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Heterogeneity in industry–university R&D collaboration and firm innovative performance

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Abstract
University–industry R&D collaboration is a key driver of participating firms' technological capability. However, there is still debate on the determinants of a firm's innovation performance, especially in relation to the characteristics of collaboration and organizational slack. We lay the foundation for our theoretical framework by establishing testable hypotheses on the effects of the characteristics of university–industry collaboration and organizational slack on the innovation performance of participating firms. Based on a panel data of 2914 firm-year cases for the top 200 U.S. R&D firms, estimates obtained from quantitative techniques produce consistent results and support our predictions. Collaboration breadth, network centrality, unabsorbed slack, collaboration experience and collaboration proactiveness are associated with innovation performance. Moreover, a firm's higher absorbed slack exerts a negative influence on innovation performance. The managerial implications and future research directions are discussed.

Keywords R&D collaboration · Breadth of collaboration · Network centrality · Absorbed slack · Unabsorbed slack · Collaboration experience

Research background and purpose

Collaborative R&D with external partners, also known as open innovation, is a crucial way to maintain firms' competitiveness under the pressure of fast technological change. An R&D-performing firm has various potential collaboration partners, including competitors, suppliers, clients, universities, and research institutes. Firms' decision on the types and numbers of collaboration partners depends on factors such as those firms' characteristics,

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technology complement, position in the knowledge chain, contextual knowledge distance, and transaction cost (Belderbos et al. 2006; Miotti and Sachwald 2003; Sampson 2004; Un and Asakawa 2015).[1] Selecting adequate R&D partners is thus crucial for firms' innovative activity and performance (Faria et al. 2010).

University–industry collaboration (UIC) is a widely adopted strategy of open innovations. New technological knowledge generated by universities is treated as a public good and recognized as a wellspring of knowledge for firms. From the view of transaction cost, it also allows inexpensive and low-risk access to specialist knowledge and basic R&D (Azagra-Caro et al. 2014; Woerter 2012). The generic and basic technologies for universities are complementary to firms' R&D (Baba et al. 2009), helping innovative firms create radical and influential innovations, and new application and/or next-generation technologies (Belderbos et al. 2006; Eom and Lee 2010; Thursby and Thursby 2002). The effect of exploiting universities' scientific knowledge on innovations is most beneficial to innovative firms early in the product life cycle (Jiang et al. 2011).[2]

One distinctive feature may induce firms to prefer R&D collaboration with universities, particularly for large companies. Amaldoss and Staelin (2010) argue that same-function alliances outperform cross-functional alliances, holding the fixed input level, because the competencies that partnering firms bring to the alliance will vary. If the same-function alliance is non-competitive with universities, partnering firms are associated with better innovation performance than are competitive R&D collaborations with firms (Huang and Yu 2011; Un and Cuervo-Cazurra 2010), even though competitive R&D collaboration is also a win–win situation. However, the UIC linkage is fraught with risks due to the uncertainty of innovation commercialization, it also requires greater expertise and absorptive capacity from firms. Thus, large firms are more likely to undertake UIC than small firms, because they have better financial and human resources to conduct UIC and assume the risks.

Although undertaking the UIC should increase participating firms' innovative performance, numerous studies in the past decades have obtained mixed results. Earlier studies by Kaufmann and Tödtling (2001), Lee et al. (2001), Monjon and Waelbroeck (2003), and Faems et al. (2005), support that linking firms to universities improves firms' capability to introduce more innovations. Eom and Lee (2010) have found no significant impact of UIC participation on the innovation probability of firms, implying that the UIC cannot guarantee a firm's success in technological innovation. The Mexico case examined by Rodríguez and Bielous (2017) indicates that UICs have significant but mixed effects on firms' innovation.

One limitation of most studies is that they tend to treat the UIC as a black box and link UIC participation to innovation performance. Participating in UICs is one thing; the content of R&D collaboration is another. The innovation effect of UIC should be more relevant to the nature and heterogeneity in the cooperation procedure, while little research has explored the heterogeneity of UIC, particularly participating firms' capability and attitude. Researchers have thus failed to well understand the innovation effect brought about by the university–industry linkage.

As indicated in George et al. (2002), the quality of university linkage matters to firm innovative outputs. The type and institutional environment of UICs vary significantly and

[1] Oliver (1990) summarizes the motivations of R&D collaborations as six contingencies: necessity, asymmetry, reciprocity, efficiency, stability, and legitimacy.

[2] Numerous previous studies have examined why firms participate in UICs. See Ankrah and AL-Tabbaa (2015) for a review.

result in diverse influences on innovation performance (Howells et al. 2012; Kafouros et al. 2015). Differences in the type and motivation of interactions with universities may also produce different innovation outcomes among participating firms (Puffal and Teixeira 2014). To enhance innovation performance through the UIC, firms' characteristics and their attitude to this linkage also matter. Some firm-specific characteristics have moderating effects that help them learn and absorb new and tacit knowledge transferred from partner universities, even though they have a complicated and contrasting influence on different innovation outcomes (Kobarg et al. 2018). Active or passive attitudes to the R&D process in UICs are vital for learning new knowledge and the success of R&D projects.

To open the UIC black box, this study conceptualizes a UIC as an attribute, resource, and network arrangement and establishes an analytical framework that models specific characteristics of UICs, such as collaboration breadth, network centrality, unabsorbed slack, collaboration experience, and collaboration proactiveness. In discussing their relevance to outcomes of UICs, we establish several hypotheses to illustrate how they affect participating firms' innovation. We then conduct empirical tests. In addition, this study contends that firms' inherent absorbed slack results in diminishing returns of innovation.

Based on a panel dataset of 2914 firm-year cases of UICs for the top 200 U.S. R&D firms, this paper systematically and comprehensively investigates how collaboration- and firm-specific attributes distinguish the innovation performance of firms participating in UICs. It contributes to this strand of literature in several ways. First, although there were several examinations of the innovation effect of participating in UICs, this study explores the UIC contents by categorizing their heterogeneity into six dimensions, and then examines their effects on the innovation performance of participating firms. Second, we use a firm-level panel dataset of persistent engagement in UICs to conduct empirical estimations, allowing us to mitigate the selection bias that R&D-performing firms self-select whether or not to engage in an UIC. Various econometric techniques are adopted to ensure the robustness of estimating results.

The remainder of this paper is organized as follows. The next section proposes a conceptual framework to model how various dimensions of heterogeneity in UICs affect engaging firms' innovation performance and establishes the hypotheses. Section 3 describes the data, variables, and estimating strategies. In Sect. 4, we report and discuss the empirical results, followed by a presentation of the management implications and concluding remarks in the final section.

Conceptual framework and hypotheses

Conceptual framework

Studies of UICs formation have identified important factors from various dimensions (Bruneel et al. 2010): (1) researchers' personal characteristics, including gender, age, race, education, centrality to the academic system, academic degree, publishing record, and scientific value (e.g. Boardman and Ponomariov 2009; Buttel and Goldberger 2002; Fox and Ferri 1992; Jensen and Thursby 2001; Klofsten and Jones-Evans 2000; Van Rijnsoever et al. 2008); (2) professional attributes, such as the source of grant activity, institutional affiliation, number of students funded, tenure status, and academic discipline (e.g. Beaver 2001; Boardman and Ponomariov 2007; Bozeman and Corley 2004; Dietz and Bozeman 2005; Giuliani et al. 2010; Owen-Smith 2003); and (3) the characteristics of the organizational contexts, mainly the type of organization, reputation effects, history, tradition, department size, culture and environment, academic status, scientific output, and peer effect (e.g., Bercovitz et al. 2001; Boardman 2009; Feldman and Desrochers 2004; O'Shea et al. 2007). Notably, heterogeneity in the UIC procedure perceived by industry may affect participating firms' innovation performance, especially in relation to the characteristics of collaboration and organizational slack. A firm's collaboration knowledge, resources and capability can also contribute to the success of its UIC strategies. These issues seem to have been less systematically examined. This section will conceptually categorize collaboration heterogeneity that matters to participating firms' innovation performance in UIC as knowledge-based, resource-based, and capability-based.

Knowledge-based collaboration heterogeneity

Knowledge-based collaboration heterogeneity is the level of knowledge and technological skills needed to meet innovation challenges in a UIC. Collaboration breadth is one possible proxy for a firm's absorptive capacity in a UIC, (Eom and Lee 2010). It enables a firm to absorb external knowledge from universities easily, thereby improving its innovation performance. In contrast, when members of R&D collaboration teams possess the same stock of technology knowledge, it may damage the creativity of team members, because they are less likely to perceive value in knowledge exchange, transfer, and integration (Amabile 1996). Novel innovations depend on scientific effort from heterogeneous areas of science (Hagedoorn 1993), thus firms seek new and complementary knowledge from UICs to build new knowledge domains or strengthen their core knowledge (Tyler and Steensma 1995). New knowledge can offer a new or hybrid approach, helping firms resolve established problems (Ahuja and Katila 2001; Wadhwa and Kotha 2006). A knowledge-based view suggests that the degree of heterogeneity in technology field of collaborative sources is a reason to engage in R&D UIC. It helps firms focus on a more relevant process of knowledge creation, thereby increasing a firm's ability to integrate and combine knowledge that can lead to successful innovation (Lin 2017).

Collaboration experience with universities is the extent to which a firm has participated in UICs or the amount of time spent on these activities. Firms not only have to learn how to work on research projects across organizational boundaries, but also possess or can build the capabilities to collaborate with universities operating within a different incentive system (Bruneel et al. 2010). The commercial interests may push firms to include non-disclosure clauses that delay or prevent publication, so establishing expectations about when and in what form the outcomes of a joint R&D project will be published is controversial (Banal-Estanol et al. 2015). Thus, the rich experience of collaboration enables firms to agree on attitudes to collaboration, reconcile conflicting views on research targets, foster attitudinal convergence, learn to share norms, and reach a mutual understanding about the nature of the collaboration (Bruneel et al. 2010).

Resource-based collaboration heterogeneity

Resource-based collaboration heterogeneity asserts that firms can use their organizational slack resources to support a more focused and intensive exploitation of collaboration to achieve superior innovation performance. Singh (1986) draws a theoretical distinction between absorbed and unabsorbed slack. The premise of organizational slack is the stock of resources in excess of the minimum requirement of producing a given output (Nohria and Gulati 1996). As the UIC relationship is an inter-organizational structural arrangement, firms should use the organizational slack that best fits the collaboration need to benefit from sustainable innovation (Peng 2001).

Studies of organizational slack argue that both types of slack resources have been conceptualized as drivers of innovation (e.g., Argote and Greve 2007; Kim et al. 2008; Nohria and Gulati 1996; Vanacker et al. 2017). Some of these studies have examined the relationship between organizational slack and firms' performance, concluding that unabsorbed slack might be necessary for knowledge creation, learning, and sharing (e.g., Chen et al. 2012; Huang and Chen 2010). However, no studies have investigated whether absorbed and unabsorbed slack play different roles in facilitating firms' innovation performance in UICs.

Capability-based collaboration heterogeneity

Network centrality is a crucial influence in facilitating UICs (Bruneel et al. 2010), because firms' network positions represent interactive opportunities for firms to access external new knowledge and information. Knowledge and resources are difficult to spread across collaborative units in which there are no pre-existing relationships between universities and industries. Indeed, innovative ideas are often at the nexus of university–industry links, suggesting that information and knowledge should be deliberately distributed to foster innovation. A network of university–industry links provides conduits for distributing information and knowledge in a way that stimulates and supports firms' innovative activities. Innovation performance often depends on communication and interactions within a UIC, implying the importance of a firm's position in the network centrality in UICs. In other words, the network is a significant indicator that firms can draw upon in the process of knowledge exchange, transfer and combination (Nahapiet and Ghoshal 1998).

Collaborative proactiveness, consisting of efforts to take initiative and anticipate future collaboration problems is relevant to the search for new innovation opportunities (Eggers et al. 2013; Rank and Strenge 2018). Empirical studies, e.g., Belschak et al. (2010) and Callaert et al. (2015), have identified the critical role of selecting collaborative proactiveness in facilitating organizational and individual performance. The most proactive firms devote considerable efforts to environmental scanning and monitoring to spot new opportunities. Such firms are also willing to discover and exploit new opportunities by gathering a large amount of diverse information (Rank and Strenge 2018). Firms that engage in collaborative proactiveness seek out and acquire knowledge that is relevant, timely, and accurate, thereby facilitating the creation of innovation. Proactive firms are action-oriented, have a sense of purpose, and are willing to undertake prolonged periods of arduous work. Thus, collaborative proactiveness promotes ideas, problem-solving and controls collaboration to ensure the innovation's success in UIC.

We therefore conceptualize a UIC as an attribute, resource and network arrangement and focus on the influence of UIC-specific attributes on firms' innovation. Figure 1 depicts the conceptual framework. It illustrates the importance of collaboration breadth, network centrality, unabsorbed slack, collaboration experience, and collaboration proactiveness in UIC activities. We then establish several hypotheses to test how heterogeneity in UIC affects participating firms' innovation. In addition, this study contends that firms' inherent absorbed slack results in diminishing returns of innovation.

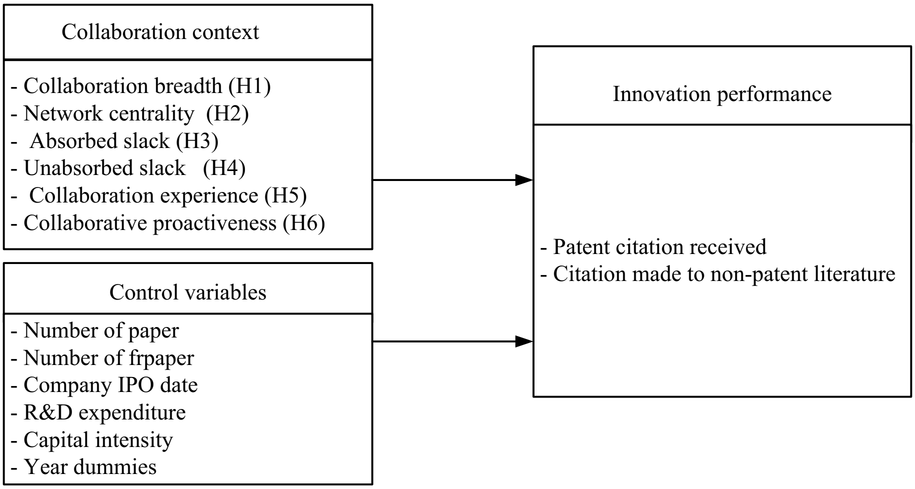

Fig. 1 Research framework

Collaboration breadth and innovation performance

Collaboration breadth is the extent of collaboration fields of a firm's technology base, revealing the profile of technological development within a UIC. Greater collaboration breadth promotes firms' innovation performance in several ways.

First, it may facilitate cognitive diversification, leading to more productive exchanges, strategic opportunities, and creative decision making. It also combines information and knowledge to reduce cognitive conflict (Smith et al. 2005). Second, by tapping into diverse technological knowledge, a wider breadth of collaboration within UICs makes it easier for firms to form new linkages and associations in the innovation process (Chesbrough 2003; Grant and Baden-Fuller 2004; Lin 2014). A wider and more diversified breadth of collaboration brings access to a larger pool of technological opportunities, knowledge sharing, knowledge acquisition, and complementarity. Thus, firms become capable of searching for and decoding newly generated knowledge to synergetic effects, thereby leading to better innovation performance (Duysters and Lokshin 2011).

Finally, an increase in collaboration breadth gives firms access to a deeper technology portfolio and diverse technology interfaces in the university. UICs are pipelines for information, know-how, resource flows, and university-firm ties. Diversified fields of collaboration provide a firm with the potential to amass more knowledge about technological trajectories and a university's research activities. Therefore, we hypothesize that the collaboration breadth within a UIC increases the firm's innovativeness.

Hypothesis 1 The wider the collaboration breadth within UICs is, the better the participating firms' innovation performance.

Network centrality and innovation performance

Network centrality is a central concept in collaboration studies. It means that a firm is a focal collaboration actor in the UIC network; this also denotes its power. As a gatekeeper and a gathering point for information, the organization will distribute more information to the network centrality. When network centrality is greater, a firm is more likely to exchange information and cooperate for mutual innovation benefit (Krackhardt 1992).

By occupying a central position in the UIC network, a firm is likely to access desired strategic knowledge and resources to resolve R&D problems (e.g., Dougherty and Hardy 1996; Tsai 2001). Such knowledge and resources will trigger the firm's innovative activities through complementary knowledge from the university, although these resources and knowledge are usually distributed unevenly within collaboration units (Szulanski 1996). As the hub of the UIC network, the firm may determine its unique access to different knowledge, thus promoting its ability to recognize and respond to new innovation opportunities. As indicated in Burt (1982), cooperation thorough various direct contacts has innovation benefits, including unique resources, more knowledge, and faster capability. Thus, firms with more direct contacts are able to obtain information more quickly, access richer sets of knowledge, and draw from broader sets of referrals and advice, thereby facilitating knowledge combination and exchange (Nahapiet and Ghoshal 1998). In terms of UICs, network centrality is relevant to innovation performance, because it notifies UIC attributes of the existence, location, and significance of the knowledge contained in a collaboration network; it also serves as a conduit of knowledge flow (Smith et al. 2005).

Hypothesis 2 The greater the firm's network centrality within UIC, the higher the likelihood of firm's innovation performance.

Organizational slack and innovation performance

Absorbed and unabsorbed slack differ in their capacity to be redeployed (Voss et al. 2008). Managers have much more discretion to redeploy uncommitted unabsorbed slack, whereas they are less able to redeploy absorbed slack that is committed to specific purposes. Unabsorbed slack, in contrast, is more flexible than absorbed slack that can be characterized by the range of alternative uses to which a resource can be applied. Unabsorbed slack can be deployed easily because it can adapt to environmental change, whereas absorbed slack has higher asset specialization (Nohria and Gulati 1996).

Absorbed slack and innovation performance

Absorbed slack is embedded in a firm's procedures and tied to a firm's operation, so that absorbed slack is difficult to redeploy and recover with more time and managerial effort (Bourgeois 1981; Huang and Chen 2010; Singh 1986; Vanacker et al. 2017). Absorbed slack is matched to projects, assets, property and equipment, suggesting that, aside from its designated purpose, it cannot be used immediately to finance new collaboration projects (Greve 2003; Wiersma 2017).

Regarding the UIC linkage, absorbed slack may exacerbate potential collaboration problems and reduce the benefits. When absorbed slack increases, participating firms lose flexibility in the use of universities' resources, knowledge, and capability. Firms burdened with excessive absorbed slack might perceive increased restrictions on their ability to use this knowledge source from the UIC. It is also difficult to divert these resources to more alternative uses, such as unpredictable future UIC outcomes (Love and Nohria 2005; Tan and Peng 2003). In this way, firms are likely to avoid having more absorbed slack, as it may negatively relate to a firm's innovation performance.

The aforementioned arguments suggest that absorbed slack prevents the potential integration of benefits and exacerbates an ineffective and rigid management style, resulting in a negative influence on innovation performance. Accordingly, the following hypothesis is proposed.

Hypothesis 3 The greater a firm's absorbed slack within UIC, the lower the likelihood of that firm's innovation performance.

Unabsorbed slack and innovation performance

Unabsorbed slack has a generic, liquid financial nature, so that is uncommitted to organizational design. It thus is readily available for redeployment within firms (Bourgeois and Singh 1983; Tan and Peng 2003; Vanacker et al. 2017). The logic linking unabsorbed slack to a firm's innovation performance emphasizes these buffering properties. Unabsorbed slack can support UIC activities in pace with performance shocks, be redeployed to alternative uses, or reduce the amount of information that must be processed during the UIC execution (Tan 2003). Firms with greater unabsorbed slack are at less risk of deviating from strategic goals when there are substantial, unexpected shifts in the collaboration environment (Malen and Vaaler 2017).

Slack empowers UICs in risky projects and protects firms from the potential exhaustion of financial resources if these efforts fail. Collaboration with various universities faces different organizational problems, perceives the same problems differently, and even has conflicting goals (Vanacker et al. 2017). With sufficient slack, firms can satisfy divergent university goals. Therefore, unabsorbed slack can be readily allocated to a range of UICs, which are required and useful for implementing innovation, such as allowing slack research, solving resources contention, establishing new collaboration offices and related equipment, recruiting R&D specialists in new technology domains, and maintaining diverse collaboration activities (Lai and Weng 2014).

Unabsorbed slack is likened to internal shock absorbers that allow resource deployment in bilateral relationships. It helps resolve latent needs of firms in absorbing a university's knowledge and prevents these relationships from rupturing, or encouraging the pursuit of collaboration benefits that do not appear justifiable in terms of a firm's controls. Thus, unabsorbed slack buffers the important resources for potential innovation activities by allowing firms to cooperate and engage in uncertain and risky UIC relationships. Accordingly, unabsorbed slack supports the resources allocation of firm's UIC toward the development of innovations.

Hypothesis 4 The greater a firm's unabsorbed slack within UIC, the higher the likelihood of that firm's innovation performance.

Collaboration experience and innovation performance

Collaboration experience is defined as the number of collaborations; it represents the amount of collaboration knowledge in a firm at a certain point in time (Smith et al. 2005).

Collaboration experience resides in the minds of the R&D researchers responsible for patents, papers or products (Drazin and Rao 2002). Collaboration knowledge is often tacit and non-codifiable, developing and expanding as researchers spend more time on R&D collaboration. Firms with R&D personnel who have extensive collaborative experience in a UIC may have greater expertise and thus more relevant knowledge to transfer and bring to the process of exchange and combination.

Collaboration experience also has great improvement potential for a firm's innovations. Given that the use of a university's knowledge is influenced by the UIC system and the underlying collaboration experience, firms understand a university's knowledge and process schemas that it applies. In this way, collaboration experience builds the learner's stock of knowledge. Knowledge shared through intense interpersonal interactions is embedded in R&D researchers, meaning that a codification of such tacit knowledge is required for UIC progress. Therefore, collaboration experience can increase the firm's internal knowledge base and inspire the development of the firm's knowledge (Clauss and Kesting 2017).

To summarize, participation in a UIC exposes firms to a variety of academic collaboration management practices, allowing them to draw conclusions about the effectiveness of their UIC strategy and management. Collaboration experience with universities allows firms to assess UIC practices to facilitate inter-organizational coordination and select an appropriate future UIC, which leads to better innovation performance. We therefore propose the following hypothesis:

Hypothesis 5 The greater the number of collaboration experiences within UIC, the higher the likelihood of a firm's innovation performance.

Collaboration proactiveness and innovation performance

Collaborative proactiveness is the process by which firms seek new collaboration opportunities and introduce new innovations for future need (Tan et al. 2010). In a more dynamic and competitive business environment, collaborative proactiveness becomes a critical determinant of UIC success and participants' innovation (Crant 2000; Pitt et al. 2002). A proactive firm often initiates collaboration to which the collaboration dilemma must react, paving the way for innovation progress (Eggers et al. 2013). Selecting collaborative proactiveness is likely to reveal more resources and opportunities within UICs. In addition, collaborative proactiveness exchanges and combines knowledge-based resources, and is expected to anticipate future collaboration through collaboration networks. This collaboration helps firms find, negotiate, and develop their learning capabilities and thus improve the collaboration capability to conduct innovation (Joshi et al. 2015; Tan et al. 2010).

Collaborative proactiveness has a considerable role in UICs. It is concerned with implementation, doing whatever is necessary to advance a firm's innovation; it involves persistence in participating in the UIC despite difficulty in achieving collaboration success and a willingness to assume responsibility. Collaborative proactiveness is also positively associated with informing or instructing a UIC to distribute strategic information and beliefs held by firms. Thus, collaborative proactiveness is directly linked to a firm's innovation performance (Pitt et al. 2002).

Moreover, collaborative proactiveness is related to each stage of a UIC. A firm's innovation begins by identifying a collaboration problem and generating novel ideas and solutions. Next, innovative firms seek university sponsorship to build a network of supporters. These activities result in papers, patents, a prototype or model of the innovation (Crant

2000). In light of these arguments, collaborative proactiveness is expected to associate with more diverse, difficult-to-imitate knowledge and is more valuable for developing new innovation (Mahr and Lievens 2012). Hypothesis 6 is thus proposed as follows:

Hypothesis 6 The greater the collaborative proactiveness within UIC, the higher the likelihood of a firm's innovation performance.

Research methods and process

Research Setting and Sample

As this study examines the innovation effect of heterogeneity in the UIC on participating firms, using firms with academic linkage in terms of collaborative R&D or academic publications can mitigate the selection problem.[3] We utilize a firm-level panel dataset that was linked from three large datasets. The first dataset is the NBER-Rensselaer Scientific Paper that contains the top 110 US universities and the top 200 R&D performing firms for 1981–1999. It includes collaborations between firms and scientific institutions, such as published co-authored papers.[4] The data also incorporate the NBER research team's efforts to fractionalize papers and citations, thereby reflecting collaborative research and avoiding over-counting of scientific output in the economy (Whalley and Hicks 2014).

The second data source is the 2010 edition of the Harvard Dataverse Network (DVN) U.S. Patent Citations Data (Fierro 2014; Sampat 2011). The Harvard DVN patent database is the most extensive collection of United States patent data (Fierro 2014). It maintains detailed information for 3.99 million US patents granted between January 1975 and December 2010 and includes the citations of more than 45 million patents. The information contained in this databank consists of comprehensive patent information, mainly numbers, issue dates, application dates, application numbers, country of origin of first named inventor, first named assignee, ownership assignment category, the primary class and subclass of each patent, and the number of claims. Its attached citations file includes the number of forward citations to the patent, the number of backward citations to previous U.S. utility patents, and the number of citations to non-patent references for 1975–2010 in terms of citing/cited patent pairs (Bhaven 2011).

The third database, Compustat, contains financial and market information on firms which are publicly traded on the New York, American, and regional stock exchanges or over-the-counter on NASDAQ. As it contains financial information, including assets, sales, and R&D expenditures, we can calculate needed covariates using this information.

Regarding the matching procedure, we first obtained annual UIC data from files in the NBER-Rensselaer Scientific Paper database from 1981 to 1999, containing more than two million papers and co-authorships among universities, scientific institutions and firms, as well as citations made to and received by individual papers (Adams and Clemnons 2008).

[3] Though this sampling strategy has mitigated the problem of selection bias to some degree, it cannot be entirely ruled out. For example, firms with more R&D can select a more intensive academic linkage. Thus, we should interpret the estimated positive effects of academic linkage on firm innovations, if any, in a more conservative manner.

[4] There are 2,836,700 scientific papers written by one or more of the top 110 US universities and 238,277 by the top 200 US R&D firms.

Then, we matched the NBER-Rensselaer Scientific Paper database with the 2010 edition of the Harvard Dataverse Network (DVN) U.S. Patent Citations Database. To make the comparisons, we collapsed the data to patent citations received and citations made to non-patent literature between January 1975 and December 2010. Finally, we merged the financial data in Compustat and the above-matched dataset to retrieve information for the 220 R&D performing firms' financial information, including assets, sales, and R&D expenditures. Our final sample consists of 2914 firm-year observations of the top 200 R&D performing firms in the United States.

Measures

Dependent variable

Innovation performance. A patent is the most widely adopted measure of innovation performance. To consider patent quality, we adopt two measures: patent citations received and citations made to non-patent literature. Patent citation rates could reflect the quality of patents and indicate the value of an original patent for the subsequent development of technologies (Huang and Chen 2010). Firms that acquire patents with more citations are ostensibly more innovative (Kelly and Rice 2002). Citations made to the non-patent literature indicate the intensity of scientific citations in a firm's patents that has a large and positive impact on the patent-owning firm's innovation performance. A patent using more scientific discoveries directly from scientific publication contributes more to a firm's innovation (Chen et al. 2016). Therefore, innovation performance is operationalized as the firm-year's patent citation received and citations made to non-patent literature for 1975 to 2010. While the first measure indicates the quality-adjusted innovative outcome, the second measures the academics' frontier values of patent performance.

Independent variables

Collaboration breadth. Breadth of a firm's UIC is measured by counting the number of collaboration portfolios of technology fields in the subcategories of the NSF-CASPAR 88 field code. NBER-Rensselaer Scientific Papers Database offers the mapping between Information Sciences Institute (ISI) 88, National Science Foundation (NSF) 12, and NSF 20. The minimum value is 1 if collaborative technology fields within the university belong to the same category; a higher value represents more diversification in collaboration technology fields.

Network centrality. We consider firms' positions in the UIC network and use Freeman degree centrality as the proxy variable. Freeman's approach to the degree of centrality is based on connections between nodes in the network that measures in-degree, out-degree, and degree percentage of entire network for each firm in the past 3 years since 1981. The indicator provides the relative importance of a firm in UICs, depending on the differences in their centralization scores. Furthermore, Freeman centralization enables comparison of several networks' relative centrality by looking at their centralization scores. If a firm's collaboration is more central, it is probably motivated to explore innovation opportunities beyond the firm's stock of knowledge (Wang et al. 2014).

Organizational slack. Organizational slack can be classified into absorbed and unabsorbed (Sharfman et al. 1988; Tan and Peng 2003). In alignment with Greve (2003), we define absorbed slack as the sum of selling, general and advertising expenses plus working capital. Unabsorbed slack is measured by the sum of a firm's cash and securities. Unabsorbed slack are resources not absorbed by costs, thus giving the amount of liquid resources in the near future (Riahi-Belkaoui 1998).

Collaboration experience. This variable is measured by the number of a firm's UIC activities in a given year. Experience accumulated through trial and error requires repeated learning-by-collaboration (Anand et al. 2016.). Such knowledge creation is repeatedly tested and adjusted so that firms can learn their course of collaboration in ways that increase the probability of successful innovation. Thus, managing UIC activities increases a firm's innovation capability.

Collaborative proactiveness. Organizational researchers have discussed the importance of proactive behavior (Crant 2000; Eggers et al. 2013; Tan et al. 2010). Collaborative proactiveness is defined as taking the initiative in anticipation of collaboration problems, needs, changes and improving current circumstances. It challenges the status quo rather than passively adapting to UIC conditions. The NBER-Rensselaer Polytechnic Institute Scientific Papers Database consists of collaborating and collaborated institutions, field and year. In addition, by distinguishing collaborating from collaborated institutions, the database identifies the type of numbers of potentially collaborating and collaborative papers (PAPERSCLBG, PAPERSCLBD). In this study, we define *collaborative proactiveness* as the number of potentially collaborating divided by the total number of potentially collaboration papers.

Control variables

Number of Frpapers. Academic knowledge could bring about increased sales, productivity, and patenting activity for firms (Lin 2014). A larger number of published papers presumably indicates that a firm's academic knowledge base has grown. Scientific publications for research collaboration provide a continuous assessment of interaction with university or firm's performance (Banal-Estanol et al. 2015). NBER-Rensselaer Scientific Papers Database provides *total number of fractional papers* written by firm, field, and year. To avoid double-counting, this database uses the term FRPAPERS, the "fractional" version of PAPERS. *FRPAPERS* is the sum of all papers of the institutional fraction for each paper that is accounted for by a firm for a given field and year. For instance, "If IBM writes a paper by itself, it is assigned a fraction of 1.0. If it writes a paper with Yale and Stanford, it is assigned a fraction of 1/3. Summing over paper fractions yields *FRPAPERS*" (Adams and Clemnons 2008).

Company IPO date. Firm age is related to a firm's capabilities, resource endowments, and collaboration experience, so it is included as a control variable of innovation production function. We thus control firm age by using the years between the IPO year and the data year.

R&D expenditures. R&D expenditures is the key driver of innovation and it serves as the proxy of absorptive capability that could influence a firm's knowledge exploration, exploitation and acquisition. This control variable is measured by the logarithm of firm's R&D expenditures in a focal year.

Capital intensity. Physical capital intensity is an important source of knowledge creation and flow. The "strategic response" hypothesis proposed in Hall and Ziedonis (2001) argues that firms with large sunk costs tend to expand their patent portfolios. To test this hypothesis, we control for a firm's capital intensity, measured by total asset divided by the number of employees in the establishment.

Year effects. A set of year dummies allows us to account for year-specific characteristics.

Model and estimation

To evaluate the way in which heterogeneity in UICs affects participating firms' innovation performance, the patent production function developed by Pakes and Griliches (1980) is adopted. The dependent variable is quality-adjusted patent. As the dependent variable is a non-negative integer, the count data model provides an adequate estimating technique (Ahuja and Lampert 2001; Hausman et al. 1984). In addition to the Poisson regression, zero-inflated Poisson regression is adopted, because some firms may not apply patents for their innovation outputs. The Poisson model has a restriction that mean equals to variable, while this condition is hard to hold due to the over-dispersion problem. To solve this problem, heterogeneity-consistent standard errors can be used. The empirical model is specified as follows:

$$\begin{aligned}\text{Innovation performance} = \text{f}(&\text{collaboration breadth, network centrality, absorbed slack,}\\ &\text{unabsorbed slack, collaboration}\\ &\text{experience and collaboration proactiveness, control variables})\end{aligned}$$

To provide more precise estimates for firms of different levels in innovations, Cameron and Trivedi's (2009) method of quantile count regression for modeling longitudinal Poisson data is adopted. The results for innovation for quantiles vary at q0.25, q0.5 and q0.75, where the estimators can be interpreted as the marginal change in innovation performance at the ith conditional quantile when there is marginal change in an explanatory variable. The standard errors in this model estimation are calculated by the bootstrap method.

Results

Hypothesis testing

In this section we present the results of econometric estimations. Table 1 gives descriptive statistics and correlation matrix of explanatory variables. All of the key variables have a substantial amount of variation. The variance inflation factors (VIFs) associated with each of the predictors range from 5.352 to 1.350 with a mean of 2.818. Tolerance values of all independent variables exceed 0.1 and range from 0.187 to 0.741 with a mean of 0.425. The statistics are within acceptable limits, suggesting that multicollinearity is not a serious problem Hair et al. (1998). Tables 2 and 3 display the results of the hierarchical moderated regressions for the main effects on innovation performance by using zero-inflated Poisson and Poisson models, respectively. Models 1–5 in Tables 2 and 3 test our six hypotheses on the direct effects; models 6–10 are the same specifications for alternative performance output.

Estimates in various specifications are similar in Tables 2 and 3, suggesting the estimated results are robust.

Hypothesis 1 posits a positive relationship between collaboration breadth and innovation performance. Estimates in models 1 and 6 show that the estimated coefficients of collaboration breadth are significantly positive ($\beta = 0.029$; 0.119; 0.028 and 0.120,

Table 1 Descriptive statistics and correlations

	1	2	3	4	5	6	7	8	9	10	11	12
1. Innovation performance (patent citations received)	1											
2. Innovation performance (citation made to non-patent literature)	0.653	1										
3. Collaboration breadth	−0.056	−0.020	1									
4. Network centrality	0.092	0.079	−0.065	1								
5. Absorbed slack	0.041	0.011	0.382	−0.071	1							
6. Unabsorbed slack	−0.017	−0.042	0.600	−0.078	0.560	1						
7. Collaboration experience	−0.026	0.019	0.687	−0.086	0.312	0.610	1					
8. Collaborative proactiveness	−0.009	−0.001	−0.600	0.158	−0.260	−0.561	−0.691	1				
9. Number of fractional papers	0.001	0.013	0.689	−0.100	0.313	0.638	0.910	−0.754	1			
10. Company IPO date	0.028	0.043	0.193	−0.182	−0.165	0.027	0.328	−0.120	0.205	1		
11. R&D expenditure	−0.035	−0.013	0.649	−0.131	0.412	0.608	0.508	−0.475	0.513	0.041	1	
12. Capital intensity	−0.053	0.023	0.128	−0.127	0.015	0.055	0.221	−0.026	0.118	0.234	0.206	1
Mean	2124.793	214.433	17.427	−0.358	1064.073	2300.993	32.341	0.853	69.344	1988.229	2.031	212.554
Standard deviation	5481.866	539.928	2.315	0.341	2459.288	4081.381	63.428	0.130	162.204	6.030	0.722	180.530
VIF			2.593	2.521	4.173	5.352	3.778	1.553	3.120	1.350	1.983	1.759
Tolerance			0.386	0.397	0.240	0.187	0.265	0.644	0.321	0.741	0.504	0.568

$n = 2914$ (two-tailed test). Correlations with absolute value greater than 0.055 are significant at $^{*}p < 0.05$, greater than 0.118 are significant at $^{**}p < 0.01$ and $^{***}p < 0.01$

Table 2 Results of the hierarchical regression model with zero-inflated Poisson estimation

Variables	Innovation performance: patent citation received					Innovation performance: citation made to non-patent literature				
	M1	M2	M3	M4	M5	M 6	M7	M 8	M 9	M10
Independent variables										
Collaboration breadth	0.028***	0.020***	0.039***	0.018**	−0.000	0.120***	0.237***	0.108***	0.095***	0.000
Network centrality		0.045**	0.283***	0.442***	0.495***		0.666***	0.144***	0.117**	0.662***
Absorbed slack ($\times 10^{-2}$)			−0.036***	−0.031***	−0.028***			−0.096***	−0.097***	−0.001***
Unabsorbed slack ($\times 10^{-2}$)			0.039***	0.035***	0.037***			0.003	0.004	0.025***
Collaboration experience				−0.017***	−0.015***				0.004*	0.008***
Collaborative proactiveness					−0.821***					−3.930***
Control variables										
Number of fractional papers	−0.016***	−0.015***	−0.015***	−0.010***	−0.011***	−0.015***	0.012***	0.009***	−0.010***	−0.012***
Company IPO date	0.006***	−0.007***	−0.004***	0.006***	0.010***	0.039***	0.079***	0.020***	0.018***	0.055***
R&D expenditure	0.950***	1.897***	2.298***	2.262***	2.132***	0.211***	2.155***	4.787***	4.754***	3.911***
Capital intensity ($\times 10^{-2}$)	0.029***	−0.050***	−0.035***	−0.008***	=0.011***	0.049***	0.040***	−0.094***	−0.095***	−0.010***
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−26.294***	78.141***	10.954***	−9.914***	−16.725***	−74.666***	−153.505***	−45.886***	−40.160***	−107.787***
Log-likelihood	−93,329.84	−13,212.70	−12,590.19	−12,326.94	−12,256.64	−21,296.34	−4935.256	−3435.591	−3432.81	−3182.655
LR *chi*^{2}	242,179.81***	85,973.78***	87,212.33***	8778.84***	87,879.43***	15,092.37***	11,482.91***	14,482.24***	14,487.80***	14,988.11***
Number of observations	2914	2914	2914	2914	2914	2914	2914	2914	2914	2914

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$, Two-tailed t-tests

Table 3 Results of the hierarchical regression model with Poisson estimation

Variables	Innovation performance: patent citation received					Innovation performance: citation made to non-patent literature				
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10
Independent variables										
Collaboration breadth	0.029***	0.117***	0.084***	0.031***	0.018**	0.119***	0.238***	0.106***	0.094***	−0.001
Network centrality		0.336***	0.524***	0.368***	0.410***		0.672***	0.151***	0.126**	0.673***
Absorbed slack ($\times 10^{-2}$)			−0.026***	−0.027***	−0.024***			−0.097***	−0.097***	−0.077***
Unabsorbed slack ($\times 10^{-2}$)			0.026***	0.029***	0.030***			0.004	0.005	0.026***
Collaboration experience				−0.018***	−0.017***				0.004*	0.008***
Collaborative proactiveness					−0.658***					−3.943***
Control variables										
Number of fractional papers	−0.017***	0.111***	0.104***	−0.011***	−0.012***	−0.015***	0.013***	−0.009***	−0.010***	−0.012***
Company IPO date	0.945***	0.015***	0.015***	0.003**	0.006***	0.041***	0.079***	0.021***	0.018***	0.055***
R&D expenditure	1.039***	2.035***	2.367***	2.266***	2.159***	0.219***	2.169***	4.811***	4.780***	3.933***
Capital intensity ($\times 10^{-2}$)	0.039***	0.026***	0.034***	−0.000	−0.003	0.047***	0.039***	−0.096***	−0.097***	−0.001***
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−18.339***	−28.270***	−28.185***	−4.445*	−9.813***	−77.223***	−154.479***	−46.590***	−41.257***	−109.154***
Log-likelihood	−93,219.03	−12,956.00	−12,661.90	−13,579.614	−13,535.966	−21,467.801	−4952.034	−3446.566	−3444.145	−3192.935
LR chi^2	245,384.90***	87,894.83***	89,563.04***	87,727.60***	87,814.90***	16,076.67***	11,864.96***	14,875.90***	14,480.74***	15,383.16***
Pseudo R^2	0.561	0.750	0.759	0.764	0.764	0.272	0.545	0.683	0.684	0.707
Number of observations	2914	2914	2914	2914	2914	2914	2914	2914	2914	2914

*$p < .05$; **$p < .01$; ***$p < .001$, Two-tailed t-tests

Table 4 Results of the quantile count regression with 500 repetitions

Innovation performance: patent citation received			
Variables	0.25	0.5	0.75
Independent variables			
Collaboration breadth	-0.006^{*}	0.099^{***}	0.126^{***}
Network centrality	0.251^{***}	0.738^{***}	0.280^{***}
Absorbed slack ($\times 10^{-2}$)	-0.016^{***}	-0.021^{***}	-0.034^{***}
Unabsorbed slack ($\times 10^{-2}$)	0.071^{***}	0.044^{***}	0.027^{***}
Collaboration experience	-0.041^{***}	-0.011^{***}	0.003^{*}
Collaborative proactiveness	-4.351^{***}	-0.079^{***}	0.365^{***}
Control variables			
Number of fractional papers	-0.013^{***}	0.001^{***}	-0.018^{***}
Company IPO date	-0.021^{***}	0.023^{***}	0.011^{***}
R&D expenditure	-0.050^{*}	1.792^{***}	2.479^{***}
Capital intensity ($\times 10^{-2}$)	0.001^{***}	-0.022^{***}	-0.022^{***}
Year dummies	Yes	Yes	Yes
Constant	50.205^{***}	-42.763^{***}	-20.013^{***}
Number of observations	2914	2914	2914

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$, Two-tailed t-tests

$p < 0.001$) in both zero-inflated Poisson and Poisson regression models. This result supports hypothesis 1. Hypothesis 2 states that network centrality has a positive effect on innovation performance. This hypothesis is supported, drawn from estimated results in models 2 and 7 in Tables 2 and 3, because the coefficients for network centrality are positive and significant at the 1% statistical level ($\beta = 0.336$; 0.672; 0.045; 0.666). In other words, there is a positive relationship between network centrality and innovation performance. Among the characteristics of heterogeneity UICs', two variables—collaboration breadth and network centrality—are significantly positive in all specifications, suggesting that greater collaboration breadth or network centrality in a UIC can promote innovation performance.

Regarding the influence of a firm's absorbed and unabsorbed slack on innovation performance, estimates in models 3 and 8 of Tables 2 and 3 show that the variable of absorbed slack is associated with a significantly negative coefficient ($\beta = -0.026$, $p < 0.001$; $\beta = -0.097$, $p < 0.001$; $\beta = -0.036$, $p < 0.001$; $\beta = -0.096$, $p < 0.001$), while the corresponding coefficient for unabsorbed slack is significantly positive ($\beta = -0.026$, $p < 0.001$; $\beta = 0.004$, $p > 0.05$; $\beta = 0.039$, $p < 0.001$; $\beta = 0.003$, $p > 0.05$). The LR chi^2 coefficient indicates that inclusion of absorbed and unabsorbed slack improves the model. Hence, hypotheses 3 and 4 are supported.

Hypothesis 5 examines the effect of collaboration experience on participating firms' innovation performance. We include the collaboration experience variable in models 4 and 9. Model 4 in Tables 2 and 3 show this variable to be negatively correlated with patent citations received ($\beta = -0.018$, $p < 0.001$; $\beta = -0.017$, $p < 0.001$). In contrast, model 9 in Tables 2 and 3 finds a positive relationship between collaboration experience and citation made to non-patent literature ($\beta = 0.004$, $p < 0.05$; $\beta = 0.004$, $p < 0.05$). These diverse findings are probably attributable to the difference in the role of collaboration experience among firms of different innovation outputs. Thus, we performed the quantile count regression estimation on collaboration experience as a dependent variable at target count quantiles of $q = 0.75$ in Table 4, enabling us to compare results in model 4 of Tables 2 and 3, which took patent citation received as a dependent variable. We found that collaboration experience has a significant positive effect ($\beta = 0.003$, $p < 0.05$) on patent citations received. Thus, these results support hypothesis 5 and indicate that a UIC's strong collaboration experience can improve innovation performance.

Hypothesis 6 is tested by adding the variable of collaborative proactiveness with UIC and assesses how this variable relates to innovation performance. As displayed in models 5 and 10 in Tables 2 and 3, the estimated coefficients of collaborative proactiveness with UIC are negative and significant ($\beta = -0.821$, $p < 0.001$; $\beta = -3.930$, $p < 0.001$; $\beta = -0.658$, $p < 0.001$; $\beta = -3.943$, $p < 0.001$). Table 4 also provides the quantile count regression estimation on collaborative proactiveness with UIC of $q = 0.75$ for a comparison with models 5 and 10 in Tables 2 and 3. High collaboration proactiveness with UIC could change effect into significant positive relationship ($\beta = 0.365$, $p < 0.001$) on patent citations received. Thus, these results lend moderate support to hypotheses 6, indicating that strong collaboration proactiveness of the UIC can improve innovation performance. Although not reported in Tables 2 and 3, all models include year dummy variables to control time-varying factors. As shown by the LR χ^2 statistics in Tables 2 and 3, the 16 models for the fixed and random effects are all statistically significant.

Robustness checks

To identify the differences in innovation effect of academic linkage across firms in UICs, we conducted quantile count regression as robustness checks. It helps investigate the effect of heterogeneity in UICs across different quantile of firms and check the sensitivity of the results. To reduce the effect of noise due to jittering, the parameters of the quantile count regression are repeatedly estimated using independent dram from the U(0,1) distribution; the multiple estimated coefficients and confidence interval endpoints are averaged (Cameron and Trivedi 2009). The *qcount* command provided by Miranda (2007) in Stata 15.0. is used to implement the quantile count regression.

Our quantile count regression estimates are based on 500 repetitions on a boot-strapping algorithm at target count quantiles of $q = 0.25$, 0.5, and 0.75. Following Miranda's (2008) method, this estimation procedure is followed iteratively until no significant changes in the independent variables are detected. Table 4 presents the results using patent citations received as the dependent variable. Several interesting results emerge. The estimates in Tables 2 and 3 show that collaboration breadth is positively related to a firm's innovation performance. The quantile estimation shows that the coefficients of collaboration breadth are significant negative for $q = 0.25$, and then become statistically significant from the 0.5 and 0.75 quantile onward. It depicts a U-shaped relation in its effect on innovation performance when quantile regression is performed. We also find that for higher quantiles firms, collaboration breadth monotonically increased with innovation performance (with coefficients of -0.006, 0.099, and 0.126 at $q = 0.25$, 0.5 and 0.75 respectively). These results indicate that this positive relation can be ascribed to the higher quantiles. One possible explanation is that, due to the knowledge of cross-fertilization and UIC, higher collaboration breadth (above the 0.25 quantile) has more advantages for a firm's innovation.

Table 4 demonstrates that our findings are robust for other covariates in all quantiles. For network centrality, it is again associated with a significantly positive coefficient, consistent with the Poisson regression results. The estimated coefficient on absorbed slack show a consistency effect that decreases in higher quantiles (with coefficients of −0.016, −0.021, and −0.034 at $q=0.25$, 0.5 and 0.75); all are significantly negative. The impact of unabsorbed slack is significant in all quantiles, confirming the findings in Tables 2 and 3. Their parameter monotonically decreases with firm values from the 0.25 quantile onward. Finally, estimates on collaborative experience (with coefficients of −0.041, −0.011, and 0.003 at $q=0.25$, 0.5 and 0.75) and collaborative proactiveness (with coefficients of −4.351, −0.079, and 0.365 at $q=0.25$, 0.5 and 0.75) show that, conditional on less collaborative experience and collaborative proactiveness, they tend to have a negative effect on innovation. Their impact, however, increases substantially from quantile to quantile and turns positive as collaborative experience and proactiveness increase, confirming Hypotheses 5 and 6. Collaborative experience and proactiveness can integrate and organize their process more efficiently in UIC, to obtain higher returns on innovation except for the lowest quantile.

Conclusion and policy implications

Industrial firms have long treated UICs as significant external sources of scientific and technical knowledge. However, many UIC projects have failed to meet their innovation objectives (Van de Ven et al. 2008). Numerous difficulties based on collaboration characteristics and resource challenges may impede the efforts of a firm to innovate and accomplish its collaboration task. Focusing on a firm's innovation paints an incomplete picture of the extent to which firms can innovate through UIC, and it is therefore crucial to improve our understanding of how heterogeneity in UICs affects firms' innovation performance.

In this study, we develop an original and rich conceptual framework to link collaboration characteristics of UIC and organizational slack with firms' innovation performance. This study contributes to the literature on innovation learning by highlighting firms' organizational learning and innovation via UIC relationship. To open the UIC black box, we use firm-level panel data from a comprehensive data set that combines three archival databases. Adopting quantitative methods to test the proposed hypotheses, our empirical estimations reach several significant results.

First, we find that firms with more collaboration breadth, network centrality, collaboration experience, and collaborative proactiveness within the academic linkage are more innovative. These results are consistent with established theories that signal a firm's critical network position and reputation for UIC collaboration may facilitate access to valuable knowledge resources and may be a source of capital (e.g. Giuliani et al. 2010). It is also plausible that more central, highly experienced and more proactive firms are more likely to be informed of, and possibly involved in, collaboration projects with a university. Collaboration proactiveness prompts reflection about the importance of policies to generate UIC environments where firms and universities have opportunities to maximize their capabilities and skills. A firm's involvement in UIC is beneficial not only for university faculty, but also for industries. This is consistent with findings in prior studies (e.g., Ankrah and AL-Tabbaa 2015; Baba et al. 2009; Faems et al. 2005; Huang and Yu 2011; Kaufmann and Tödtling 2001; Lee et al. 2001; Monjon and Waelbroeck 2003; Phibin 2008; Un and Cuervo-Cazurra 2010). This is especially true of the university-firm R&D collaboration systems investigated here. This interesting result has another implication: being a central firm within a UIC and in the interface between university and industry may induce collaboration, and be conducive to a richer flow of knowledge from and to the firm. Furthermore, universities are interested in collaborating with the most central, most experienced and most proactive firm, because they bring access larger to communities of firms, which then increase opportunities for novel information and innovation.

This study focuses on two types of organizational slack: absorbed and unabsorbed. We find that firms' absorbed and unabsorbed slack can be a risky facilitator of strategic collaboration behavior. Absorbed slack weakens firms' innovation performance; unabsorbed slack enables a firm to generate new innovations with few structural constraints (Tan 2003; Tan and Peng 2003). There are two plausible explanations for this finding. The negative significance of absorbed slack suggests that organizational absorbed slack give less weight to UIC, while unabsorbed slack is perceived to be or is valued more superficially by universities in the UIC; firms are more likely to innovate than firms with less unabsorbed slack and which give prominence to UIC linkages. Firms engaging in UIC relationships must develop unabsorbed slack so that they can reconfigure their technology resources and adapt to changing collaborative relationships. Because of the longer-term and unknown nature of payoffs related to innovation uncertainty, firms can mitigate the negative effects of absorbed slack on innovation performance (Bourgeois 1981; Bowen 2002; Bowen et al. 2010). As a result, unabsorbed slack should be more easily deployable in support of a firm's innovation through UIC (Nohria and Gulati 1996).

UICs are multifaceted relationships, suggesting the empirical analysis can be interpreted through complementary theories (Parmigiani and Rivera-Santos 2011). Because firms engaging in UICs may be innovative, it is fruitful to use two theoretical lenses. This study endeavors to make some progress in several directions. Both knowledge- and resource-based theory that are hard to buy or imitate in UIC enhance our understanding of the combination of the interactive and transfer processes that are relevant for innovation creation (Cohen and Levinthal 1990; Kobarg et al. 2018; Prime and Bulter 2001). Our study adds new lines to link both theories to UICs. It helps identify resource- and knowledge-based collaboration characteristics that explain its impact path.

For example, if firms have many UICs, these investments must jointly support and result in more unabsorbed slack to compensate for the hazards and opportunism that are created by multiple collaboration parties in relation to innovation performance. Absorbed slack has a negative association with a firm's innovation performance, implying that this resource is a decreasing function of the firm's innovation investments within the UIC mode, and this function can be condensed by organizational slack resources. This study articulates the positive role of collaboration breadth, network centrality, collaboration experience and collaborative proactiveness, unabsorbed slack and the negative role of absorbed slack with UIC in innovation performance and determines that these resources are important inputs in collaborative learning in UIC.

Finally, this study uses firms within a single country so the results may be specific to the UICs in the United States. However, some of our findings could stimulate debate and be interesting for developing countries. Our UIC data are obtained from the NBER-Rensselaer Scientific Papers database. This study included 2.4 million scientific papers written in the top 110 US universities and the top 220 R&D performing firms from 1981 to 1999, so the data is obsolete. In addition, constrained by information contained in three available archival databases, our sample firms are only public traded firms in the United States. However, it may be worthwhile to test whether our conclusions remain consistent for other firms or UIC in other countries. Future studies could also survey or interview managers of firms to evaluate their performance or satisfaction with UIC.

In conclusion, despite its limitations, this study broadens the roles of collaboration breadth, network centrality, collaboration experience, collaboration proactiveness and slack resources in UICs, all of which have policy implications for managers. Firms engaging in more UIC activities use these characteristics and resources to avoid or confront pressure and the possible drawbacks of joining UICs. Since UICs are conducive to a firm's innovation performance, this specificity of collaboration heterogeneity and slack resource setting could justify the strong orientation of the UIC investments towards firms' innovation and ensure their competitiveness in the industry.

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