How to Benefit from Balancing External Knowledge Acquisition? A Chinese EIT Industry Case

Abstract: This paper develops an integrated framework and examines how implicit properties-knowledge heterogeneity, acquisition costs and interactivity embedded in external knowledge acquisition (EKA) affect firms' innovation performance through distinguishing three forms of EKA including patent backward citations, patent collaboration and patent purchase. It contributes to the EKA and open innovation literature by studying whether EKA and internal R&D serve as substitutes or complements for firms' innovation performance. Using a panel sample of 77 publicly listed firms in the electronic and information technology (EIT) industries of mainland China from 2004 to 2016, we have reached the following new findings. First, the EKA through patent backward citations and patent collaboration has significantly positive effect on firms' innovation performance, while the effect of patent purchase is non-significant. Second, the EKA through patent backward citations complements firms' internal R&D, but the EKA through patent collaboration and patent purchase substitutes for the internal R&D. Third, an inverted U-shaped relationship exists between the level of balance among three different forms of EKA and firms' innovation performance. Finally, there are contingent interaction effects between the level of balance among three different forms of EKA and the internal R&D on firms' innovation performance. There is complementary relationship with the internal R&D when firms have a high-level balance among three different forms of EKA, whereas there is substitution relationship with the internal R&D when firms have a low-level of balance among three different forms of EKA.

Keywords: external knowledge acquisition; open innovation; innovation performance; internal R&D; patent backward citations; patent collaboration; patent purchase

1. Introduction

With increasingly fierce competition and highly complex technological innovation, firms need to rethink how to deploy their internal R&D strategy and how to rely on external knowledge acquisition (EKA) to achieve desired innovation outcomes during the open innovation paradigm (Cassiman and Veugelers, 2006; Grimpe and Kaiser, 2010; Laursen et al., 2012; Rigby and Zook, 2002). The concept of open innovation, which focuses on harnessing external knowledge in conjunction with firms' internal R&D, has received great attention from both the business world and academic circle in the past decades (Chesbrough, 2003a, 2003b). Academic scholars have recognized the innovation implications of the interaction between EKA and internal R&D of firms (e.g. Berchicci, 2013; Bianchi et al., 2016; Cassiman and Veugelers, 2006; Crescenzi and Gagliardi, 2018; Denicolai et al., 2016; Díaz-Díaz and de Saá Pérez, 2014). However, there remain the disputes about how the relationship between EKA and internal R&D affect firms' innovation performance (Hagedoorn and Wang, 2012).

Many studies have proposed that EKA and internal R&D have complementary effect on firms' innovation performance (e.g. Caloghirou et al., 2004; Cassiman and Veugelers, 2006; Grimpe and Kaiser, 2010; Lin and Wu, 2010; Noseleit and de Faria, 2013; Zhou and Li, 2012). Firms with the superior internal R&D can benefit more from the EKA because they have high absorptive capacity (Cohen and Levinthal, 1990; Crescenzi and Gagliardi, 2018; Denicolai et al., 2016; Flor et al., 2018). Besides, the EKA can also enhance the marginal benefits of internal R&D (Cassiman and Veugelers, 2006), especially when a firm wants to overcome the "not invented here" syndrome (Katz and Allen, 1982, p.7).

However, other studies have identified a substitution relationship between the EKA and internal R&D when they affect firms' innovation performance (Berchicci, 2013; Hess and Rothaermel, 2011; Marco-Lajara et al., 2019; Vega-Jurado et al., 2009; Watkins and Paff, 2009). Since firms' resources are limited, the simultaneous pursuit of internal R&D and EKA may increase both transaction cost and switching cost, reducing firms' innovation performance marginally (Bianchi et al., 2016; Noseleit and de Faria, 2013; Rothaermel and Hess, 2007).

Some contingent factors have been taken into account to clarify the above paradoxical arguments about the interaction between firms' internal R&D and EKA, including the in-house

R&D investments (Hagedoorn and Wang, 2012), internal R&D capacity (Berchicci, 2013) and knowledge management capability (Ferraris et al., 2017). However, there are limited studies that have examined the balance of different forms of EKA, which is another important contingent factor. The publicly available patent information makes it possible for us to study the various forms of EKA adopted by firms, especially in the technology-intensive industries (Gao et al., 2014; Wagner et al., 2014; Wang, 2011). This paper aims to clarify whether EKA and internal R&D serve as substitutes or complements for firms' innovation performance by distinguishing three different forms of EKA, namely, patent backward citations, patent collaboration and patent purchase.

We distinguish three different forms of EKA in terms of knowledge heterogeneity, acquisition costs and interactivity, which determines if EKA can substitute or complement internal R&D of firms. First, based on the absorptive capacity theory (ACT), firms' benefits from EKA are subject to the heterogeneity or homogeneity between external knowledge and internal knowledge base (Sun, 2016). Second, according to the transaction cost theory (TCT), EKA and internal R&D of firms substitute with each other because of high acquisition costs (Pisano, 1990; Williamson, 1985). Third, the high interactivity helps firms to absorb external knowledge more effectively with social capital (Lane and Lubatkin, 1998; Yli-Renko et al., 2001). Meanwhile, the uncertainty and opportunistic behavior associated with in-depth interactivity may lead to higher transaction cost arising from negotiation and monitoring. There are intricate mechanisms underlying the interactions between internal R&D and different forms of EKA, so it is important for firms to benefit from open innovation through maintaining a good balance among three different forms of EKA.

The paper proposes a series of theoretical hypotheses about the effect of EKA, the balance among different forms of EKA on firms' innovation performance, and the interaction effect between internal R&D and EKA on firms' innovation performance. These hypotheses are tested by using a panel sample of 77 publicly listed firms in the electronic and information technology (EIT) industries in mainland China from 2004 to 2016.

This study has made the following contributions to the extant literature. First, the paper contributes to the EKA literature through distinguishing three different forms. The extant literature has affirmed that firms can benefit from the EKA to improve their innovation performance through upgrading technology (Wang et al., 2013), recombining knowledge elements (Wang et al., 2014), and learning (Díaz-Díaz and de Saá Pérez, 2014). However, other properties of EKA have been generally ignored, such as the characteristics of external knowledge (heterogeneity or homogeneity), the costs of acquiring external knowledge, and the interactivity with external resources. Few studies have examined different forms of EKA and their comprehensive effects on firms' innovation performance. The paper distinguishes three different forms of EKA including patent backward citations, patent collaboration and patent purchase, based on heterogeneity, cost and interactivity. By synthesizing two theoretical views (TCT and ACT) with three properties (heterogeneity, cost and interactivity) embedded in EKA, this study has proposed an integrated framework to examine their effect on firms' innovation performance. It has introduced a new concept "the balance among three different forms of EKA" to explore the comprehensive impact. The empirical findings show an inverted U-shaped relationship between the level of balance among three different forms of EKA and firms' innovation performance.

Second, this study contributes to the open innovation literature by following the calls for further investigation of the interactions between internal R&D and EKA (Cassiman and Veugelers, 2006; Hagedoorn and Wang, 2012). Although the extant literature has examined the interactions between firms' internal R&D and EKA in terms of R&D investment and capability (Berchicci, 2013; Ferraris et al., 2017; Hagedoorn and Wang, 2012), the effects of different forms of EKA on firms' innovation performance have been neglected. This paper has examined whether EKA and internal R&D serve as substitutes or complements for firms' innovation performance. It depends on three different forms of EKA, including patent backward citations, patent collaboration and patent purchase. Besides, the research has explored the interaction effects between EKA and internal R&D when firms are engaged in different forms of EKA simultaneously.

The rest of paper is organized as follows. The second section reviews the existing studies on open innovation and EKA, transaction cost theory and absorptive capacity theory, and proposes eight hypotheses on the role of three different forms of EKA and the interaction relationship between EKA and internal R&D on firms' innovation performance. The third section are the research methods including the data, sample, variables and estimation procedures. Afterwards, the empirical results are discussed in the fourth section. The discussion and conclusions are in the final section.

2. Theory and hypotheses

2.1. Open innovation and external knowledge acquisition

Open innovation is defined as "the use of purposive inflows and outflows of knowledge to accelerate internal innovation and expand the markets for external use of innovation, respectively" (Chesbrough et al., 2006, p.1). Open innovation strategy and closed innovation strategy are not a simple dichotomy, but belong to a continuum (Chesbrough, 2003a; Denicolai et al., 2016; Hung and Chou, 2013). At one end, firms are with entirely closed innovation, whereas at the other end, firms are with fully open approaches to innovation.

Although open innovation has become increasingly popular, firms cannot entirely depend on it. It is necessary for them to undertake internal R&D while absorbing external knowledge effectively. Possessing the capability to combine both internal and external knowledge can help firms achieve competitive advantage in the market (Cassiman and Veugelers, 2006; Kim et al., 2016). Under the open innovation paradigm, external and internal knowledge are equally important.

Open innovation and EKA are two related but not completely overlapping concept. Open innovation has two directions of knowledge flow, EKA and external knowledge exploitation (EKE) (Hung and Chou, 2013; Lichtenthaler, 2008). EKA refers to "innovative ideas and technological knowledge flow into the firm's innovation system such that the firm can access external innovative knowledge and internal ideas to complement its business model" (Hung and Chou, 2013, p. 368). EKA has been explored in the management literature including complementary assets, organizational learning, absorptive capacity and dynamic capabilities (Cruz-Gonzalez et al., 2015).

How EKA and internal R&D of firms interact is one of the core research topics in the open innovation literature (Chesbrough, 2003a; Hung and Chou, 2013). Open innovation provides an insightful theoretical perspective to address the research question of this study about the interplay between EKA and internal R&D on firms' innovation performance.

2.2. The Three forms of EKA

Firms acquiring knowledge from external sources, such as clients, suppliers, competitors, universities or research centers, can take various forms, ranging from merges and acquisitions (M&A), joint ventures, strategic alliances, to in-licensing, purchase technology, citing the prior art, R&D collaboration and outsourcing (e.g. Berchicci, 2013; Bianchi et al., 2016; Kotlar et al., 2013; Lichtenthaler, 2008; Suh and Jeon, 2019). Although M&A, joint ventures and strategic alliances are some of the important forms of EKA, their data sample is minuscule (Suh and Jeon, 2019). However, the patent as a proxy for tangible knowledge has been widely used in the open innovation and EKA literature (Suh and Jeon, 2019; Gao et al., 2014; Wagner et al., 2014; Wang, 2011). Patent data, which are publicly available, provide a large amount of useful information such as assignees, legal status and references, making it possible to study various forms of firms' EKA (Gao et al., 2014; Wagner et al., 2014; Wang, 2011).

This study distinguishes the different forms of EKA based on knowledge heterogeneity, acquisition cost and interactivity. These properties indicate whether EKA can substitute or complement internal R&D and ultimately influence firms' innovation performance (see Table 1).

[Table 1 about here]

2.2.1 Patent backward citations

When firms apply for a new patent, they need to reveal the "prior art", namely, backward citations, to indicate what prior knowledge the new patent is based on. Many scholars rely on patent citation information to trace knowledge flow (Jaffe and Trajtenberg, 2002; Kim et al., 2016; Suh and Jeon, 2019). Backward citations represent the knowledge flow from the previous patents to a current patent (Chen et al., 2012; Wagner et al., 2014; Wirsich et al., 2016). Patent citations can be used as an understandable source of open innovation in terms of knowledge inflow (backward citations) and outflow (forward citations) (Choi and Park, 2009; Suh and Jeon, 2019; Wang et al., 2017).

The extant literature indicates that patent backward citations, as a form of EKA, reflect firms' open innovation actions because they can trace the sources of knowledge from other organizations (e.g. Han et al., 2020; Kim et al., 2016; Lyu et al., 2019; Moaniba et al., 2020; Petruzzelli et al., 2015; Suh and Jeon, 2019; Wang et al., 2017; Yun et al., 2016). They are often used to trace and understand the search undertaken by firms for external knowledge. One of the most adopted methods to quantify EKA is to track the citations by counting the number of references a patent has. Lim et al. (2010) suggest that patent backward citations reflect to what extent firms rely upon external sources of knowledge. Firms with higher citations are more dependent on external organizations for technology.

Although the effectiveness of patent backward citations as a proxy for knowledge flow has been questioned due to the bias introduced by the examiner citations (Moser et al., 2017; Park et al., 2017), it is not a big concern for this study because all of these citations represent prior knowledge, which is relevant with the current patent. Compared with the inventors who prefer to cite old patents to describe technology basis, the examiners prefer to cite more recent ones (Li et al., 2014). Mixed citations can overcome knowledge limitations and help make new inventions through a recombination of diversified knowledge elements. The extant literature also shows that the bias is not necessarily bad because both inventor citations and examiner citations might be able to track each other closely (Alcacer and Gittelman, 2006; Schoenmakers and Duysters, 2010; Wang et al., 2017).

EKA through patent backward citations shows the following characteristics. First, it is confined to the homogenous knowledge because the citations represent prior knowledge the current patent is based on (Stolpe, 2002). Second, a focal firm needs only bear low acquisition cost because the prior patents are public and can be easily searched for. Finally, patent backward citations are a temporary one-way process, so a focal firm usually has few interactivity with external organizations possessing the cited patents (Suh and Jeon, 2019; Wang et al., 2017).

2.2.2 Patent collaboration

The open innovation paradigm suggests that firms acquire external knowledge through collaborating with their partners (Chesbrough, 2003b; Chesbrough et al., 2006). Patent collaboration implies joint ownership of collaborative R&D outcomes, which means that more than one applicant possesses full ownership of one patent (Belderbos et al., 2014; Briggs, 2015).

Firms can integrate internal and external knowledge to make innovations through patent collaboration (Belderbos et al., 2014; Cassiman and Veugelers, 2006; Chesbrough, 2003c). However, there are also some concerns. For example, Hagedoorn (2002) labels co-patenting as a second-best strategy for firms. Belderbos et al. (2014) argue that firms may face liabilities in appropriating returns from the collaborations, especially when their partners compete with each other. In addition, patent collaboration brings about technological contamination in some cases (Chesbrough et al., 2006). It is important for firms to integrate external new knowledge with their existing knowledge. These are complex tasks and can pose great risks if firms have poor understanding of external new knowledge (Chesbrough, 2003c).

Therefore, whether firms can benefit from patent collaboration partially depends on the properties of internal and external knowledge. First, patent collaboration, which may involve both homogeneous and heterogeneous knowledge acquisition, is affected by the knowledge, geographic and institutional distance between collaboration partners. Firms tend to search for and collaborate with partners that have similar technological domains because it is easier for them to understand and absorb homogeneous knowledge than heterogeneous knowledge (Cohen and Levinthal, 1990; Fleming, 2001; Martin and Mitchell, 1998; Wagner et al., 2014). However, some propositions indicate that collaborating with distant partners has advantages of having access to heterogeneous knowledge and can contribute to improving firms' innovation performance (Sammarra and Biggiero, 2008; Sun and Liu, 2016). Second, patent collaboration involves reciprocal, longitudinal and high interactivity with partners, which facilitates firms to understand and assimilate external knowledge. However, high costs are usually incurred for searching, negotiating, contracting and implementing the collaboration.

2.2.3 Patent purchase

The open innovation paradigm suggests that firms should be active buyers and sellers of intellectual property (IP) (Chesbrough, 2003b; Hung and Chou, 2013). In practice, the development of technology market provides a lot of transaction opportunities and makes open innovation a more feasible option for firms. Some scholars suggest that in-licensing of patents work as a pervasive strategy for firms to acquire external knowledge to promote innovation (e.g. Lyu et al., 2019; Han et al., 2020; Wang and Li-Ying, 2015; Tsai and Chang, 2008). Hence, patent purchase is also one of the important forms of EKA because of the following reasons.

First, compared with patent backward citations and patent collaboration, patent purchase is more likely to acquire heterogeneous knowledge. Firms intend to buy patents from other technology classes (Chen et al., 2012). Second, it is a market transaction process, in which patent buyers and patent sellers exchange their capital and knowledge, but hardly have any in-depth interactivity (Sun and Liu, 2016). Finally, firms have to bear high costs of purchasing patents. When making their decisions to purchase new patents, firms usually face the big challenge of assessing the potential value of patents. It is important to learn if firms can benefit from developing new technology after purchasing the patents. Assessing the potential value of a patent in the technology market is not an easy task because it increases the transaction cost of firms, especially for those with limited relevant knowledge.

2.2.4 Balance among three different forms of EKA

Firms can acquire complementary knowledge through various means. For example, some firms are engaged in the different forms of EKA simultaneously and equally. How to deploy these different forms of EKA is critical for firms to adopt open innovation strategy. This study introduces a new concept of balance among three different types of EKA. Balance means the extent to which a focal firm is engaged in three different types of EKA simultaneously. If a focal firm is only engaged in one type of EKA, the level of balance is the lowest. However, if the focal firm is engaged in three different types of EKA simultaneously and equally, its level of balance reaches the highest.

2.3. *Theoretical perspectives and hypotheses*

This section discusses the theoretical perspectives and develops the hypotheses about three different types of EKA, and their interaction effects with internal R&D on firms' innovation performance.

ACT focuses on the role of firms' capability in assimilating and utilizing external knowledge (Cohen and Levinthal, 1990；Zobel, 2017). Firms' capability to recognize, assimilate and exploit external knowledge partly depends on the similarity of knowledge stock with their exchange partners (Inkpen, 2000; Lane and Lubatkin, 1998). Whether firms can benefit from EKA partly depends on the heterogeneity of external knowledge. However, TCT suggests that firms that are engaged in EKA with high costs substitute their internal R&D, so firms should adopt either external R&D strategy or internal R&D strategy (Vega-Jurado et al., 2009).

In-depth interactivity helps firms to absorb external knowledge more effectively with social network ties (Lane and Lubatkin, 1998; Yli-Renko et al., 2001). Meanwhile, uncertainty and opportunistic behavior associated with the in-depth interactivity may lead to high transaction cost, such as negotiation and monitoring cost, to protect firms from knowledge leakage. As a result, firms that have high interactivity with external sources can absorb external knowledge more effectively, but they have to incur higher transaction cost.

2.3.1 Patent backward citations and firms' innovation performance

When adding backward citations to a new patent, firms can internalize external knowledge through searching for the prior art (Dosi, 1982). Economic historians suggest that past success and failure could be used to guide the direction of subsequent innovation (Rosenberg, 1975). Patent backward citations contain these information, so they can be used to trace the existing advanced technology (Singh, 2005). Second, patents, which are public information, can be easily searched for and absorbed by firms when they undertake internal R&D activities. Besides, as a one-way and non-marketized form, patent backward citations can help firms acquire external knowledge at low acquisition cost. Finally, firms can deepen their internal knowledge base and train their own innovators by learning external knowledge from the cited patents (Wang et al., 2013), thereby improving firms' innovation performance.

Therefore, firms can benefit from patent backward citations to trace their existing technology and deepen their internal knowledge base through accumulating external homogeneous knowledge. As a result, firms' innovation performance can be improved through recombining internal and external knowledge. Accordingly, we propose the following hypothesis:

H1a: EKA through patent backward citations has a positive effect on firms' innovation performance.

The interaction between patent backward citations and internal R&D has a complementary effect on firms' innovation performance. The complementarity between these two types of innovation strategy can be interpreted that adding investments in one type increases the marginal gains from the other (Cassiman and Veugelers, 2006).

According to the ACT, firms' internal R&D is conducive to searching for, exploiting and integrating the external knowledge (Cohen and Levinthal, 1990; Zobel, 2017). Firms with superior internal R&D capabilities can benefit more from EKA through patent backward citations (Lin and Wu, 2010). In turn, EKA through patent backward citations can intensify the depth of firms' internal knowledge. Besides, firms can acquire external homogeneous knowledge through patent backward citations.

However, according to the TCT, acquiring homogeneous knowledge increases the marginal returns of internal R&D because of lower integration cost. Under the condition, firms can learn and accumulate external knowledge more effectively. Thus, EKA through patent backward citations can enhance the positive effect of internal R&D on firms' innovation performance (Laursen et al., 2012; Robins and Wiersema, 2003). Hence:

H1b: The interaction between EKA through patent backward citations and internal R&D has a positive effect on firms' innovation performance. That is, EKA through patent backward citations and internal R&D serve as complements for firms' innovation performance.

2.3.2 Patent collaboration and firms' innovation performance

As an increasingly significant form of EKA, patent collaboration can improve firms' innovation performance. First, patent collaboration facilitates firms to integrate internal and external knowledge synergistically to develop new technologies (Belderbos et al., 2014; Briggs, 2015; Cassiman and Veugelers, 2006; Wang et al., 2017). Collaboration with partners helps firms to catch up with the advanced technology and gain complementary resources.

Second, patent collaboration provides firms with technology learning opportunities (Sammarra and Biggiero, 2008; Sun and Liu, 2016). It is viewed as strong ties of knowledge flow between organizations, involving reciprocal and longitudinal interactivity (Wang et al., 2017). It facilitates tacit knowledge transfer (Uzzi and Lancaster, 2003; Wang et al., 2017), such as technical know-how, and enhance firms' innovation performance (Lodh and Battaggion, 2015).

Finally, firms can improve their patents' quality by collaborating with others. The quality of co-patents is usually higher than that of single-owners (Belderbos et al., 2014; Briggs, 2015). Patent collaboration is also positively related to technological newness (Wirsich et al., 2016). Technology quality and newness are associated with superior firms' innovation performance. Hence:

H2a: EKA through patent collaboration has a positive effect on firms' innovation performance.

The interaction between patent collaboration and internal R&D have substitution effect on firms' innovation performance. The substitution between these two types of innovation strategy can be interpreted that adding investments in one type decreases the marginal gains from the other (Cassiman and Veugelers, 2006).

Firms with superior internal R&D capability enjoy less benefit from the collaboration due to relatively high acquisition cost. While firms can gain access to their partners' knowledge through the collaboration, they face value-appropriation risks of sharing intellectual property (Briggs, 2015). Especially when firms have superior internal R&D, they have to bear high monitoring cost to protect internal core technologies from appropriation by opportunistic partners. Therefore, the contribution of EKA through patent collaboration to firms' innovation performance will decrease.

Although deep interactivity makes it possible for firms to learn more from their partners, it may reduce flexibility of internal R&D activities because firms must invest much time, capital and other resources to develop mutual trust and share norms. These investments lock the firms into particular collaboration relationship and limit their resources to explore and exploit external new knowledge. As a result, the long-term collaboration usually causes incumbent inertia, whereby firms may become content with their external relationships and overlook promising internal R&D programs

(Wang et al., 2017).

Therefore, patent collaboration is a second-best strategy for firms with superior internal R&D capabilities because they can rely on their internal R&D to meet innovation goals. On the basis, the following hypothesis is proposed:

H2b: The interaction between EKA through patent collaboration and internal R&D has a negative effect on firms' innovation performance. That is, EKA through patent collaboration and internal R&D serve as substitutes for firms' innovation performance.

2.3.3 Patent purchase and firms' innovation performance

Because acquiring external knowledge through patent purchase can enhance firms' innovation performance, patent purchase has become more and more popular with the rapid development of technology market. Firms can acquire advanced technology through patent purchase to avoid risks of internal R&D failure (De Marco et al., 2017; Park et al., 2013). Patent purchase can be very helpful for firms to catch up with their technical leaders in the short term (Denicolai et al., 2016). Besides, when firms intend to introduce new products or enter into new niche markets, patent purchase can be effective to remedy internal technological limitations, overcome resource barriers and stimulate future innovations (Ye et al., 2016). Moreover, patent purchase in technology market offers firms opportunities to access their desired technologies (Chatterji and Manuel, 1993; De Marco et al., 2017; Wang and Li-Ying, 2015). Firms can learn from the purchased patents by making reverse engineering and training their own innovators. Hence:

H3a: EKA through patent purchase has a positive effect on firms' innovation performance.

The interaction between patent purchase and internal R&D have a substitution effect on firms' innovation performance. First, acquiring external knowledge through patent purchase hampers firms' internal R&D depth. Although firms can broaden their horizons about innovation activities through patent purchase, it will weaken firms' internal R&D capability in the long term. For example, when we interviewed some R&D managers from the electronic and information technology firms in 2020, one interviewee[1] emphasized that, 'patent purchase is an expedient strategy when we enter into a new technology domain. Firms can learn and gather experience at an early stage. However, firms

[1] We interviewed Mr. Du, CEO of Suzhou Zhito Technology Co., Ltd located in East China. The firm is dedicated to research and development of intelligent vehicle software and hardware system, and the provision of total smart logistics solutions to customers.

are also easily trapped in business diversification and may lose their internal R&D capabilities.'

Second, compared with heterogeneous knowledge, firms can understand and assimilate homogeneous knowledge more easily (Wagner et al., 2014). Acquiring heterogeneous knowledge is not always beneficial for firms with superior internal R&D capabilities within a given domain because of high absorption and integration cost (Cohen and Levinthal, 1990; Ye et al., 2016). In this aspect, engaging in internal R&D and patent purchase simultaneously may decrease firms' innovation performance, at least marginally (Rothaermel and Hess, 2007). Therefore, EKA through patent purchase can substitute firms' internal R&D because of heterogeneous knowledge and high acquisition cost. Hence:

H3b: The interaction between EKA through patent purchase and internal R&D has a negative effect on firms' innovation performance. That is, EKA through patent purchase and internal R&D serve as substitutes for firms' innovation performance.

2.3.4 Balance among three different forms of EKA and firms' innovation performance

Maintaining a good balance among three different forms of EKA has both advantages and disadvantages for firms' innovation performance (see Figure 1). First, acquiring homogeneous knowledge through patent backward citations and patent collaboration strengthens firms' internal knowledge depth, while acquiring heterogeneous knowledge through patent collaboration and patent purchase diversify firms' knowledge elements (Ye et al., 2016). Second, firms can make innovations through collaborating with their partners or purchasing patents in the technology market directly to reduce internal R&D costs (Hagedoorn, 2002). Finally, firms can learn from their collaborators with reciprocal and longitudinal interactivity, improving firms' absorptive capacity and making more benefits from the other EKA forms such as patent backward citations and patent purchase (Lane and Lubatkin, 1998).

However, as firms' resources are limited, keeping a high level of balance among three different forms of EKA also has the following disadvantages. First, acquiring diversified external knowledge increases complexity and difficulty in integration (Berchicci, 2013; Ye et al., 2016). Second, keeping a high level of balance among three different forms of EKA increases firms' operation risks due to high switch cost and monitoring cost (Kang and Park, 2012). Finally, although high interactivity can enhance firms' capability to identify and assimilate external knowledge (Cohen and Levinthal, 1990; Lane and Lubatkin, 1998), firms are vulnerable to the leakage of core technology in the open innovation environment.

[Figure 1 about here]

On the whole, firms can make more innovation by adopting multiple forms of EKA (Sampson 2007; Wuyts and Dutta 2014), but the integration, coordination, monitoring, transaction and adjustment costs are likely to increase considerably (Gkypali et al., 2017; Hagedoorn and Wang, 2012). Thus, firms should maintain a moderate level of balance among three different forms of EKA because there is a trade-off between homogeneous and heterogeneous knowledge, costs and benefits, as well as knowledge absorption and knowledge leakage. Therefore:

H4a: The level of balance among three forms of EKA have an inverted U-shaped effect on firms' innovation performance.

Since three different forms of EKA have distinct interaction with firms' internal R&D, it is important to study how the contingent interaction between internal R&D and the level of balance among three forms of EKA affect firms' innovation performance.

A low-level of balance, which focuses on only one form of EKA, may constrain firms' internal R&D flexibility due to the following reasons. First, firms might lose flexibility to change their innovation strategies. They might be content with the time and resources they have invested in internal R&D. Under this condition, firms become less efficient and proactive in pursuing other novel innovation opportunities (Gnyawali and Ryan Charleton, 2018). Second, keeping a low-level of balance among three forms of EKA may reduce internal R&D efficiency over time because of lacking diversified knowledge acquisition (Sun and Liu, 2016). Therefore, a low-level of balance among three different forms of EKA has a substitution effect on firms' internal R&D.

Conversely, when firms keep a high-level of balance among three different forms of EKA, they complement the internal R&D with knowledge diversity and organizational flexibility. First, firms can broaden their knowledge base through maintaining a high-level of balance among three different forms of EKA. 'Medici effect' explains why diversity drives innovation. It is because innovation does not arise from one particular domain, but from combinations of knowledge across diversified fields (Johansson, 2006). Thus, through maintaining a good balance of different forms of EKA can firms enhance their internal R&D efficiency. Second, a high-level of balance among three different forms of EKA has a complementary effect with internal R&D because it can strengthen firms' flexibility in the rapidly changing business environment and make it possible for firms to grasp more opportunities and achieve higher marginal benefits from their investment in internal R&D. Hence:

H4b: Internal R&D and the level of balance among three forms of EKA have a contingent interaction effect on firms' innovation performance. They have a complementary effect on firms' innovation performance when there is a high-level balance of three forms of EKA, whereas they have a substitution effect on firms' innovation performance when there is a low-level balance of three forms of EKA.

3. Methods

3.1. Sample and data

The sample used for this study consists of publicly listed firms in the electronic and information technology (EIT) industries in mainland China. EIT refers to information technology, any equipment, interconnected system and subsystem of equipment, which are used in the creation, conversion, duplication of data or information. Computers, software and telecommunications, which are three main components of EIT industries, specifically produce communication products (such as telephones), electronic information and component, multimedia, office equipment, safety equipment, home appliances and so on.

We choose this particular research setting because EIT are some of the most R&D-intensive high-tech industries in the world. The patent activities in the EIT industries have been increasing rapidly and playing a critical role in firms' innovation performance (Müller et al., 2018). We focus on mainland China because it has witnessed some of the most significant development of innovation in the EIT industries in the past decades (Zhang and Xie, 2015). At present, the new generation of information technology represented by 5G provides the EIT firms in mainland China substantial R&D and rapid growth opportunities.

The impact of EKA on firms' innovation performance was examined by a panel dataset. First, 566 publicly listed firms in the EIT industries of mainland China were selected from China Listed Company Database (CLCD), part of CSMAR database that provides high-quality comprehensive information of publicly listed firms in mainland China.

Second, we collected the patent information of sample EIT firms in the United States Patent and Trademark Office (USPTO) database. USPTO patents are generally considered as high value. The patent files have rich information on patent ownership changes, which are not included in China National Intellectual Property Administration (CNIPA) database. As not all of the Chinese firms have applied for their patents in the USPTO, our sample comprised 77 Chinese publicly listed firms in the EIT industries after excluding those that had no patents in USPTO. Because the sample firms applied for few patents in the USPTO before 2004, we chose to use a panel data between 2004 and 2016 in the research. For each sample firm, we collected its patent data including the number of patent applications, the number of patent backward citations, the number of joint patents that had more than one applicant, and the number of patents that had been transferred from other organizations.

Third, the basic information of sample firms was collected from the CLCD and their annual reports published in the corporate websites, including the ownership, R&D expenses, the year of IPO, the number of full-time employees, the number of R&D employees, business types and registered addresses.

Finally, in order to clarify whether the sample firms adopted open innovation strategy, we conducted a study based on the text mining to increase the reliability of our empirical results. The related information such as "open innovation" and "R&D collaboration" was searched for in the sample firms' official websites, annual reports and the formal interviews with their executives and media reports. Python program was first used to acquire information released in "Baidu", a world's leading Internet search engine commonly used to obtain Chinese information, about "open innovation" of our sample firms. Then we read and process the information manually to confirm the open innovation strategy adopted by the sample firms.

The text mining study shows that all of the sample firms adopted open innovation strategy. The detailed algorithm we used to conduct the text mining is in Appendix A. Table A1 in Appendix B includes the statements about open innovation strategy of sample firms in the research. For example, Dongsheng Li, Chairman of TCL Electronics Holdings Limited, commented in the interview as follows:

"TCL's innovation strategy shifts from independent R&D to open innovation model with 'independent R&D + collaboration'."

"Open innovation helps TCL develop a technological competitive edge with lower

cost and at faster speed. We collaborated with Baidu launching a flagship TV with AI system. We also collaborated with Rokid closely, which provides the solutions for voice interaction technology. Besides, we signed an agreement with the University of Hong Kong to establish HKU-TCL Joint Research Institute of Artificial Intelligence, and cooperation agreements with several institutions in mainland China such as Suzhou Institute of Nanotechnology of Chinese Academy of Sciences."

Lirong Shi, CEO of ZTE, a leading telecommunications and information technology company in mainland China, remarked in the interview as follows:

"ZTE adopts open innovation strategy, in which customers, upstream and downstream suppliers, external experts and partners are attracted to our value chain. Innovation can be seen as a joint action of all of our partners."

The above interview quotes clearly indicate that the sample listed firms in the study are suitable for examining the interaction effect between EKA and internal R&D under the open innovation framework.

3.2. Variables

3.2.1 Dependent variable

Firms' innovation performance: this study adopts a commonly used measure-the number of patents that a sample firm applied for divided by its R&D expenses (in RMB 10 million) as the dependent variable. Lin and Chen (2005) supported the use of the ratio of patents a firm receives to its R&D expenses as a proxy of firms' innovation performance. The combination of patent data with financial data increases the accuracy of measuring firms' innovation performance because it reflects the efficiency of R&D investment. Firms' innovation performance in this study focuses on the focal firm's patent count applied for by itself, which excludes buy-in patents. This approach can get rid of the possible noise caused by buy-in patents and buy-in costs.

3.2.2 Independent variables

Independent variables include the three different forms of EKA and the level of balance among these three forms of EKA. *Patent backward citations* is measured as the total number of references of all patents applied for by a focal firm during the observation period[2]. *Patent collaboration* is

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[2] Although that almost all the patents in USPTO have references, the effect of references on firms' innovation performance may depend on their number and type. First, some patents cite a large number of references, while

measured as the total number of co-patents with its partners applied for by a focal firm during the observation period. *Patent purchase* is measured as the total number of patents whose ownership was transferred to a focal firm during the observation period. The patent transfer that took place between the innovators and the organizations they had worked for were excluded (De Marco et al., 2017). When the patent ownership was transferred to an assignee, the assignee became the owner of the patent and had the same rights as the original patentee. This information was collected from Patent Assignment Database, a comprehensive dataset of about 2 million patents granted by the USPTO instead of CNIPA.

Balance among three different forms of EKA: balance means the extent to which a focal firm is engaged in different forms of EKA simultaneously and evenly. The existing studies mainly use the absolute difference to measure the level of balance (Cao et al., 2009), which is suitable to calculate between two different types of activities, but is not appropriate to measure the level of balance among three different types of EKA in the study. Therefore, we measured the level of *balance* by using the entropy index, which takes into account both the number of EKA forms (three) and the distribution of firms engaged in them (Barker and Duhaime, 1997). The entropy index can be used to calculate the level of balance in several fields (Sun and Liu, 2013; Zheng and Shi, 2018).

The entropy index is given by:

$$Entropy\ \ index = \sum_{i=1}^{3} P_i\, ln(1/P_i) \tag{1}$$

where P_i =the proportion of EKA through patent backward citations, patent collaboration or patent purchase, for a firm with one or more forms of EKA. For instance, if a firm has four patents containing EKA, one patent containing reference (1/4), two patents collaboration with others (2/4 or 1/2), and one patent purchased from others (1/4), the level of balance is $\frac{1}{4} \times \ln 4 + \frac{1}{2} \times \ln 2 + \frac{1}{4} \times \ln 4$, which equals “1.040”. The larger the value, the higher the level of balance. In an extreme case, when firms use only one form of EKA, the entropy index is equal to 0. In contrast, when firms are engaged in three forms of EKA equally, the entropy index equals “1.0986”. The value of the

others only cite a small number of references, so they acquire different amounts of knowledge. Second, patent backward citations can be distinguished between self-citations and non-self-citations. Strictly speaking, self-citations cannot belong to the external knowledge acquisition. Excluding self-citations from the total patent backward citations can reduce the potential bias arising from the self-citations.

entropy index ranges from 0 to 1.0986. The minimum value of entropy index is zero while the maximum value emerges when three different forms of EKA are used in equal proportions.

Internal R&D is measured by the sample firms' knowledge depth of internal R&D activities (Lin and Wu, 2010; Zahra et al., 2006). Knowledge depth refers to a firm's expertise within a technological field (George et al., 2008), which can drive firms' innovation performance dramatically. This variable is operationalized as the maximum number of patents in any one technological class based on the international patent classification (IPC 4-digit classification) (George et al., 2008).

3.2.3 Control variables

Several variables were controlled because they might affect firms' innovation performance. We controlled *firm age*, which was measured as the number of years elapsed between a firm's IPO and the observation year. We also controlled *firm size*, which was measured as the logarithmic form of the number of full-time employees. Besides, firms' *technological domains* were controlled because new ideas could be developed with a combination of different technological elements. This control variable was measured by the sum of technical classes in which a firm had applied for its patents following George et al. (2008). Because firms may apply for patents in several different countries that are related with each other, we controlled *patent family size* by calculating the number of countries where the family was represented (Dechezleprêtre et al., 2017). *Business diversification* was measured as the number of a firm's main business. *Firm ownership* was measured as a dummy variable with a value of "0" if the state was the main investor of the sample firm. Otherwise, the value was set as "1". *Firm region* was also measured as a dummy variable that took the value of "1" if the firm was located in East China, including Beijing City, Shanghai City, Tianjin City, Hebei province, Shandong province, Jiangsu province, Zhejiang province, Fujian province, Guangdong province and Hainan province, which are the most developed cities and provinces in China, otherwise "0". Finally, *industry type* was controlled based on the sub-industries the focal firm was engaged in, including electronic information and component (Type 1), communication (Type 2), and others including safety equipment, home appliances, materials, auto and so on.

3.3. Models

The effect of three different forms of EKA on firms' innovation performance was tested with a panel dataset consisting of 77 Chinese publicly listed firms in EIT industries across 13 years from

2004 to 2016. To test the hypotheses, random effects models were used to control for unobservable individual heterogeneity and time effects (Xu et al., 2013). If unobservable heterogeneity was correlated with the explanatory variables, a fixed effects approach should be adopted. However, if the effects were not correlated with the independent variables, unconditional inference using the random effects method should be used (Campbell and Minguez-Vera, 2008). Random effects models were applied in the research because an unbalanced panel data in this study failed to meet the requirements of adopting the fixed effects approach, which required at least three consecutive observations per firm (Grimpe and Kaiser, 2010).

The empirical analysis was conducted with regressions for EKA through patent backward citations, patent collaboration and patent purchase, and their interaction terms with internal R&D respectively. Subsequently, the level of balance among three forms of EKA were used to test how the simultaneous use of different forms of EKA affect firms' innovation performance. The interaction term between the level of balance among three forms of EKA with internal R&D was added. As there was usually a time lag between firms' EKA and their innovation performance, all independent variables were lagged by one year compared with the dependent variable. The lag structure was used to alleviate the potential simultaneity between EKA and firms' innovation performance. Following the existing literature, mean centered variables were transformed before two variables formed an interaction term, which reduced the risk of multicollinearity (Aiken and West, 1991).

To test the hypotheses, four regression models are proposed. Equation (2) examines the effect of three different forms of EKA on the innovation performance of firm i.

$$Innovation\ \ performance_i = \beta_0 + \beta_1 EKA_i + \beta_2 Internal\ \ R\&D_i + \sum \gamma_n Control_{n_i} \tag{2}$$

Equation (3) examines the interaction effect between internal R&D and three different forms of EKA on the innovation performance of firm i. In Equation (3), if the interaction effect between internal R&D and EKA is positive (i.e., when $\beta_3 > 0$), they have a complementary relationship. Conversely, if the interaction effect is negative (i.e., when $\beta_3 < 0$), they have a substitution relationship.

$$Innovation\ \ performance_i = \beta_0 + \beta_1 EKA_i + \beta_2 Internal\ \ R\&D_i + \beta_3 EKA_i \times Internal\ \ R\&D_i + \sum \gamma_n Control_{n_i} \tag{3}$$

Equation (4) is used to test the inverted U-shaped relationship between the level of balance among three forms of EKA and innovation performance for firm i.

$$Innovation\ \ performance_i = \beta_0 + \beta_1 EKA_i + \beta_2 Internal\ \ R\&D_i + \beta_3 Balance_i + \beta_4 Balance_i^2 + \sum \gamma_n Control_{n_i} \tag{4}$$

Equation (5) is used to test the interaction effects between internal R&D and the level of balance among three forms of EKA on innovation performance of firm i.

$$Innovation\ \ performance_i = \beta_0 + \beta_1 EKA_i + \beta_2 Internal\ \ R\&D_i + \beta_3 Balance_i + \beta_4 Balance_i^2 + \beta_5 Internal\ \ R\&D_i \times Balance_i + \beta_6 Internal\ \ R\&D_i \times Balance_i^2 + \sum \gamma_n Control_{n_i} \tag{5}$$

To test H4b, following the existing literature (Hagedoorn and Wang, 2012; Wiersema and Bowen, 2009), we examine the interaction effects between firms' internal R&D and the level of balance among three forms of EKA. Because the estimation model (Equation 5) is nonlinear, the interaction effect is not equal to the coefficient of interaction term directly, but by the cross-partial derivative of firms' innovation performance first with respect to the level of balance among three forms of EKA, and then with respect to internal R&D. Therefore, taking the first derivative of Equation (5) with respect to the level of balance among three forms of EKA yields Equation (6). Then differentiating Equation (6) with respect to internal R&D yields Equation (7) to demonstrate the true interaction effect between firms' internal R&D and the level of balance among three forms of EKA.

$$\frac{\partial Invention\ \ performance_i}{\partial Balance_i} = \beta_3 + 2\beta_4 Balance_i + \ \beta_5 Internal\ \ R\&D_i + 2\beta_6 Internal\ \ R\&D_i \times Balance_i \tag{6}$$

$$\frac{\partial\left({\partial Invention\ \ performance_i}/{\partial Balance_i} \right)}{\partial Internal\ \ R\&D_i} = \beta_5 + 2\beta_6 Balance_i \tag{7}$$

As shown in Equation (7), if the interaction effect between firms' internal R&D and the level of balance among three forms of EKA is positive (i.e., when $\beta_5 + 2\beta_6 Balance_i > 0$), they have a complementary relationship. Conversely, if the interaction effect is negative (i.e., when $\beta_5 + 2\beta_6 Balance_i < 0$), internal R&D and the level of balance among three forms of EKA have a substitution relationship.

4. Results

4.1. Descriptive statistics analysis

The descriptive statistics analysis is shown in Table 2. Because the correlation coefficients between some variables are higher than 0.6, there might be the multicollinearity issue. We have conducted a robustness test of variance inflation factors (VIFs). The average value is 4.96 and it is much less than the receivable level (Neter et al., 1996). Therefore, multicollinearity does not have an undue influence on the estimates in this study.

[Table 2 about here]

Table 3 shows the frequencies and average innovation performance for the firms engaged in EKA. The share of firms that are not engaged in any EKA activities (62.6%) are higher than that of firms that are engaged in the EKA activities (37.4%). It implies that not all sample firms were engaged in EKA activities every year although they adopted open innovation strategy. The empirical data also indicate that the ratio of patent backward citations (96.47%) and patent collaboration (16.08%) were higher than that of patent purchase (10.55%) among the sample firms. Most importantly, the firms engaged in the EKA activities achieved higher average innovation performance (5.998) than those not engaged in any EKA activities (0.222). Besides, the firms engaged in the EKA activities had higher average internal R&D activities (14.03) than those did not undertake any EKA activities (0.131).

[Table 3 about here]

The above analysis clearly shows the positive relationship between EKA and firms' innovation performance as well as the complementary effect between EKA and internal R&D of the sample firms. Since firms' innovation performance may be driven by firm size, technological domains and patent family size, we have reported the average of these variables. The results show that the firms with bigger size, broader technological domains and higher patent family size are more inclined to be engaged in EKA activities. Firms age, business diversification, ownership, region and industry type show the similar patterns. Table 4 shows the basic format of panel data we used to conduct the regression analysis. The real names of case firms were replaced by the alphabet due to the privacy protection. The case firms' names have been provided in Appendix B Table A1.

[Table 4 about here]

4.2. *Regression results*

Table 5 shows the results of random effects estimation models, with which we tested the effect of three different forms of EKA on firms' innovation performance. We also examined whether EKA had substitution or complementary relationship with firms' internal R&D.

[Table 5 about here]

The first regression is the baseline model including the control variables only (Model 1). In Model 2, the main explanatory variables, EKA through patent backward citations, patent collaboration and patent purchase, are introduced. In Model 3, 4, 5, the interaction terms between internal R&D and three different forms of EKA are added respectively. In Model 6 and 7, the level of balance among three forms of EKA and its interaction terms with internal R&D are added respectively. In the full model (Model 8), all of independent variables and interaction terms are included.

Hypothesis 1a, 2a and 3a predict that EKA through patent backward citations, patent collaboration and patent purchase play a positive role in firms' innovation performance respectively. The results in Model 2 provide support for Hypothesis 1a and 2a. EKA through patent backward citations has a positive effect on firms' innovation performance ($\beta=0.011$, $p<0.01$). EKA through patent collaboration also has a positive effect on firms' innovation performance ($\beta= 0.678$, $p<0.01$). However, the effect of patent purchase on firms' innovation performance is positive but not significant, so H3a is not confirmed ($\beta=0.068$, $p>0.1$).

Hypothesis 1b, 2b and 3b focus on the interaction effects between EKA and internal R&D of firms. In Model 3, the regression coefficient of interaction term between internal R&D and patent backward citations is positive and statistically significant ($\beta=0.00004$, $p<0.01$), which supports H1b that there is a complementary relationship between EKA through patent backward citations and internal R&D on firms' innovation performance despite the relatively small coefficient. In Model 4, the regression coefficient of interaction term is negative and statistically significant (β=-0.003, $p<0.01$), which confirms H2b that there is a substitution relationship between EKA through patent collaboration and internal R&D on firms' innovation performance.

The regression coefficient of interaction term in Model 5 is negative and statistically significant (β=-0.062, $p<0.1$), which indicates that there is a substitution relationship between EKA through patent purchase and internal R&D on firms' innovation performance, which supports H3b. These empirical results suggest that EKA not only influence firms' innovation performance directly, but also interact with internal R&D to affect firms' innovation performance.

Hypothesis 4a suggests that the level of balance among three different forms of EKA have an inverted U-shaped relationship with firms' innovation performance. In Model 6, the balance variable shows a positive and statistically significant coefficient while the balance squared shows a negative and statistically significant coefficient (β_1= 38.320, $p<0.05$; β_2= -58.662, $p<0.05$). This result confirms that the level of balance among three different forms of EKA has an inverted U-shape effect on firms' innovation performance, which supports H4a.

To examine the interaction effects between internal R&D and the balance among three forms of EKA on firms' innovation performance (Hypotheses 4b), we checked the magnitude and statistical significance of the value expressed in Equation (7), $\beta_5 + 2\beta_6 Balance_i$. We also conducted a graphical analysis to identify the interaction effects intuitively by plotting its value over the range of different levels of balance among three forms of EKA (Hagedoorn and Wang 2012; Wiersema and Bowen 2009).

Figure 2 is plotted based on Equation (7) by using the parameters in Model 7 of Table 5. In Figure 2, the estimated value of interaction effects, ranging from -1.812 to 0.964, can be visually observed from the middle scattered line. The upper and lower lines are plotted with 90% confidence intervals. Figure 2 presents the varying value of interaction effects when the level of balance among three different forms of EKA changes. More specifically, as the value of balance among three forms of EKA ranges from 0 to 0.830, the value of interaction effects between internal R&D and the level of balance among three forms of EKA may be either positive or negative. It equals to zero when the balance is at the level of 0.542. The interaction effects are negative and statistically significant

($p<0.10$) when the level of balance is less than 0.425, indicating that internal R&D and the level of balance among three forms of EKA serve as substitutes for firms' innovation performance. By contrast, when the level of balance is larger than 0.625, the interaction effects are positive and statistically significant ($p<0.10$). It shows that internal R&D and the level of balance among three forms of EKA serve as complements for firms' innovation performance.

[Figure 2 about here]

In Model 8, the coefficients of EKA through patent backward citations, patent collaboration, patent backward citations × internal R&D, balance × internal R&D and balance^2×internal R&D are still statistically significant. Therefore, Hypotheses 1a, 1b, 2a and 4b are supported. However, we find that the coefficients of patent collaboration × internal R&D, patent purchase× internal R&D, balance and balance^2 are not statistically significant. It means that the hypothesized main effect and interaction effects are "diluted" to some extent when including all independent variables and interaction terms.

The findings of control variables are in the following. First, Model 1 shows that the coefficient of firm age is positive and statistically significant. It means that the incumbent firms have better innovation performance compared with the younger firms in our sample. Second, the coefficient of firm size is negative and statistically significant. It indicates that the medium-sized firms, which are the engine of technological innovation in the high-tech industry, play an increasingly crucial role in stimulating innovation in China. Third, the coefficient of technological domains is positive and statistically significant. It suggests that the breadth of technological domains enhance firms' innovation performance. Fourth, the coefficient of business diversification is positive and statistically significant. It means that diversified business layout can potentially contribute to firms' innovation performance. Finally, the firms having expertise in electronic information and component industry achieve higher innovation performance than those in other sub-industries.

4.3. *Robustness tests*

We conducted additional tests to assess the robustness of our empirical results. First, a major concern arose from the potential bias due to the self-citations, which meant that a sample firm might cite its own patents. Thus, we distinguished between self-citations and non-self-citations, which allowed us to examine the role of EKA in firms' innovation performance more accurately.

Afterwards, some additional tests were carried out by excluding those self-citations from the total patent backward citations. Because self-citations accounted for only a small percentage of total backward citations (2.47%), the similar findings were confirmed as shown in Table 6.

[Table 6 about here]

Second, an alternative measure of firms' innovation performance was used to investigate whether the idiosyncratic nature of R&D investment efficiency strictly determined the empirical findings. We used the ratio of the number of patents that a sample firm applied for to the number of its R&D employees as dependent variable to re-estimate the models. The results in Table 7 are highly consistent with those in Table 5, thereby confirming the proposed hypotheses.

[Table 7 about here]

Third, an additional test was conducted to exclude those firm-year observations that had not been engaged in any forms of EKA. Similar findings were made as shown in Table 8, thereby confirming the proposed hypotheses.

[Table 8 about here]

Fourth, a Tobit estimation model was used to reduce the inconsistency of random-effects estimates. If the value of dependent variable is greater than or equal to zero, it fails to meet the requirement of an even distribution on number lines without interception (Berchicci 2013; Kafouros et al. 2015). Model 2 in Table 9 shows that there is a positive relationship between EKA through patent backward citations, patent collaboration and firms' innovation performance respectively. Model 3, 4, 5 indicate that the interactions between EKA and internal R&D are in accordance with the random-effects regression results. Besides, the regression coefficient of balance is still positive and statistically significant. The regression coefficient of balance^2 remains negative and statistically significant in Model 6, which confirms the results in Table 5. Model 7 shows that the interaction effects between internal R&D and the level of balance among three forms of EKA are highly similar with those in Table 5.

[Table 9 about here]

Finally, in order to illustrate how the interaction effects between internal R&D and EKA on firms' innovation performance is affected by different levels of balance, we have plotted one quadratic graph by dividing our sample into two cohorts (see Figure 3). Figure 3 shows two curvilinear trends about the relationship between the level of balance of three forms of EKA and firms' innovation performance on the condition of high internal R&D and low internal R&D. As shown in Figure 3, when the level of balance is low, high internal R&D is associated with smaller marginal effect from the level of balance of EKA on firms' innovative performance, indicating that internal R&D and the level of balance serve as substitutes for firms' innovation performance. However, as the level of balance increases, the substitution effect gradually changes into the complementary effect. When the level of balance is high, high internal R&D is associated with greater marginal effect from the balance level of EKA on firms' innovation performance, indicating that internal R&D and the level of balance of EKA serve as complements for firms' innovation performance. Taken together, these findings are highly similar with those created by the second derivative method, indicating that both hypotheses 4a and 4b are supported.

[Figure 3 about here]

5. Discussion and conclusions

EKA plays critical role in firms' innovation performance, especially for technology-intensive firms because they face the challenges of rapidly changing technologies. This paper has examined whether EKA and internal R&D serve as substitutes or complements for firms' innovation performance by distinguishing three forms of EKA including patent backward citations, patent collaboration and patent purchase. It is argued in the paper that these three forms of EKA, which are characterized by knowledge heterogeneity, acquisition cost and interactivity with external resources, have interaction effects with internal R&D on firms' innovation performance. Using a sample of 77 Chinese publicly listed firms in the EIT industry during 2004-2016, we have reached the following new findings.

First, different forms of EKA have different effects on firms' innovation performance. For example, CEO of Fujitsu Limited said: "Innovation is very hard for firms in developing countries. If firms rely on themselves, it is inevitable to spend much money and also bear high risks. Fujitsu Limited has achieved a win-win goal by adopting the open innovation strategy." Indeed, both patent backward citations and patent collaboration have positive effect on firms' innovation performance, and the latter has greater effect. Patent purchase cannot promote firms' innovation performance. From the research framework based on heterogeneity, cost and interactivity, firms may have to bear high cost of patent purchase in the technology market. Patent purchase may have crowding-out effect on firms' innovation performance. When firms become increasingly reliant on patent purchase, their internal R&D capability may weaken in the long term.

Actually, many firms have achieved their superior innovation performance through collaborations. For example, Hikvision, an Internet of Things (IoT) solution provider, has reached joint R&D agreements with Peking University, Zhejiang University, China and its suppliers such as Texas Instruments in the United States to conduct AI technology research. BOE, a leading IoT company providing intelligent interface products and professional services for information interaction and human health, has opened up and collaborated with global innovation partners to jointly build an intelligent ecosystem.

Second, EKA, which complements internal R&D through patent backward citations, has positive interaction effects on firms' innovation performance. However, EKA can also substitute firms' internal R&D through patent collaboration and patent purchase. For example, Suzhou Zhito Technology holds that patents purchase is an expedient strategy when entering into a new technology domain. Firms can learn and gather experience at an early stage. However, firms can also be easily trapped in business diversification and may lose their internal R&D capabilities. Its CEO believe that patent purchase is only a temporary alternative to internal R&D. Firms should strengthen their internal R&D capabilities and grasp the core technologies in their own hands.

Third, our empirical results have shown an inverted U-shaped relationship between the level of balance among three forms of EKA and firms' innovation performance. Balance is a contingency variable affecting the interaction between firms' internal R&D and the level of balance among three different forms of EKA. For example, Hikvision has adopted open innovation strategy through actively conducting various EKA activities, such as R&D collaborations with its upstream and downstream firms, joint R&D, M&A and purchasing outstanding technologies. After integrating internal and external knowledge, it has entered into AI domains, and expanded its products and services to smart home.

5.1. Theoretical implications

This paper has made the following contributions to extant literature. First, it contributes to the EKA literature through synthesizing two theoretical views (TCT and ACT) with three properties (heterogeneity, cost and interactivity) embedded in EKA. An integrated framework has been developed to examine how the implicit properties embedded in EKA affect firms' innovation performance. The extant literature affirms that firms can benefit from EKA to improve their innovation performance in terms of learning (Díaz-Díaz and de Saá Pérez, 2014), technology upgrading (Wang et al., 2013) and recombining the knowledge elements (Wang et al., 2014). However, the properties of EKA have been ignored such as homogeneous or heterogeneous external knowledge, the cost of acquiring external knowledge, and the interactivity with external knowledge sources.

The research has examined the implicit mechanisms determining how different forms of EKA affect firms' innovation performance. Theoretically, each form of EKA is characterized by knowledge heterogeneity, acquisition cost and interactivity. The empirical study in this paper based on the perspective of patent is just an example. When a focal firm chooses to make EKA to improve its innovation performance, it needs to fully consider these characteristics. For example, when a focal firm obtains external knowledge through M&A, it needs to fully take into account the knowledge heterogeneity of the acquired unit and internal R&D, which is largely related to the later integration. It is essential to evaluate the cost of M&A by undertaking a cost-benefit analysis of M&A assets. Meanwhile, it is necessary to consider the interaction and integration activities with the acquired unit to assess if in-depth interaction and resource sharing can be achieved.

This study has also introduced a new concept of balance to explore the comprehensive effects of different forms of EKA. The empirical results suggest that firms, which maintain a moderate level of balance among three forms of EKA, can gain the optimal benefits in firms' innovation performance because it can help firms trade off between homogeneous and heterogeneous knowledge, current costs and future earnings, knowledge absorption and knowledge leakage under the open innovation paradigm.

Second, this study contributes to the open innovation literature by following the calls for further investigation of the interaction effects between internal R&D and EKA on firms' innovation performance (Cassiman and Veugelers, 2006; Hagedoorn and Wang, 2012). Extant literature has explained the interaction effects between internal R&D and EKA from the perspective of firms' internal R&D investment and capacity (Berchicci, 2013; Ferraris et al., 2017; Hagedoorn and Wang, 2012). The paper has enriched the open innovation literature through distinguishing three different forms of EKA. It has clarified the implicit properties embedded in EKA and explored further the interaction effects between different forms of EKA and internal R&D on firms' innovation performance. It is argued that heterogeneity, costs and interactivity jointly determine whether different forms of EKA activities increase or decrease the marginal benefits from firms' internal R&D.

Further, the paper has explored the interaction effects between EKA and internal R&D when firms are engaged in different forms of EKA simultaneously, which is represented by the level of balance. The empirical results have shown that there is a complementary relationship with internal R&D when firms have high-level of balance among three forms of EKA, whereas there is a substitution relationship with internal R&D when firms have low-level of balance among three forms of EKA.

5.2. Managerial implications

The paper provides some useful implications to managers about how to implement the open innovation strategy more effectively and how to improve firms' innovation performance through undertaking different forms EKA activities at the same time. First, managers should realize that different forms of EKA have distinct properties including knowledge heterogeneity, acquisition cost and interactivity, which affect firms' innovation performance. From the perspective of patent activity, patent backward citations and patent collaboration can enhance firms' innovation performance directly through absorbing homogeneous or complementary knowledge. Patent collaboration makes it possible for firms to achieve superior innovation performance by learning from their partners through close interactivity. However, patent purchase has no significant effect on improving firms' innovation performance because of high acquisition costs.

Second, managers need to recognize that EKA and internal R&D are not always complementary. From the perspective of patent activity, patent backward citations and internal R&D have complementary effects on firms' innovation performance, so firms can leverage patent backward citations to improve their internal R&D efficiency. However, EKA through patent collaboration and patent purchase can substitute internal R&D in the short term. Thus, it is very important for firms to strengthen their internal R&D capability and grasp core technologies in their own hands.

Finally, managers should realize the implicit benefits and risks when adopting different EKA strategies. Because many firms are engaged in different forms of EKA simultaneously, how to deploy different types of EKA effectively is critical for them to develop and implement their open innovation strategies. Entropy index can be used to help firms develop their EKA strategies so that they can make more benefits from the open innovation practice. In addition, it is important for managers to maintain a moderate level of balance among different forms of EKA to keep a good balance between homogeneous knowledge and heterogeneous knowledge, current costs and future earnings, knowledge absorption and knowledge leakage under the open innovation paradigm.

5.3. Limitations and future research

There are some limitations in this research. As the three forms of EKA are confined to patent activities, we have not taken into account firms' other EKA activities such as M&A, joint ventures, strategic alliances, R&D outsourcing and so on. Other forms of EKA, including both patent and non-patent activities, should also be considered in the future research. Meanwhile, only the patent data was used to measure firms' internal R&D activities in this study without considering know-how and technological experience embedded within the organizational process. Therefore, it is important to take into account firms' non-patented internal R&D activities in the future research.

Another limitation is the generalizability of research findings because the sample in the paper has only focused on the Chinese publicly listed firms in the EIT industries. We used the patent information of sample firms in the USPTO database instead of the CNIPA database. Although the USPTO database has been widely used and provided rich information on patent ownership changes, some useful information contained in the CNIPA database might have been missed. Future research should focus on the publicly listed firms in other R&D-intensive industries of China or other emerging economies to increase the robustness of empirical findings. Moreover, future studies can collect patent information from various sources so as to have more comprehensive empirical results.

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