**	0.340**	0.327**
	(3.66)	(3.62)	(3.65)	(2.37)	(2.34)	(2.25)
Log(Asset)	0.153***	0.152***	0.154***	0.210***	0.208***	0.204***
	(10.69)	(10.73)	(10.81)	(7.44)	(7.39)	(7.23)
RD/AT	0.006	0.006	0.006	0.037**	0.037**	0.037**
	(0.85)	(0.80)	(0.88)	(2.22)	(2.19)	(2.19)
Institutional Ownership	0.000	0.000	0.000	-0.002**	-0.002**	-0.002**
	(0.19)	(0.22)	(0.04)	(-2.37)	(-2.33)	(-2.29)
Log(Firm Age)	-0.025	-0.024	-0.027	-0.065*	-0.064*	-0.064*
	(-1.50)	(-1.45)	(-1.63)	(-1.79)	(-1.76)	(-1.75)
ROA	-0.024	-0.024	-0.023	0.082	0.083	0.087
	(-0.90)	(-0.88)	(-0.87)	(1.25)	(1.26)	(1.32)
Tangible Asset	0.077	0.078	0.070	0.139	0.142	0.141
	(1.36)	(1.39)	(1.26)	(1.07)	(1.08)	(1.08)
Leverage	-0.142***	-0.143***	-0.139***	-0.373***	-0.373***	-0.368***
	(-3.59)	(-3.61)	(-3.50)	(-4.17)	(-4.17)	(-4.11)
Capex/TA	0.156*	0.158**	0.154*	0.313	0.314	0.312
	(1.96)	(1.98)	(1.93)	(1.56)	(1.56)	(1.55)
Tobin's Q	0.017***	0.017***	0.017***	0.034***	0.033***	0.033***
	(8.23)	(8.21)	(8.29)	(6.83)	(6.79)	(6.70)
KZ_Index	0.000	0.000	0.000	0.000	0.000	0.000
	(1.00)	(0.98)	(1.01)	(0.30)	(0.29)	(0.25)
H_Index	0.073	0.072	0.068	0.179*	0.180*	0.178*
	(1.50)	(1.50)	(1.42)	(1.75)	(1.75)	(1.73)
Mkt Share	-0.045	-0.042	-0.039	0.097	0.096	0.091
	(-0.58)	(-0.54)	(-0.50)	(0.67)	(0.66)	(0.62)
Constant	-0.084	-0.082	-0.078	0.641***	0.646***	0.664***
	(-1.19)	(-1.17)	(-1.11)	(4.47)	(4.51)	(4.62)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36,046	36,046	36,046	36,046	36,046	36,046
R-squared	0.04	0.04	0.05	0.09	0.09	0.09
# of Firms	5,967	5,967	5,967	5,967	5,967	5,967

Internet Appendix: Robustness Tests: Determinants of The Formation of R&D-Related Strategic Alliances

This table presents robustness results of the formation of R&D alliances using alternative industry classifications (one-digit, two-digit, or three-digit SIC code) to define peers. We calculate the fraction of connected peers using these alternative industry measures. *% of Connected Peers* is the fraction of industry peers that are connected to this firm by a common block shareholder (i.e., if there is at least one shareholder who holds a block larger than 5% of shares outstanding in both firms, then the two firms are said connected). All control variables are measured in year *t*. T-statistics based on robust standard errors clustered at firm level are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

Dep. Var. =	Log(1+# RDA)	Log(1+# RDA)	Log(1+# RDA)
	(1)	(2)	(3)
% of Peers Connected (SIC1)	0.040**		
	(2.08)		
% of Peers Connected (SIC2)		0.045***	
		(3.17)	
% of Peers Connected (SIC3)			0.031***
			(3.13)
Illiquidity	-0.052***	-0.052***	-0.052***
	(-4.21)	(-4.20)	(-4.22)
Log(Asset)	-0.007	-0.007	-0.007
	(-1.58)	(-1.56)	(-1.59)
RD/AT	-0.001	-0.001	-0.001
	(-0.56)	(-0.57)	(-0.56)
Institutional Ownership	0.000	0.000	0.000
	(1.51)	(1.45)	(1.55)
Log(Firm Age)	0.007	0.007	0.007
	(1.39)	(1.42)	(1.42)
ROA	0.010	0.010	0.011
	(1.42)	(1.39)	(1.43)
Tangible Asset	0.045***	0.045***	0.046***
	(2.97)	(2.96)	(3.02)
Leverage	0.004	0.004	0.003
	(0.41)	(0.39)	(0.36)
Capex/TA	0.022	0.023	0.022
	(1.07)	(1.10)	(1.04)
Tobin's Q	-0.001	-0.001	-0.001
	(-1.16)	(-1.16)	(-1.18)
KZ_Index	-0.000	-0.000	-0.000
	(-0.35)	(-0.36)	(-0.35)
H_Index	0.022**	0.022**	0.022**
	(2.06)	(2.02)	(2.05)
Mkt Share	-0.041	-0.041	-0.041
	(-1.60)	(-1.59)	(-1.57)
Constant	0.091***	0.090***	0.090***
	(4.67)	(4.64)	(4.65)
Firm Fixed Effects	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes
Observations	36,046	36,046	36,046
R-squared	0.04	0.04	0.04
# of Firms	5,967	5,967	5,967