Is collaborative innovation a double-edged sword for firms? The contingent role of ambidextrous learning and TMT shared vision

ABSTRACT: Previous research has documented the relationship between collaborative innovation and innovation performance, but such studies have presented inconsistent results. Therefore, the first aim of this study is to examine the nonlinear relationship between collaborative innovation and innovation performance. And the second is to provide an organisational learning theory and upper-echelon contingency perspective from which to examine the moderating effects of ambidextrous learning and shared vision of top management teams (TMTs) on this relationship. Using survey data from manufacturing firms located in the Yangtze River Delta region, one of the most populous and highly developed regions in China, we find that collaborative innovation has an inverted U-shaped effect on firms' innovation performance. Further, we find that the relationship between collaborative innovation and innovation performance is steeper when firms possess high ambidextrous learning and low TMT shared vision. Overall, this work not only enhances our theoretical understanding of how collaborative innovation influences firms' innovation performance but also provides important managerial implications for manufacturing firms' collaborative innovation practices.

Keywords: Collaborative innovation; Ambidextrous learning; TMT shared vision; Inverted U-shaped relationship

1. Introduction

In an increasingly open and dynamic global market, in which resources are frequently changing, it is difficult for a single firm to achieve a high level of performance in innovation consistently (Davis and Eisenhardt, 2011; Yildiz et al., 2021). Moreover, global competition has reduced the competitive advantages of traditional closed innovation practices (Dunning, 2015). The focus of firms has, accordingly, shifted away from purely individual innovation practices to a more collaborative approach (Mueller et al., 2020; Xie and Wang, 2020). Collaborative innovation "describes the structured joint process—for designing and developing new products, services or processes—that requires information sharing, joint planning, joint problem solving, and integrated activities" (Serrano and Fischer, 2007: 605). In the present study, collaborative innovation denotes two or more external actors, such as suppliers, customers, competitors, or research organisations, that share knowledge with each other and work jointly to conduct R&D in collaborative networks (Najafi-Tavani et al., 2018). Collaborative innovation can help firms leverage the expertise of internal and external actors, increase the volume and variety of their innovation activities, and foster stronger engagement in such activities (Kafouros et al., 2020; Wang and Hu, 2020). Hence, firms engaged in collaborative innovation can both reduce R&D costs and risks and improve innovation performance (Davis and Eisenhardt, 2011; Wang and Hu, 2020). Overall, collaborative innovation has become an essential strategy that enables firms to overcome challenges to successful innovation (Kafouros et al., 2020; Ketchen et al., 2007; Mueller et al., 2020).

The specific factors that affect the innovative outputs of firms engaged in collaborative innovation have been highlighted in several previous studies. They include prior collaboration experience (e.g., Kafouros et al., 2020), absorptive capacity (e.g., Xie et al., 2018), collaboration diversity (e.g., Gkypali et al., 2017), collaborative networks (e.g., Najafi-Tavani et al., 2018), and innovation spaces (e.g., Caccamo, 2020). There is, too, a large body of empirical research documenting the link between collaborative innovation and innovation performance (e.g., Clauss and Kesting, 2017; D'Angelo and Baroncelli, 2020; Kafouros et al., 2015; Luzzini et al., 2015; Ritala et al., 2015; Öberg et al., 2016; Xie et al., 2013; Zeng et al., 2010). The findings in this area are, however, somewhat inconsistent, so our understanding of the contribution of collaborative innovation to firms' innovation performance remains incomplete and uncertain.

Firstly, some studies show that collaborative innovation affects innovation performance positively (e.g., Clauss and Kesting, 2017; D'Angelo and Baroncelli, 2020; Luzzini et al., 2015; Zeng et al., 2010), while others show that there are negative implications (e.g., Belderbos et al., 2004; Hou et al., 2019). Whatever the specific findings, though, the studies mentioned all assume that the relationships—positive or negative—are linear, and little attention has been given to the possibility that the association could be nonlinear. In the current work, we consider a nonlinear relationship between collaborative innovation and innovation performance.

Secondly, the inconsistencies of the previous studies can be attributed to a lack of attention to the factors affecting the link between collaborative innovation and innovation performance (Najafi-Tavani et al., 2018). Without delving deeply into these contingent factors, we cannot be clear whether such collaboration can lead to successful innovation (Narayanan et al., 2015). Although the previous research helps to establish a link between innovation and organisational learning, it neglects the role of ambidextrous learning (Bilan et al., 2020; Jiménez-Jiménez and Sanz-Valle, 2011). Ambidextrous learning—defined as simultaneously pursuing exploratory and exploitative learning—has gained greater prominence in the field of innovation research (Cao et al., 2009; March 1991; Wu et al., 2021). However, excessive emphasis on either exploratory learning or exploitative learning can lead to real challenges (Bedford, 2015), since both compete for the same types of resources (Li et al., 2013). This is why Atuahene-Gima and Murray (2007) assert that firms need to balance their exploratory learning and their exploitative learning if they are to enhance overall performance. Overall, ambidextrous learning is seen as a major factor in improving organisational performance (March, 1991; Wu et al., 2021). In the current study, therefore, it is regarded as a learning capability that can achieve a healthy combination of both exploratory learning and exploitative learning (Gabriel Cegarra-Navarro et al., 2011; Lubatkin et al., 2006). We discuss how ambidextrous learning moderates the relationship between collaborative innovation and innovation performance.

Thirdly, several previous studies have examined the relationship between collaborative innovation and firms' innovation outputs but ignored the actors that steer this relationship, the firms' top management teams (TMTs) (Mihalache et al., 2012; Wei et al., 2021). While some research suggests that TMTs play a fundamental role in influencing innovation performance (e.g., Li and Huang, 2019; Su et al., 2021; Yan et al., 2020; Cheah and Ho, 2020), this research overlooks the possibility that the effect of a TMT on organisational innovation performance may be moderated by an important TMT attribute, namely TMT shared vision (Li and Huang, 2019; Ruiz-Jiménez and Fuentes-Fuentes, 2016). Collaborative innovation provides firms with plenty of opportunities for innovation (Mihalache et al., 2012), and TMT shared vision influences the degree to which firms take advantage of these opportunities. The TMT shared vision that facilitates the convergence of team behavior will affect the usefulness of the application of collaborative innovation (Chen et al., 2016a). Given that TMT shared vision can help to explain the impact of specific situations and enrich our understanding of collaborative innovation, the present study also examines how TMT shared vision moderates the relationship between collaborative innovation and innovation performance.

Overall, the current study contributes to the research on collaborative innovation by proposing an inverted U-shaped relationship between collaborative innovation and innovation performance and suggests that collaborating with different partners will cause reduced innovation performance. Thus, our study provides insights into the impact of collaborative innovation on a firm's innovation performance. After examining the contingent roles of ambidextrous learning and TMT shared vision in the relationship between collaborative innovation and innovation performance, we propose a more integrative view of how firms can find the optimal threshold, and thus best exploit collaborative innovation to improve their innovation performance.

2. Theories and hypotheses

2.1. Collaborative innovation and innovation performance

Collaborative innovation is defined as "the creation of innovations across firm boundaries through the sharing of ideas, knowledge, expertise, and opportunities" (Ketchen et al., 2007: 371). Previous research demonstrates that firms may cooperate with various partners, including suppliers, customers, competitors, and research institutions, in order to realise collaborative innovation (Tsai, 2009). Collaborative innovation is a complex strategy used for organisational innovation. According to "network theory," on the one hand, collaborative innovation is the organic collection of various elements, such as R&D, human resources and capital, processes, and systems (Chen et al., 2018). On the other hand, it is the dynamic integration of complementary resources to achieve mutual complementarities between all the partners (Dyer et al., 2018). However, integrating innovation resources is challenging because of the potential risks and costs. First, firms need to consider the administrative costs arising from both the coordination and the monitoring of interactions between partners (Kohtamäki et al., 2013), including the potential problems of information overload and intellectual property rights (IPRs) (e.g., Candelin-Palmqvist et al., 2012; Lee et al., 2016). Second, firms conducting high levels of collaborative innovation may lose their own core competencies (Barney, 2017), which may result in possible overdependence on partners within the joint value-creating, collaborative innovation processes. Thus, a firm undertaking collaborative innovation might not only obtain resource advantages but also encounter various challenges. We put forward below a hypothesis that examines the relationship between collaborative innovation and firms' innovation performance (see H1).

According to the resource-based view (RBV), the basis of a firm's competitive advantage lies mainly in its ability to use its valuable resources (Wernerfelt, 1984). RBV maintains that firms can integrate diverse external resources into one framework to produce synergistic effects to improve internal advantages. Collaborative innovation can create strategic competencies that are inimitable and non-substitutable (Schneckenberg et al., 2015). Accordingly, we claim that collaborative innovation allows firms to meet their resource challenges in ways that allow them to improve their innovation performance (Levitt and March, 1988; Ritala, 2015), on the following grounds. Firstly, in the face of the difficulty of acquiring critical knowledge in today's competitive arenas, collaborative innovation enables firms to acquire and exchange knowledge in order to reduce risks and increase innovative interactions at the firm level (Carmeli and Paulus, 2015; Benhayoun et al., 2020). Secondly, inter-firm communication generated by collaborative innovation is a critical factor in facilitating strategic collaborations among firms (Chen et al., 2014; Gattringer and Wiener, 2020). External knowledge obtained via inter-firm collaboration can enable employees to deliver more innovative ideas (Xie et al., 2018), thus further facilitating their firms' innovation activities. Thirdly, collaborative innovation is often seen as a way of sharing innovation risks and costs (Benhayoun et al., 2020). Specifically, trust among collaborating partners, which is regarded as an essential element of collaboration, can help reduce both target inconsistency and preference discrepancies among the partners (Gattringer and Wiener, 2020; McEvily et al., 2017). Furthermore, firms' trust in each other during the collaboration process can reduce dependence on their own structures, thereby allowing each firm to put more energy into focusing on their collaborative innovation activities (Cesinger et al., 2016; De Maeijer et al., 2017). Overall, we believe that effective collaborative innovation can create innovative outputs.

However, if the level of collaborative innovation goes beyond a particular threshold, the initial benefits from improving innovation performance could eventually weaken—or even hamper—a firm's ability to receive innovative inputs. There are three reasons for this. First, as mentioned above, firms that conduct high levels of collaborative innovation may lose their own core competencies (Barney, 2017). Accordingly, as global competition is conducted under varying rules and with different risks in different markets, a difficult choice of prioritization arises between core competitiveness and collaborative innovation (Ritala et al., 2015). Second, a high level of collaborative innovation can produce the problem of "information overload," which can make the application of useful information more difficult (Lee et al., 2016). This is especially important because the activities involved in high-level collaborative innovation require constant flows of information and co-adjustment between the partners (Leiblein and Madsen, 2009). Moreover, due to the information processing and management costs involved in avoiding the risk of information overload, a high level of collaborative innovation might impede efficient innovation (Van Beers and Zand, 2014). Third, the problem of IPRs becomes significant for firms seeking collaborative innovation to enhance their innovation performance (Candelin-Palmqvist et al., 2012), as high levels of collaborative innovation can cause IPR disputes. Given that intellectual property becomes a source of both wealth and risk for firms, it is necessary to consider the complexity of IPRs in the collaborative innovation process (Liu et al., 2016). In sum, when firms become over-committed to collaborative innovation, the benefits they obtain from such collaboration appear to decrease over time, leading to lower gains.

Considering the above discussion of the benefits and drawbacks associated with collaborative innovation, we propose an inverted U-shaped relationship between collaborative innovation and innovation performance to specify the ways in which innovation performance changes as collaborative innovation increases:

Hypothesis 1 (H1): There is an inverted U-shaped relationship between collaborative innovation and firms' innovation performance, such that the impact is initially positive, but becomes more negative as the level of collaborative innovation increases.

2.2. The moderating effect of ambidextrous learning

Organisational learning is defined as “the process by which the firm develops new knowledge and insights from the common experiences of people in the organisation” (Huber, 1991: 95). The optimal balance of exploratory and exploitative learning is crucial to firms because it is not just a source of organisational dynamics but also a contributor to organisational performance (Bodwell and Chermack, 2010; Pereira et al., 2021). A firm may fall into a “competency trap” or a “failure trap” if it is overly dependent on either exploitation or exploration (Wang et al., 2015b: 29). Therefore, firms should attempt to engage in ‘ambidextrous learning’: the organisational action of using exploratory learning and exploitative learning together (Cao et al., 2009; Fu et al., 2021). Firms can benefit from the synergic effect of the coexistence of both types of learning strategies, with exploitation executed through external sources for product or process improvements, and exploration conducted internally for new product or process innovation (Hahn et al., 2015; Felício et al., 2019). Ambidextrous learning can lead to fruitful innovative actions. It can also provide a foundation for future exploration and development to ensure a firm’s long-term performance (Salehi and Yaghtin, 2015; Pereira et al., 2021). Moreover, according to organisational learning theory, being capable of ambidextrous learning helps a firm maintain its competitiveness in dynamic environments (Camps et al., 2016). Below, we detail the effect of ambidextrous learning on firms’ innovation performance when they engage in collaborative innovation.

At first, ambidextrous learning can strengthen the positive effects of collaborative innovation on firms’ innovation performance, as it improves a firm’s ability to identify and exploit knowledge acquired through the collaborative innovation process in order to increase internal skills and to adapt to external environment changes (Felício et al., 2019; Fraj et al., 2015). Ambidextrous learning expands a firm’s innovation possibilities and internal ways of thinking (Choi and Chandler, 2015; Fu et al., 2021). Meanwhile, firms with a high capacity for ambidextrous learning possess more ways of transforming resources than firms with less capacity (Mihalache et al., 2012), leading to better innovation performance. In addition, ambidextrous learning can enhance firms’ ability to integrate information and the (linked) cognitive capacities needed to manage different operations among partners (Hansen et al., 2017; Pereira et al., 2021). Therefore, firms skilled in ambidextrous learning perform better in acquiring external resources and integrating internal knowledge. The joint occurrence of these external and internal knowledge acquisition actions yields a complementary relationship among collaborative innovation activities (Cassiman and Valentini, 2016), which leads to better innovation performance. In summary, ambidextrous learning can provide an optimal combination of resources for firms to update their capabilities, leading to better innovation performance (Piening and Salge, 2015).

However, ambidextrous learning may magnify the latent negative implications of collaborative innovation on firms' innovation performance levels. Heterogeneous perspectives make it more difficult to transfer and integrate knowledge among different partners (Mindruta et al., 2016). Van Der Vegt and Bunderson (2005) indicate that firms heavily engaged in collaborative innovation can meet problems, as more intricate knowledge and information can easily delay both decision-making and the implementation of innovation activities. Firms engaged in collaborative innovation may also find it challenging to strike the right balance between exploratory and exploitative learning when managing high levels of ambidextrous learning. This can also hinder the innovation performance of firms (Fraj et al., 2015). Given that interactions between partners with different learning styles may bring challenges when integrating behaviours in the collaborative innovation process, ambidextrous learning could exacerbate the negative impact of high levels of collaborative innovation on innovation performance. Therefore, we propose the following hypothesis:

Hypothesis 2 (H2): Ambidextrous learning moderates the inverted U-shaped relationship between collaborative innovation and firms' innovation performance, such that the inverted U-shaped relationship will be steeper for firms with high ambidextrous learning than for those with low ambidextrous learning.

2.3. The moderating effect of TMT shared vision

The term 'TMT (top management teams) shared vision' refers to "the shared values and collective goals among TMT members regarding a common and desired strategic direction of the firm" (Li, 2014: 307). TMT shared vision promotes equal awareness among members of how strategic resources are integrated and how they interact (Chang and Huang, 2012), which ensures that TMT decisions focus on long-term goals (Helsen et al., 2017; Koryak et al., 2018; Mihalache et al., 2012). Furthermore, prior research suggests that TMT shared vision serves as a social mechanism for cooperative actions (Chen et al., 2016a). Therefore, applying the 'upper-echelon contingency perspective' (Patzelt et al., 2008), we propose that the nonlinear relationship of collaborative innovation and innovation performance can be influenced by TMT shared vision, since the identification of opportunities and the application of knowledge acquired from various partners depend so much on TMT shared vision.

At first, a better understanding of the firms' joint vision—or TMT shared vision—can bring more opportunities for the TMTs; it can give rise to a slight but clear, positive relationship between collaborative innovation and innovation performance. Since a common understanding of goals means that the TMTs share the same understanding of the criteria that determine their firms' development, TMTs with a strong shared vision can form opinions about the value of collaborative innovation without challenging implicit assumptions (Ndofor et al., 2015). Furthermore, given that a shared vision between TMTs can accelerate meaningful mutual goals, firms with high levels of TMT shared vision tend to facilitate a coupled organisational structure. They also work toward improved collaboration thanks to their shared goals (Wang et al., 2015a), which maximises the use of collaborative innovation to achieve innovation outputs. Therefore, a shared vision that can help firms recognise and associate organisational structures and resources can encourage TMTs to leverage the underlying roles of collaborative innovation, because TMTs with a strong shared vision may value the limited integration of resources more than TMTs with a weakly shared vision (Wang and Rafiq, 2014).

On the other hand, high TMT shared vision can weaken the negative impact of high collaborative innovation on firms' innovation performance levels for several reasons. First, the shared vision of the TMTs may lower barriers to knowledge transfer and resource-sharing during collaborative innovation programmes (Chen et al., 2016b; Luo et al., 2014). A shared vision facilitates the organisation-level support needed to minimize and handle the underlying issues related to collaboration-linked innovative behaviours (Ashford et al., 2018). Second, TMT shared vision assists firms in eliminating short-term objectives from numerous potential collaborative opportunities, which may help the firms develop unique capabilities vis-à-vis their long-term innovation performance goals (Tikas and Akhilesh, 2017). Furthermore, TMTs may meet obstacles when pursuing innovative ideas without having a certain level of trust (Heyden et al., 2012; Loonam et al., 2014). TMT shared vision can instil a healthy, cooperative spirit by nurturing the trust that can prevent disruptive conflicts (Li et al., 2014; Wu et al., 2010). It can also enhance the firms' corresponding viewpoints about cooperation, which helps to create a conducive environment for knowledge-sharing to accelerate collaborative innovation. The factors and interactions mentioned above result in competitive, innovative outcomes (Hewett and Bearden, 2001; Shafique and Kalyar, 2018). Thus, we hypothesise:

Hypothesis 3 (H3): TMT shared vision moderates the inverted U-shaped relationship between collaborative innovation and firms' innovation performance, such that the inverted U-shaped relationship will be flatter for firms with high TMT shared vision than for those with low TMT shared vision.

3. Methods

3.1. Data and sample

Our data were collected from manufacturing firms in China's Yangtze River Delta region, which we consider a suitable target population for this study for various reasons. As the development of regional integration has accelerated, collaborative innovation has become a new driver for regional development (Esposito and Rigby, 2019). Correspondingly, collaborative innovation in the Yangtze River Delta region has helped this region improve its economic growth (Li and Phelps, 2019). The abundance of resources found here, including the area's broad economic strength and the well-established intellectual property system, have all contributed to the high level of innovation of the Yangtze River Delta region, which is beneficial for firms' collaborative innovation practices. Moreover, the Yangtze River Delta region is one of the world's major manufacturing centres. The area's manufacturing industry is highly developed, and the local governments actively support innovative activities to maintain competitiveness (Wang et al., 2021), which stimulates collaborative innovation in the manufacturing industry. Overall, the manufacturing firms in the

Yangtze River Delta region are a good sample to use in investigating collaborative innovation. Knowledge about them may also enlighten researchers studying collaborative innovation in other regions. The individual participants of this study needed to meet the following three criteria to be included: (a) they must be top managers who have extensive management experience in a manufacturing firm, (b) they must be participating in the formulation of their firm's collaborative innovation strategies and (c) they must understand their firm's innovation processes and learning mechanisms.

We distributed questionnaires to manufacturing firms in 16 cities in the Yangtze River Delta region. To improve the reliability and representativeness of the data, the questionnaires were distributed and collected both on-site and via email. A total of 1,020 questionnaires were distributed, and 431 valid questionnaires were received back, representing a response rate of 42.25%. The respondents' profiles are shown in Table 1. In terms of managerial positions, the respondents who held the positions of CEO and vice-CEO accounted for 26.91% and 55.92% of the sample, respectively. Those who had studied management accounted for 42.92% of the total sample, and those who had studied humanities or social sciences 24.36%. 65.20% of the respondents held a bachelor's degree or higher. This demographic information reveals the high quality of the data.

<Insert Table 1>

The characteristics of the sample are given in Table 2. There were 54.52% private enterprises (PEs), 18.09% state-owned enterprises (SOEs), 21.05% foreign-invested enterprises (FIEs), and

5.34% collectively run enterprises (CREs). Among all business types, 87.01% of the firms employed fewer than 1,000 employees. In terms of annual sales in the prior three years, the category of '3 to 400 million yuan' accounted for 51.98% of the sample. Among the industry sectors, the largest sector in our sample was the electronic equipment manufacturing industry (10.79% of the firms).

<Insert Table 2>

3.2. Measures

3.2.1. Collaborative innovation

Following Zeng et al. (2010), collaborative innovation was measured using five indicators to identify the degree of a firm's collaboration with different partners. The construct indicators were assessed using a seven-point Likert scale, ranging from 1 = '*very low*' to 7 = '*very high*'.

3.2.2. Innovation performance

Innovation performance is defined as "the increase in the value of the company after the implementation of new technologies" (Hitt et al., 1991: 694). Following the work of Soto-Acosta et al. (2017), we measured innovation performance using four indicators: new or improved products, new or improved processes, new or improved management practices, and new or improved marketing methods. The respondents were asked to indicate the level of change in their firms over the prior three years, assessed using a seven-point Likert scale, ranging from 1 = '*absolutely disagree*' to 7 = '*absolutely agree*'.

3.2.3. Ambidextrous learning

Ambidextrous learning consists of exploratory learning and exploitative learning. Following Cai et al. (2017, we measured exploratory learning using a three-item scale and, following Valaei et al. (2016), we also evaluated exploitative learning using a three-item scale. The items for the construct were assessed on a seven-point Likert scale, ranging from 1 = '*absolutely disagree*' to 7 = '*absolutely agree*'.

Prior research has adopted the combined dimension (CD) and the balanced dimension (BD) to measure firm ambidexterity (Cao et al., 2009). The former is calculated by the absolute difference between the scores of exploratory learning and exploitative learning, and the latter is computed by the product of the exploratory learning and the exploitative learning (Cao et al., 2009). The results represent two properties of ambidexterity: balance and synergy (Cao et al., 2009; He and Wong, 2004). Neither CD nor BD alone, however, can represent ambidextrous learning comprehensively. Therefore, following Zang and Li (2017), we used the formula in Eq. (1) to measure the ambidextrous learning of the firms.

$$\begin{aligned} \textit{Ambidextrous learning} &= h\left(X_{\exp lor}, X_{\exp loi}\right) \\ &= \frac{\left(n - \left|x_{\exp lor} - x_{\exp loi}\right|\right) * \sqrt{x_{\exp lor} * x_{\exp loi}}}{n} \qquad (1) \end{aligned}$$

In Eq. (1), $x_{\exp lor}$ and $x_{\exp loi}$ denote exploratory learning and exploitative learning, respectively. In addition, $\left|x_{\exp lor} - x_{\exp loi}\right|$ and $x_{\exp lor} * x_{\exp loi}$ represent BD and CD, respectively; either a small BD or a large CD indicates high levels of ambidextrous learning. Lastly, *n* represents the score on the Likert scale. Overall, the greater the score of Eq. (1), the higher the level of ambidextrous learning.

3.2.4. TMT shared vision

TMT shared vision is a key indicator of team effectiveness (Ensley et al., 2003). Adapted from Mihalache et al. (2012), TMT shared vision was measured using a four-item scale. The respondents were asked to describe the TMT shared vision of their respective firms over the prior three years; the items for the construct were assessed on a five-point Likert scale, ranging from 1 = '*absolutely disagree'* to 5 = '*absolutely agree*'. The measures of each item are summarised in Table 3.

3.2.5. Control variables

The variables used to control for established effects included ownership, size of firm, age of firm, annual sales, industry, work experience and gender. We controlled for firm size because it has been found to influence firm growth (Gubbi et al., 2015; Hambrick et al., 2015); it was measured by the number of the firm's employees (Zahra et al., 2000). Ownership was measured by categorical variables and included four categories: SOEs, CREs, PEs, and FIEs. It is desirable to control for annual sales, as this can influence both current sales and current collaborative innovation (Wu and Voss, 2015). Annual sales were measured by a firm's average sales over the previous three years. We also controlled for the type of industry in order to illustrate differences in the levels of innovation by industry (Kochhar and David, 1996). Each respondent's age was measured by their actual legal age, their work experience by how many years they had worked in their current position and their gender by using dummy variables (0 = female; 1 = male).

3.3. Adequacy of the measures: reliability and validity test

Several common methods were used to guarantee the reliability and validity of the data. Regarding the questionnaire, we consulted many previous studies to ensure the content validity of our constructs. The results in Table 3 show that the reliability of each scale was greater than the recommended threshold of 0.70, indicating an acceptable level of reliability. Next, a confirmatory factor analysis was used to assess the convergent and discriminant validity of this study. The results of the confirmatory factor analysis, which are also presented in Table 3, demonstrated that the model matched the data well (χ^2 = 118.62, p = 0.000; χ^2/df = 1.46, comparative fit index [CFI] = 0.955, incremental fit index [IFI] = 0.955, normed fit index [NFI] = 0.952, and root mean square error of approximation [RMSEA] = 0.014). We also found that all items loaded significantly on their corresponding construct, with the lowest t-value being 5.592, thus verifying convergent validity.

<Insert Table 3>

3.4. Model specifications

Three models were used to validate the assumptions discussed earlier. The first model tested the effect of collaborative innovation on firms' innovation performance. The second model examined how ambidextrous learning moderates the curvilinear relationship between collaborative innovation and innovation performance. The third model investigated how TMT shared vision moderates the curvilinear relationship between collaborative innovation and innovation performance. The three models are shown below in Eqs. (2) to (4):

$$IP_i = \alpha + \beta_1 CI_i + \beta_2 CI_i^{\ 2} + \delta_i CONT_i + \varepsilon_i \qquad (2)$$

$$IP_i(AL) = \alpha + \beta_1 CI_i + \beta_2 CI_i^{\,2} + \beta_3 AL_i + \beta_4 (CI_i * AL_i) + \beta_5 (CI_i^{\,2} * AL_i) + \delta_i CONT_i + \varepsilon_i \quad (3)$$

$$IP_i(TMT) = \alpha + \beta_1 CI_i + \beta_2 CI_i^{\,2} + \beta_3 TMT_i + \beta_4 (CI_i * TMT_i) + \beta_5 (CI_i^{\,2} * TMT_i) + \delta_i CONT_i + \varepsilon_i \quad (4)$$

In these equations, IP_i is the innovation performance of firm i ; CI_i is an index of the collaborative innovation of firm i ; $CI_i^{\,2}$ is the squared term of collaborative innovation; AL_i is a moderating variable, specifically, ambidextrous learning; $CI_i * AL_i$ is the interaction term of ambidextrous learning and collaborative innovation; and $CI_i^{\,2} * AL_i$ is the interaction term of ambidextrous learning and collaborative innovation squared. In the equations, TMT_i is a second moderating variable, namely, TMT shared vision. $CI_i * TMT_i$ is the interaction term of TMT shared vision and collaborative innovation. $CI_i^{\,2} * TMT_i$ is the interaction term of TMT shared vision and collaborative innovation squared. $CONT_i$ is a vector of the control variables and ε_i is a normal error term.

4. Results

Table 4 provides the descriptive statistics and correlations, including the means (M), standard deviations (SD, and correlation results of the variables. The results show that collaborative innovation is significantly related to innovation performance.,They further demonstrate that exploratory learning, exploitative learning, and TMT shared vision are all significantly related to firms' innovation performance. We also tested for multicollinearity, by calculating the variance inflation factors (VIFs) for all predictors in each model. All VIF values were below the 10.0 benchmark, revealing that multicollinearity was not a major concern (Kalnins, 2018).

<Insert Table 4 >

4.1. Main findings

The regression results are presented in Table 5. Model 1 includes the control variables noted above. The results in Model 2 indicate that collaborative innovation has a significant positive effect on firms' innovation performance (β = 0.813, $p < 0.01$). The results in Model 3 show that the relationship between collaborative innovation and innovation performance is significant and positive (β= 1.348, $p < 0.01$) and that the relationship between collaborative innovation squared and innovation performance is significant and negative (β= -0.057, $p < 0.1$). Therefore, H1 is supported.

<Insert Table 5>

The findings from Model 4 demonstrate that the interaction of collaborative innovation squared and ambidextrous learning is significant and negative (β = -0.059, $p < 0.05$). Thus, H2 is also supported. Then, to examine further how ambidextrous learning moderates the inverted U-shaped relationship between collaborative innovation and innovation performance, we followed the work of Aiken et al. (1991) and plotted the moderating relationships. The results are illustrated using both 2-D and 3-D graphs in Figure 1. We found that firms with high levels of ambidextrous learning exhibit a steep inverted U-shaped relationship. Conversely, firms with low levels of ambidextrous learning appear to present a slightly flat relationship. Overall, these results reinforce H2.

<Insert Figure 1>

The results from Model 5 reveal that the interaction between collaborative innovation squared and TMT shared vision is significant and positive ($\beta = 0.059$, $p < 0.05$). Therefore, H3 is supported. Again following Aiken et al. (1991), we plotted the moderating relationships of TMT shared vision. The results are illustrated using both 2-D and 3-D graphs in Figure 2. These results indicate that firms with a low level of TMT shared vision exhibit a steep inverted U-shaped relationship, while firms with a high level of TMT shared vision present a rather flat relationship. Note also that a high level of TMT shared vision not only restrains the negative effects of high-level collaborative innovation but also causes an upward sloping curve. Thus, these findings are consistent with H3.

<Insert Figure 2>

4.2. Robustness tests

To check further the inverted U-shaped relationship, the following additional analyses were conducted as robustness checks. First, following Li et al. (2009), we used three randomly selected subsamples for regression analysis (90%, 80%, and 70%). As shown in Table 6, the results of the subsamples accorded with the results of the full sample. Second, we used exploratory and exploitative learning as alternative measures for ambidextrous learning. These findings, which are given in Table 7, showed that the interactions between collaborative innovation squared and exploratory learning ($\beta = -0.128$, $p < 0.05$) as well as between collaborative innovation squared and exploitative learning (β = -0.181, $p < 0.01$), are all significant and negative, thus providing further support for H2. Third, following both Haans et al. (2016) and Qian et al. (2010), we performed a simple slope analysis, where the data were segmented according to the confirmed turning points. The results showed that the regression with X-values below the turning point produces a positive relationship between X and Y, whereas the regression above the turning point yields a negative relationship between X and Y. Thus, the slope given by these two linear regressions is consistent with the predicted shape of the curve (Haans et al., 2016). These robustness tests verified the nonlinear relationship between collaborative innovation and innovation performance, thus providing additional support for our earlier findings.

<Insert Tables 6 and 7>

4.3. Supplementary analyses

Given that SOEs may get more external support and resources to further their own development, and also that they may operate with better technological resources than non-SOEs (Karolyi and Liao, 2017; Liang et al., 2015), the possibility of conducting collaborative innovation may be lower for SOEs than for non-SOEs. On the other hand, however, due to the effects of competition and the need to maximise profit, non-SOEs may possess more flexibility and coordination than SOEs (Gaio et al., 2016). Accordingly, we posed an important follow-up question: Does the relationship between collaborative innovation and innovation performance vary across firm ownership types? To answer this question, we conducted a supplementary analysis by dividing the full sample into two subsamples according to the type of ownership: (a) SOEs and (b) non-SOEs. The regression results are given in Table 8.

The results of Model 2 indicate that the impact of collaborative innovation on innovation performance in SOEs is negative and significant (β = - 1.793, $p < 0.1$) and that its squared term is positive and significant (β = 0.238, $p < 0.05$). However, the interaction between collaborative innovation squared and ambidextrous learning, and that between collaborative innovation squared and TMT shared vision, are positive and not significant. These results reveal that SOEs are less sensitive to collaborative innovation than non-SOEs. One possible reason for this finding is that SOEs often enjoy preferential treatment in terms of policies and resource allocation (Chu and Song, 2015). According to Guan and Yam (2015), financial resources supporting innovation in firms are generally more favourable to SOEs. However, some SOEs may accept these privileges without making full use of these financial resources for innovative activities, as they are often conditional on their undertaking tasks assigned by the government and its agencies (Guan et al., 2009).

As for non-SOEs, the results in Model 4 suggest that the relationship between collaborative innovation and innovation performance is significant and positive (β = 2.021, $p < 0.01$), and the relationship between collaborative innovation squared and innovation performance is significant and negative (β = -0.128, $p < 0.05$). Additionally, the interaction between collaborative innovation squared and TMT shared vision is significant and positive (β = 0.113, $p < 0.05$). Because non-SOEs have limited access to government-controlled resources (Li et al., 2012), collaborative innovation becomes more critical for these firms in acquiring the resources and social connections they require. In addition, non-SOEs possess coordinating mechanisms that bind their organisational learning together, including exploratory learning and exploitative learning (Loebbecke et al., 2016). Furthermore, non-SOEs tend to improve their current formal systems by linking their organisational goals with the TMTs in order to achieve higher levels of performance (Nguyen, 2012).

<Insert Table 8>

5. Discussion and conclusions

5.1. Theoretical contribution

In response to the increasing interest of researchers and professionals in collaborative innovation, we used data from 431 Chinese manufacturing firms to examine the inverted U-shaped relationship between collaborative innovation and innovation performance and to explore how ambidextrous learning and TMT shared vision affect this relationship in transition economies. Our findings provide new insights into the role of collaborative innovation, and the study contributes to the literature in the three ways described below.

First, it enriches the research on collaborative innovation by presenting a sharper framework for the theoretical arguments and the empirical analyses of the relationship between collaborative innovation and innovation performance. In recent years, the existing literature on innovation research has broadly indicated that the relationship between collaborative innovation and innovation performance is either positive (e.g., Ritala et al., 2015; West and Bogers, 2014; Wang and Hu, 2020) or negative (e.g., Belderbos et al., 2004; Najafi-Tavani et al., 2018), and the nonlinear relationship has rarely been mentioned. For example, Xie et al. (2013: 952) claimed that "the capability of collaborative innovation is extremely important to improve firms' innovation output." However, Najafi-Tavani et al. (2018: 2) stated that "as the frequency of direct interactions between firms and their external participants increases, the firm may be unable to effectively identify external innovation, or there is not enough innovation to handle new ideas or technologies that ultimately degrade their innovative performance".

Our study confirms that moderate collaborative innovation enhances innovation performance but that high-level collaborative innovation may dampen innovation performance. In other words, our findings reveal that there is, indeed, an inverted U-shaped relationship rather than a simple linear relationship. Thus, this work answers the call in the recent literature for a better understanding of the puzzling implications of collaborative innovation on innovation performance (e.g., Zhang et al., 2019) by considering the different levels of collaborative innovation, given the difficulty faced by managers trying to find a balance between internal and external innovative practices in the open innovation process.

Therefore this study deepens our understanding of the relationship between collaborative innovation and innovation performance in two ways. First, it reconciles the positive (e.g., Ritala et al., 2015; Wang and Hu, 2020) and the negative (e.g., Najafi-Tavani et al., 2018) assertions put forward in prior studies. Second, it incorporates the contradictory views of collaborative innovation into a coherent theoretical framework using a nonlinear model. Overall, by considering resource allocation, information integration, and knowledge utilisation associated with different partners (Berry, 2014; Kogan et al., 2017; Obeidat et al., 2016), our findings provide new insights into how collaborative innovation can avoid the adverse effects and harness the potential of moderate collaborative innovation in order to pursue excellent innovation output.

Second, this study contributes to the literature by examining the moderating effect of ambidextrous learning on the nonlinear relationship between collaborative innovation and innovation performance. We find that the impact of collaborative innovation on innovation performance is dependent on the level of ambidextrous learning. A firm's survival depends on "its abilities to engage in enough exploitation to ensure the organisation's current viability and to engage in enough exploration to ensure future viability" (March 1991: 71). Prior research suggests that ambidextrous learning could encourage firms to detect and exploit the numerous opportunities available via cooperation (O'Reilly et al., 2011). Ambidextrous learning reconciles paradoxical demands by building internally consistent frameworks among different business units (Smith and Tushman, 2005). Ambidextrous learning is particularly necessary when a firm makes a consistent effort to learn and is open to absorbing events outside of its own domain (Reyt and Wiesenfeld, 2015). Based on organisational learning theory, our findings reveal that ambidextrous learning moderates the inverted U-shaped relationship between collaborative innovation and innovation performance, thus extending previous arguments that ambidextrous learning is critical for firms' innovation in collaborative networks (Felício et al., 2019; Fu et al., 2021). This work also complements previous research, which has shown that cognitive skills from knowledge heterogeneity under more complicated situations will be decreased because of relational difficulties, such as lower relational coordination capabilities (Guillaume et al., 2017). Overall, our study contributes both to the collaborative innovation literature and to the organisational learning literature by identifying the contingent mechanism of ambidextrous learning, through which the function of collaborative innovation is transmitted more effectively to innovation performance.

Third, this study provides theoretical and empirical guidance on how the interaction of TMT shared vision with collaborative innovation can profoundly affect firms' innovation performance. TMT shared vision can motivate the active involvement of members in the implementation of organisational goals (Wang and Rafiq, 2014). Thus, a shared vision seems to be a significant factor in helping firms overcome the difficulties of knowledge transfer in high-level collaborative innovation networks (Mihalache et al., 2012). While previous research has mainly focused on the idea of TMT diversity (Gkypali et al., 2017; Li and Huang, 2019), our findings highlight the importance of TMT convergence in both long-term corporate strategies and the implementation of innovation plans (Helsen et al., 2017; Yan et al., 2020). Our results also augment previous studies that suggest that TMTs with high shared vision tend to initiate more competitive actions with increasing resources in order to enhance innovation performance (Carmeli and Paulus, 2015). Moreover, by deepening our understanding of the moderating role of TMT shared vision in terms of the impact of collaborative innovation on innovation performance, our work complements the existing perspective, i.e., the impact of target consensus among partners on innovation performance (Lin et al., 2016). Overall, our results contribute to a context-based understanding of the effect of collaborative innovation on firms' innovation performance by considering TMT shared vision as a contingent variable in the nonlinear relationship.

5.2. Managerial implications

This study offers important managerial implications for both managers and policymakers, who need to understand that collaborative innovation is a double-edged sword. Since collaborative innovation is often sophisticated, it is essential to understand that pursuing it could be both expensive and time-consuming (Sheng et al., 2015). Nonetheless, according to our results, it is valuable for firms to cooperate with different organisations (Pahnke et al., 2015). Thus, owing to the inverted U-shaped relationship between collaborative innovation and innovation performance, managers should balance the benefits of tapping into external sources from collaborative innovation networks against the costs and risks involved in seeking and coordinating linkages in their collaborative innovation processes. Therefore, if they are to capture value from collaborative innovation effectively, firms making decisions about cooperative innovation strategies need to consider their own and other firms' technological knowledge bases and innovation capabilities. Managers should also understand the conditions under which collaborative innovation may be beneficial, or detrimental, to their innovation output (Ritala et al., 2015). For example, firms should be wary of the dangers of high levels of collaborative innovation, where external partners may create collaborative innovation risk rather than collaborative innovation competence (Sheng et al., 2015).

Given the moderating role of ambidextrous learning, managers should try to develop relationships with people both inside and outside their firms in order to augment their existing knowledge and to gain new knowledge beyond their current boundaries. For example, to develop more collaborative innovation, firms could try to create an open learning climate by conducting workshops, which could be important in establishing enthusiasm for inter-organisational work among collaborative partners (Gattringer and Wiener, 2020). They should also strengthen the trust among TMTs by sharing their firms' goals and visions. A shared vision can be a bonding mechanism for resource alignment and integration (Tsai and Ghoshal, 1998), especially when opportunities arise and the resources available to the firms are limited. When pursuing innovation, managers should value the innovative outcomes for their firms, as well as the individual benefits for TMTs.

5.3. Limitations and further research

Several limitations of this work are worth noting, as they may help the direction of future research. The main limitation relates to the choice of a particular region with special characteristics: we focused only on the data of manufacturing firms in the Yangtze River Delta region of China. This raises an important question: Are the findings of this work replicable for other industries in regions experiencing innovative vitality and competitiveness? Simply put, we do not know whether or not our findings are region- or industry-specific. Thus, future research could extend this study to other contexts to confirm or query the applicability of the findings. Second, this study only examined the moderating roles of ambidextrous learning and TMT shared vision. Future research is needed to refine the proposed and empirically validated model, in order to identify other potential managerially meaningful moderators that may also affect this relationship. For example, future research could test whether TMT informational diversity (Mihalache et al., 2012) or the characteristics of collaboration (e.g., the frequency of collaboration) (Bedwell et al., 2012) or employee creativity (e.g., Daud and Alfisah, 2020) influence the relationship between collaborative innovation and innovation performance. Finally, since this work was limited to survey data, we did not examine the threshold point that some studies report when using second-hand data (e.g., Hottenrott and Lopes-Bento, 2016; Un and Rodríguez, 2018). Future research could adopt other methods or use different data (e.g., second-hand data) to investigate the threshold of productive collaborative innovation, thereby providing a more detailed guide for firms' collaborative innovation projects.

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Table 1. Characteristics of the respondents

Classification		Percentage (%)
Managerial positions	● Chairman	8.12
	● CEO	26.91
	● Vice CEO	55.92
	● Director	7.89
	● Engineer	1.16
	Total	100.00
Major	● Natural science	15.55
	● Agricultural science	9.05
	● Management	42.92
	● Engineering and technology science	8.12
	● Humanities and social sciences	24.36
	Total	100.00
Education	● Specialist or below	34.80
	● Bachelor’s degree	55.92
	● Master’s degree	8.35
	● Doctorate	0.93
	Total	100.00

Table 2. Characteristics of the samples

Items	Profile	Number	Percentage (%)
Ownership	SOEs	78	18.09
	CREs	23	5.34
	PEs	235	54.52
	FIEs	95	21.05
	Total	431	100.00
Items	Profile	Number	Percentage (%)
Firm size	<50	144	33.41
	50-500	175	40.61
	501-1000	56	12.99
	>1000	56	12.99
	Total	431	100.00
Items	Profile	Number	Percentage (%)
Annual sales (million yuan)	< 3	121	28.07
	3-20	112	25.99
	20-400	112	25.99
	>400	86	19.95
	Total	431	100

Note: Firm size= Number of employees; Annual sales =Average sales of an enterprise in the past three years; SOEs (state-owned enterprises), CREs (collectively-run enterprises), PEs (private enterprises), and FIEs (foreign-invested enterprises).

Table 3. Construct measurement and confirmatory factor analysis

Item description summary	Standardized loading	*t*-value
Collaborative innovation (Zeng et al., 2010; α = 0.771; CR = 0.793)		
CI1. The extent of their firm's cooperation with customers	0.771	9.157
CI2. The extent of their firm's cooperation with suppliers	0.694	11.168
CI3. The extent of their firm's cooperation with competitors	0.520	13.328
CI4. The extent of their firm's cooperation with government agencies	0.712	10.781
CI5. The extent of their firm's cooperation with research institutions	0.586	13.554
Innovation performance (Soto-Acosta et al., 2017; α = 0.866; CR = 0.868)		
IP1. The number of new or improved products launched to market over the prior 3 years is above average for your industry	0.732	12.119
IP2. The number of new or improved processes over the prior 3 years is above average for your industry	0.782	11.127
IP3. The number of new or improved management practices over the prior 3 years is above average for your industry	0.803	10.570
IP4. The number of new or improved marketing methods over the prior three years is above average for your industry	0.836	9.431
Exploratory learning (Cai et al., 2017; α = 0.743; CR = 0.753)		
ERL1.We search for new information that is useful for acquiring and allocating new resources	0.557	12.703
ERL2.We search for new information that is useful for exploring new fields	0.751	7.557
ERL3.We search for new information that is useful for meeting market demands	0.809	5.592
Exploitative learning (Valaei et al., 2016; α = 0.809; CR = 0.810)		
EIL1. Employees aim to search for information to refine common methods and ideas for solving problems in the company	0.693	10.017
EIL2. Employees use generated and disseminated knowledge in market activities	0.794	6.633
EIL3.Employees search for standards and generally proven methods and solutions to product/service development problems	0.722	10.681
TMT shared vision (Mihalache et al., 2012; α = 0.731; CR = 0.792)		
TMT1. There is 'agreement on the firm's vision' among the members of the management team	0.723	10.315
TMT2. There is 'commitment to the collective goals of the firm' among the members of the management team	0.674	11.389
TMT3. There is 'enthusiasm about the collective ambition of the firm' among the members of the management team	0.733	10.041
TMT4. There is 'a common goal within the firm' among the members of the management team	0.664	11.565
Model fit index		
χ^2 = 118.62; p = 0.000; χ^2/df = 1.46; NFI = 0.952; CFI = 0.955; IFI = 0.955; RMSEA = 0.014		

Table 4. Descriptive statistics and correlations

Variables	1	2	3	4	5	6	7	8	9	10	11	12
1. Ownership	1											
2. Firm size	-0.252**	1										
3. Annual sales	-0.418**	0.713**	1									
4. Industry	-0.040	0.112*	0.172**	1								
5. Age	-0.001	0.068	0.020	-0.033	1							
6. Work experience	-0.054	0.115*	0.073	-0.002	0.475**	1						
7. Gender	0.148**	0.053	-0.100*	-0.046	-0.152**	-0.119*	1					
8. Exploratory learning	0.069	0.044	0.067	-.073	0.062	-0.022	0.048	1				
9. Exploitative learning	0.045	-0.033	-0.054	-0.013	0.040	-0.009	0.054	0.612**	1			
10. TMT shared vision	-0.085	0.128**	0.084	0.000	0.178**	0.177*	-0.034	0.085	0.132**	1		
11. Collaborative innovation	-0.033	0.117*	0.077	-0.017	0.016	0.016	0.043	0.596**	0.628**	0.103*	1	
12. Innovation performance	-0.108*	0.103	0.001	-0074	-0.019	0.030	-0.045	0.429**	0.54**	0.028	0.657*	1
Mean	2.58	2.09	2.37	13.34	28.49	3.78	1.39	5.07	5.10	2.68	4.929	4.61
SD	1.004	1.023	1.096	8.612	6.609	5.009	0.487	1.175	1.150	0.778	1.022	1.271

Significance level: ** $p < 0.01$; * $p < 0.05$ ($N = 431$, two-tailed).

Table 5. Regression results

Variables	DV: Innovation performance					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Ownership	-0.093 (0.063)	-0.084* (0.048)	-0.095** (0.048)	-0.105** (0.047)	-0.093* (0.048)	-0.105** (0.047)
Firm size	0.229*** (0.087)	0.135** (0.066)	0.136** (0.065)	0.149** (0.065)	0.125* (0.065)	0.140** (0.064)
Annual sales	-0.159** (0.080)	-0.159*** (0.060)	-0.170*** (0.060)	-0.188*** (0.060)	-0.158*** (0.060)	-0.178*** (0.060)
Industry	-0.011 (0.007)	-0.009 (0.005)	-0.009 (0.005)	-0.008 (0.005)	-0.009 (0.005)	-0.008 (0.005)
Age	-0.010 (0.011)	-0.012 (0.008)	-0.011 (0.008)	-0.013 (0.008)	-0.010* (0.008)	-0.011* (0.008)
Work experience	0.009 (0.014)	0.009 (0.100)	0.009 (0.010)	0.009 (0.010)	0.011 (0.010)	0.011 (0.010)
Gender	-0.113 (0.128)	-0.203** (0.096)	-0.211** (0.096)	-0.229** (0.095)	-0.193** (0.096)	-0.211** (0. 094)
Collaborative innovation		0.813*** (0.045)	1.348*** (0.302)	1.462*** (0.484)	1.420*** (0.301)	1.592*** (0484)
Collaborative innovation squared			-0.057* (0.032)	-0.073* (0.048)	-0.064** (0.032)	-0.086* (0.048)
Ambidextrous learning				0.216*** (0.056)		0.221*** (0.056)
Ambidextrous learning * Collaborative innovation				-0.046 (0.050)		-0.037 (0.049)
Ambidextrous learning * Collaborative innovation squared				-0.059** (0.024)		-0.059** (0.025)
TMT shared vision					-0.127* (0.072)	-0.135* (0.071)
TMT shared vision * Collaborative innovation					0.163*** (0.058)	0.156*** (0.057)
TMT shared vision * Collaborative innovation squared					0.059** (0.030)	0.048** (0.030)
R^2	0.035	0.457	0.461	0.482	0.474	0.494
Adj.R^2	0.019	0.447	0.450	0.467	0.459	0.476
F-value	2.213*	44.346***	39.980***	32.331***	31.292***	26.987***

Significance level: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. Standard errors in parentheses.

Table 6. Robustness tests: Regression results for three randomly selected subsamples

Variables	DV: Innovation performance		
	90% (*N*=388)	80% (*N*=345)	70% (*N*=302)
	Model 1	Model 2	Model 3
Ownership	-0.112** (0.051)	-0.154*** (0.054)	-0.199*** (0.057)
Firm size	0.152** (0.069)	0.134* (0.072)	0.169** (0.077)
Annual sales	-0.190*** (0.064)	-0.168** (0.066)	-0.198*** (0.072)
Industry	-0.005 (0.006)	-0.011* -0.011*	-0.012* (0.007)
Age	-0.016* (0.008)	-0.011 (0.009)	-0.016* (0.009)
Work experience	0.013 (0.011)	0.015 (0.011)	0.015 (0.012)
Gender	-0.218** (0.102)	-0.235** (0.107)	-0.218** (0.113)
Collaborative innovation	1.718*** (0.516)	1.845*** (0.520)	1.966*** (0.552)
Collaborative innovation squared	-0.098* (0.052)	-0.113** (0.052)	-0.128** (0.055)
Ambidextrous learning	0.231*** (0.059)	0.215*** (0.061)	0.199*** (0.066)
Ambidextrous learning * Collaborative innovation	-.041 (0.053)	-0.050* 0.054)	-0.041 (0.056)
Ambidextrous learning * Collaborative innovation squared	-0.068** (0.026)	-0.074*** (0.027)	-0.067** (0.030)
TMT shared vision	-0.153** (0.076)	-0.117* (0.080)	-0.072** (0.084)
TMT shared vision * Collaborative innovation	0.149** (0.060)	0.159*** (0.062)	0.151** (0.065)
TMT shared vision * Collaborative innovation squared	0.045* (0.032)	0.040 (0.032)	0.028** (0.033)
R^2	0.488	0.487	0.480
Adj. R^2	0.467	0.464	0.453
F-value	23.606***	20.858***	17.589***

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

Table 7. Robustness tests: Regression results for exploratory learning and exploitative learning

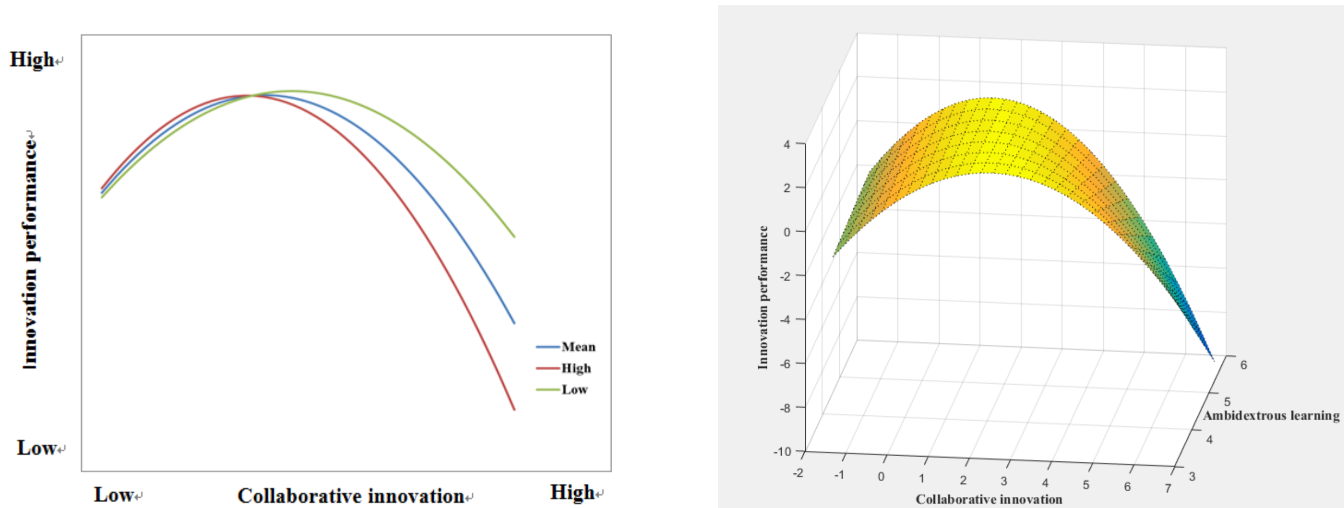
Variables	DV: Innovation performance		
	Model 1	Model 2	Model 3
Ownership	-0.075** (0.048)	-0.082** (0.048)	-0.086** (0.046)
Firm size	0.110** (0.065)	0.116** (0.065)	0.126** (0.063)
Annual sales	-0.146*** (0.060)	-0.164*** (0.060)	-0.149*** (0.059)
Industry	-0.060 (0.005)	-0.049 (0.005)	-0.061 (0.005)
Age	-0.065 (0.008)	-0.064 (0.008)	-0.065* (0.008)
Work experience	0.035 (0.010)	0.035 (0.010)	0.040 (0.010)
Gender	-0.081** (0.096)	-0.085** (0.096)	-0.091** (0.093)
Collaborative innovation	1.086*** (0.302)	1.437*** (0.488)	1.398*** (0.462)
Collaborative innovation squared	-0.435* (0.032)	-0.780** (0.049)	-0.820*** (0.047)
Exploratory learning		0.126** (0.057)	
Exploratory learning * Collaborative innovation		0.011 (0.053)	
Exploratory learning * Collaborative innovation squared		-0.128** (0.023)	
Exploitative learning			0.299*** (0.055)
Exploitative learning * Collaborative innovation			-0.004 (0.049)
Exploitative learning * Collaborative innovation squared			-0.181*** (0.023)
R^2	0.461	0.474	0.505
Adj. R^2	0.450	0.459	0.491
F-value	39.980***	1.377***	5.427***

Significance level: $^{*}p$<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses.

Table 8. Supplementary analyses: Regression results for subsamples with different ownerships

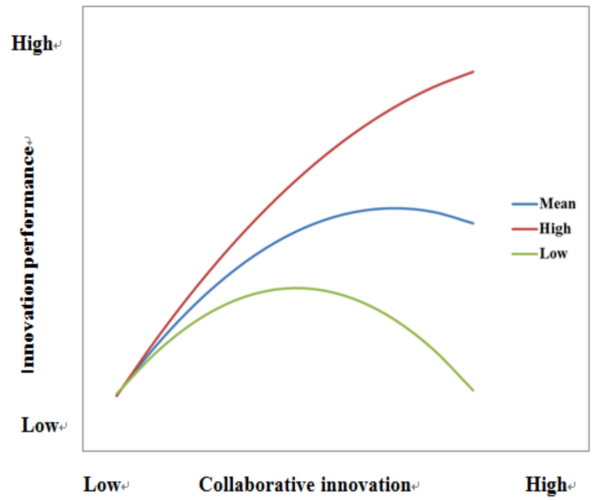
Variables	DV: Innovation performance			
	SOEs		Non-SOEs	
	Model 1	Model 2	Model 3	Model 4
Firm size	0.235 (0.160)	0.154 (0.105)	0.225** (0.110)	0.124 (0.085)
Annual sales	-0.173 (0.160)	-0.174 (0.106)	-0.152 (0.096)	-0.151** (0.073)
Industry	-0.015 (0.016)	-0.010 (0.011)	-0.011 (0.008)	-0.004 (0.006)
Age	0.002 (0.025)	0.005 (0.018)	-0.013 (0.012)	-0.016* (0.009)
Work experience	-0.020 (0.036)	-0.010 (0.023)	0.015 (0.015)	0.012 (0.011)
Gender	0.256 (0.316)	0.040 (0.214)	-0.203 (0.141)	-0.268*** (0.107)
Collaborative innovation		-1.793* (1.070)		2.021*** (0.576)
Collaborative innovation squared		0.238** (0.103)		-0.128** (0.058)
Ambidextrous learning		0.139 (0.109)		0.295*** (0.067)
Ambidextrous learning * Collaborative innovation		-0.319*** (0.110)		0.013 (0.056)
Ambidextrous learning * Collaborative innovation squared		0.078 (0.049)		-0.122*** (0.031)
TMT shared vision		-0.324* (0.183)		-0.184** (0.083)
TMT shared vision * Collaborative innovation		0.085 (0.111)		0.127* (0.071)
TMT shared vision * Collaborative innovation squared		0.079 (0.056)		0.113** (0.050)
R^2	0.042	0.651	0.027	0.462
Adj. R^2	-0.017	0.597	0.006	0.436
F-value	0.713	12.005***	1.259	17.721***

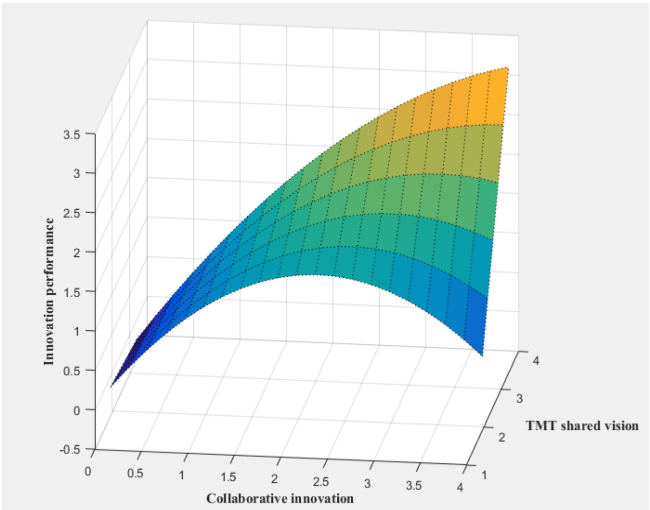
Significance level: $^*p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$. Standard errors in parentheses.



(a) A 2-D graph (b) A 3-D graph

Figure 1. The moderating effect of ambidextrous learning on the relationship between collaborative innovation and innovation performance





(a) A 2-D graph (b) A 3-D graph

Figure 2. The moderating effect of TMT shared vision on the relationship between collaborative innovation and innovation performance