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Differential effects of geographic-cluster and alliance resources on firm innovation: The moderating role of firm technological capability

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ABSTRACT

In this study, we focus on two significant sources of a firm's external knowledge—geographic clusters and strategic alliances—and examine whether a firm's technological capability influences the effectiveness of these two sources of knowledge for firm innovation performance in different ways. We theorize that clusters and alliances differ in their knowledge flow mechanisms, leading to varying roles of internal technological capability. Specifically, we argue that a firm's capability is more crucial for absorbing and integrating knowledge from clusters, where information flows in a fragmented form through informal channels. Furthermore, firms are less concerned about knowledge loss due to the nature and pattern of knowledge flows in clusters. In contrast, in alliances, where knowledge flow is more integrated and structured, technologically capable firms are generally more concerned about knowledge loss, which adversely affects reciprocity and, consequently, the flow of knowledge between partners. Moreover, since knowledge in alliances is transferred through structured mechanisms, the advantages of high internal capability in absorbing and integrating partner knowledge become less significant. Using 15 years of longitudinal data from the U.S. semiconductor industry—a sector characterized by innovation, strategic alliances, and clustering tendencies—we find that technologically stronger firms derive greater innovation benefits from clusters in enhancing the value of their innovations. In contrast, technologically weaker firms gain more from strategic alliances. Overall, our study supports our hypotheses and provides a nuanced understanding of how internal technological capability operates differently in leveraging external knowledge from clusters versus alliances.

1. Introduction

With the world increasingly shifting toward a knowledge-based economy, firms face pressure to develop new technologies, particularly in technology-intensive industries. Research emphasizes the critical role of external knowledge sources, such as geographic clusters and strategic alliances, in enhancing a firm's innovation performance (Funk, 2014; Guo et al., 2023; Hottenrott and Lopes-Bento, 2015; Phene and Tallman, 2014; Speldekamp et al., 2020; Srivastava et al., 2015). Researchers have also examined the

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relative effectiveness of various external knowledge sources, focusing on entities such as customers, suppliers, and universities (Doloreux et al., 2018). While research on geographic clusters and strategic alliances has grown substantially, the two streams have primarily developed in parallel (Devarakonda et al., 2018; Kumar and Zaheer, 2022). Empirical work, in particular, has often treated clusters and alliances as distinct phenomena, despite a few integrative studies (e.g., Bell, 2005; Hohberger, 2014; Ryu et al., 2018; Zaheer and George, 2004). Some scholars argue that these streams share "some common theoretical mechanisms that provide the basis for joining these research streams" (Devarakonda et al., 2018: 1113). Nevertheless, only a few studies thus far have directly compared the relative effectiveness of clusters versus alliances for firm performance.

An important factor influencing how firms leverage external resources is their internal technological capability (Song et al., 2018), and a significant body of research has examined its role in accessing knowledge from clusters (Audretsch and Belitski, 2022; Crescenzi and Gagliardi, 2018; Howell, 2020; Phene et al., 2006; Speldekamp et al., 2020; Ubeda et al., 2019) and strategic alliances (Lin et al., 2012; Phelps et al., 2012; Seo et al., 2023; Srivastava and Gnyawali, 2011; Subramanian et al., 2018; Vasudeva and Anand, 2011). However, findings remain inconclusive: some studies indicate that technologically weaker firms benefit more from knowledge flows in clusters (Acs et al., 1994; Wennberg and Lindqvist, 2010), while others suggest the opposite (McCann and Folta, 2011). Similarly, some scholars argue that firms with stronger technological capabilities gain greater advantages from partners' knowledge in alliances (Ahuja et al., 2008; Phelps et al., 2012), but others report contrary results (Kim and Inkpen, 2005; Nooteboom et al., 2007; Srivastava and Gnyawali, 2011).

One possible reason for these inconsistencies is that prior research has not considered the influence of clusters and alliances simultaneously in evaluating the role of firm capabilities. Clusters and alliances offer distinct pathways for accessing technological resources, and their relative attractiveness may vary depending on a firm's characteristics, making clusters more appealing for some firms versus alliances for others. Therefore, given the need to join the two research streams and inconsistent findings, examining how the same type of external knowledge (e.g., technological knowledge) derived from clusters versus alliances influences innovation, and how these effects differ based on a firm's internal capability profile, could be especially illuminating. Accordingly, this paper investigates the following research question: To what extent do a firm's internal technological capabilities similarly or differently affect the innovation benefits the firm derives from technological resources in clusters versus alliances? Addressing this question will deepen our understanding of when and why internal capability is more or less advantageous in leveraging external resources and will help managers craft more targeted technology strategies for innovation.

Since geographic clusters are characterized by physical proximity and strategic alliances are marked by formal relational proximity (Phene and Tallman, 2014; Zaheer and George, 2004), we theorize that clusters and alliances, which are essential sources of external knowledge, differ not only in their significance but also in their primary mechanisms of knowledge transfer (Gnyawali and Srivastava, 2013). Geographic clusters facilitate knowledge flow through physical proximity and informal interactions (Dahl and Pedersen, 2004; Pouder and St. John, 1996; Saxenian, 1994), whereas strategic alliances promote knowledge flows through relational proximity and formal structures (Oxley and Wada, 2009; Phene and Tallman, 2014; Podolny, 2001; Soh and Roberts, 2005). We argue that clusters and alliances differ regarding the mechanisms governing knowledge flows, the level of control firms have over knowledge exchange, and the interdependence of knowledge inflows and outflows. Consequently, we propose that a firm's internal technological capability matters differently concerning knowledge in the clusters vs alliances, thus serving as a critical moderator.

We test our hypotheses using a longitudinal sample of semiconductor firms—a high-technology industry context. We examine the effects of technological resources within a firm's geographic cluster and strategic alliances as baseline models. Our hypotheses focus on the moderating role of the firm's technological capability. We measure a firm's technological capability by the number of pioneering patents—those without prior precedence—it produces annually. Geographic clusters are identified by the co-location of firms, and strategic alliances are determined through formal partnership announcements. To provide a robust test for our hypotheses, we employ a random effect negative binomial regression model, tailored for our dependent variable, the value of innovation, which is a count variable and notably skewed. Our longitudinal research design aids in distinctly assessing the impacts of clusters and alliances. We also conduct robustness checks to ensure reliability of our findings.

Our results show that both clusters and alliances enhance the value of firm innovation; however, firms with stronger technological capabilities more effectively leverage technological resources accessed through clusters, but the opposite is true for strategic alliances. Our theory and results suggest that firms perceive the risks and trade-offs with the mechanisms associated with various sources of external resources differently, leading to new insights into why firms with specific resource profiles benefit differently from these external resources. Thus, our research enhances scholarly understanding of how a firm's internal capabilities can enable or limit its leveraging of resources in clusters and alliances in pursuit of innovation. Furthermore, our insights stimulate a meaningful dialogue between the literatures on clusters and strategic alliances (Audretsch and Belitski, 2022; Devarakonda et al., 2018; Funk, 2014; Giuliani, 2013; Kumar and Zaheer, 2022; Phelps et al., 2012; Whittington et al., 2009). From a managerial standpoint, our study offers valuable guidance for devising firm innovation strategies by carefully evaluating complementary and substitutive roles of internal and external knowledge.

2. Theory and hypothesis

Both geographic clusters and strategic alliances represent invaluable external knowledge sources for firms (Aharonson et al., 2007; Ahuja et al., 2008; Audretsch and Belitski, 2022; Funk, 2014; Maskell, 2001; Porter, 2000; Speldekamp et al., 2020; Tallman et al., 2004). A geographic cluster is a "group of firms from the same or related industries located geographically near to each other" (Geoffrey, 2005: 288). For our analytical purpose, we focus on firms' geographic proximity, which is often viewed as an informal form of relationship between firms (Dahl and Pedersen, 2004; Pouder and St. John, 1996; Saxenian, 1994). In contrast, a strategic alliance is a formal, voluntary cooperative agreement among firms to pursue value chain activities jointly (Gulati, 1995; Serrat and Serrat, 2017). We focus on a firm's entire set of direct strategic alliances, often called its ego network or alliance portfolio (Kumar and Zaheer, 2019; Lavie, 2007). Below, we first discuss the underlying distinctions in the cluster and alliance knowledge mechanisms and then build on these distinctions in developing our hypotheses.

First, Marshall (1920) famously described the knowledge flow phenomenon in clusters as "knowledge in the air," highlighting that knowledge flows primarily through informal channels in geographic clusters. Knowledge flow occurs through casual interactions (Dahl and Pedersen, 2004; Saxenian, 1994) and the mobility of employees (Almeida and Kogut, 1999), resulting in a highly fragmented dissemination of knowledge. In contrast, alliances with their formalized mechanisms, guided by contractual agreements and established interorganizational routines, establish systematic and well-directed "pipelines" for knowledge flow, facilitating the exchange of knowledge in a more integrated form (Phene and Tallman, 2014; Podolny, 2001; Soh and Roberts, 2005).

Second, the nature of knowledge flows also affects a firm's ability to control the flows. In clusters, where knowledge transfer often occurs unintentionally—a phenomenon commonly referred to as "knowledge spillover"(Audretsch and Belitski, 2022; Shaver and Flyer, 2000; Storper, 1995)—it can be challenging to control the flow of knowledge to and from any co-located firm. Conversely, the presence of formalized mechanisms in alliances, including governance structures and contractual agreements, makes it more feasible for firms to control knowledge flows (Oxley and Wada, 2009). Firms can restrict knowledge access, institute monitoring mechanisms, and regulate the scope of cooperative activities, including enforcing sanctions in cases of knowledge-sharing agreement violations (Oxley and Sampson, 2004; Reuer and Ariño, 2007).

Third, the conditions of control impact the interdependence of knowledge flows. In alliances, where knowledge transfer is formalized, inflows and outflows of knowledge are highly interdependent, as restrictions imposed by one firm often lead to corresponding adjustments by its partner to maintain a reasonable balance between knowledge inflows and outflows (Buckley et al., 2009; Zobel and Hagedoorn, 2020). In contrast, in clusters, where knowledge transfer is informal and often random, it is challenging to map inflows and outflows from a specific firm to others, creating untraded interdependencies (Storper, 1995; Tallman et al., 2004) and making reciprocity at the interfirm level difficult to enforce. Consequently, inflows and outflows of knowledge exhibit high interdependence within alliances but not so within clusters.

2.1. The role of firm technological capability on the effects of cluster and alliance resources on firm innovation performance

We suggest that the differences discussed above about how knowledge flows occur in clusters and alliances lead to identifiable differences in the focal firm's leveraging of the knowledge from these sources. Accordingly, theorize why and how the technological capability of a firm interacts with technological knowledge residing in the firm's cluster and alliance partners and shapes the innovation output of the firm. We depict our conceptual model in Fig. 1.

Literature on absorptive capacity (Cohen and Levinthal, 1990) has long recognized that a firm's internal technological knowledge is a critical element of its absorptive capacity, i.e., ability to recognize the value of external knowledge, assimilate such knowledge, and use it for innovation (Cohen and Levinthal, 1990; Song et al., 2018). This logic suggests that a technologically strong firm should be capable of absorbing externally sourced technologies more efficiently and effectively than a weaker firm. However, as we noted earlier, both conceptual and empirical studies suggest that the effect of internal capability on external learning is not so straightforward (Cohen and Levinthal, 1990; McCann and Folta, 2011; Srivastava and Gnyawali, 2011; Wennberg and Lindqvist, 2010). Below, we discuss three critical reasons why a firm's technological strength would limit its leveraging of external knowledge: the cost of knowledge loss, the efforts to stem knowledge loss, and the likelihood of assimilating external knowledge.

Cost of Knowledge Loss. Technologically capable firms worry about potentially losing their valuable knowledge to other firms (Hamel, 1991). However, the extent of their concern is likely to be lower with respect to other firms in the cluster and higher with

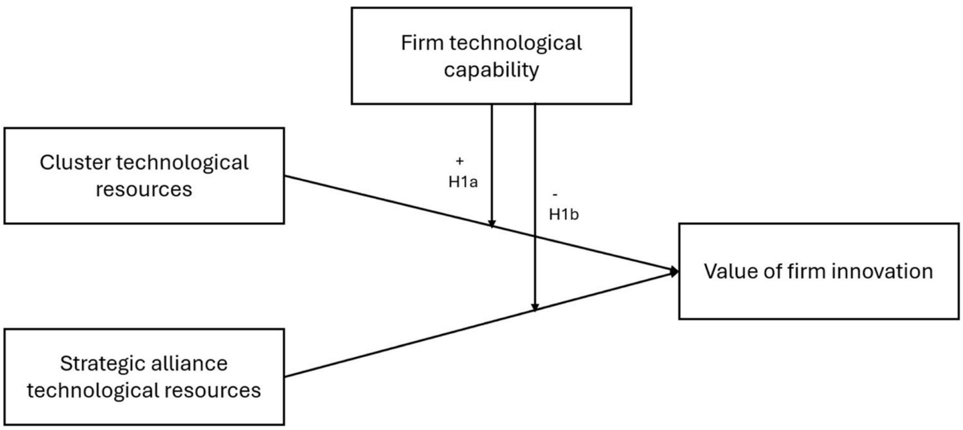

Fig. 1. Moderating Role of Firm Technological Capability on the Effects of Cluster Technological Resources and Alliance Technological Resources on Value of Firm Innovation.

respect to alliance partner firms. In clusters, since knowledge flows occur via unsystematic, random, and fragmented spillovers (Dahl and Pedersen, 2004; Pouder and St. John, 1996; Saxenian, 1994), the competitive costs and risks associated with outward knowledge flows would be low. Informal interactions among employees of cluster firms and mobility of employees within the cluster (Almeida and Kogut, 1999; Saxenian, 1994) are two primary ways in which knowledge spillovers occur in clusters. Informal interactions are most likely to produce the sort of fragmented partial knowledge transfer discussed above, and outward mobility of employees may "disseminate jargon and some personal knowledge on useful social ties, but not *all* the firm-specific knowledge, despite this being codified" (Lissoni, 2001: 1499). A firm's knowledge base essentially constitutes two kinds of knowledge: component and architectural. Informal interaction or mobility of employees (Zucker et al., 1998) would mostly diffuse fragmentary component knowledge. The architectural knowledge that provides the core of firm-specific advantage (Tallman et al., 2004) is difficult to transfer since it is tacit, organizationally bound, highly sticky, and generally not fully comprehended by specific individual employees. Therefore, the mobility of some employees to other cluster firms is less likely to lead to costly knowledge transfer.

In contrast, given that knowledge flows in alliances are intentional and systematic, and that inter-organizational routines encourage and assist knowledge transfer (Phene and Tallman, 2014; Podolny, 2001; Soh and Roberts, 2005; Zollo et al., 2002), the potential costs associated with unintended outward flows of knowledge in alliances are much greater. An opportunistic partner may, for instance, misappropriate knowledge intended only for use within the alliance (Hamel, 1991). Firms with strong internal capabilities have more to lose, so the fear of losing valuable knowledge increases for technologically stronger firms. In addition, technologically capable firms tend to attract capable partners (Chung et al., 2000) and their critical knowledge resources are at an even greater risk of unwanted intentional exploitation by their skilled alliance partners (Hamel, 1991; Norman, 2002). Thus, the joint consideration of systematic, focused, and integrated forms of knowledge flow and the characteristics of technologically strong firms suggests that the expected costs associated with unintended outward knowledge flows to the firm's alliance partners are much greater than those of knowledge spillovers to co-located or cluster firms.

Efforts to Stem Knowledge Loss. Cluster firms can do little to mitigate the risk of knowledge loss in clusters unless they choose to leave the location, and firms cannot control knowledge spillovers in the cluster (Shaver and Flyer, 2000). While firms have policies and procedures in place to limit knowledge loss, clusters are characterized by "untraded interdependencies" (Storper, 1995) and "knowledge in the air"(Marshall, 1920), so cluster firms expect access to inward spills from other member firms (Zucker et al., 1998) and are aware that they risk some spillover. Therefore, we do not expect the focal firm to change its behavior in response to knowledge spillover risks in a cluster. Firms may impose non-compete clauses on employees to keep them from joining competitors (Balasubramanian et al., 2024), but these restrictions may affect both neighboring cluster firms and allied partner firms alike.

In the case of alliances, knowledge flows occur directly from partner to partner, so limiting knowledge movement is more feasible; therefore, technologically stronger firms are more likely to take actions to limit knowledge leakage, as they can exercise greater control over outward knowledge flows (Heiman and Nickerson, 2004; Norman, 2002). Prior studies show that firms introduce more sophisticated contractual controls when an alliance is strategically important (Reuer et al., 2006). Yet contracts by themselves rarely stop unintended knowledge leakage (Jiang et al., 2013; Oxley and Wada, 2009). To curb this risk, companies may narrow the scope of cooperation (Oxley and Sampson, 2004) or, if they possess superior technical capabilities, leverage their bargaining power to impose tighter, more protective terms (Yan and Gray, 1994). These defensive moves, however, come with a cost: restricting knowledge outflows can adversely affect valuable inflows from alliance partners (Friedmann, Lavie, & Rademaker). Since in contractual settings, the interdependence between knowledge inflows and knowledge outflows is high, as we noted before, success in protecting the outward flow of knowledge will limit the inflow of valuable knowledge from the alliance partner as the partner firm undertakes reciprocal actions/reactions. Thus, in the case of alliances, for a technologically strong firm, heightened concern for the cost of knowledge loss, greater ability to exercise control over knowledge flows, and interdependence between knowledge inflows and knowledge outflows together create conditions that are likely to adversely affect the inflow of valuable knowledge from its alliance partners.

Assimilation of External Knowledge. Technologically stronger firms may have a higher potential to absorb new technologies from either clusters or alliances. However, we suggest that technologically strong firms should be relatively more effective in applying their technological understanding to assimilating cluster-derived knowledge than alliance-derived knowledge for two primary reasons: knowledge familiarity and ability to absorb.

Cluster member firms share cluster-level architectural knowledge and context (Tallman et al., 2004), i.e., an understanding that is common to members of the cluster. So, spillovers from the co-located cluster firms will likely be familiar to the focal firm. Due to this familiarity, the firm will have less resistance or more willingness to assimilate and adapt those ideas and knowledge. In contrast, since complementarity is the basis for knowledge-driven alliances (Madhok and Tallman, 1998), firm will be less familiar with the ideas and knowledge coming from alliances, and more unique knowledge will appear cognitively more distant (Gilsing et al., 2008). This is particularly true for the larger part of the organization that is not directly involved with the alliance. Internally stronger firms suffer more from what is known as "not-invented-here" (Katz and Allen, 1985) syndrome and consequently exhibit greater resistance to external ideas seen as replacements for internal ones. As a result, even if the teams directly involved in the alliances try to champion ideas that are perceived to be rooted in their alliance partners, the rest of the organization will continue to show strong resistance (Kim and Song, 2007; Song and Shin, 2008). Prior studies show that highly capable firms are likely to underutilize alliance resources because behavioral traps—like a "not-invented-here" bias, fears of knowledge leakage, and limited managerial attention—get in the way (Martynov, 2016; Norman, 2004; Srivastava and Gnyawali, 2011; Stuart, 2000; Wu, 2014).

The second reason why technologically strong firms would be relatively more effective in assimilating cluster knowledge than alliance knowledge is their ability to absorb new knowledge. This ability is based on the nature of knowledge and its flow as discussed above. Due to the fragmented and unsystematic flow of knowledge in clusters (Dahl and Pedersen, 2004; Pouder and St. John, 1996;

Saxenian, 1994), a firm's ability to separate more valuable knowledge from less valuable knowledge and to integrate bits of knowledge is more critical in benefiting from the spillover of fragmented and incomplete spillovers in clusters than in absorbing more complete and organized knowledge transfers in alliances. Firms with superior technological capabilities have organizational architectural frameworks that let them absorb and integrate external know-how, so they benefit more from cluster spillovers. Although every firm in a cluster possesses some cluster-specific know-how (Tallman et al., 2004), technologically strong firms are more likely to identify and weave together the fragmented knowledge that circulates locally (Marshall, 1920; Storper, 1995) and apply the cluster knowledge more effectively. Thus, stronger firms can more effectively recombine fragmented cluster knowledge from multiple sources (Kogut and Zander, 1992) because of their robust internal frameworks.

Compared with geographic clusters, strategic alliances deliver knowledge through formal, well-supported transfer routines (Oxley and Wada, 2009; Phene and Tallman, 2014; Podolny, 2001; Soh and Roberts, 2005). Because the know-how arrives largely intact and often comes with technical assistance, a firm's internal integration capability matters less in this setting. Weaker firms that actively seek to learn but lack sophisticated absorptive architectures (Hamel, 1991) can therefore reap outsized benefits from alliances, as the alliance itself supplies much of the scaffolding they would otherwise need. By contrast, technologically strong firms enjoy a bigger edge when they tap the more diffuse spillovers circulating in their home clusters. These differences in how cluster- and alliance-based ideas enter the firm ultimately shape the pace and direction of its innovation efforts.

Overall, technologically strong firms situated in geographic clusters perceive little risk of knowledge leakage, making them more open to ideas from neighboring firms; their superior integration capabilities then enable them to transform these diffuse spillovers into valuable innovations. In alliances, however, the same strong firms fear losing proprietary know-how and likely erect stringent safeguards that partners often mirror, creating a defensive climate that restricts knowledge inflows and heightens their reluctance to engage with unfamiliar partner expertise. Weaker firms, by contrast, lack sophisticated architectural frameworks; they struggle to capture scattered insights in clusters but benefit disproportionately from the formal, well-supported transfer routines typical of alliances, which compensate for their internal deficiencies. Together, these contrasts suggest that strong firms benefit more from cluster spillovers than from alliances, whereas weak firms harvest greater learning gains from alliances than from clusters. Accordingly, we hypothesize that

Hypothesis 1a. *: The greater the technological capability of a firm, the greater the positive effect of its cluster technological resources on the value of its innovations.*

Hypothesis 1b. *: The greater the technological capability of a firm, the lower the positive effect of its alliance technological resources on the value of its innovations.*

3. Methods

3.1. Data

We tested our hypotheses using a sample of firms from the U.S. semiconductor industry, an industry that is characterized by a strong patenting propensity, the prevalence of strategic alliances, and clustering tendencies (McCann et al., 2016; Podolny et al., 1996; Ryu et al., 2018; Yayavaram et al., 2018; Yeung, 2022). Our study design is an unbalanced panel of 155 U.S.-based semiconductor firms from 1986 to 2000. The alliance data source limited the starting year of observation. The patent data source limited the end year of observation, as some lag time is needed for a patent to be cited. We started with the entire population of publicly traded dedicated semiconductor firms listed in the Standard and Poor's Compustat database under the SIC code 3674. A total of 258 dedicated semiconductor firms appeared in the database. We chose SIC 3674 as the primary SIC of firms to ensure that the sample firms are predominantly semiconductor firms, so diversified firms such as Toshiba, Motorola, IBM, NEC, and Samsung are not included in the sample. After dropping firms that were not in existence as public firms during the initial observation period of 1986–1999 (1999 is the last year of the independent variable due to one year lag used in data analysis) or were foreign firms but listed on NYSE or NASDAQ and therefore appeared in the Compustat database, our final sample consists of 155 US public semiconductor firms. Of these 155 firms, 69 were fabless (or design), 66 were integrated semiconductor manufacturing (ISM), 17 were manufacturing-only, and 3 were chip-testing firms.

Alliance data. We collected alliance data for the sample firms using the SDC database, which is the most comprehensive database available (Phelps, 2003; Schilling, 2009) providing information on the date of alliance announcement, details of partners involved, and the alliance's purpose. However, this database has some limitations as it includes information based on alliance announcements rather than on actual formations, and data on items such as the duration of alliances are missing (Phelps, 2003). We therefore used Factiva to trace and verify the existence of the announced alliances. Following Schilling and Phelps (2007), we took a conservative approach and assumed the duration of alliances as three years, but also did a sensitivity analysis using four and five-year durations. Adopting the approach used by Ahuja (2000), we converted all multilateral alliances among partners into a set of bilateral alliances between those partners.

Cluster data. Following the approach of Zaheer and George (2004), we define a cluster as a set of co-located firms within 200 miles of the focal firm. Further, following Baptista and Swann (1998) and Zaheer and George (2004), we considered each focal firm as part of one primary cluster based on the location of its corporate headquarters. We also used 100 miles and 150 miles as alternative radii for identifying the clusters to examine this choice's sensitivity and ensure the results' robustness. We recorded the zip codes of all the firms in the database from the 10-K report filed with the Securities and Exchange Commission. We first converted those zip codes into latitudes and longitudes, then using spherical geometry we calculated the distance between two firms in miles based on the following formula: *Distance (F1, F2) = 3963*arcos [sin (lattitude1)*sin (lattitude2) + cos (lattitude1)*cos (lattitude2)*cos (longitude2- longitude1)].*

Patent Data. We used the NBER patent database (Hall et al., 2001) as the initial step to construct the patent data and expanded the data through additional steps described below. The NBER database contains patent information regarding patent number, assignee name, assignee number, filing year, and grant year, among others, but does not contain CUSIP numbers (used in the Compustat database) of the assignee firms. Moreover, the SDC database provides fictitious CUSIP numbers for many firms. To overcome these limitations, we also used the name-matching database (*coname* database) provided by Hall and colleagues (2001). This database has standardized names of assignee firms, matched with the names in the Compustat file. This *coname* database is the bridge between the Compustat database and the patent database. However, using this database, we could find patent information for only 210 firms (focal and alliance-partners/co-located firms) due to the limited number of firms in this database. We could not ascertain whether the rest of the firms had no patents or had patents but did not appear in the *coname* database. We pursued two additional steps to overcome this limitation. First, using the Google patent database, we collected patent data on an additional 151 firms. To ensure the procedure's reliability, we matched the total number of patents (n1) for a firm from the Google patent database during 1986–2000 with the total number of patents (n2) for the same firm during the same period from the NBER patent database. Next, we wrote a name-matching program, and through this program, we found patent information for an additional 98 firms. With the procedures described above, we gathered patent data for a total of 459 firms (focal and alliance partners/co-located firms) and ensured that the rest had no patents with the USPTO.

3.2. Measures

Dependent variable: Value of firm innovation. Patents have often been used in the literature to measure technological innovation. Researchers have stressed the need to assess the importance of the patents and have used citation-weighted patent count as a way to discern this (Lahiri, 2010). Therefore, following Singh (2008), we use a citation-weighted count of patents to measure the value of firm innovation. Patent citations have considerable economic and technological significance (Hall et al., 2005; Jaffe et al., 2000) as each additional patent citation captures 3 % increase in a firm's market value (Hall et al., 2005). A greater number of citations received by a patent suggests a greater value of such patents to the patent holder firm (Harhoff et al., 1999).

3.3. Independent variables

Our measures of the independent variables, Cluster technological resources and Alliance technological resources, are based on the citation-weighted patent counts of the focal firm's co-located firms and alliance partners, respectively. Patents indicate valuable, inimitable, and non-substitutable knowledge-based resources (Henderson and Cockburn, 1994). In addition, codified knowledge resources such as patents are also highly complementary to non-codified knowledge (Patel and Pavitt, 1997). To isolate and estimate the independent effects of cluster and alliance, we dropped a few observations with overlapping memberships in their cluster and strategic alliances. To ensure that the cause precedes the effect, we utilized independent, moderator, and control variables with a one-year time lag relative to the observed dependent variable.

Cluster technological resources. We measured *Cluster technological resources* using the citation-weighted count of patents successfully filed by the cluster firms (other than the focal firm) in year t-1.

$Cluster\_tech\_resources_{it-1} = \gamma \cdot \sum_{j=1}^{n} \sum_{k=1}^{m} Cw_k . p_{jkt-1}$, where p_{jkt-1} is the k_{th} patent of the co-located firm j in the year t-1, Cw_k is the number of citations that the patent has received, and γ is a scaling constant.

For alliance based measures, we used a weighing scheme consistent with the approach used by Contractor and Lorange (1988) by assigning higher weights to alliances that contained higher intensity of relationships. Since many alliances span multiple value chain activities, we slightly modified the weighting scheme to incorporate this possibility. Thus, each alliance weight became a function of the value chain activities within the alliance scope. Higher weights were assigned to areas that are more important in the semiconductor industry such as R&D and manufacturing (Henisz and Macher, 2004). Further, using a linear weighing scheme (Stuart, 2000) we assigned higher weights to real dyadic alliances in comparison to multilateral alliances that were converted to dyadic alliances. We devised the following computation by incorporating both considerations: *alliance_weight(ALw)* = (4*R&D+3*Manufacturing + 2*Cross_licensing + Licensing + Marketing + Tech-Transfer)*partner_weight, where partner_ weight (>=.25,<=1.0) factored the number of partners involved in the alliance. If in a multilateral alliance there were three partners (apart from the focal firm), each partner received the weight of 0.70 (instead of 1.0 for a true bilateral alliance).

Alliance technological resources. We measured *alliance technological resource* as the sum of citation-weighted count of the focal firm's alliance partners' patents successfully applied each year. We calculated this variable for the focal firm (i) in the year (t) using the following formula (Srivastava and Gnyawali, 2011):

$Alliance\_tech\_resource_{it-1} = \gamma \cdot \sum_{j=1}^{n} ALw_{ij} \sum_{k=1}^{m} Cw_k . p_{kt-1}$, where *ALw* is the weight of the alliance with partner j, n is the total number of partners of focal firm in the year t-1, Cw_k is the citation weight of the p_k^{th} patent of the partner j, and m is the total number of patents successfully filed by the partner j in the year t-1, p_k is one of those m patents, and γ is a scaling constant.

Moderator variable: Focal firm's technological capability. We measured a firm's technological capability as the number of pioneering patents generated by the firm each year. Pioneering patents are those that have no prior precedence or do not cite any prior patents, and reflect the firm's ability to generate pioneering technologies (Ahuja and Lampert, 2001) and stay at the forefront of technological developments. Patents are a valuable resource, but the ability to generate pioneering patents reflects a firm's underlying technological capabilities (Henderson and Cockburn, 1994; Nerkar, 1997; Patel and Pavitt, 1997; Quintana-García and

Benavides-Velasco, 2008; Srivastava et al., 2015). In the robustness test, we used an alternative measure of technological capability of patent share (Chen et al., 2019; Lee and Lee, 2017) of the focal firm each year. To be able to compare the effects of firm technological capability, cluster technological resources, and alliance technological resources, we standardized these variables.

Control variables. We controlled for systematic differences among firms that may influence a firm's ability to generate valuable technological innovations. Since age and size of a firm could affect the firm's likelihood of generating innovations (Damanpour, 1991; Sorensen and Stuart, 2000), we controlled for them. We measured *Firm age* as the difference between the year of observation and firm incorporation. We used the log value of firm sales to measure firm size (Damanpour, 1991). The presence of unobservable permanent heterogeneity in innovation models may produce biased estimates (Blundell et al., 1995). Therefore, following Schilling and Phelps (2007), we controlled for prior knowledge stock of focal firms that may account for permanent unobserved heterogeneity among the sample firms by including the variable *Pre sample patents* (Ahuja and Katila, 2001) and measured it as the sum of patents obtained by the focal firm during the five years before entering into the sample. A firm's level of technological diversification may also impact its recombinatory opportunities and innovation generation, therefore we controlled for it using *firm technological diversity* computed using the square root of Hirshmann-Herfindahl index (Hirschman, 1964). We controlled for firms dropping from the sample (*sample drop*) if a firm dropped from the sample due to acquisition and bankruptcy during the observation period. We also controlled for the capital structure of the firm using the *debt-to-equity ratio,* as a firm's capital structure may impact its risk-taking behavior. Following Miller and colleagues (2007) we also controlled for the *number of assignees* a firm has in the patent database.

3.4. Statistical analysis

Our dependent variable, *Value of firm innovation*, is a count variable that takes only non-negative integer values and has over-dispersion. Therefore, neither linear regression nor Poisson was an appropriate analytical model. Under such conditions, a negative binomial regression is considered a more appropriate econometric model (Cameron and Trivedi, 2009), therefore we used negative binomial panel regression. We report random effects results as our primary results (Table 2), as there was no qualitative difference between the conclusions from the fixed effects models (Table 3), and as the fixed effects model accounted for 76 fewer firm years and 23 fewer firms.

4. Results

Table 1 provides summary statistics for and correlations among all the variables used in the estimations. Given the importance of innovation in the industry, large firms typically have more patents. These trends are reflected in the high correlations (Table 1) between firm size, firm age, pre-sample patents, and firm technological diversity. To examine the extent and nature of the multi-collinearity problem, we used the *collin* procedure in Stata 18 for conducting the Belsley, Kuh, and Welsch multicollinearity diagnostic test (Belsley et al., 1980). We report the conditioning index numbers for all the models (Table 2). A conditioning index number less than 10 is considered a desirable number, suggesting the lack of a multicollinearity problem, whereas a number higher than 30 suggests that multicollinearity is a serious concern. Conditioning index numbers range from 8.93 (Model 1) to 9.87 (Model 4); the slight increase in the number is due to the presence of interacting variables, but it was still way below 30 for multicollinearity to become a serious concern.

Table 2 shows the maximum likelihood estimates of random-effect negative binomial regression panel models for Firm technological capability and technological resources in geographic clusters and strategic alliances. Model 1 reports the results for the control variables. The effect of Log of firm sales (firm size) is positive, which is consistent with prior findings (Yayavaram and Ahuja, 2008). The effect of Firm age is negative, implying that as firms become older, their chances of generating more valuable innovations decline, which is also consistent with the prior findings (Sorensen and Stuart, 2000). We further find that Firm technological diversity has a positive impact on the Value of firm innovation, which is also consistent with our expectations and prior literature (Lahiri, 2010). Consistent with prior literature, we also find that the effects of Cluster technological resources (Fang, 2015) and Alliance technological resources are positive and significant (Model 1). We also find that there is a positive impact of Firm technological capability on the Value of firm innovation (Model 2), which is consistent with our base line expectations.

In Model 3, we introduce the interaction between Cluster technological resources and Firm technological capability. The coefficient of interaction term of Firm technological capability with Cluster technological resources is positive and significant (β=0.083, SE 0.020, $p < 0.01$). We graphically depict their relationship in Fig. 2a, which shows that the average marginal effects of Firm's technological capability increase with the increasing values of Cluster technological resources indicating the presence of complementarity between Firm technological capability and cluster resources, lending support for Hypothesis 1a. In the presence of complementary effects we would expect the effectiveness of independent variable to increase when the moderating variable is high, while in the presence of substitution effects we would expect it to decrease (Siggelkow, 2002; Voss et al., 2010).

Model 4 depicts the interaction of Alliance technological resources with Firm technological capability. In Hypothesis 1b, we predicted that Firm technological capability negatively moderates the effect of Alliance technological resources on Value of firm innovation. As shown in Model 4, the interaction term between Alliance technological resources and Firm technological capability is negative and significant (β=-0.029, SE 0.006, $p < 0.01$). We graphically depict the interaction in Fig. 2b, which shows that Firm technological capability negatively moderates the positive effects of Alliance technological resources, lending support to Hypothesis 1b. In contrast to the complementary effects of Cluster technological resources, Fig. 2b shows that there is a substitution effect between Alliance technological resources and Firm technological capability.

Table 1
Descriptive Statistics and Correlations.

	Variable	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10
1.	Value of innovation$_t$	492.87	1813.38	0	19041										
2.	Log of sales $_{t-1}$	4.02	1.88	−3	10.11	0.51									
3.	Firm age $_{t-1}$	16.33	11.98	0	69	0.23	0.33								
4.	Pre sample patents	24.69	118.65	0	1018	0.56	0.43	0.49							
5.	Firm technological diversity $_{t-1}$	0.39	0.38	0	0.94	0.33	0.59	0.06	0.26						
6.	Sample drop (YES=1)	0.13	0.34	0	1	−0.08	−0.07	−0.02	−0.07	−0.05					
7.	Number of assignees	1.16	0.62	0	4	−0.01	0.15	0.14	0.01	0.17	−0.20				
8.	Debt equity ratio $_{t-1}$	0.37	3.07	−12.08	81.3	−0.01	0.01	0.05	0.00	−0.03	0.05	−0.01			
9.	Cluster tech resources $_{t-1}$ †	0	1	−1.2	1.65	−0.12	−0.04	−0.19	−0.13	0.08	−0.04	−0.03	−0.10		
10.	Alliance tech resources $_{t-1}$ †	0	1	−0.26	9.7	0.67	0.45	0.28	0.56	0.29	−0.05	0.04	−0.01	−0.10	
11.	Firm technological capability $_{t-1}$†	0	1	−0.23	9.09	0.72	0.46	0.34	0.73	0.29	−0.05	−0.01	−0.01	−0.10	0.61

Number of firm years= 1068, * $p < 0.05$; † variables standardized

Table 2
Effect of cluster technological resources and alliance technological resources on value of firm innovation using Negative Binomial Random Effects Model.

	Control		Baseline		H1a		H1b	
Variable	**Model 1**		**Model 2**		**Model 3**		**Model 4**	
Log of sales $_{t-1}$	0.342***	(0.032)	0.334***	(0.031)	0.335***	(0.032)	0.332***	(0.031)
Firm age$_{t-1}$	−0.029***	(0.005)	−0.031***	(0.005)	−0.032***	(0.005)	−0.033***	(0.005)
Pre sample patents	0.002***	(0.001)	0.002***	(0.001)	0.003***	(0.001)	0.002***	(0.000)
Firm technological diversity $_{t-1}$	1.912***	(0.129)	1.928***	(0.129)	1.925***	(0.129)	1.915***	(0.128)
Sample drop (YES=1)	−0.224	(0.140)	−0.228	(0.140)	−0.233*	(0.139)	−0.235*	(0.139)
Number of assignees	0.361***	(0.076)	0.366***	(0.075)	0.350***	(0.074)	0.392***	(0.076)
Debt equity ratio $_{t-1}$	−0.025	(0.025)	−0.025	(0.025)	−0.024	(0.025)	−0.021	(0.024)
Cluster tech resources $_{t-1}$	0.120***	(0.038)	0.119***	(0.038)	0.110***	(0.038)	0.117***	(0.037)
Alliance tech resources $_{t-1}$	0.117***	(0.017)	0.115***	(0.016)	0.096***	(0.015)	0.203***	(0.024)
Firm technological capability $_{t-1}$			0.048**	(0.020)	0.085***	(0.019)	0.163***	(0.024)
Cluster tech resources $_{t-1}$#Firm technological capability $_{t-1}$					0.083***	(0.020)	0.072***	(0.020)
Alliance tech resources $_{t-1}$#Firm technological capability $_{t-1}$							−0.029***	(0.006)
Constant	−2.977***	(0.153)	−2.919***	(0.154)	−2.888***	(0.154)	−2.858***	(0.156)
Wald's chi-square	1027		1048		1124		1190	
Degrees of freedom	9		10		11		12	
Number of firms	155		155		155		155	
Observations	1068		1068		1068		1068	
Log likelihood	−4618		−4615		−4609		−4596	
Base Model 1			5.67**		18.48***		43.21***	
Base Model 2					12.82***		37.55***	
Base Model 3							24.73***	
Conditioning Index number	8.93		9.08		9.24		9.87	

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

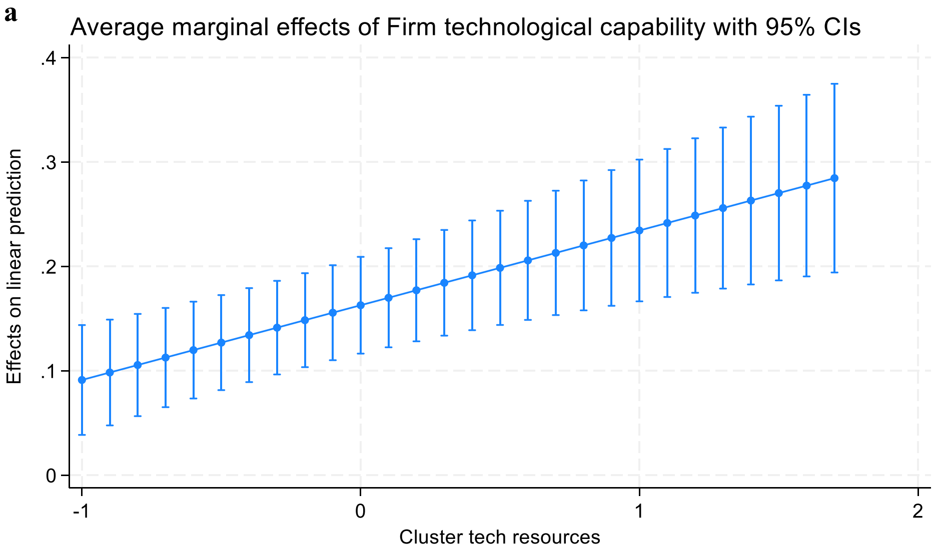

Fig. 2a. Marginal Effects of Firm Technological Capability and Cluster Tech Resources.

4.1. Additional analyses

Since firms simultaneously access cluster and alliance resources, in our additional analysis, we examine how cluster and alliance tech resources jointly impact the value of firm innovation, and how they together interact with firm technological capability. Accordingly, in Model 5 (Table 3), we introduce the interaction between Alliance technological resources and Cluster technological resources, as well as the three-way interaction between Firm technological capability, Cluster technological resources, and Alliance technological resources. The interaction between alliance and cluster technological resources is positive and significant, showing their complementary effects. However, the interaction between the Firm's technology capability, Cluster technological resources, and Alliance technological resources is negative. To understand the joint implications of these interactions shown in Model 5 (Table 3), we graphically depict their relationship in Fig. 3. The graph illustrates that firms with high technological capability benefit significantly

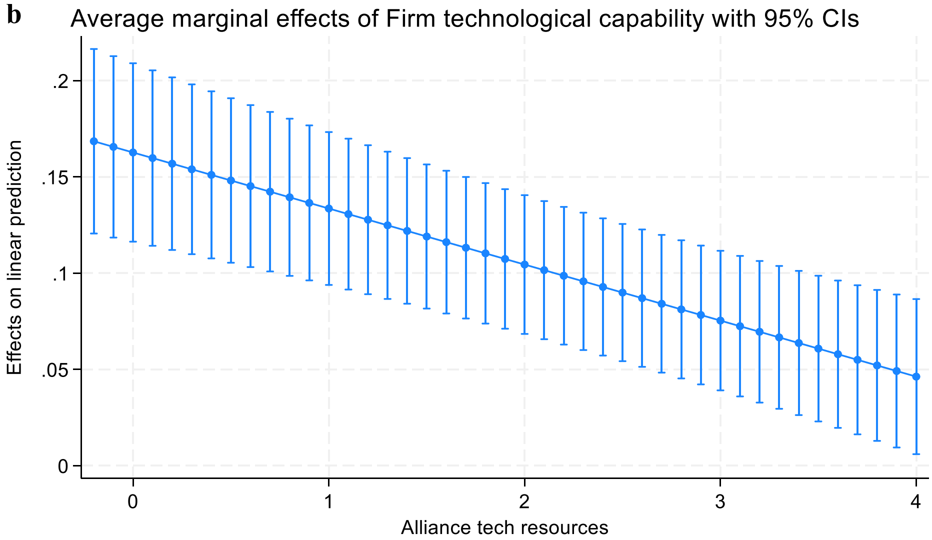

Fig. 2b. Marginal Effects of Firm Technological Capability and Alliance Tech Resources.

Table 3
Additional analysis and robustness checks.

Variable	Cluster and Alliance tech resources, and Firm technological capability Interaction Model 5		Fixed effects Model 5a		Endogeneity of Cluster and Alliances, Random Effects Model 5b	
Log of sales $_{t-1}$	0.333***	(0.03)	0.358***	(0.04)	0.205***	(0.03)
Firm age $_{t-1}$	−0.034***	(0.01)	−0.029***	(0.01)	−0.036***	(0.01)
Pre sample patents	0.003***	(0.00)	0.002***	(0.00)	0.002***	0.00
Firm technological diversity	1.914***	(0.13)	1.518***	(0.14)	1.741***	(0.13)
Sample drop (YES=1)	−0.243*	(0.14)	−0.187	(0.19)	−0.18	(0.13)
Number of assignees	0.393***	(0.08)	0.296***	(0.11)	0.319***	(0.07)
Debt equity ratio $_{t-1}$	−0.019	(0.02)	−0.025	(0.02)	−0.025	(0.02)
Cluster tech resources $_{t-1}$	0.117***	(0.04)	0.135***	(0.04)	0.037	(0.04)
Alliance tech resources $_{t-1}$	0.254***	(0.03)	0.238***	(0.03)	0.207***	(0.03)
Firm technological capability $_{t-1}$	0.167***	(0.03)	0.154***	(0.03)	0.110***	(0.02)
Cluster tech resources $_{t-1}$ # Firm technological capability $_{t-1}$	0.097***	(0.02)	0.088***	(0.03)	0.066***	(0.02)
Alliance tech resources $_{t-1}$ # Firm technological capability $_{t-1}$	−0.040***	(0.01)	−0.038***	(0.01)	−0.029***	(0.01)
Cluster tech resources $_{t-1}$#Alliance tech resources $_{t-1}$	0.102***	(0.03)	0.088**	(0.04)	0.079***	(0.03)
Cluster tech resources $_{t-1}$#Alliance tech resources $_{t-1}$# Firm technological capability $_{t-1}$	−0.022***	(0.01)	−0.020**	(0.01)	−0.017***	(0.01)
Inverse Mills ratio -Alliance					−1.253***	(0.15)
Inverse Mills ratio -Cluster					0.575***	(0.14)
Constant	−2.839***	(0.16)	−2.665***	(0.19)	−1.007***	(0.27)
Wald's chi-square	1241		807		1614	
Degrees of freedom	14		14		16	
Number of firms	155		133		155	
Observations	1068		994		1066	
Log likelihood	−4592		−3597		−4534	

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

from being in resource-rich clusters. By contrast, firms with lower technological capability derive greater benefits from alliance resources than from resource-rich clusters. Furthermore, when alliance resources are high, firms with limited technological capabilities also benefit from being in resource-rich clusters. However, for firms with high technological capability located in resource-rich clusters, additional alliance resources do not provide further advantage.

To ensure the robustness of our findings, we subjected our models to multiple rigorous tests. We used the results from negative effects fixed effects (Table 3, Model 5a), we also used an alternative model specification (Poisson panel regression with robust standard errors that uses quasi-maximum likelihood estimators), and tested models without any control variables (results available on request). Further, unobservable factors can influence a firm's decision to tap alliance-based or cluster-based technological resources, raising

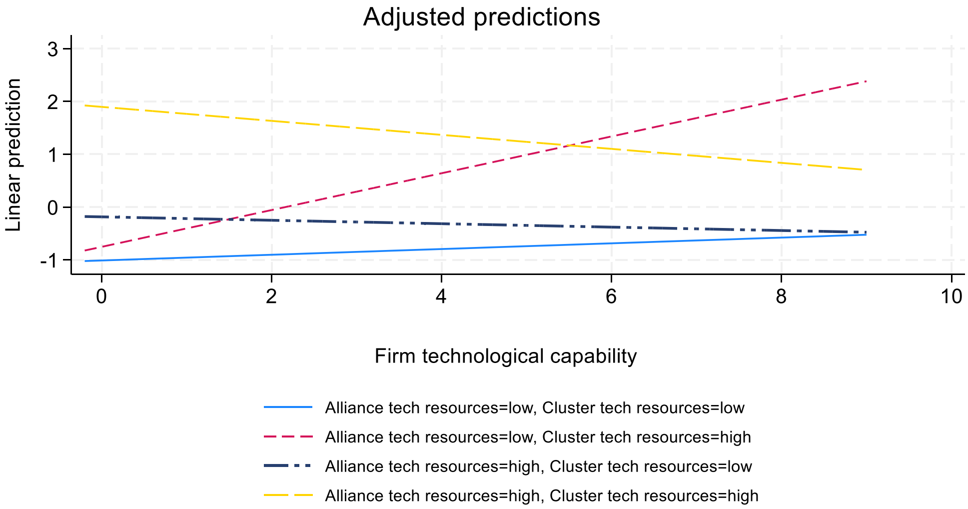

Fig. 3. Interaction Effects of Firm Technological Capability, Cluster Tech Resources and Alliance Tech Resources.

selection-endogeneity concerns (Hawk et al., 2024; Kumar and Zaheer, 2022; Ryu et al., 2018; Wang et al., 2020; Yu et al., 2022). To correct for this endogenous selection bias, we employ a Heckman two-stage procedure. In the first-stage probit we model the probability that a firm holds non-zero Alliance technological resources and non-zero Cluster technological resources, using three exclusion variables—cash reserves, invested capital, and technological depth—that affect partnering and locational choices but not patent output directly. The fitted values yield inverse Mills ratios (IMRs) for alliance and cluster resources, which we include as controls in the second-stage patent equation (Table 3, Model 5b).

A second issue is endogenous response—reverse causality in which unobserved shocks to Value of firm innovation feed back into the explanatory variables. Two kinds of unobservable could generate such feedback. First, time-invariant traits are swept out by firm fixed effects. Second, time-varying shocks might prompt firms to seek new partners or relocate. Alliance formation through access to alliance technological resources is explicitly handled by the Heckman correction above. Relocation, by contrast, is not common. Taken together, the fixed-effects specification, the Heckman selection correction, and the empirical rarity of relocation make reverse causality an unlikely source of bias in our estimates.

Overall, we find results across these additional tests fully consistent with our primary results. Based on these rigorous tests, our confidence in our results is greatly enhanced.

5. Discussion and implications

This paper was motivated by a critical research question that is poorly understood: how do the characteristics of external knowledge interact with a firm's internal capability, commonly referred to as absorptive capacity (Cohen and Levinthal, 1990; Song et al., 2018), in deriving innovation benefits from external knowledge? We focused on two important sources of external technological knowledge—geographic clusters and strategic alliances—to examine this research question. While the literature has clearly emphasized the importance of knowledge present in clusters (e.g.,Audretsch and Belitski, 2022; McCann and Folta, 2011; Tallman et al., 2004) and alliance partners (e.g., Phelps et al., 2012; Powell et al., 1996) for firm innovation, we know little about how the extent of innovation benefits firms derive from the knowledge present in these sources varies depending on their internal technological capability. By juxtaposing knowledge that is similar in content (technological knowledge of other firms) but different in location—co-located firms versus alliance partners—we isolate their distinct effects and reveal when cluster and alliance resources complement or substitute for a focal firm's capabilities. Since the literature on each of the two sources of knowledge has largely developed independently (Devarakonda et al., 2018; Kumar and Zaheer, 2022), our research is one of the few attempts to consider these sources of knowledge simultaneously and to examine their differential effects on firms with similar resource profiles.

Conceptually, we proposed that clusters and alliances differ fundamentally in the nature of knowledge flows among firms, the extent to which firms can control these flows, and the level of interdependence in knowledge inflows and outflows. We further theorized that these distinctions have critical implications for firms with varying internal technological capabilities. Because knowledge flows in clusters often occur through spillovers of fragmented forms of technical knowledge (Aharonson et al., 2007; Caniels and Romijn, 2005; Dahl and Pedersen, 2004), a firm's ability to integrate such dispersed knowledge increases the firm's likelihood of acquiring and assimilating cluster-based resources. Firms with stronger internal capabilities—those more adept at acquiring and integrating fragmented knowledge—enjoy greater innovation benefits from the knowledge in the cluster. Although strong firms may worry about knowledge leakage, the fragmented and often unintended nature of cluster spillovers mitigates this concern.

Conversely, alliances typically rely on more formal mechanisms or "pipes" that enable directed, integrated flows of knowledge, making a firm's internal integration abilities less critical. Since knowledge exchanges in alliances are more systematic and integrated (Inkpen, 2000), technologically strong firms face a heightened fear of knowledge loss (Norman, 2004) and take steps to safeguard their expertise, efforts that partners often reciprocate. Our empirical findings support these arguments and highlight the importance of simultaneously considering both clusters and alliances.

5.1. Contributions and implications

Our study contributes to the literature in several ways. First, to our knowledge, this is the first research to examine the relative attractiveness of cluster and alliance resources for a firm with a given technological capability. Our results indicate that, for technologically strong firms, geographic cluster resources have complementary effects, while strategic alliance resources act as substitutes. In contrast, for technologically weaker firms, both cluster and alliance resources are complementary, with alliance resources exerting a more substantial influence. These findings highlight different innovation outcomes for technologically strong firms and underscore the need for future research to distinguish between these two types of external knowledge sources.

Second, our research highlights the importance of examining how internal and external resources interact to foster innovation. While many studies address whether external resources benefit firms (Audretsch and Belitski, 2022; Crescenzi and Gagliardi, 2018; Howell, 2020; Lin et al., 2012; Phelps et al., 2012; Seo et al., 2023; Speldekamp et al., 2020; Srivastava and Gnyawali, 2011; Ubeda et al., 2019; Vasudeva and Anand, 2011), comparatively little work has explored how the effectiveness of similar external knowledge—such as the technological knowledge of other firms—may depend on the underlying knowledge flow mechanisms and firm capabilities. Our theory suggests that firms perceive and manage the risks and trade-offs of external knowledge sources in different ways, explaining why and how specific resource profiles yield varying innovation benefits. Consequently, our research clarifies how a firm's internal resources can serve either as enablers or constraints in the pursuit of learning and innovation.

Third, our theory and findings also provide insights into how a firm's internal strengths can become a trap in its approach to external knowledge and innovation (Ahuja and Lampert, 2001). More broadly, our study demonstrates how and why the context in which external resources are embedded, along with the firm's resource profile, leads to specific behaviors. Thus, we contribute to the literature on the behavioral theory of strategy (Bromiley and Rau, 2018; Gavetti, 2012; March, 2018; Powell et al., 2011; Srivastava et al., 2015) by illustrating how a firm's internal capabilities influence its behavior and how behavioral failures may occur concerning external resources. Our theory suggests that these failures can stem from risk perception regarding external knowledge; concerns about potential knowledge loss could jeopardize the anticipated gains.

Finally, our research both supports and extends existing insights into the role of knowledge in clusters and alliances. From a cluster perspective, our findings reinforce the idea that firms with stronger capabilities benefit from the opportunities offered by geographic proximity and can leverage their superior firm-specific architectural knowledge (Tallman et al., 2004). In such settings, stronger firms appear to engage in vicarious learning and may even benefit from the knowledge that others have acquired from them (Yang et al., 2010). Thus, while outward spillovers can be risky, they may ultimately prove advantageous for technologically advanced firms. Regarding alliances, our results align more closely with the competitive view of learning in alliances (Hamel, 1991; Norman, 2002, 2004) than with the generally positive "recombination" perspective proposed by Kogut and Zander (1992) or the altruistic perspective suggested by Arora et al., 2021.

6. Limitations and directions for future research

We recognize several limitations in our current research that also present compelling opportunities for future studies. First, while firms often cooperate with their strategic alliance partners, they may also compete with them in a dynamic known as coopetition (Gnyawali and Park, 2011). Our study does not consider competition among the alliance partners. Future research could explore the role of competition among alliance partners as a moderating factor. Second, geographic clusters vary in their structures and organization, which can impact their effectiveness and the flow of knowledge. Investigating the influence of different cluster characteristics could provide valuable insights. Third, while we focused on alliances in the high-tech context and on technological knowledge due to our interest in its role in technological innovation, future research could provide comprehensive insights by examining whether and how the effects vary across different types of alliances and governance structures (Choi, 2020; Faems et al., 2008) and other firm outcomes. Moreover, firms are embedded within larger networks, and factors such as their structural position (Burt, 2005), the strength of their ties (Granovetter, 1983; Uzzi and Gillespie, 2002), and the quality of their alliance partners' networks (Aggarwal, 2020) can significantly affect the efficacy of their strategic alliances. Future research could expand upon our study to examine cluster and alliance/network factors in a more nuanced manner.

Additionally, we propose several promising directions for future research based on our theoretical framework and findings. Firstly, future research could further explore the dynamics of knowledge flows and firms' strategies to mitigate knowledge loss. It could examine how different characteristics of knowledge, such as its novelty or complexity (Fleming and Sorenson, 2001), influence firms' perceptions and strategic behavior towards external knowledge sources. Secondly, investigating firms' knowledge search strategies could provide deeper insights. Research could examine how technologically advanced firms adjust their search for knowledge within alliances and clusters in response to innovation challenges and how their innovation outcomes influence subsequent searches. Thirdly, to gain a clearer understanding of the motivations and behaviors surrounding cluster and alliance resources based on firms' capability profiles, future studies could employ direct assessment methods such as in-depth case studies and surveys. Finally, the manner in which firms leverage cluster and alliance resources may also depend on their size and degree of internationalization. Exploring these differences could open valuable avenues for future research.

In conclusion, by highlighting how a firm's technological knowledge resources can create varying effects on innovation outcomes based on whether the knowledge exists within the cluster or alliances, our research emphasizes the necessity of analyzing the simultaneous impacts of cluster and alliance knowledge resources on firm innovation, as well as the contingent effects of firm capabilities on the influence of these resources. We empirically demonstrated that the strength of a firm's internal capability serves as an enabling condition regarding cluster resources but as a limiting condition concerning alliance resources. Overall, this study contributes to a nuanced, behaviorally based understanding of why and how firms achieve differential gains from cluster and alliance resources.

CRediT authorship contribution statement

Srivastava Manish: Writing – original draft, Visualization, Methodology, Conceptualization. **Gnyawali Devi:** Writing – original draft. **Stephen Tallman:** Writing – original draft.

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