More is not always better: Reconciling the dilemma of R&D collaboration in high-tech industries in transition economies

ABSTRACT: To cope with highly competitive business environments, firms in high-tech industries are increasingly opening up their organizational boundaries in order to tap into external resources via research and development (R&D) collaboration. Drawing upon organizational boundary theories, our study indicates that the marginal benefits of R&D collaboration in driving firms' product innovations decrease while its marginal costs increase. Our study develops a conceptual framework to account for the relationship between R&D collaboration and firms' product innovations. Further, drawing on the knowledge-based perspective and the institutional perspective, we also examine the moderating effects of absorptive capacity and political ties on the R&D collaboration-product innovation relationship. Using the data from 315 high-tech manufacturing firms in China, we find that R&D collaboration has an inverted U-shaped impact on firms' product innovations, meaning that firms' product innovations initially increase and then decrease as the level of R&D collaboration increases. Further, our work finds that this inverted U-shaped effect is moderated by the absorptive capacity (as an internal factor) and political ties (as an external factor), such that firms with stronger absorptive capacities will show a higher point of maximum innovation performance at higher levels of R&D collaboration than is the case with firms having lower absorptive capacities. We also reveal that for firms with stronger political ties, the benefits of R&D collaboration are enhanced while the risks and costs of R&D collaboration are mitigated. Overall, this study contributes to a better understanding on the nonlinear relationship between the R&D collaboration of a firm and its product innovation outcome, as well as the contingent conditions of the relationship.

Keywords: R&D collaboration; New product innovation; Political ties; Transition economies

1. Introduction

In the era of rapid technological changes, firms, especially those in high-tech industries, are increasingly engaged in various types of external R&D collaborations, such as university-industry interaction, R&D outsourcing, R&D alliance, and open R&D, to acquire outside knowledge and to stimulate product innovation (Aiello et al., 2021; Belderbos et al., 2004; Fernandes and O'Sullivan, 2021; Haeussler et al., 2012; Mueller et al., 2019; Xie and Wang, 2020). Here, R&D collaboration is defined as "any contractual or non-contractual arrangement that links a firm to another firm, that does not rely on purely market-based relationships and that aims at developing a new product or process" (Negassi, 2004, p. 368). R&D collaboration can promote knowledge transfer, resource exchanges, and the sharing of costs and risks (Ahuja, 2000a; Niedergassel and Leker, 2011; Hu and Tseng, 2007). Accordingly, R&D collaboration is regarded as a critical strategy for firms' innovation, especially when they lack sufficient internal R&D resources as they undertake innovation processes (Becker and Dietz, 2004; Huang and Yu, 2011; Lin, 2003).

Given the importance of R&D collaboration, previous research has provided valuable insights into the specific factors that enable firms to cooperate efficiently with various types of partners, including prior collaboration experience (e.g., Kafouros et al., 2020; Chen et al. 2022), organizational proximity (e.g., Nan et al., 2018), collaborative innovation networks (e.g., Rojas et al., 2018; Broekel et al., 2015), partner types (e.g., Belderbos et al., 2018; Jun et al., 2021), and appropriability mechanisms (e.g., Brunetta et al., 2020; Henttonen et al., 2015; Kleine et al., 2022). Moreover, previous research has examined the impact of R&D collaboration on firms' new product innovations (e.g., Belderbos et al., 2015; Hottenrott and Lopes-Bento, 2016; Hou et al., 2019; Maietta, 2015; Un and Rodríguez, 2018; Un et al., 2010), yet the effect of R&D collaboration on new product innovations, whether positive or negative, remains unclear. Some of these studies have demonstrated that R&D collaboration is positively related to new product innovations (e.g., D'Angelo and Baroncelli, 2019; Frankort, 2016; Michelfelder and Kratzer, 2013), while others have indicated that the impacts of R&D collaboration on new product innovations are negative (e.g., Hou et al., 2019; Maietta, 2015) or not significant (e.g., Belderbos et al., 2015; Klievink et al., 2017). Hence, there is still an incomplete understanding regarding the impact of R&D collaboration on either promoting or hampering a firm's new product innovations.

According to organizational boundary theories (Santos and Eisenhardt, 2005), a "boundary" in the business context is the demarcation line between an organization and its environment; the firm's activities, including R&D collaboration, operate under a specific logic of identity that shapes how things are done both within the organization and outside the boundary (Bäck and Kohtamäki, 2015). For high-tech firms in highly competitive environments, firms must frequently integrate and reconfigure internal and external resources to cope with these competitive environmental challenges (Bäck and Kohtamäki, 2015). In this respect, R&D collaboration becomes a critical strategy for them to address these challenges by extending their R&D actions across organizational boundaries and coordinating their innovative actions to search for competencies and cost advantages. Hence, there is a need to better understand the operations and management of R&D collaborations that cross the organizational boundary, as well as to examine how efficiently firms draw upon resources outside the boundary and use collaboration embeddedness while undertaking R&D processes, which shape organizational growth trajectories and determine practices in the collaborative partnerships.

However, companies often face a dilemma in their R&D collaboration processes: they must balance the sharing of resources with their partners to create joint value while simultaneously protecting themselves from each other's private value misappropriation (Dussauge et al., 2000). Integrating R&D resources during the R&D collaboration process is challenging because of the potential risks and costs, that is, firms should be wary of high governance costs and more dependency on their partners to promote R&D outputs during this process. Building on the organizational boundary theories, we provide a solution to the debate on the impact of R&D collaboration on firms' new product innovation by proposing a separation between two influences that may have been confounded in previous studies: "gains" and "pains" from R&D collaboration. We propose that R&D collaboration has a nonlinear relationship with new product innovations because the initial "gains" of R&D collaboration in the product innovations are outweighed at higher levels of R&D collaboration by high governance costs and dependency on their partners which may hollow out firms' innovation outputs. Therefore, we believe that the mixed views in the literature may overlook the impact of different levels of R&D collaboration, as determined by the boundaries between collaborative organizations, as well as the possible contingent conditions that underlie the relationship between R&D collaboration and new product innovation.

Moreover, following organizational boundary theories (Santos and Eisenhardt, 2005), high-tech firms must know which resources and firm capabilities can be coordinated within the organization (Caloghirou et al., 2020; Jafari-Sadeghi et al., 2022), and which need to be acquired from the outside to complement their competencies, to share costs, and to alleviate risks for R&D operations (Bäck and Kohtamäki, 2015; Lavie, 2006). Given that the contingent mechanisms of absorptive capacity (an internal capability within an organization) and political ties (a type of social capital from the external environment) may impact the effectiveness of R&D collaboration (Gkypali et al., 2018; Kokshagina et al., 2017; Zhang et al., 2015), we believe it is critical to deepening our understanding of the link between R&D collaboration and new product innovation in transition economies. To do so, we provide contingency perspectives both within and outside the organizational boundary that allow us to analyze the impact of absorptive capacity and political ties, as this work may determine the specific contexts in which R&D collaboration can be transformed into yielding higher new product innovations. In addition, we focus our work on absorptive capacity and political ties for two reasons: First, given that absorptive capacity can help firms turn newly acquired knowledge into marginally improved products via R&D collaboration (Limaj and Bernroider, 2017), the effect of R&D collaboration on innovation depends on firms' absorptive capacities to apply that new knowledge (Ferreras-Méndez et al., 2016; Kotabe et al., 2011; Muller et al., 2021). Second, it is crucial to investigate political ties, as they can help firms access valuable resources (Du et al., 2015), secure government contracts and property rights protections (Zhou, 2013), and obtain political legitimacy and institutional advantages (Li and Zhou, 2010; Li et al., 2015; Oguguo et al., 2020), especially for firms in transition economies operating in weak institutional contexts (Du and Mickiewicz, 2016).

In this work, we propose a conceptual framework to examine the nonlinear relationship between R&D collaboration and new product innovation and to explore the moderating effects of absorptive capacity and political ties on this nonlinear relationship. First, we contribute to the R&D collaboration literature by exploring the inverted U-shaped relationship between R&D collaboration and new product innovations using data drawn from high-tech manufacturing firms in China's transition economy. Using a new perspective of organizational boundary theories, we integrate the contradictory findings in the literature that pertain to R&D collaboration and new product innovations by considering two different influences of R&D collaboration on firms' innovation. Second, we contribute to the literature by investigating the contingent conditions both within and outside the organizational boundary concerning when R&D collaboration might effectively promote firms' new product innovations by proposing that the impact of R&D collaboration on firms' new product innovations needs to be considered together with its contingent effects of absorptive capacity (as an internal factor) and political ties (as an external factor).

The remainder of this paper is organized as follows. Section 2 describes the theory and hypotheses. Section 3 provides the data and measures. Section 4 describes the empirical results. Lastly, Section 5 provides our concluding remarks, presents our theoretical contributions and managerial implications, discusses the limitations of this paper, and points to possible future research in this area.

2. Theory and hypotheses

2.1. R&D collaboration and new product innovations

In the highly competitive environment of high-tech industries, firms need to understand how R&D collaboration activities are coordinated between collaboration partners and themselves. Building on organizational boundary theories, we discuss three boundary conceptions—competence, efficiency, and power—to provide a deeper understanding of high-tech firms' strategic decisions about organizational boundaries (Santos and Eisenhardt, 2005). Firms having "high competence" means that such firms are continuously searching for external resources to configure into combinations that function as a source of competitive advantage (Santos and Eisenhardt, 2005), which allows them to complement internal resources with external ones, such as the R&D capabilities of collaborative partners (Bäck and Kohtamäki, 2015; Parmigiani and Mitchell, 2009). However, integrating R&D resources is challenging because of the potential risks and costs. On the one hand, in terms of "efficiency," firms must consider the costs that come from both the coordination and monitoring that result from the interaction between different dimensions (Santos and Eisenhardt, 2005; Williamson, 2008). For example, the information asymmetries and efforts put into negotiations and monitoring R&D collaborations raise administration costs (Kohtamäki et al., 2013). On the other hand, from the perspective of "power," firms must concentrate on the power-dependency between partners operating within the joint value-creating processes of R&D collaboration, and analyze how firms control the relationships they are involved in to avoid possible overdependence (Bäck and Kohtamäki, 2015). For example, as the level of R&D collaboration increases, firms in knowledge-intensive high-tech areas may become overdependent on their partners' specialized competencies and skills (Gulati and Sytch, 2007; Belitski et al., 2020); this may lead some firms to change partners so that they are not placed in a vulnerable position, even though such changes incur switching costs. Therefore, firms must either tolerate high governance costs and dependency on their partners to promote R&D output (Gulati and Sytch, 2007) or must bring strategically crucial development projects in-house to avoid dependency, which leads them to lose access to their partners' competencies (Mayer and Nickerson, 2005). Overall, firms can be both aided and constrained by their collaborative partnerships (Jiang et al., 2018). Thus, a firm in the process of undertaking an R&D collaboration may face a dilemma between lacking the external resources needed to promote innovation and taking on the potential risks of excessive dependence and higher administration costs. Viewing the situation in this way helps us better understand the mixed, sometimes puzzling, findings regarding the effects of R&D collaboration on new product innovations. The positive implications of R&D collaboration on firms' new product innovations have long been noted (e.g., D'Angelo and Baroncelli, 2019; Frankort, 2016), but the optimum degree to which a firm's new product innovation may benefit from its R&D collaboration has yielded different conclusions (e.g., Hou et al., 2019; Kang and Kang, 2010). Therefore, building on organizational boundary theories, we assert several hypotheses below to discuss the relationship between R&D collaboration and firms' new product innovations.

Generally, firms can benefit from R&D collaborations in product innovation processes (e.g., D'Angelo and Baroncelli, 2019; Frankort, 2016; Michelfelder and Kratzer, 2013). First, R&D collaboration can equip a firm with the knowledge, resources, and technological competencies that it would otherwise lack to create new or improved products (Un et al., 2010). Taking business knowledge as an example, given that no firm can supply itself with all the knowledge it needs for new product innovation (Un et al., 2010), firms that engage in R&D collaborations can benefit from knowledge sharing, allowing them to expand the breadth and depth of their knowledge pool (Ahuja, 2000b; Dyer and Nobeoka, 2000; Bouncken et al., 2022). This enables such firms to obtain the advantages of knowledge specialization and knowledge diversity, and also to better utilize their existing knowledge pool for new product innovations. Moreover, external knowledge that is shared via collaboration can enable firm employees to deliver more innovative ideas (Xie et al., 2018b); this can promote innovative behaviors, and thus, advance new product innovations. Second, R&D collaboration is often seen as a way of sharing innovation risks and costs, which are frequently very high at the R&D stage (Belderbos et al., 2004), especially for firms with limited internal resources (Hottenrott and Lopes-Bento, 2016). On the one hand, firms engaged in R&D collaborations are often motivated by coordinating their actions with their partners and reducing duplicate investment in R&D activities (Un et al., 2010). On the other, firms often rely on their collaboration partners to gain new competencies, improve input quality, and move quickly into new markets, thereby reducing the likelihood of failure during the product innovation process (Takeishi, 2002; Wynstra and Weggemann, 2001).

However, as R&D collaborations continue, firms' marginal costs increase rapidly and can exceed the partnership benefits discussed above, with the returns of R&D collaboration to new product innovations moving increasingly into negative territory. First, as R&D collaboration steers the actions of all of the members (Polidoro et al., 2011), firms embedded in R&D collaborations not only enjoy the shared knowledge that comes from their R&D partners but also must share their knowledge. Consequently, firms may be more likely to feel threatened by the risk of knowledge leakage (Hottenrott and Lopes-Bento, 2015). In addition, knowledge sharing during R&D collaboration will simultaneously enhance a firm's dependence on its partners' intangible assets (Gulati and Sytch, 2007). This may cause the firm to be severely constrained by its partners (Zhang et al., 2019a). Second, some have suggested that when firms become too embedded in R&D collaborations, the high familiarity between partners will eventually decrease the diversity and novelty of their knowledge and skills (Ahuja, 2000b), thereby impeding all collaboration members from benefiting from the knowledge sharing (Zhang et al., 2019a). This can lead to the weakening of individual firms' own product innovations because of the knowledge homogeneity. Third, firms may find it difficult to guarantee what their partners' final value to them may be due to information asymmetries and potential secrecy. High R&D collaboration intensity requires a great deal of effort to search for and select the ideal cooperation partners, and then coordinate effectively with those partners (Hottenrott and Lopes-Bento, 2016). Each additional R&D collaboration activity increases the burden on management, including the monitoring and transaction costs (Berchicci, 2013; Caminati, 2016; Hottenrott and Lopes-Bento, 2016). Furthermore, the coordination and monitoring of new collaborations can drain valuable resources that would otherwise be available for other R&D activities, which may also negatively influence a firm's product innovation (Hottenrott and Lopes-Bento, 2016; Alzamora-Ruiz et al., 2021). In sum, when firms become over-embedded in R&D collaborations, the net benefits they obtain from such collaboration would appear to decrease over time, leading to lower marginal gains.

Based on the above analysis of the benefits and drawbacks associated with R&D collaborations, we build a conceptual model to specify how new product innovation changes as R&D collaboration increases by explicating how the benefits and costs vary across different collaboration levels. Our main argument is illustrated in Figure 1. Hence, we propose that:

H1. R&D collaboration has an inverted U-shaped impact on firms' new product innovations, such that the impact is initially positive, but becomes more negative as the level of R&D collaboration increases.

<Insert Figure 1 here>

2.2. The moderating effect of absorptive capacity

Absorptive capacity is defined as "the ability to recognize, assimilate, and apply the value of new external information to commercial ends" (Cohen and Levinthal, 1990, p. 39). According to the "competence" conception in organizational boundary theories, firms need to continuously search for external resources and processes to cultivate competitive advantages via their R&D collaborations (Bäck and Kohtamäki, 2015). Moreover, from the knowledge-based perspective, knowledge is a key strategic resource that explains the differences among firms and why some firms are better than others that provides the firm with a more sustainable competitive advantage (Un and Rodríguez, 2018), and the ability to generate, combine, recombine, and exploit knowledge is essential to a firm's ability to innovate (Xie et al., 2018a). Thus, absorptive capacity, as a competence that allows firms to continuously acquire and utilize external knowledge, has become a crucial process for firms to use new knowledge to achieve their innovation aims (Xie et al., 2018a).

Since strong absorptive capacity allows firms to benefit more from R&D collaborations through the expanded external information sources (e.g., knowledge and skill sets) shared by the R&D partners (Adamides and Karacapilidis, 2020; Zuo and Lin, 2022), absorptive capacity is likely to alter the R&D collaborations—firms' new product innovation relationships—as absorptive capacity has important impacts on expanding the marginal benefits when the level of R&D collaboration increases. Previous research has suggested that absorptive capacity can be decomposed into four aspects: knowledge acquisition, assimilation, transformation, and exploitation (Xie et al., 2018a; Zahra and George, 2002). Reviewing these aspects in more detail, we see that, firstly, regarding the aspect of knowledge acquisition, firms with strong absorptive capacity might be able to better identify and acquire externally generated knowledge and technologies (Zahra and George, 2002). Secondly, about the accumulation of knowledge and technologies gained through R&D collaborations, such firms are likely to become more capable and experienced in assimilating external knowledge for product innovation (Zhou and Wu, 2010), and their capability to assimilate external knowledge can potentially accelerate the speed of problem-solving and shorten the new product life cycle (Xie et al., 2018a; Xie et al., 2018b), hence facilitating product innovation. Thirdly, knowledge transformation suggests a firm's ability to combine its existing knowledge with the new knowledge obtained from its R&D partners (Mueller et al., 2019; Zahra and George, 2002). Thus, we can see that firms with strong absorptive capacity can develop new cognitive structures via knowledge transformation (Todorova and Durisin, 2007), thereby promoting their new product innovations and, ultimately, avoiding over-dependence on their partners' intangible assets. Fourth, regarding the aspect of knowledge exploitation, firms that effectively incorporate the transformed knowledge into their product innovation processes are more likely to produce new competencies and better systems (Camisón and Forés, 2010). On the whole, then, firms with high absorptive capacity are more likely to benefit from R&D collaboration through knowledge sharing and organizational learning, eventually leading them to increase new product innovations.

Although firms with high absorptive capacity can be equally vulnerable to the potential drawbacks discussed above (e.g., knowledge leakage and administration costs), a firm's strong absorptive capacity allows it to be involved in R&D collaborations so that it can acquire, assimilate, transform, and exploit external knowledge from its partners more efficiently. Thus, for these firms, the net benefits gained from R&D collaboration would seem to offset the potential drawbacks. That is, firms with higher absorptive capacity show a higher point of maximum innovation performance than firms with lower absorptive capacity, and such a maximum point for firms with stronger absorptive capacity is reached at the higher levels of R&D collaboration. Hence, we propose that:

H2. Absorptive capacity moderates the inverted U-shaped relationship between R&D collaboration and firms' new product innovations, such that stronger absorptive capacity is related to a higher point of maximum innovation performance along the inverted U-shaped curve.

2.3. The moderating effect of political ties

Political ties, called *guan-xi* in China, are defined as individual connections with officers at various levels of government (Peng and Luo, 2000). From the institutional perspective, informal governance mechanisms act as a substitute to facilitate economic activities when formal institutions fail, such as social ties which serve as key forms of informal governance mechanisms during transition economies in which market-supporting institutions are not perfect yet (Sheng et al., 2011). Hence, political ties are commonly regarded as a key component of firms' social capital in transition economies (Arnoldi and Villadsen, 2015; Hillman et al., 2004), and informal governance mechanisms allow firms to bypass institutional hurdles (Xie et al., 2014). For example, in China, political actors often powerfully affect policy preferences, resource allocations, and legitimacy gain (Peng and Luo, 2000; Sheng et al., 2011). Thus, in transition economies, the institutional environment makes political ties particularly crucial for firms (Fan et al., 2013). Moreover, according to organizational boundary theories, firms need to understand which resource can be obtained from outside the boundary to complement their competencies and mitigate their risks (Bäck and Kohtamäki, 2015). In this vein, firms' political ties can facilitate a situation where they can effectively optimize the formal institutional environments in which they operate, thereby ensuring a better chance for superior economic returns (Li and Zhang, 2007). Furthermore, firms with strong political ties are often able to take advantage of market opportunities before those without such political ties, which gives the former group a significant competitive advantage (Xie et al., 2014).

Given that political ties play an important role in expanding the marginal benefits and mitigating the marginal costs associated with high levels of R&D collaboration, we propose that political ties may alter the relationship between R&D collaborations and firms' new product innovations. First, as those in the government often control resources that are essential for firms' product innovation (e.g., funding and market access), firms may leverage their political ties to obtain valuable resources, which can potentially substitute for their lack of access to external resources from R&D partners and which can allow firms to avoid the possible overdependence on R&D collaborations. Second, high institutional status and political legitimacy rooted in political ties can facilitate firms' involvement in R&D collaborations, enabling them to secure resources and support from nongovernmental stakeholders (Jia, 2014; Zhang et al., 2019a). Such an enlarged pool of resources (e.g., knowledge, skill sets, and technological competencies) can advance product innovation. Meanwhile, government officials can assist firms in building effective collaboration monitoring and profit distribution insurance mechanisms; this promotes knowledge spillover (Shahzad et al., 2022), which consequently widens the available absorbable knowledge that can be tapped through R&D collaborations (Ma et al., 2017; Shahzad et al., 2022). Third, to reduce the potential risk of knowledge leakage during R&D collaborations, firms may leverage their political ties to secure institutional protections from the government, thus enabling them to effectively protect their knowledge and innovations (e.g., intellectual-property protections, industrial policies, etc.) (Hernandez et al., 2015; Li and Zhang, 2007).

In sum, political ties can not only increase firms' benefits gained from R&D collaborations by providing them alternative resources but also alleviate drawbacks by drawing on institutional support in order to avoid potential R&D collaboration risks. Such political ties thus create a higher net return in the long run for these firms. Thus, we propose that:

H3. Firms' political ties moderate the inverted U-shaped relationship between R&D collaboration and new product innovations, such that when firms' political ties with the government are stronger, the positive impact of R&D collaboration on new product innovations will be enhanced and the negative effect of R&D collaboration will be reduced.

Figure 2 illustrates the above conceptual framework, showing the nonlinear relationship between R&D collaboration and firms' new product innovations. The framework also puts forward two contingency factors discussed above that can affect this nonlinear relationship—absorptive capacity and political ties.

<Insert Figure 2 here>

3. Data and methods

3.1. Data source

We obtained the data for this investigation by using a survey method. Specifically, we sent questionnaires to high-tech manufacturing firms in China's Yangtze Delta Region, where the country's most developed high-tech manufacturing industries are located. It is considered a suitable sample in this study that Yangtze River Delta region, as one of the world's urban agglomerations, is full of vitality and competitiveness, which is beneficial for the firms' R&D collaboration. We distributed the surveys to managers with rich experience in their firms' operation and innovation processes. The questionnaire was first pretested by using some representative firms that had participated in R&D collaboration activities in the past three years. Following the pretest, we modified the survey according to the feedback and then conducted the full survey. For the final survey, a total of 500 questionnaires were sent to high-tech manufacturing firms via field survey and e-mail. All firms were randomly selected using a stratified random sample method based on firm size and industry type (i.e., six high-tech sectors: the new energy industry, high-tech equipment industry, new materials industry, bioengineering industry, information technology industry, and energy-saving and environment-friendly industries). A total of 315 valid responses were received, providing a valid survey response rate of 63.00%.

Nonresponse bias was tested in this study. Firstly, the first and fourth quartiles of the responses were compared for differences in their independent and dependent variables. As displayed in Table A1, the results showed that the *t*-statistics for R&D collaboration (t = 0.250, p = 0.803), new product innovation (t = 0.723, p = 0.471), absorptive capacity (t = 0.930, p = 0.354), and political ties (t = -1.151, p = 0.251) were all statistically insignificant ($p > 0.05$). Secondly, by conducting *F*-tests, differences between firms that responded and those that did not were compared using firm size, firm age, and industry type. These findings, presented in Table A2, indicated no significant differences between the two groups ($p > 0.05$). We thus concluded that nonresponse bias was not a concern in this study.

The characteristics of the respondents, including their levels of education, position, functional department, and work experience, are shown in Table 1. Regarding education, 90.79% of the respondents held at least a bachelor's degree. In terms of position, 76.19% of the respondents were senior or middle-level general managers and R&D managers. About functional departments, 67.62% of the respondents worked in departments closely aligned to their firms' R&D collaboration endeavors (i.e., R&D departments, production departments, and marketing departments). Additionally, 80.00% of the respondents claimed to have held their management position for five years or more, which likely helped them better comprehend the content of the questionnaire. Overall, the distribution of the respondents confirmed that we had a comprehensive pool of participants in this study, thus helping to ensure the validity of the construct.

< Insert Table 1 here >

The sample profile, including firm size, firm age, annual sales, industry sector(s), R&D

personnel intensity, and R&D expenditure intensity, is shown in Table 2. Regarding firm size, 95.24% of the firms had fewer than 1,000 employees (i.e., were small- and medium-sized enterprises). About firm age, 92.07% of the firms had been established more than five years before. In terms of annual sales, 86.35% of the firms were in the category of 'fewer than 400 million RMB.' Regarding R&D intensity, 94.92% of the firms stated that they were in the 'over 3%' category in terms of R&D personnel intensity, and 95.87% stated that they were in the 'over 3%' category in terms of R&D expenditure intensity. The high-tech manufacturing industries in our survey included the new energy industry (3.17%), high-tech equipment industry (13.65%), new materials industry (15.87%), bioengineering industry (22.86%), information technology industry (26.67%), and energy-saving and environment-friendly industries (17.78%).

< Insert Table 2 here >

3.2. Variables and measures

3.2.1. Dependent variable

Following the work of Zhang and Li (2010), new product innovation was measured using five items (see Table 3). The respondents were required to assess the level to which their firms had been successful relative to their major competitors in the prior three years, measuring their answers on a seven-point Likert scale (1 = '*not at all*' to 7 = '*very much*').

3.2.2. Independent variable

Using the work of Becker and Dietz (2004) and Berchicci (2013), we designed the measurement scale of R&D collaboration in two respects—the number of R&D collaboration partners, and the input intensity of R&D collaboration (see Table 3). Specifically, R&D collaboration was evaluated using three items: (a) the number of R&D collaboration partners (1 = '*no partners*', 2 = '*one up to two partners*', 3 = '*three up to four partners*', 4 = '*five up to six partners*', 5 = '*seven up to eight partners*', 6 = '*nine up to ten partners*', 7 = '*eleven or* *more partners*'); (b) R&D collaboration expenditure intensity, defined as the ratio of annual R&D collaboration expenditure to total sales, was evaluated using a six-point Likert scale (1 = '*<1%*' to 6 = '*>15%*'); and (c) R&D collaboration personnel intensity, defined as the ratio of the number of employees working in the area of R&D collaboration to the total number of firm employees, was evaluated using a six-point Likert scale (1 = '*<1%*' to 6 = '*>15%*'). These last two items indicated the intensity of the firms' R&D collaboration input activities in the prior three years, which captured the degree to which the firms were involved in R&D collaboration, as compared to the intensity of firms' internal R&D activities. Thus, the larger the values of R&D collaboration expenditure intensity and personnel intensity were, the higher the level of R&D collaboration was.

3.2.3. Moderating variables

Absorptive capacity. Following Crescenzi and Gagliardi (2018), the data we received on R&D investment was used as a proxy for the firm's absorptive capacity. Absorptive capacity was measured by examining the ratio of annual R&D expenditure to total sales. This item was evaluated on a five-point Likert scale (1 = '*<3%*' to 5 = '*>15 %*').

Political ties. Utilizing Guo et al. (2014), we assessed political ties using a three-item scale (see Table 3). The respondents were required to indicate the extent to which they agreed with statements regarding their firms' political ties. The items were evaluated on a seven-point Likert scale (1 = '*strongly disagree*' to 7 = '*strongly agree*').

3.2.4. Control variables

Similar to Li and Zhou (2010), in this study, we introduced four control variables: firm size, firm age, annual sales, and industry. Firm size was measured by the number of employees using a four-item scale: 1 = '*<20*' to 4 = '*>1000*'. Firm age was evaluated by using the number of years the firm had been listed by their local Industrial and Commercial Bureau at the end of the survey year, using a five-item scale: 1 = '*<3*' to 5 = '*>15*'. Annual sales were evaluated by using a four-item scale: 1 = '*<3 million yuan*' to 4 = '*>400 million yuan*'. Additionally, an industry type was assessed with a bivariate variable, which took the value of 1 when the firm was involved in a particular industry type, and 0 otherwise; therefore, an industry type was measured by six dummy variables.

< Insert Table 3 here >

3.3. Reliability, validity, and common method variance

This study adopted various measures to ensure the data's reliability and validity. As shown in Table 3, all the Cronbach's alpha values were found to be greater than 0.6, and the composite reliability values were shown to be greater than 0.8, thus demonstrating acceptable reliability (Nunnally, 1978). Additionally, confirmatory factor analysis (CFA) was performed to access the constructs' convergent and discriminant validity. As shown in Table 3, the results revealed that the model fit the data well ($\chi^2/df = 2.300$; comparative fit index [CFI] = 0.933; incremental fit index [IFI] = 0.934; Tucker-Lewis Index [TLI] = 0.912; root mean square error of approximation [RMSEA] = 0.064; standardized root of the mean square residual [SRMR] = 0.051) (Schermelleh-Engel et al., 2003). Furthermore, all factors loaded significantly on their corresponding latent constructs ($p < 0.01$), and the average variance extracted (AVE) values of the variables were statistically acceptable, indicating good convergent validity (Fornell & Larcker, 1981). Regarding the discriminant validity, the results, shown in Table 4, indicated that the square roots of the AVE values in the diagonal were greater than the correlation coefficients in the same lines and columns, signifying good discriminant validity (Fornell & Larcker, 1981).

As is commonly the case in surveys, the use of perceptual data for variables may lead to the concern of common method variance (CMV). Therefore, we adopted both procedural and statistical methods to decrease the concern of CMV. Regarding the procedural methods, first, we used multiple items to measure the constructs; second, we assured the respondents that the questionnaire was anonymous and that there were no "right" or "wrong" answers to the questions; and, third, we placed independent and dependent variables in separate parts of the questionnaire. In terms of the statistical techniques used, first, we adopted Harman's one-factor test to check for CMV. The results revealed that the first factor accounted for only 20.02% of the total variance, demonstrating that CMV was not a concern. Second, using the CFA approach, we allowed the items to load on a latent CMV factor, and then tested the significance of the structural parameters with the latent CMV factor. The results here indicated that the model did not fit the data well (χ^2/df = 6.660; CFI = 0.687; RMSEA = 0.134); however, when all of the items were loaded on their theoretical constructs, the model did fit the data well, indicating that CMV was not a concern in this work.

3.4. Model

To test the main effect and the moderating effects, we constructed the models shown in *Eq.* (1) for the main effect and *Eq.* (2) for the moderating effects. Following the work of Aiken and West (1991), NPI_i signified a firm's new product innovation; RDC_i represented the R&D collaboration; and AC_i and PT_i signified the absorptive capacity and political ties, respectively.

$$NPI_i = \alpha + \beta_1 RDC_i + \beta_2 RDC_i^2 + \delta_i Controls_i + \varepsilon_i \tag{1}$$

$$\begin{aligned} NPI_i = \alpha + \beta_1 RDC_i + \beta_2 RDC_i^2 + \beta_3 AC_i + \beta_4 (RDC_i * AC_i) + \beta_5 (RDC_i^2 * AC_i) \\ + \beta_6 PT_i + \beta_7 (RDC_i * PT_i) + \beta_8 (RDC_i^2 * PT_i) + \delta_i Controls_i \\ + \varepsilon_i \end{aligned} \tag{2}$$

4. Results

4.1. Major findings

Table 4 displays the means, standard deviations (SDs), and correlations among the variables. As expected, we found that firms' new product innovation was correlated with R&D

collaboration (r = 0. 298, $p < 0.01$), absorptive capacity ($r = 0.282$, $p < 0.01$), and political ties ($r = 0.549$, $p < 0.01$). To exclude the concern of the variance inflation factor (VIF), we centered all the variables before conducting the analysis; and the results showed that the largest VIF value was 8.093 and all the VIF values were below the threshold value of 10.0, demonstrating that multicollinearity was not a concern in this study (Aiken and West, 1991).

< Insert Table 4 here >

Table 5 shows the findings of the hierarchical regression. According to *Eq.* (1), Model 2 added the R&D collaboration variable, which had a significant positive effect on new product innovation ($\beta = 0.252$, $p < 0.01$). Moreover, Model 3 investigated whether R&D collaboration had an inverted U-shaped effect, and thus we included its squared term. The results demonstrated that R&D collaboration had a positive and significant coefficient ($\beta_1 = 0.120$, $p < 0.01$), while R&D collaboration squared had a negative and significant coefficient ($\beta_2 = -0.347$, $p < 0.05$). Taken together, these two effects suggest that R&D collaboration has a curvilinear impact on new product innovations (Lind and Mehlum, 2010). This result implies that firms engaged in R&D collaboration have greater benefits in terms of new product innovations. However, this was only the case up to a certain point, beyond which, a higher level of R&D collaboration reduced the firms' new product innovations. Moreover, using parameter estimates from the model, we estimated the turning point of the inverted U-curve, i.e., the value of R&D collaboration that maximizes new product innovation at $-\beta_1/2\beta_2$, where β_1 = *coefficient of R&D collaboration*, and β_2 = *coefficient of (R&D collaboration)* ^{2}. Our results showed that the value of the turning point was 0.173, while the value of the untransformed turning point was 4.219, which is well within the sample range, thus presenting reasonable certainty of an inverted U-curve (Lind and Mehlum, 2010). Hence, H1 is strongly proven.

Using *Eq.* (2), we examined the moderating roles of absorptive capacity and political ties in the relationship between R&D collaboration and new product innovation. The results from Model 5 showed that the interaction of R&D collaboration and absorptive capacity was positively and significantly correlated with new product innovation (β_4 = 0.334, $p < 0.05$), while the interaction of R&D collaboration squared and absorptive capacity was not statistically significant (β_5 = 0.108, $p > 0.1$). Moreover, for Model 5, we estimated $\beta_1\beta_5$-$\beta_2\beta_4$ (in *Eq*. (2)), where β_1 = *coefficient of R&D collaboration*, β_2 = *coefficient of (R&D collaboration)* ^{2}, β_4 = *coefficient of the interaction of absorptive capacity and R&D collaboration*, and β_5 = *coefficient of the interaction of absorptive capacity and (R&D collaboration)* ^{2}. The results showed that the value was 0.114, revealing that the turning point moves to the right when absorptive capacity increases (Haans et al., 2016). Hence, H2 is supported. To present the interaction effect more intuitively, we developed 2-D and 3-D graphs, shown in Figure 3. This finding reveals that for firms with strong absorptive capacity, the optimal value of R&D collaboration, where the maximum innovation value is achieved, is higher than the equilibrium points for firms with weak absorptive capacity. In other words, firms with strong absorptive capability can enjoy the positive returns of high R&D collaboration.

To test H3, the results in Model 7 suggested that the interaction of R&D collaboration and political ties was significantly related to new product innovation (β_7= 0.274, $p < 0.05$), while the interaction of R&D collaboration squared and political ties was also significant (β_8 = 0.308, $p < 0.05$). Similarly, for Model 7, $\beta_1\beta_8$-$\beta_2\beta_7$ (in *Eq*. (2)) was estimated to test for the shift of the turning point. Here, we received the value is 0.027, validating that the turning point moves to the right as political ties increase (Haans et al., 2016). Therefore, H3 is supported. Again, we developed 2-D and 3-D graphs to present the interaction effects, as shown in Figure 4. The results demonstrate that the amplitude of new product innovation is greater for firms with stronger political ties at all levels of R&D collaboration, which suggests that strong political ties increase the positive effect of R&D collaboration. Moreover, our findings demonstrate that optimal R&D collaboration is greater when political ties are stronger, indicating that strong political ties might mitigate the costs and risks associated with increased R&D collaboration. Therefore, H3 is strongly supported.

Additionally, we constructed a full model to consider all the variables involved in our conceptual framework. The results of this model, Model 8, shown in Table 5, revealed that the findings were consistent with the findings above, further supporting our results.

< Insert Table 5, Figures 2 and 3 here >

4.2. Robustness tests

To further evaluate our findings, we undertook several robustness analyses. First, to test the robustness of the inverted U-shaped relationship between R&D collaboration and new product innovation, we followed the work of Haans et al. (2016) and added a cubic term of R&D collaboration into the models. As shown in Table 6, the results indicated that the cube of R&D collaboration was not statistically significant ($p > 0.1$), revealing that our data fit the inverted U-shape better than other curves. Second, according to Li et al. (2009), we re-estimated the model using two randomly selected subsamples (i.e., 90% and 70% of total observations). These results, displayed in Table 7, indicated that the new findings were consistent with the results from the full sample, which, again, strongly supported our initial results.

< Insert Tables 6 and 7 here >

5. Discussion and conclusions

5.1. Theoretical contributions

In recent years, researchers have paid growing attention to R&D collaboration in terms of it acting as an engine for product innovation (e.g., Frankort, 2016; Haeussler et al., 2012; Zhang et al., 2019a). Yet, there has been no consensus regarding the effect of R&D collaboration on either promoting or hampering a firm's new product innovations. Thus, based on organizational boundary theories, we developed an integrative framework to address the theoretical dilemma posed by the mixed and sometimes contradictory implications discussed in the literature (e.g., D'Angelo and Baroncelli, 2019; Hou et al., 2019) by highlighting the nonlinear relationship between R&D collaboration and firms' new product innovations, and also by examining the contingent conditions by which R&D collaboration might effectively improve firms' new product innovations. Thus, this study provides new theoretical insights in several respects.

First, we enrich the R&D collaboration research by providing a novel perspective of organizational boundary theories and by offering empirical research to examine a practical paradox about R&D collaboration in firms' new product innovation processes. Some scholars have recognized that firms' product innovation depends not only on internal R&D activities but also on R&D collaborations, as these allow the firms to access resources outside the firm's boundaries (Belderbos et al., 2018). However, the previous research has mainly focused on the benefits that firms gain through their R&D collaborations (e.g., Rojas et al., 2018; Frankort, 2016), while few studies have pointed out that R&D collaborations can also expose firms to potential drawbacks (e.g., Hottenrott and Lopes-Bento, 2016). To respond to this research gap and to reconcile the inconsistent views about R&D collaboration vis-à-vis new product innovation, we applied a survey method and used respondent data from high-tech manufacturing firms in China. Our examination confirmed that R&D collaboration has an inverted U-shaped impact on firms' new product innovations. The findings here suggest that as the level of R&D collaboration increases, the returns that firms can obtain by collaborating with R&D partners will first increase and then decrease, while the drawbacks intensify. Therefore, this work answers the call in the recent literature for a better understanding of the puzzling implications of R&D collaboration on innovation performance (e.g., Berchicci, 2013; Hottenrott and Lopes-Bento, 2016) and provides one solution to the debate on the influences of R&D collaboration by considering the different levels of R&D collaboration. Moreover, we incorporated organizational boundary theories into this R&D collaboration research; this work responds to the call by Zhang et al. (2019a), who suggested that R&D collaboration research needs to embrace novel theoretical perspectives. Drawing on organizational boundary theories (Bäck and Kohtamäki, 2015), we reconciled the puzzle about firms' R&D collaboration embeddedness by highlighting the implications of three boundary conceptions (i.e., competence, efficiency, and power) in the context of R&D collaboration. As the "competence" conception suggests, firms have to complement internal resources with external resources and technological competencies through knowledge sharing and organizational learning among their R&D partners to make innovative products (Frankort, 2016; Un et al., 2010; Zhang et al., 2019a; Xie et al., 2022). Then, as the conceptions of "efficiency" and "power" imply, firms should be aware of the risks and costs associated with high levels of R&D cooperation, including knowledge leakage and misappropriation, the overdependence on partners, and high administration costs (Caminati, 2016; Gulati and Sytch, 2007; Hottenrott and Lopes-Bento, 2015). Overall, the current work allows us to better comprehend the link between R&D collaboration and firms' new product innovations by exploring the inverted U-shaped effect using a novel perspective, thereby contributing significantly to both R&D collaboration research and organizational boundary theories.

Second, we theoretically and empirically examined the contingent conditions both within and outside the organizational boundary in terms of when R&D collaboration might effectively promote new product innovation. Previous studies have centered on the direct impacts of R&D collaboration on innovation performance from multiple dimensions, such as partner types and collaboration diversity (e.g., D'Angelo and Baroncelli, 2019; Gkypali et al., 2017), yet the boundary conditions by which R&D collaboration matters for improved innovation performance remain relatively under-researched. Moreover, although some previous studies have taken notice of the roles played by firms' internal capacities and external resources in terms of innovation performance, such as in terms of knowledge acquisition, cognitive capital, and institutional support (e.g., Berchicci, 2013; Frankort, 2016; Zhang et al., 2019b), few researchers have connected R&D collaboration with firms' internal capacities and external resources. Hence, to fill this gap, we examined how internal absorptive capacity (within the organization) and external political ties (outside the organization) function in the relationship between R&D collaboration and firms' new product innovations. Our findings showed that the curvilinear relationship between R&D collaboration and firms' new product innovations is moderated by both absorptive capacity and political ties. As it pertains to absorptive capacity, we found that firms with stronger absorptive capacity may be in a better position to obtain the benefits from knowledge sharing and organizational learning while undertaking R&D collaboration, thereby intensifying the positive impact of R&D collaboration on firms' new product innovations. Furthermore, our findings revealed that firms with stronger absorptive capacity are better equipped to acquire, assimilate, transform, and exploit external knowledge and technologies gained through their R&D collaborations, potentially allowing them to shorten the new product development life cycle (Todorova and Durisin, 2007; Xie et al., 2018a); ultimately, this allows them to advance their product innovation and avoid overdependence on their partners. As it pertains to political ties, we found that strong political ties can help firms intensify the positive effects of R&D collaboration on new product innovation while also impeding the negative effects of high levels of R&D collaboration on new product innovations (Nedjah et al. 2022; Romijn, and Albaladejo, 2002). Our findings revealed that the institutional support acquired through firms' strong political ties could help those firms guard against potential drawbacks and achieve better R&D collaboration (Hernandez et al., 2015; Ma et al., 2017). Thus, we conclude that the optimal R&D collaboration for firms is not fixed, but rather, depends on various internal and external factors. This work thus adds to the scarce literature on this subject (e.g., Hottenrott and Lopes-Bento, 2016; Zhang et al., 2019a) by investigating the conditions by which R&D collaboration yields improvements in the area of new product innovations. Furthermore, this work extends scholars' and practitioners' current understandings by considering the moderating roles of absorptive capacity and political ties in the inverted U-shaped relationship between R&D collaboration and new product innovation by using the new perspective of organizational boundary theories. Thus, this work provides a more nuanced understanding of which resources and capabilities are most important for firms to coordinate among themselves, as these resources and capabilities can lead them to further stimulate their innovation processes and improve their product innovation efforts. Overall, this work identified the contextual conditions within and outside the organizational boundary that shape the impact of R&D collaboration on firms' new product innovations, which contributes to the fine-grained understanding of the innovation performance of firms involved in R&D collaboration in transition economies.

5.2. Managerial implications

This research also yields several practical implications for managers involved in their firms' R&D collaboration practices. First, according to our results, managers should mindfully leverage the level of their R&D collaborations to optimize the gains of R&D collaboration. More specifically, firstly, firms should actively attempt to cooperate with multiple partners so that they can tap into various external information and resources, as well as share the risks and costs with those partners. Secondly, while emphasizing the significant value of R&D collaboration, firms should be cautious of the "dark side" of R&D collaboration. They can protect themselves by strengthening their management of partner interactions, including in the areas of knowledge sharing, organizational learning, and joint innovation. Furthermore, firms should discreetly select their partners by learning as much as possible about the technological capabilities of possible partners and potential collaborative matching, using this information to create collaborations with mutually trustful partners that hold common visions. Furthermore, firms should also formulate formal and informal collaboration mechanisms to build congruent objectives and compatible values with their partners.

Second, our findings suggest that firms with stronger absorptive capacity tend to leverage their R&D collaborations better to improve their new product innovations. Therefore, managers should strengthen their respective firms' absorptive capacity. As employees' knowledge sharing is a major component of organizational absorptive capacity (Cohen and Levinthal, 1990), firms could cultivate a strong innovative atmosphere for their employees' knowledge acquisition and exploitation. In this respect, firms could set up a specific department that would be responsible for the acquisition of new information and new knowledge. Moreover, managers should promote external knowledge transformation and exploitation by holding periodic meetings to discuss potential approaches for using that external knowledge in their product innovation processes.

Third, our results show that political ties may increase a firm's benefits gained through R&D collaboration and may alleviate some adverse effects on new product innovation. On the one hand, given that firms often lack formal institutional support in transition economies, managers should make great efforts to secure informal institutional support via political ties. More specifically, managers need to leverage their political ties effectively to construct a favorable operational environment and to increase market acceptance of new products to mitigate the risks and costs of uncertainties involved in R&D collaboration. On the other hand, governments should formulate and perfect formal market institutions to decrease the influence of political ties on the allocation of governmental resources. More specifically, these policies should be designed to avoid government officials from undue favoritism toward individuals and firms when formulating regulations.

5.3. Limitations and further research

Some limitations in the present work should be taken into consideration in future research on this subject. First, we tested our theoretical hypotheses using survey data from Chinese manufacturing firms, and thus, our findings might be both industries- and country-specific. Therefore, future research could use the actual panel data to examine this topic further. Moreover, given that political ties play a crucial role in the operation of Chinese firms (Arnoldi and Villadsen, 2015), future research might wish to extend our single-country and single-industry study by using evidence from other countries or industries. Second, in this work, we examined the moderating roles of absorptive capacity and political ties in the relationship between R&D collaboration and firms' new product innovations. Future research could examine other factors that might be at play, such as different types of R&D collaborations (e.g., Gkypali et al., 2017; Kobarg et al., 2019; Lee et al., 2009), managers' business ties (e.g., Zhang et al., 2019b), and former R&D collaboration experience (e.g., Kafouros et al., 2020).

On the whole, this work offers new insights on the role of R&D collaboration in firms' new product innovations and the effects of two contextually unique moderators in high-tech industries in transition economies—absorptive capacity and political ties. Ultimately, hope we hope that this research will create new value for R&D collaboration practices and inspire future research on how R&D collaborations influence firms' new product innovations.

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Table 1. Characteristics of the respondents

Education	Percentage (%)	Position	Percentage (%)
• College degree or below	9.21	• Low-level managers	23.81
• Bachelor's degree	72.70	• Middle-level managers	45.40
• Master's degree	17.46	• Senior managers	20.00
• Doctor's degree or above	0.63	• R&D managers	10.79
Functional department	Percentage (%)	Work experience (years)	Percentage (%)
• R&D	33.33	• < 3	2.86
• Accounting	12.06	• 3-5	17.14
• Human resources	20.32	• 6-10	41.59
• Production	25.40	• 11-15	25.71
• Marketing	8.89	• > 15	12.70
Total	100.00	Total	100.00

Table 2. Characteristics of sample

Number of employees	Percentage (%)	Annual sales (million yuan)	Percentage (%)
● < 20	0.63	● < 3	2.22
● 20-300	53.97	● 3-20	37.46
● 301-1000	40.64	● 20-400	46.67
● > 1000	4.76	● > 400	13.65
Firm age (years)	**Percentage (%)**	**R&D personnel intensity [a]**	**Percentage (%)**
● < 3	0.63	● < 3%	5.08
● 3-5	7.30	● 3%-5%	31.11
● 6-10	37.78	● 5%-10%	38.73
● 11-15	33.65	● 10%-15%	20.64
● > 15	20.64	● > 15%	4.44
Industrial sectors	**Percentage (%)**	**R&D expenditure intensity [b]**	**Percentage (%)**
● New energy industry	3.17	● < 3%	4.13
● High-tech equipment industry	13.65		
● New materials industry	15.87	● 3%-5%	20.64
● Bioengineering industry	22.86	● 5%-10%	48.25
● Information technology industry	26.67	● 10%-15%	22.22
● Energy-saving and environment-friendly industries	17.78	● >15%	4.76
Total	100.00	Total	100.00

Note: a = Number of R&D employees/total number of employees; b = Annual R&D expenditure/total sales.

Table 3. Construct measurement and confirmatory factor analysis (CFA)

Constructs	Factor Loading
R&D collaboration (Becker and Dietz, 2004; Berchicci, 2013) (Cronbach's α = 0.642; CR = 0.806; AVE = 0.582)	
RD1. The number of outside R&D partners your company has.	0.768***
RD2. The percentage of R&D collaboration expenditures that account for the total sales of your company.	0.662***
RD3. The percentage of employees working on R&D collaborations versus total employees in your company.	0.848***
Political ties (Guo et al., 2014) (Cronbach's α = 0.654; CR = 0.813; AVE = 0.593)	
PT1. Your company improves relationships with the government and ensures good relationships with influential government officials.	0.774***
PT2. Your company has invested heavily in building relationships with government officials.	0.701***
PT3. Your company spends a lot of time dealing with government affairs.	0.830***
New product innovation (Zhang and Li, 2010) (Cronbach's α = 0.742; CR = 0.833; AVE = 0.501)	
NPP1. Your company frequently introduces new products.	0.738***
NPP2. Your company is first in new product introductions in the market.	0.664***
NPP3. Your company launches new products into the market quickly.	0.698***
NPP4. Your company develops new products having superior quality.	0.666***
NPP5. Your company uses its newly developed products to penetrate new markets.	0.766***
Model fit index	
χ^2/df = 2.300; CFI = 0.933; IFI = 0.934; TLI = 0.912; RMSEA = 0.064; SRMR = 0.051	

Table 4. Descriptive statistics and Pearson correlation matrix

Variables	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Firm size	2.500	0.599	–												
2. Firm age	3.660	0.907	0.324***	–											
3. Industry 1	0.180	0.383	-0.100*	-0.104*	–										
4. Industry 2	0.270	0.443	-0.003	-0.012	-0.280***	–									
5. Industry 3	0.230	0.421	-0.059	-0.048	-0.253***	-0.328***	–								
6. Industry 4	0.160	0.366	0.058	0.128**	-0.202***	-0.262***	-0.236***	–							
7. Industry 5	0.140	0.344	0.088	0.053	-0.185***	-0.240***	-0.216***	-0.173***	–						
8. Industry 6	0.030	0.176	0.074	-0.001	-0.084	-0.109*	-0.099*	-0.079	-0.072	–					
9. Annual sales	2.720	0.722	0.405***	0.384***	-0.104*	-0.090	0.048	0.088	0.046	0.065	–				
10. R&D collaboration	3.057	0.841	0.211***	0.124**	-0.197***	0.032	0.100*	0.055	-0.005	0.007	0.201***	***0.763***			
11. Absorptive capacity	3.450	1.184	0.133**	0.012	-0.197***	0.046	0.033	0.028	0.062	0.054	0.119**	0.665***	–		
12. Political ties	5.270	0.971	0.154***	0.089	-0.073	0.047	0.053	0.067	-0.115**	-0.002	0.169***	0.349***	0.269***	***0.770***	
13. New product innovation	5.359	0.819	0.230***	0.128**	-0.085	0.089	-0.007	0.030	-0.017	-0.051	0.149***	0.298***	0.282***	0.549***	***0.708***

Significance level: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$ ($N = 315$, two-tailed). The root value of AVE is on the diagonal.

Table 5. Results of the regression analysis

Variables	*New product innovation*							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Firm size	0.196* (0.051)	0.158*** (0.050)	0.131*** (0.050)	0.159*** (0.049)	0.161*** (0.049)	0.128** (0.044)	0.145*** (0.044)	0.146*** (0.044)
Firm age	0.038 (0.044)	0.034 (0.042)	0.032 (0.042)	0.055 (0.042)	0.038 (0.042)	0.038 (0.037)	0.039 (0.037)	0.035 (0.037)
Industry 1	-0.106 (0.014)	-0.064 (0.014)	-0.010 (0.014)	0.025 (0.014)	-0.044 (0.014)	0.017 (0.013)	-0.043 (0.012)	-0.042 (0.012)
Industry 3	-0.064 (0.013)	-0.076 (0.013)	-0.015 (0.013)	0.072 (0.013)	-0.077 (0.013)	0.072 (0.011)	-0.065 (0.011)	-0.066 (0.011)
Industry 4	-0.051 (0.015)	-0.052 (0.014)	-0.009 (0.014)	0.022 (0.015)	-0.039 (0.014)	0.010 (0.013)	-0.051 (0.012)	-0.053 (0.013)
Industry 5	-0.088 (0.015)	-0.076 (0.015)	-0.017 (0.015)	-0.021 (0.015)	-0.094 (0.015)	0.046 (0.014)	-0.013 (0.013)	-0.032 (0.013)
Industry 6	-0.094 (0.028)	-0.089 (0.027)	-0.041 (0.027)	-0.063 (0.027)	-0.097* (0.027)	-0.045 (0.024)	-0.081* (0.023)	-0.090* (0.023)
Annual sales	0.061 (0.043)	0.032 (0.042)	0.032 (0.042)	0.044 (0.042)	0.048 (0.042)	-0.004 (0.037)	-0.026 (0.037)	-0.024 (0.037)
R&D collaboration		0.252*** (0.035)	0.120*** (0.040)	0.102 (0.048)	0.054 (0.053)	0.076 (0.036)	0.039 (0.037)	-0.062 (0.047)

R&D collaboration squared			-0.347**	-0.111*	-0.323***	-0.047	-0.053	-0.190*
			(0.164)	(0.165)	(0.300)	(0.146)	(0.157)	(0.273)
Absorptive capacity				0.147**	0.183**			0.128*
				(0.035)	(0.039)			(0.034)
Political ties						0.489***	0.446***	0.432***
						(0.042)	(0.052)	(0.052)
R&D collaboration × Absorptive capacity					0.334**			0.257**
					(0.306)			(0.269)
R&D collaboration squared × Absorptive capacity					0.108			0.103
					(0.823)			(0.741)
R&D collaboration × Political ties							0.274**	0.258**
							(0.434)	(0.443)
R&D collaboration squared × Political ties							0.308**	0.297**
							(1.510)	(1.553)
R squared	0.073	0.131	0.143	0.155	0.171	0.342	0.356	0.371
Adjusted *R* squared	0.049	0.105	0.115	0.124	0.136	0.318	0.328	0.337
F-value	3.024***	5.092***	5.082***	5.037***	4.792***	14.289***	12.774***	10.975***

Significance level: * $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$. Standard errors in parentheses.

Table 6. Robustness tests: Results of the regression analysis for cubic items

Variables	New product innovation			
	Model 1	Model 2	Model 3	Model 4
Firm size	0.196* (0.051)	0.158*** (0.050)	0.131*** (0.050)	0.162*** (0.050)
Firm age	0.038 (0.044)	0.034 (0.042)	0.032 (0.042)	0.044 (0.042)
Industry 1	-0.106 (0.014)	-0.064 (0.014)	-0.010 (0.014)	-0.038 (0.014)
Industry 3	-0.064 (0.013)	-0.076 (0.013)	-0.015 (0.013)	-0.072 (0.013)
Industry 4	-0.051 (0.015)	-0.052 (0.014)	-0.009 (0.014)	-0.047 (0.014)
Industry 5	-0.088 (0.015)	-0.076 (0.015)	-0.017 (0.015)	-0.072 (0.015)
Industry 6	-0.094 (0.028)	-0.089 (0.027)	-0.041 (0.027)	-0.090 (0.027)
Annual sales	0.061 (0.043)	0.032 (0.042)	0.032 (0.042)	0.044 (0.042)
R&D collaboration		0.252*** (0.035)	0.120*** (0.040)	0.126 (0.056)
R&D collaboration squared			-0.347** (0.164)	-0.055 (0.258)
R&D collaboration cube				0.133 (0.854)
R squared	0.073	0.131	0.143	0.146
Adjusted *R* squared	0.049	0.105	0.115	0.115
F-value	3.024***	5.092***	5.082***	4.713***

Significance level: * $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$. Standard errors in parentheses.

Table 7. Robustness tests: Results of the regression analysis for two randomly selected subsamples.

Variables	70% of the total observations ($N = 221$)				90% of the total observations ($N = 284$)			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Firm size	0.261*** (0.061)	0.226*** (0.060)	0.254*** (0.059)	0.177*** (0.050)	0.212*** (0.051)	0.182*** (0.050)	0.186*** (0.050)	0.143** (0.043)
Firm age	-0.023 (0.054)	-0.030 (0.053)	-0.070 (0.054)	-0.029 (0.045)	0.046 (0.043)	0.052 (0.043)	0.050 (0.043)	0.052 (0.037)
Industry 1	-0.023 (0.016)	-0.003 (0.016)	0.015 (0.016)	0.077 (0.014)	-0.058 (0.014)	-0.018 (0.014)	0.001 (0.014)	0.067 (0.013)
Industry 2	-	-	-	0.076 (0.013)	-	-	-	0.076 (0.011)
Industry 3	-0.030 (0.015)	-0.050 (0.015)	-0.036 (0.015)	-	-0.061 (0.013)	-0.073 (0.013)	-0.065 (0.013)	-
Industry 4	-0.038 (0.016)	-0.030 (0.016)	-0.033 (0.016)	-0.002 (0.014)	-0.042 (0.015)	-0.035 (0.014)	-0.045 (0.014)	-0.015 (0.013)
Industry 5	-0.026 (0.018)	-0.011 (0.017)	-0.021 (0.017)	0.057 (0.015)	-0.055 (0.015)	-0.048 (0.015)	-0.068 (0.015)	0.027 (0.013)
Industry 6	-0.072 (0.032)	-0.059 (0.031)	-0.091 (0.031)	-0.035 (0.026)	-0.032 (0.028)	-0.024 (0.027)	-0.047 (0.027)	-0.002 (0.023)
Annual sales	0.029 (0.051)	0.022 (0.051)	0.024 (0.050)	-0.035 (0.043)	0.018 (0.044)	0.015 (0.044)	0.010 (0.044)	-0.059 (0.038)

R&D collaboration		0.179**	-0.052	0.004		0.140**	-0.034	0.008
		(0.045)	(0.064)	(0.041)		(0.040)	(0.054)	(0.036)
R&D collaboration squared		-0.120*	-0.244**	0.013		-0.116*	-0.177	0.039
		(0.236)	(0.378)	(0.219)		(0.174)	(0.322)	(0.171)
Absorptive capacity			0.088				0.144*	
			(0.046)				(0.039)	
Political ties				0.265***				0.373***
				(0.063)				(0.054)
R&D collaboration ×			0.395**				0.288*	
Absorptive capacity			(0.396)				(0.312)	
R&D collaboration squared			0.390**				0.266*	
× Absorptive capacity			(1.233)				(0.853)	
R&D collaboration ×				0.184**				0.141*
Political ties				(0.492)				(0.450)
R&D collaboration squared ×				0.501***				0.361***
Political ties				(2.067)				(1.725)
R squared	0.074	0.126	0.171	0.397	0.061	0.104	0.133	0.352
Adjusted *R* squared	0.039	0.085	0.119	0.359	0.034	0.071	0.091	0.320
F-value	2.104**	3.038***	3.283***	10.477***	2.229**	3.157***	3.178***	11.265***

Significance level: * $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$. Standard errors in parentheses.

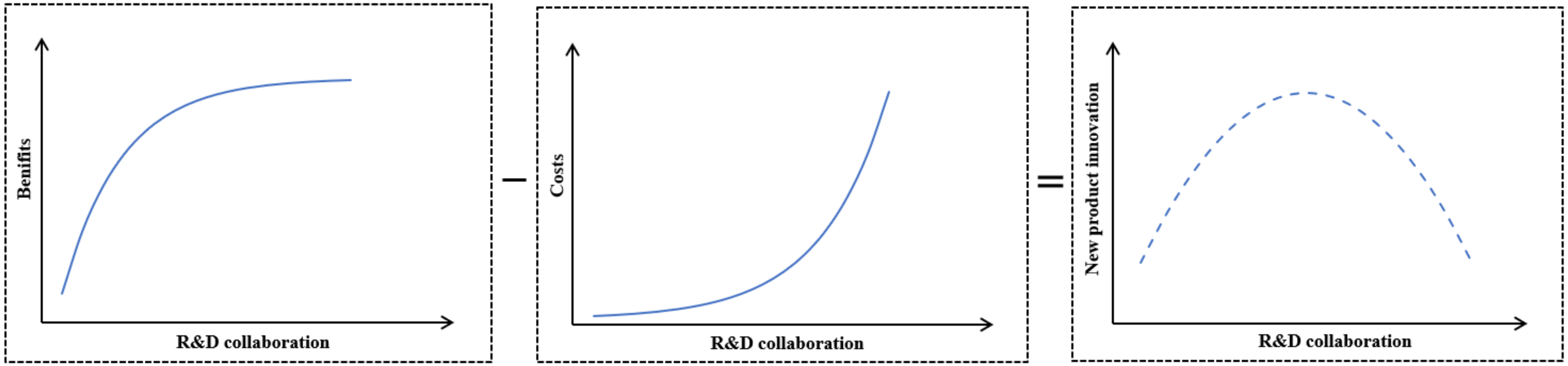


Figure 1. R&D collaboration and firms' new product innovation

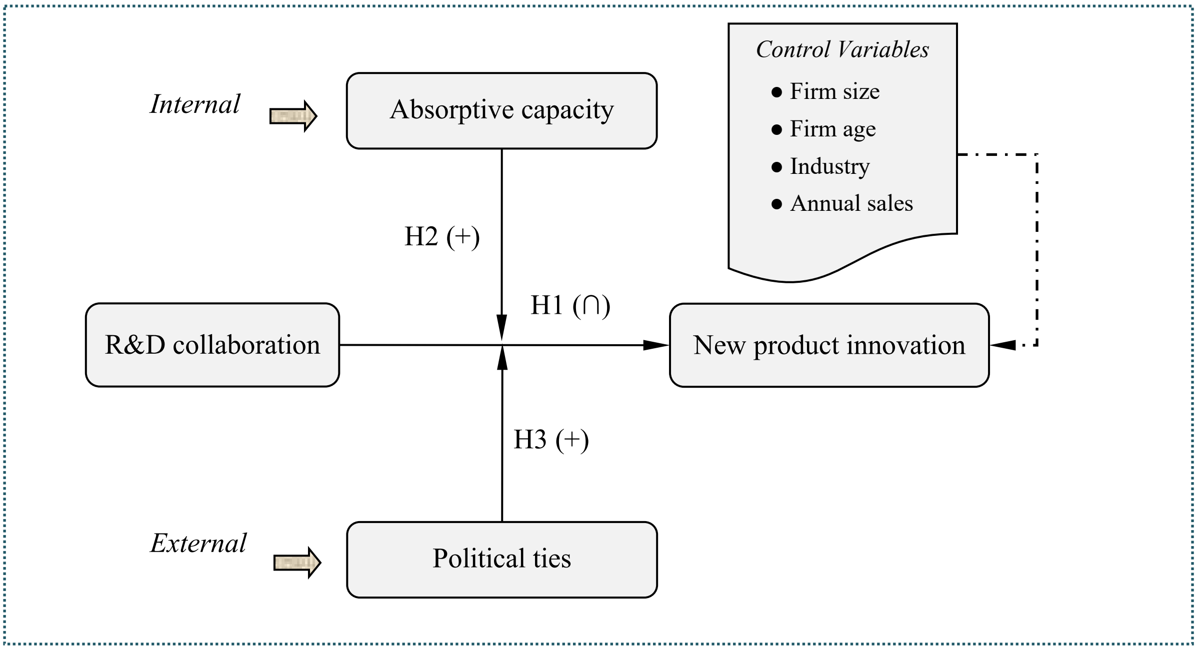
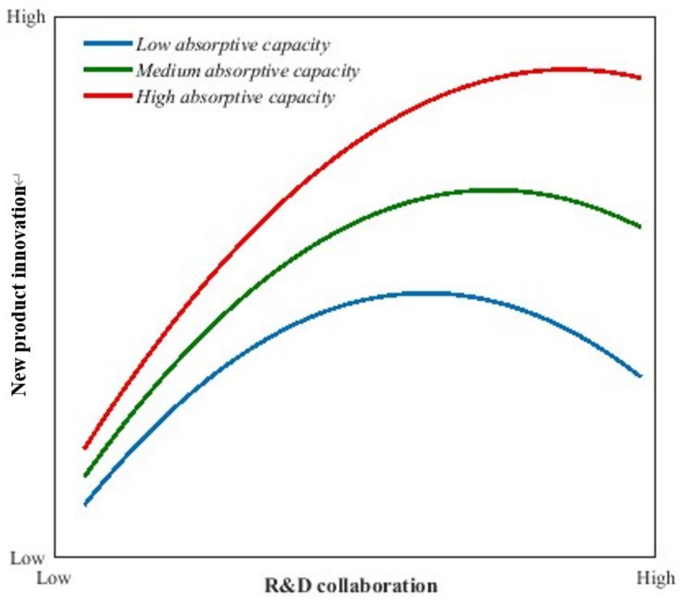
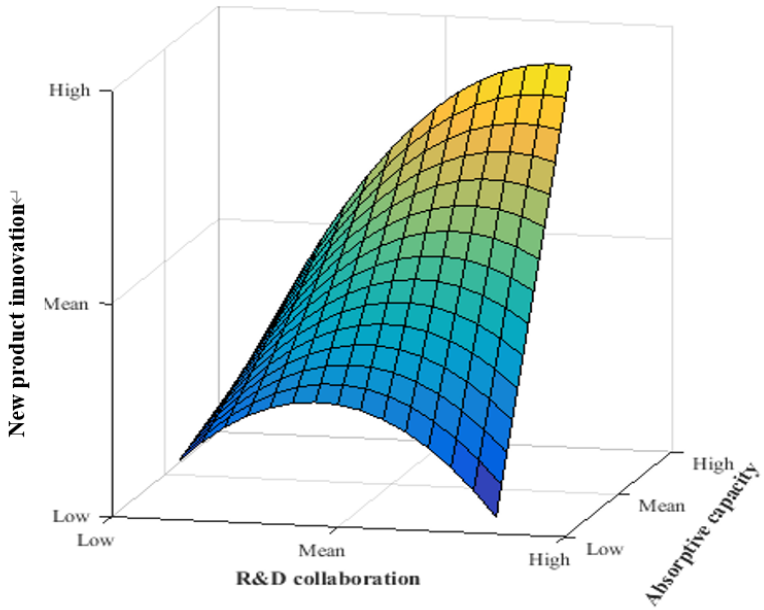


Figure 2. Conceptual model

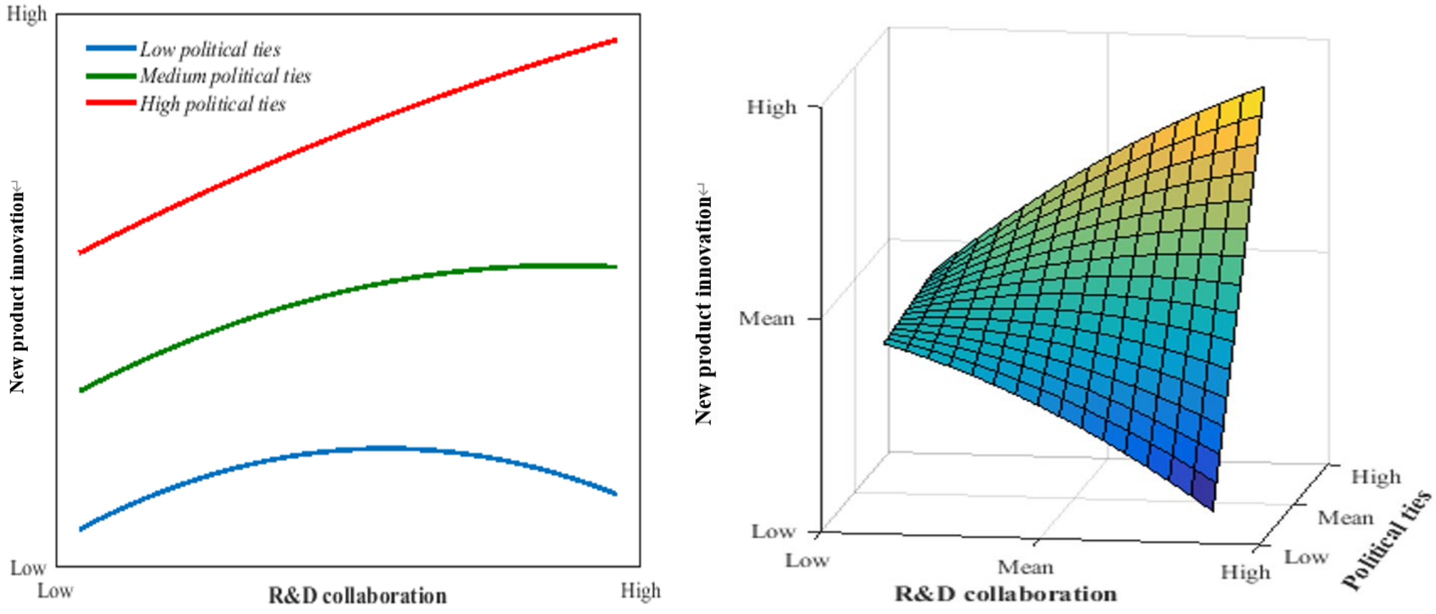


(a) 2-D graph



(b) 3-D graph

Figure 3. The 2-D and 3-D graphs for the moderating effects of absorptive capacity on the nonlinear relationship between R&D collaboration and firms' new product innovations



(a) 2-D graph

(b) 3-D graph

Figure 4. The 2-D and 3-D graphs for the moderating effects of political ties on the nonlinear relationship between R&D collaboration and firms' new product innovations

Appendix A.

Table A1. Independent samples test

Variables		Levene's test for equality of variances		*t*-test for equality of means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% confidence interval of the difference	
									Lower	Upper
R&D collaboration	Equal variances assumed	0.084	0.772	0.250	156	0.803	0.006	0.024	-0.042	0.054
	Equal variances not assumed				155.860			0.024		
New product innovation	Equal variances assumed	0.247	0.620	0.723	155	0.471	0.010	0.014	-0.017	0.037
	Equal variances not assumed				142.431			0.014		
Absorptive capacity	Equal variances assumed	0.505	0.479	0.930	155	0.354	0.027	0.030	-0.031	0.086
	Equal variances not assumed				154.979			0.030		
Political ties	Equal variances assumed	0.562	0.455	-1.151	156	0.251	-0.016	0.014	-0.042	0.011
	Equal variances not assumed				155.897			0.014		

Table A2. Analysis of variance (ANOVA)

Variables		Sum of squares	*df*	Mean square	*F*	Sig.
	Between groups	1.168	3	0.389	1.673	0.172
Firm size	Within groups	115.382	496	0.233		
	Total	116.550	499			
	Between groups	0.774	4	0.186	0.795	0.529
Firm age	Within groups	115.806	495	0.234		
	Total	116.550	499			
	Between groups	1.516	5	0.303	1.302	0.262
Industry sectors	Within groups	115.034	494	0.233		
	Total	116.550	499			