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Not every coopetitor is the same: The impact of technological, market and geographical overlap with coopetitors on firms' breakthrough inventions

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ABSTRACT

Whereas most coopetition research tends to conceptualize coopetitors as a homogeneous group, we explicitly consider the heterogeneity of coopetitors. In particular, we examine the impact of a focal firm's technological, market, and geographical overlap with coopetitors on its ability to generate breakthrough inventions. We expect that these different dimensions of overlap and their interactions shape knowledge acquisition opportunities and knowledge leakage risks in coopetition, which in-turn influences the ability of the focal firm to generate breakthrough inventions. To examine our theoretical arguments, we construct a unique data set from 323 firms in the global solar photovoltaic industry between 1995 and 2015. Our results indicate an inverted U-shaped relationship between a focal firm's technological overlap with its portfolio of coopetitors and its breakthrough inventions. In addition, we find that its market and geographical overlap with the portfolio of coopetitors moderate this curvilinear relationship. However, when both market overlap and geographical overlap are simultaneously considered, the moderation effect of geographical overlap becomes insignificant. Jointly, these findings enrich the coopetition literature, pointing to the relevance and importance of considering the interactions between technological, market and geographic heterogeneity of coopetitors.

Introduction

Breakthrough inventions or “inventions that serve as the source of many subsequent inventions” (Ahuja and Lampert, 2001: 523) are an important source of competitive advantage (Park et al., 2018; Srivastava and Gnyawali, 2011). At the same time, generating such impactful inventions is challenging as it requires recombining non-redundant knowledge (Dong et al., 2017; Kaplan and Vakili, 2015; Park et al., 2018). Scholars (e.g., Bouncken and Kraus, 2013; Dong et al., 2017; Ritala and Hurmelinna-Laukkanen, 2013; Ritala and Sainio, 2014) point to coopetition — i.e., collaboration with competitors from the same industry sector (Gnyawali et al., 2006; Gnyawali and Park, 2009) — as a viable strategy to boost firms' ability to generate breakthrough inventions.

Although coopetitors are active in the same sector, they are likely to experiment with different technologies. When a focal firm¹

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¹ In this paper, we conduct a firm-level analysis on how coopetition impacts breakthrough inventions of a particular firm. We consistently refer to this latter actor as the “focal firm”. When a focal firm engages in formal collaboration with competitors (i.e., firms from the same industry sector), we refer to the focal firm and its competitors as “coopetitors” with each other.

collaborates with coopetitors, it can more easily identify and absorb such non-redundant knowledge. In this way, coopetition provides *knowledge acquisition opportunities*, expanding the focal firm's pool of non-redundant knowledge, which increases its probability of generating breakthrough inventions (Chen, 1996; Gnyawali and Park, 2011; Ritala and Sainio, 2014). However, coopetition also brings along *knowledge leakage risks* (Gnyawali and Park, 2011; Zaheer et al., 2000). When a focal firm engages in coopetition relationships, knowledge can spillover to coopetitors. These coopetitors can subsequently use this knowledge to generate inventions, which restricts the focal firm's knowledge recombination space, hampering the latter's ability to generate breakthrough inventions.

Theorizing on the knowledge recombination opportunities and risks of coopetition, scholars tend to conceptualize and operationalize coopetitors as a homogeneous group of partners, operating in the same industry. In this way, limited attention has been given to the heterogeneity among coopetitors. A notable exception is the work of Park et al. (2014a, 2014b). Developing a novel measure of coopetition intensity, they explicitly recognize heterogeneity among coopetitors in terms of technological and market overlap among coopetitors.² Moreover, they provide first evidence that such heterogeneity influences the knowledge recombination benefits of coopetition.

In this paper, we aim to expand our understanding of coopetitor heterogeneity and its knowledge recombination implications in two ways. First, whereas Park et al. (2014b) look at technological and market overlap as two independent dimensions, we explore potential interactions between different dimensions of coopetitor heterogeneity. We argue that considering such interactions is important, as they are likely to shape both the knowledge acquisition opportunities and knowledge leakage risks of coopetition. Second, whereas Park et al. (2014a, 2014b) consider coopetitor heterogeneity in terms of technological and market overlap, we also introduce the dimension of geographical overlap. Looking at geographical overlap is important because scholars (e.g., Faems et al., 2019; Ryu et al., 2018) have recently shown that it can have significant implications for firms' ability to acquire knowledge from external partners.

In sum, the core objective of this paper is to test the extent to which the interactions between technological, market and geographical overlap between a focal firm and its portfolio of coopetitors influence the focal firm's ability to generate breakthrough inventions. To do so, we construct a panel data set from 323 firms in the global solar photovoltaic (PV) industry between 1995 and 2015. Merging data from multiple archival sources, we identify for each firm its portfolio of coopetitors and operationalize for each coopetition relationship the level of technological, market and geographical overlap. We then conduct a firm-level analysis, examining the impact of a focal firm's average level of technological, market, and geographical overlap with its portfolio of coopetitors on its ability to generate breakthrough inventions. Taking the quantity and quality of breakthrough inventions into account, we rely on the focal firm's number of highly cited patents to measure their breakthrough inventions (Ahuja and Lampert, 2001; Dong et al., 2017). Our analysis provides support for an inverted U-shaped relationship between technological overlap with coopetitors and breakthrough inventions. This relationship is moderated by the level of market and geographical overlap with coopetitors. However, we observe that, when simultaneously considering market and geographical overlap, the moderation effect of geographical overlap becomes insignificant.

Our study advances our understanding of the knowledge recombination tradeoffs of coopetition by illuminating the importance of interactions among different dimensions of coopetitor heterogeneity. We also contribute to the emerging research stream on the role of geography in interorganizational collaboration (e.g., Faems et al., 2019; Ryu et al., 2018). In particular, we point to the importance of considering market-related dimensions when exploring the performance implications of geographical characteristics. From a practical perspective, our findings provide specific recommendations on how firms can actively manage the tension between knowledge acquisition and knowledge leakage when engaging in coopetition relationships.

Coopetition, knowledge acquisition and knowledge leakage

In this section, we rely on extant research to discuss how coopetition can influence the ability of focal firms to generate breakthrough inventions. We point to knowledge acquisitions opportunities and knowledge leakage risks as two core mechanisms. Subsequently, we introduce our key constructs (i.e., technological, market and geographical overlap with coopetitors).

Coopetition, knowledge recombination and breakthrough inventions

Only a limited set of inventions have a strong impact by serving as the starting point for many subsequent inventions (Arts and Veugelers, 2014; Jung and Lee, 2016). These high-impact inventions are labelled as breakthrough inventions (Ahuja and Lampert, 2001). Although they are relative rare, breakthrough inventions are important for value creation, innovation and growth. Scholars (e.g., Dong et al., 2017; Park et al., 2018; Subramanian and Soh, 2017) have therefore examined the process of generating breakthrough inventions. A common observation is that generating breakthrough inventions requires the recombination of non-redundant knowledge (Fleming, 2001). Hargadon and Sutton (1997), for instance, stress the need of technological brokering — i.e., the creation of new inventions by combining formerly uncombined technologies — to generate breakthrough inventions. Testing these arguments in the biotechnology industry, Arts and Veugelers (2014) find that inventions, which recombine particular knowledge elements or technologies for the first time in history, are more likely to become breakthrough inventions.

Coopetition has been recognized as a strategy that can help a focal firm in recombining non-redundant knowledge (Gnyawali and

² To measure coopetition intensity, Park et al. (2014a) solely focus on market overlap, whereas both market and technological overlap are considered in the Park et al. (2014b) paper.

Park, 2009; Gruber et al., 2013). Although coopetitors are active in the same industry, this does not imply that their knowledge is redundant.³ In contrast, coopetitors can engage in a wide variety of explorative activities, such as, experimenting with novel, emerging and pioneering technologies (Ahuja and Lampert, 2001), implying the generation of knowledge that might be non-redundant for the focal firm. Collaboration with such competitors allows the focal firm to access non-redundant knowledge, expanding its pool of non-redundant knowledge, which increases the likelihood of generating high-impact or breakthrough inventions (Carnabuci and Operti, 2013; Fleming, 2001). In sum, coopetition supports the process of creating breakthrough inventions as it gives the focal firm more recombinant opportunities based on non-redundant knowledge from its coopetitors.

However, coopetition also implies knowledge leakage risks (Bouncken and Kraus, 2013; Nieto and Santamaría, 2007). When partners pool knowledge together, a shared knowledge pool emerges from which all partners can benefit even when their contributions to the generation of this knowledge are unbalanced. As a result, a focal firm could lose valuable knowledge to competitors with whom it collaborates and competes at the same time (Lavie, 2006). These coopetitors might subsequently recombine this knowledge, which in turn restricts the focal firm's set of recombinant possibilities, hampering the generation of breakthrough inventions for the focal firm. Existing research (e.g., Bouncken and Kraus, 2013; Nieto and Santamaría, 2007) has shown that coopetition indeed entails the risk of opportunistic actions, particularly knowledge leakage. In this way, coopetition can also hamper the focal firm's ability to generate breakthrough inventions.

Coopetitors as a heterogeneous group

While the role of coopetition in helping firms to generate technological breakthroughs has been recognized in the coopetition literature, prior coopetition research mainly conceptualized coopetitors operating in the same industry as a rather homogenous group. Further building on the work of Park et al. (2014a, 2014b), we expect that coopetitors can vary considerably in terms of their technological overlap, market overlap, and geographical overlap.

We define a focal firm's technological, market and geographical overlap with its coopetitors as the extent to which a focal firm's technological fields, market domains and geographical locations are, on average, similar to the technological fields, market domains and geographical locations of competitors with whom the focal firm collaborates. Technological overlap indicates the average degree to which a focal firm is active in the same technological domains with its portfolio of coopetitors (Sears and Hoetker, 2014). We consider a focal firm's technological overlap with coopetitors as a core factor, shaping its knowledge acquisition opportunities and knowledge leakage risks in coopetition relationships. We therefore rely on the relationship between a focal firm's technological overlap with coopetitors and its breakthrough invention as the baseline relationship in our theoretical framework.

Market conditions might affect a firm's behavior, such as its learning and response behavior (Chen and MacMillan, 1992; Gimeno, 2004). When firms face different markets, they might behave and perform differently (Nelson, 1994). In this study, we specifically focus on market overlap, which indicates the average degree to which a focal firm is involved in the same marketplaces as its portfolio of coopetitors (Luca and Atuahene-Gima, 2007). When a focal firm has high market commonality with its coopetitors, they are more likely to speak similar commercial language and have common user experiences, which can intensify technological knowledge transfer activities between them. We therefore expect that the relationship between technological overlap and breakthrough inventions is moderated by a focal firm's market overlap with coopetitors.

Geographical overlap indicates the average degree to which a focal firm is operating in common geographical locations with its portfolio of coopetitors. Geographic agglomeration scholars (e.g., Bell and Zaheer, 2007; Lublinski, 2003) argued that higher geographical overlap between firms might generate more benefits that spring from regular face-to-face contacts that can be easily realized between nearby firms. For example, Bell and Zaheer (2007) found that interorganizational ties act as transmitters of knowledge only when they are geographically proximate. Because geographical overlap also influences technological knowledge transfer, we also expect that it moderates the relationship between a focal firm's technological overlap with coopetitors and its breakthrough inventions.

Hypotheses

Technological overlap with coopetitors and breakthrough inventions

We propose that higher technological overlap between a focal firm and its portfolio of coopetitors increases the ability of the focal firm to acquire non-redundant knowledge from these coopetitors. The extent to which the focal firm can acquire such non-redundant knowledge and create breakthrough inventions depends on its ability to (i) spot non-redundant elements and (ii) absorb such elements. First, breakthrough inventions require much search costs in recombining relatively new knowledge elements (Ahuja and Lampert, 2001), but we expect that technological overlap can improve the ability of the focal firm to identify non-redundant knowledge from its coopetitors. When the focal firm's technological overlap with its coopetitors is high, it can better associate coopetitors' technological activities with what it already knows (Dong et al., 2017; Reagans and McEvily, 2003; Shane, 2000). In this way, technological overlap helps the focal firm to spot particular non-redundant elements in the knowledge pool of its coopetitors. Second, technological overlap facilitates the absorption of non-redundant knowledge by the focal firm. When knowledge is

³ In our sample of firms in the solar PV industry, the mean of technological overlap between a focal firm and its coopetitors is very low (i.e., 0.008), indicating considerable differences in their knowledge domains.

transmitted, the risk of distortion is present (Faems et al., 2019). Technological overlap reduces this risk as the focal firm and its coopetitors have a shared cognitive framework. In this way, the focal firm's risk of misunderstanding or misinterpreting non-redundant knowledge from its coopetitors is reduced.

However, as a focal firm's technological overlap with coopetitors increases, the marginal benefits of increasing technological overlap for acquiring non-redundant knowledge are likely to diminish. Whereas increasing technological overlap reflects an increased ability to spot and absorb non-redundant knowledge, there is the challenge that, when technological overlap is very high, coopetitors become less likely to provide the focal firm access to non-redundant knowledge. Compared to a transition from low to medium levels of technological overlap, a transition from medium to high levels of technological overlap therefore implies a smaller number of additional non-redundant knowledge elements, which can be acquired from the focal firm's coopetitors. Therefore, the non-redundant knowledge acquisition benefits for the focal firm are greater when technological overlap is moving from a low to a medium level than when technological overlap is moving from a medium to a high level. A focal firm's technological overlap with coopetitors therefore provides diminishing benefits in terms of knowledge acquisition opportunities.

Shifting attention from knowledge inflows to knowledge outflows, we also consider the knowledge leakage risks of increased technological overlap. Higher technological overlap also implies that the coopetitors are more able to spot and absorb knowledge from the focal firm. When a focal firm's coopetitors use the leaked knowledge for their own knowledge recombination activities, the recombination options for the focal firm decrease, reducing its ability to generate breakthrough inventions. In contrast to the knowledge acquisition opportunities, however, we do not expect that the knowledge leakage risks become less pronounced in the case of high levels of technological overlap. When technological overlap becomes very high, the coopetitors will have relatively limited options to acquire non-redundant knowledge from the focal firm. However, they might still have plenty of options to spot and absorb other knowledge elements from the focal firm. Although it will be challenging for the coopetitors to use these other knowledge elements to generate breakthrough inventions, it can still use them for other types of inventions (e.g., exploitative and incremental inventions). These inventions generated by the coopetitors might still restrict the recombination maneuvering space of the focal firm, hampering its ability to generate breakthrough inventions. Thus, we do not expect that the knowledge leakage risks will diminish as technological overlap increases.

In sum, as technological overlap between a focal firm and its portfolio of coopetitors, on average, increases, the focal firm will experience (i) diminishing marginal benefits from the opportunities to acquire non-redundant knowledge from its coopetitors and (ii) higher risks of knowledge leakage to its coopetitors. Haans et al. (2016) describe that, when an independent variable generates marginal diminishing benefits and linear costs, these additive mechanisms result in an inverted U-shaped relationship between the independent variable and the performance outcome (see Fig. 1). Therefore, we formulate the following hypothesis:

H1. A focal firm's technological overlap with its portfolio of coopetitors has an inverted U-shaped relationship with its breakthrough inventions.

The moderating role of market overlap with coopetitors

We further argue that the inverted U-shaped relationship between technological overlap and breakthrough inventions is moderated by a focal firm's market overlap with coopetitors. Market overlap refers to the average degree to which a focal firm and its portfolio of coopetitors overlap in their market domains. We propose that market overlap is likely to intensify the knowledge acquisition opportunities of technological overlap. Given a particular level of technological overlap, we expect that, when a focal firm's market overlap with coopetitors increases, its opportunities to recognize non-redundant knowledge elements from its coopetitors are amplified. When a focal firm and its coopetitors have high market overlap the focal firm will have a better understanding of the commercial context in which the technological activities of the focal firm are embedded (Sammarrà and Biggiero, 2008). Such commercial understanding can foster the focal firm's ability to spot which knowledge elements of its coopetitors have most recombination potential for breakthrough inventions. Market overlap can therefore amplify the focal firm's benefits of technological overlap in terms of spotting non-redundant technological knowledge from its coopetitors (Tsai, 2002), increasing knowledge recombination opportunities and the associated likelihood to generate breakthrough inventions.

Due to the curvilinearity of knowledge acquisition opportunities associated with technological overlap (i.e., diminishing benefits

Fig. 1. Additive mechanisms of the inverted U-Shaped relationship between technological overlap and breakthrough inventions.

Fig. 2. Market overlap and geographical overlap steepen the inverted U-Shaped relationship between technological overlap and breakthrough inventions.

from knowledge acquisition opportunities with increasing technological overlap), market overlap will amplify the curvilinearity of the inverted U-shaped relationship between technological overlap and breakthrough inventions, leading to a steepening shape as shown in Fig. 2 (Haans et al., 2016). We therefore propose the following hypothesis:

H2. A focal firm's market overlap with its portfolio of coopetitors moderates the inverted U-shaped relationship between technological overlap and breakthrough inventions, such that the inverted U-shaped curve becomes steeper when market overlap is higher.

The moderating role of geographical overlap with coopetitors

We also argue that the inverted U-shaped relationship between technological overlap and breakthrough inventions is moderated by a focal firm's geographical overlap with coopetitors. Geographical overlap with coopetitors refers to the average degree to which the focal firm and its portfolio of coopetitors overlap in their geographical locations. We propose that geographical overlap is likely to intensify the knowledge acquisition opportunities of technological overlap. It is well established that knowledge tends to spillover locally and takes time to transfer across geographic distance (Jaffe et al., 1993). The lower the distance between a focal firm and its coopetitors, the higher the likelihood of frequent face-to-face interactions between them. This implies that, in the case of high geographical overlap, knowledge acquisition of the focal firm from its coopetitors is not only possible via impersonal channels but can also be realized via personal channels (Faems et al., 2019). In contrast, when geographic distance is high, direct contact becomes more difficult (Bouquet and Birkinshaw, 2008). As a result, knowledge absorption is more restricted to impersonal channels and less effective, and is especially problematic in the case of transferring tacit knowledge (Breschi and Malerba, 1997), which is particularly useful for developing breakthrough inventions (Mascitelli, 2000). Given a particular level of technological overlap, we expect that, the higher the geographical overlap between a focal firm and its coopetitors, the broader the scope of communication channels between them, allowing the focal firm to more effectively absorb non-redundant technological knowledge from its coopetitors. In other words, we expect that geographical overlap can strengthen the knowledge acquisition benefits of technological overlap, increasing the likelihood to generate breakthrough inventions.

Because of the curvilinearity of knowledge acquisition opportunities associated with technological overlap (i.e., diminishing benefits from knowledge acquisition opportunities with increasing technological overlap), geographical overlap will amplify the curvilinearity of the inverted U-shaped relationship between technological overlap and breakthrough inventions, leading to a steepening shape as shown in Fig. 2 (Haans et al., 2016). We therefore hypothesize:

H3. A focal firm's geographical overlap with its portfolio of coopetitors moderates the inverted U-shaped relationship between technological overlap and breakthrough inventions, such that the inverted U-shaped curve becomes steeper when geographical overlap is higher.

Haans et al. (2016) suggest that the moderation of a curvilinear relationship is not only represented by a flattening or steepening of the curve, but also is manifested by the upward or downward movement of the turning point. A byproduct of the aforementioned amplifying knowledge acquisition opportunities by market and geographical overlap could be an upward movement of the turning point of the inverted U-shaped relationship between technological overlap and breakthrough inventions, because knowledge acquisition opportunities are increased (see Fig. 2).

However, market and geographical overlap may also amplify the knowledge leakage risks associated with technological overlap. Increased market and geographical overlap do not only imply a firm's greater ability to spot and absorb non-redundant knowledge from its coopetitors, it also implies that these coopetitors will become more able to spot and absorb valuable knowledge from the focal firm. Given a particular level of technological overlap, the knowledge leakage risks could become larger as market and geographical overlap increases. In contrast, when market and geographical overlap is limited, knowledge leakage risks might be less pronounced for a given level of technological overlap. Because market and geographical overlap is likely to amplify knowledge leakage risks of technological overlap, it may also lead to a downward movement of the turning point of the inverted U-shaped relationship between technological overlap and breakthrough inventions.

Taking together the influences of market and geographical overlap on the knowledge acquisition opportunities and knowledge leakage risks of technological overlap, the overall movement of the turning point might be (i) upward if the moderating effect on knowledge acquisition opportunities dominates, (ii) downward if the moderating effect on knowledge leakage risks dominates, or (iii) unchanged if the two moderating effects cancel each other out. The actual movement of the tuning point is therefore an empirical question so we do not develop a hypothesis for it upfront.

Methodology

Data

We test our hypotheses in the context of the global solar PV industry. In this industry, firms mainly develop, manufacture, supply and install solar PV modules, which convert sunlight into useable electricity at the atomic level. A typical PV module employs solar panels that consist of a few solar cells. We choose the solar PV industry as our empirical setting for two reasons. First, this industry has become one of the most important pillars in renewable energy sectors (Kapoor and Furr, 2015). Second, the solar PV industry is very technology intensive (Furr and Kapoor, 2018; Wu and Mathews, 2012). Firms in this industry have a high propensity to patent, allowing us to use patent data to measure breakthrough inventions.

We constructed a unique data set at the firm level from five archival sources. We obtained the alliance data from the Securities Data Company (SDC) Platinum database as well as the LexisNexis database. One of SDC Platinum database's main advantages is its extensive alliance information. The SDC Platinum database offers participant and parent names, SIC codes, the description text and applied text for each alliance. However, this database also has limitations, such as missing information about alliances, occasional errors, and lack of specific industry classifications (Anand and Khanna, 2000; Schilling, 2009). We addressed these limitations by complementing the SDC Platinum database by news searches using the LexisNexis database. The LexisNexis database provides the historical full-text documents of news from more than 17,000 business, legal and news sources in the world. We took the following steps in LexisNexis. First, we collected PV related items⁴ from the scientific literature and experts (Cho et al., 2015; Leydesdorff et al., 2015). Second, we applied a power search, considering all regions of the world, and including all news from English sources for three alliance-related subject indexes⁵ (i.e., Alliances & Partnerships, Divestitures, and Technology Transfer). With these criteria, we obtained 57,689 pieces of news in the solar PV industry between 1995 and 2015. Subsequently, we manually read and coded all the news, resulting in data for 1115 solar PV alliances in 1995–2015. We reviewed every piece of news and supplemented omitted information (e.g., firms' nationality and company name) using secondary sources (e.g., Orbis and Google news). Fourth, we utilized the same PV related items to search in the SDC Platinum database and obtained 514 solar PV alliances in 1995–2015, suggesting that the LexisNexis database is a necessary complement. Finally, using the Bureau van Dijk's (BVD) Orbis database, we cleaned our dataset by unifying similar company names. For example, "Sharp", "Sharp Inc", "Sharp Corp" and "Sharp Corporation" were unified to be "Sharp Corporation". We matched each firm with a unique BVD ID in the Orbis database. These procedures resulted in 1210 unique solar PV alliances.

We also relied on the Orbis database to collect data on competition. The Orbis database uses industry classification codes to categorize each firm into one of 19 major sectors (e.g., machinery, agriculture, chemicals, electricity, etc.). In this study, we considered two allying firms as coopetitors if they belong to the same major sector. For example, EMCORE Corporation and AMP Inc. allied in the year 1998. Because both of them belong to the machinery sector, we considered them to be coopetitors in the year 1998. Based on this information, we identified 323 firms that engaged in at least one alliance with a competitor in the observed time period.⁶ Most of these firms are offering machinery (60.99%), electricity (8.66%) and chemical (4.02%) products. In our analyses, we consider all operational alliances with coopetitors. As some alliances have no precise termination dates, we assumed that an alliance with a coopetitor is operational for five years (Bos et al., 2017; Kogut, 1988; Stuart, 2000). For each focal firm, we relied on this information to measure the number of operational alliances with coopetitors for each year. For 82.35% of our observations, the firms were collaborating with one coopetitor in a particular year. For these observations, the values of technological, market and geographical overlap reflect their overlap with a coopetitor in that particular year. For the rest 17.65% of observations, where a focal firm was engaged in more than one coopetition relationships in a particular year, the values of technological, market and geographical overlap reflect the average overlap with all its coopetitors at the portfolio level in a particular year.

We obtained patent data from the European Patent Office's (EPO) PATSTAT database for three reasons. First, the PATSTAT

⁴ "Photovoltaic" or "PV array" or "PV system" or "PV cell" or "PV module" or "solar array" or "solar cell" or "solar panel" or "solar module" or "solar PV" or "backside electrode" or "conversion efficiency" or ("hydrogenated amorphous" or "nanocrystalline" or "microcrystalline amorphous") and "silicon") or ("low resistance metal" and "contact") or (photovoltaic and module) or (bandgap and (engineering or conversion)) or "photo-voltaic module" or "roll-to-roll process" or "tandem structure" or "transparent conducting oxid".

⁵ To make sure that the subject index can cover alliances news accurately, we did the following work. For one thing, we consulted the senior experts in LexisNexis Company. According to their explanations, the indexing is fully automated and based on thesauri, word matrixes and text mining. The subject index can calculate relevancy score with alliances for all news, indicating that it has technological reliability. For another thing, we did a test by searching two companies "Astropower" and "Suryachakra" with and without alliance-related subject indexes. After coding, we found the same seven alliances under two situations, which mean the subject index is reliable.

⁶ Firms that only engaged in PV alliances with non-competitors (i.e., firms that belong to a different major sector) were not considered in this study.

database contains all patent information from more than 40 patent authorities worldwide, with information about filing date, the name and address of inventors and applicant, the technological classes, forward and backward citations (Wagner et al., 2014). Second, each patent application is assigned to one or more International Patent Classification (IPC) corresponding to the invention. IPCs are based on the information included in the description text of inventions as well as drawings, examples and claims. Different from IPC, the U.S. Patent Office Classification (USPOC) classifies patents based on the claims (i.e., the scope of protection) stated within application documents (Gruber et al., 2013). Thus, PATSTAT provides the assigned technological classes determined objectively by the officers, and not by the inventors themselves. For a study interested in the technological overlap with competitors, the IPC thus provides a more suitable classification system for technologies than others. Third, the PATSTAT database is available for linking to the Orbis database. Each applicant was recognized and assigned a unique BVD ID code in the Orbis database. Thus, using BVD ID codes to match patent data can reduce the bias resulting from different forms of company names different databases. We used the application year to assign each patent to a focal firm because this year can closely indicate the timing of technology creation (Guan et al., 2015). Relying on BVD ID codes, we found 36,459 patents filed by our sampled firms in the PATSTAT database. Considering that a patent may be applied for in different countries, we calculated its citations by summing up the citations of all patents belonging to the same patent family.

Financial data were collected from the Standard and Poor's Compustat database and the Orbis database. The Compustat database is one of the most widely used databases for financial data. Compared with the Orbis database, the Compustat database provides longer historical data. However, the Orbis database covers both private and public companies around the world. Since over 99% of the companies in the Orbis database are private, it is a good complement to the Compustat database, allowing us to include more companies in our final sample. In the end, we obtained 2582 firm-year level observations.

Measures

Breakthrough inventions: Following prior research on breakthrough inventions (Srivastava and Gnyawali, 2011; Zheng and Yang, 2015), we used the number of patents that were above the 97th percentile in terms of their forward citations in each year to measure breakthrough inventions. To calculate this measure, we first used the same PV related keywords to collect all relevant patents (more than 420,000), and ranked all the forward citations for all patents in each year. We then calculated the 97th percentile for forward citations in each year. Finally, breakthrough inventions were calculated by each firm's number of patents with citations that fell above the 97th percentile of forward citations in each application year. In a robustness check, we also calculated alternative measures based on 99th, 98th and 95th percentiles of forward citations. Considering that creating breakthrough ideas takes time, we measure breakthrough inventions in three years (i.e., year $t + 1$ to $t + 3$) subsequent to the year in which we measure all the independent and control variables. In a robustness check, we found consistent results by using two-, four- or five-year lags. We also calculated breakthrough inventions by using the citation-weighted number of patents with forward citations above the 97th percentile in each year.

Technological overlap: We measured technological overlap by calculating the degree to which a focal firm's six-digit IPC codes are the same with its competitors' six-digit IPC codes in their patent portfolios (Park et al., 2014a; Song et al., 2003). To compute this variable, we collected all sampled firms' patents from the PATSTAT database. We then produced each firm's vector of IPC codes and computed the angle cosine — that is, the angle of length between two vectors. Angle cosine is a reverse similarity measure as the greater the angle between two vectors of IPC codes the lower is their similarity (Guan and Yan, 2016; Guellec and de la Potterie, 2001). Technological overlap of competitors i and j can be calculated as follows:

$$\text{Technological overlap}_i = \frac{1}{n} \sum_{j=1}^n \frac{f_i f'_j}{\sqrt{(f_i f'_i)(f_j f'_j)}} \quad (1)$$

where f_i and f_j are multidimensional vectors indicating the distribution of patents filed by the focal firm i and by its competitor j across the six-digit IPC codes in the current and past four years (i.e., year $t - 4$ to t) based on the application year. When firms i and j have identical technological classes, the fraction in the formula equals 1. When their class vectors are orthogonal, the value is 0. Finally, we took average to calculate the focal firm's technological overlap with all its competitors in the portfolio if the focal firm had more than one competitor.

Market overlap: To operationalize market overlap, we considered the degree to which a focal firm's four-digit SIC codes overlap with its competitors' four-digit SIC codes in the current and past four years (i.e., year $t - 4$ to t) (Oxley and Sampson, 2004; Park et al., 2014b). We obtained all four-digit SIC codes of each sampled firm from the Orbis database. Consistent with technological overlap, we measured market overlap by using the angle cosine between two vectors of SIC codes. Market overlap of competitors i and j can be calculated as follows:

$$\text{Market overlap}_i = \frac{1}{n} \sum_{j=1}^n \frac{s_i s'_j}{\sqrt{(s_i s'_i)(s_j s'_j)}} \quad (2)$$

where s_i and s_j are multidimensional vectors showing the industry distribution of the focal firm i and by its competitor j in four-digit SIC codes. The other symbols have the same meanings with the above. For example, when $s_i = (0,1,0,1,1,0)$ and $s_j = (1,1,0,1,1,0)$, then the fraction in the equation is $\sqrt{3}/2$. Finally, we took average to calculate the focal firm's market overlap with all its competitors in the portfolio if the focal firm had more than one competitor.

Geographical overlap: We collected all coopetitors' branch location information from the Orbis database and calculated the *geographical overlap* between the focal firm and its coopetitors as the degree to which their branches are co-located in the same countries or regions in the current and past four years (i.e., year $t - 4$ to t). Consistent with technological overlap, we measured geographical overlap by using the angle cosine between two vectors of branch locations (see Appendix A for an example). Geographical overlap of coopetitors i and j can be calculated as follows:

$$\text{Geographical overlap}_i = \frac{1}{n} \sum_{j=1}^n \frac{l_i l_j'}{\sqrt{(l_i l_i')(l_j l_j')}} \quad (3)$$

where l_i and l_j are multidimensional vectors indicating the geographical distribution of all branch locations of the focal firm i and its coopetitor j . When firms i and j have all their branches in the same locations, the fraction in the formula equals 1. We took average to calculate the focal firm's geographical overlap with all its coopetitors in the portfolio if it had more than one coopetitor.

Control variables: We controlled for several factors that may impact breakthrough inventions (e.g., Ahuja and Lampert, 2001). A firm's technological activity is correlated with the resources it allocates to R&D. We therefore included *R&D intensity*, which was measured by the average ratio of R&D expenditure to total assets in a five-year period (year $t - 4$ to t). We took the natural logarithm of this variable, plus one as the minimum is zero, to reduce the skewness of distribution (Söderblom et al., 2015). We also included *firm size*, measured by the average number of employees (in thousands) over a five-year period (year $t - 4$ to t). We took the natural logarithm of this variable, plus one as the minimum is zero. We controlled for the number of coopetitors and the number of non-coopetitors that are other types of alliance partners (e.g., suppliers, customers, and universities, etc.) of the focal firm over a five-year period (year $t - 4$ to t), respectively. We took the natural logarithm of these variables, plus one as the minimum is zero. Specifically, considering a potential nonlinear relationship (e.g., Park et al., 2014a, 2014b), we included both *coopetitors* and *coopetitors squared*. We also included *non-coopetitors* and *non-coopetitors squared* to allow for the curvilinear impact on our dependent variable.

We controlled for several factors that are particularly relevant to breakthrough inventions. Specifically, we controlled for *knowledge stock* of the focal firm as the total number of granted patents in a five-year period (i.e., year $t - 4$ to t), according to the patent application year (Conti et al., 2014). We took the natural logarithm of this variable, plus one as the minimum is zero. Furthermore, we controlled for *technological diversity* by calculating the average number of technological classes of all the granted patents that were applied by the focal firm in a five-year period (i.e., year $t - 4$ to t). Arts and Veugelers (2014) and Jung and Lee (2016) found that *recombinant novelty* has a positive impact on firms' breakthrough inventions. Specifically, we calculated this variable by subtracting the ratio of patent subclass combinations that have been used by the focal firm over total number of patent subclass combinations from the maximum ratio in our sample in a five-year period (i.e., year $t - 4$ to t), which reflects a firm's degree of recombination is away from reuse of its exiting combinations (Carnabuci and Operti, 2013) — namely, novel to the firm. Firms' intensity of *self-citation* has been found to negatively influence breakthrough inventions (Kelley et al., 2013). We thus included the number of self-citations for each firm over a five-year period (year $t - 4$ to t). We took the natural logarithm of this variable, plus one as the minimum is zero. Also, we created a dummy variable, *past knowledge spillover*, indicating whether a focal firm's coopetitors cite its patents when developing incremental or breakthrough inventions in the past five years (i.e., year $t - 4$ to t). We further created a set of dummy variables (*Asia*, *Europe* or *North America*) to indicate a firm's headquarter location, because geographic origin can impact the likelihood of creation of breakthrough inventions (Phene et al., 2006).

Finally, we controlled for a focal firm's technological, market and geographical overlap with other alliance partners who are non-coopetitors, which may confound with our independent variable and moderators. When the focal firm has no non-coopetitors in a specific year, the overlap was set as zero. In all analysis, we included 34 patent class dummies to control for the fixed effects of a firm's knowledge domains. Table 1 shows the descriptive statistics and correlations of our variables.

Analytical strategy

In line with the focus on the focal firm in our theorizing, our empirical unit of analysis is the firm. Below is the model used for firm i in time t to examine the curvilinear effect of technological overlap on breakthrough inventions and the moderating effects of market overlap and geographical overlap. Our dependent variable has a count scale and includes only non-negative integers with a skewed distribution. In this case, a Poisson or negative binomial model is appropriate to analyze the data (Greene, 2003). Because of the over dispersion of our dependent variable (mean = 0.695, SD = 4.161), we used a negative binomial model.

$$\begin{aligned} \text{Breakthrough inventions}_{it+1 \sim t+3} = & \beta_0 + \beta_1 \text{Technological overlap}_{it-4 \sim t} + \beta_2 \text{Technological overlap}_{it-4 \sim t}^2 + \\ & \beta_3 \text{Market overlap}_{it-4 \sim t} + \beta_4 \text{Geographical overlap}_{it-4 \sim t} + \beta_5 \text{Technological overlap}_{it-4 \sim t} \times \text{Market overlap}_{it-4 \sim t} + \\ & \beta_6 \text{Technological overlap}_{it-4 \sim t}^2 \times \text{Market overlap}_{it-4 \sim t} + \beta_7 \text{Technological overlap}_{it-4 \sim t} \times \text{Geographical overlap}_{it-4 \sim t} + \\ & \beta_8 \text{Technological overlap}_{it-4 \sim t}^2 \times \text{Geographical overlap}_{it-4 \sim t} + \beta_9 \text{Controls}_{it-4 \sim t} + \varepsilon_{it-4 \sim t} \end{aligned} \quad (4)$$

We conducted a Hausman test and found that fixed effects and random effects models generated significantly different results ($p < 0.01$). Thus, we chose a firm fixed effects model, which helps to control for time-invariant, unobserved firm characteristics. Our data did not have heteroskedasticity issues ($p > 0.1$). We also found no evidence of the presence of serial autocorrelation in the error terms. The maximum variance inflation factor (VIF) is 4.730 and the condition number of our complete model is 13.260 well below the threshold of 30 (Zheng and Yang, 2015), which indicates that multicollinearity is not a concern.

Table 1
Descriptive statistics and correlations.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Breakthrough inventions										
(2) R&D intensity (log)	0.566***									
(3) Firm size (log)	0.128***	-0.022								
(4) Cooperators (log)	0.028	-0.034	0.125***							
(5) Non-cooperators (log)	0.102***	0.015	0.093***	0.335***						
(6) Knowledge stock (log)	0.386***	0.081**	0.447***	0.196***	0.223***					
(7) Technological diversity	0.097***	0.362***	0.027	0.091***	0.004	0.177***				
(8) Recombinant novelty	0.198***	0.106	0.115***	-0.007	0.014	0.006	-0.325***			
(9) Self-citation (log)	0.170***	0.083**	0.185***	0.116***	0.154***	0.542***	0.045**	-0.020		
(10) Past knowledge spillover	-0.001	-0.011	0.077**	0.116***	0.177***	0.143***	0.027	0.041**	0.142***	
(11) Asia	0.095***	-0.095***	0.077**	-0.016	-0.073***	0.289***	0.011	0.041**	0.044**	-0.06***
(12) Europe	-0.093***	-0.074**	0.192***	0.050	0.108***	-0.154***	-0.037*	-0.003	-0.034*	-0.048**
(13) Technological overlap with non-cooperators	0.040**	0.046	-0.021	0.025	0.042**	0.403***	0.264***	-0.380***	-0.117***	-0.068***
(14) Market overlap with non-cooperators	-0.003	-0.008	0.029	-0.007	0.028	0.128***	0.013	-0.008	-0.013	0.296***
(15) Geographic overlap with non-cooperators	0.014	0.095***	-0.084**	0.046**	0.071***	0.318***	0.139***	0.010	0.035*	0.172***
(16) Technological overlap with cooperators	0.083***	0.072**	0.033	0.028	0.266***	0.029	0.372***	-0.037*	0.114***	0.041**
(17) Market overlap with cooperators	-0.031	-0.061**	0.018	-0.015	0.010	-0.031	0.069***	-0.020	0.002	-0.031
(18) Geographic overlap with cooperators	0.085***	0.056	0.317***	0.041**	0.141***	-0.035*	0.105***	0.075***	0.121***	-0.048**
Mean	0.695	0.134	9.284	0.786	0.346	1.077	0.254	6.049	0.076	0.009
SD	4.161	0.973	4.263	0.222	0.590	1.818	0.778	2.211	0.283	0.096
Min	0	0	0	0.693	0	0	0	0	0	0
Max	69	10.219	16.323	2.197	3.045	7.670	25	7.420	1.791	1

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) Breakthrough inventions								
(2) R&D intensity (log)								
(3) Firm size (log)								
(4) Cooperators (log)								
(5) Non-cooperators (log)								
(6) Knowledge stock (log)								
(7) Technological diversity								
(8) Recombinant novelty								
(9) Self-citation (log)								
(10) Past knowledge spillover								
(11) Asia	-0.366***							
(12) Europe	0.122***	-0.067***						
(13) Technological overlap with non-cooperators	-0.037*	-0.034*	0.086***					
(14) Market overlap with non-cooperators	-0.114***	-0.122***	0.023	0.002				
(15) Geographic overlap with non-cooperators	0.088***	-0.048**	0.125***	0.071***	0.006			
(16) Technological overlap with cooperators	-0.038*	-0.081***	0.109***	-0.025	0.013	0.076***		
(17) Market overlap with cooperators	-0.038*	-0.158***	0.073***	0.121***	-0.026	0.083***	0.073***	
(18) Geographic overlap with cooperators	0.277	0.260	0.034	0.017	0.043	0.008	0.158	0.700
Mean	0.448	0.439	0.064	0.291	0.120	0.035	0.256	0.443
SD	0	0	0	0	0	0	0	0
Min	0	0	0	0	0	0	0	0
Max	1	1	0.320	0.067	0.500	0.500	1	1

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Results

Hypotheses testing

Table 2 reports the regression results. Model (1) shows the baseline model including control variables only. Model (2) includes the effects of technological overlap and technological overlap squared. Models (3) and (4) include the interaction terms between

Table 2
Fixed effects negative binomial regression results.

	(1)	(2)	(3)	(4)	(5)
R&D intensity	0.049 (0.079)	0.039 (0.074)	0.088 (0.084)	0.043 (0.075)	0.090 (0.084)
Firm size	−0.338 (0.293)	−0.443 (0.301)	−0.159 (0.346)	−0.361 (0.317)	−0.123 (0.360)
Coopetitors	5.624** (2.372)	5.358** (2.262)	5.408** (2.340)	4.562** (2.282)	4.900** (2.365)
Coopetitors ²	−2.942*** (1.078)	−2.901*** (1.023)	−2.930*** (1.061)	−2.577** (1.025)	−2.710** (1.068)
Non-coopetitors	−0.851* (0.497)	−0.947** (0.446)	−0.810* (0.414)	−0.895** (0.430)	−0.860** (0.418)
Non-coopetitors ²	0.726*** (0.244)	0.729*** (0.260)	0.612** (0.263)	0.723*** (0.264)	0.649** (0.267)
Knowledge stock	−0.177 (0.273)	0.035 (0.256)	−0.001 (0.261)	−0.036 (0.261)	−0.072 (0.271)
Technological diversity	0.087* (0.045)	0.084* (0.044)	0.059 (0.046)	0.083* (0.045)	0.062 (0.046)
Recombinant novelty	0.561*** (0.186)	0.400** (0.169)	0.371** (0.174)	0.374** (0.167)	0.366** (0.173)
Self-citation	0.256 (0.312)	0.434 (0.318)	0.211 (0.330)	0.599* (0.325)	0.346 (0.343)
Past knowledge spillover	−0.794 (1.141)	1.527 (1.041)	1.496* (0.891)	1.406 (0.946)	1.304 (0.901)
Asia	0.485 (1.889)	1.052 (1.858)	−0.598 (2.121)	0.543 (1.962)	−0.765 (2.183)
Europe	−0.0855 (2.184)	3.790 (9.640)	2.014 (7.661)	3.591 (9.348)	1.607 (5.478)
Technological overlap with non-coopetitors	22.79** (10.63)	17.155* (9.117)	11.453 (8.837)	16.947* (8.950)	12.684 (8.926)
Technological overlap with non-coopetitors ²	−72.92* (43.18)	−47.844 (35.964)	−26.629 (34.401)	−40.533 (34.021)	−28.404 (34.292)
Market overlap with non-coopetitors	−3.559 (425.100)	−3.910 (0.769)	−4.084 (1.377)	−4.109 (1.141)	−4.127 (1.463)
Geographic overlap with non-coopetitors	−0.326 (1.710)	−0.891 (1.754)	−1.044 (1.762)	−1.011 (1.751)	−0.770 (1.791)
Technological overlap with coopetitors		0.575*** (0.219)	0.658*** (0.196)	0.453** (0.222)	0.534** (0.236)
Technological overlap with coopetitors ²		−0.992** (0.500)	−1.153*** (0.437)	−0.923** (0.459)	−1.035** (0.486)
Market overlap with coopetitors		0.375 (0.313)	0.364 (0.317)	0.632** (0.314)	0.494 (0.332)
Geographic overlap with coopetitors		0.166 (0.137)	0.149 (0.142)	−0.181 (0.225)	−0.103 (0.237)
Technological overlap × Market overlap (with coopetitors)			1.011*** (0.307)		0.840** (0.367)
Technological overlap ² × Market overlap (with coopetitors)			−2.320*** (0.689)		−1.842** (0.845)
Technological overlap × Geographic overlap (with coopetitors)				0.704** (0.280)	0.430 (0.312)
Technological overlap ² × Geographic overlap (with coopetitors)				−1.342*** (0.472)	−0.709 (0.554)
Patent class dummies	Yes	Yes	Yes	Yes	Yes
Constant	2.478 (2.767)	3.496 (2.617)	1.391 (2.833)	3.518 (2.705)	1.467 (2.996)
Log likelihood	−298.046	−292.860	−287.410	−289.010	−286.400
Likelihood ratio test		10.372***	21.272***	18.072***	23.292***
Wald Chi-sq.	70.760***	89.400***	106.750***	98.460***	107.600***

Note: $n = 2582$. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are in parentheses. Maximum VIF = 4.730; maximum condition number = 13.260.

Fig. 3. The relationships between technological overlap and breakthrough inventions at varying levels of market overlap.

technological overlap and market overlap, and between technological overlap and geographical overlap. Following prior research (Phelps, 2010), we conducted each likelihood ratio test for incremental improvement in fit relative to the baseline model. The likelihood-ratio statistics at the bottom of Table 2 indicate that Models (2) to (5) provide significant improvement in fit relative to Model (1).

Model (2) shows that the coefficient for technological overlap is statistically significant and positive whereas the coefficient for technological overlap squared is statistically significant and negative. Taken together, these results support the hypothesized inverted U-shaped relationship between technological overlap and breakthrough inventions.

In Table 2, Model (3) include market overlap, and its interaction term with both technological overlap and technological overlap squared. In Model (3), the interaction terms of technological overlap and market overlap, and technological overlap squared and market overlap were statistically significant. Because the coefficient of the interaction term between technological overlap squared and market overlap is negative, the inverted U-shaped relationship is steepening with increasing market overlap (Haans et al., 2016). We followed Haans et al. (2016) to calculate the slopes at highest and lowest levels of technological overlap and again found the inverted U-shaped relationship is steepening, which implies a confirmation of H2.

To better understand the nature of the moderating effect, we plot the moderating effect in Fig. 3, showing that the inverted U-shaped relationship steepens as market overlap increases, consistent with our theoretical arguments that higher market overlap can intensify the curvilinearity of knowledge acquisition opportunities. Specifically, the inverted U-shaped relationship is steeper when market overlap is high (i.e., 25th percentile) and flatter when market overlap is low (i.e., 75th percentile). We used “nlcom” command in Stata to formally test the up and down shift of the turning point when market overlap increases (see Appendix B). The results show the shift of turning point is miniscule ($z = 1.480$, $p = 0.138$). In theoretical terms, our results seem to suggest that market overlap strengthens both knowledge acquisition benefits and knowledge leakage risks, resulting in an unchanged turning point.

Regarding geographical overlap, Model (4) seems to suggest that the inverted U-shaped relationship becomes steepening when geographical overlap increases. However, Model (5) indicates that the moderating role of geographical overlap becomes insignificant when simultaneously considering the moderating effects of market overlap. Therefore, we do not find robust support for our H3. We further discuss this surprising result in the discussion section. We also tested the up and down shift of turning point when geographical overlap increases and found that the shift of turning point is miniscule ($z = -0.460$, $p = 0.648$).

Robustness checks

We conducted several robustness checks. First, to test the sensitivity of our measure for breakthrough inventions, we created alternative measures using different percentiles, such as the 99th, 98th, and 95th percentiles (see the results for the 95th percentile in Table 3 as an example). To avoid the influence of outliers in breakthrough inventions, we re-ran all models using its winsorized values at 99th and 98th percentiles and obtained similar results. Further, we measured Cook's Distance to inspect the influence of outliers and found that all values were much less than 1, suggesting that outliers are not a concern (Ryu et al., 2018).

Second, we measured breakthrough inventions by using two-, four- and five-year lags. The results were consistent with that of three-year lag (see the results for the five-year lag in Table 3 as an example).

Third, we used citation-weighted number of patents that were above the 97th percentile in terms of forward citations in each year to measure breakthrough inventions. Citation-weighted number is used because forward citations above the 97th percentile in each year show a large standard deviation (i.e., $SD = 89.128$, $Mean = 8.583$), indicating a high level of dispersion of citations. Consistent results were obtained (see Table 3).

Fourth, Tobit model accounts for the censoring and can be used to handle the issue of having a highly skewed dependent variable with many zeros (Greene, 2003). Given the skewed distribution of breakthrough inventions, we ran our models using Tobit regression and found that our results still hold (see Table 3).

Fifth, even though two firms are operating in the same SIC codes, they may not compete with each other if they are producing

Table 3
Sensitivity analysis.

	Breakthrough inventions (95th percentile)			Breakthrough inventions (five-year lag)			Breakthrough inventions (citation weighted)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
R&D intensity	0.132* (0.073)	0.053 (0.078)	0.132* (0.073)	0.090 (0.056)	0.011 (0.053)	0.029 (0.055)	0.271*** (0.061)	0.283*** (0.062)	
Firm size	-0.049 (0.195)	-0.224 (0.208)	-0.047 (0.200)	-0.020 (0.232)	-0.295 (0.249)	-0.165 (0.254)	0.336*** (0.103)	0.330*** (0.109)	
Coopetitors	4.548** (2.178)	3.973* (2.161)	3.957* (2.181)	5.317*** (2.012)	3.672* (2.046)	4.733** (2.082)	2.028 (2.463)	1.584 (2.436)	
Coopetitors ²	-2.602** (1.016)	-2.355** (0.974)	-2.362** (1.004)	-2.487*** (0.926)	-1.879** (0.924)	-2.299** (0.938)	-1.328 (1.089)	-1.036 (1.074)	
Non-coopetitors	-0.786* (0.416)	-0.660 (0.448)	-0.819** (0.408)	-0.765** (0.353)	-0.605 (0.373)	-0.620* (0.353)	-0.130 (0.512)	-0.634 (0.531)	
Non-coopetitors ²	0.503* (0.264)	0.530** (0.266)	0.564** (0.265)	0.403* (0.238)	0.427* (0.247)	0.371 (0.237)	0.214 (0.294)	0.568* (0.301)	
Knowledge stock	-0.314 (0.237)	-0.267 (0.232)	-0.363 (0.242)	-0.500** (0.211)	-0.497** (0.226)	-0.492** (0.221)	-0.815*** (0.242)	-1.015*** (0.250)	
Technological diversity	0.049 (0.044)	0.087* (0.046)	0.056 (0.044)	0.018 (0.032)	0.052 (0.033)	0.045 (0.033)	0.057 (0.043)	0.077* (0.043)	
Recombinant novelty	0.389** (0.158)	0.476*** (0.172)	0.385** (0.157)	0.224 (0.143)	0.331** (0.154)	0.329** (0.158)	0.544*** (0.153)	0.524*** (0.152)	
Self-citation	0.444 (0.313)	0.604* (0.309)	0.618* (0.322)	0.226 (0.281)	0.524* (0.301)	0.309 (0.312)	0.280 (0.292)	0.563* (0.288)	
Past knowledge spillover	0.864 (0.813)	-0.782 (0.979)	0.697 (0.813)	1.327* (0.731)	-0.468 (1.019)	-0.395 (1.057)	1.519* (0.848)	1.204 (1.015)	
Asia	-0.518 (1.209)	-0.044 (1.275)	-0.582 (1.247)	-1.983 (1.525)	-1.163 (1.687)	-2.174 (1.921)	-1.285 (0.830)	-1.099 (0.788)	
Europe	2.494 (10.147)	-0.120 (1.592)	2.064 (6.126)	9.339 (534.993)	-1.099 (1.936)	-2.163 (2.141)	-0.535 (1.328)	-0.027 (1.424)	
Technological overlap with non-coopetitors	18.545** (9.339)	26.232*** (9.906)	19.763** (9.372)	14.907** (7.263)	22.913*** (8.195)	21.119** (8.765)	15.346* (8.133)	20.045** (8.363)	
Technological overlap with non-coopetitors ²	-56.539 (34.673)	-80.288** (38.276)	-56.266 (34.628)	-47.064 (29.920)	-71.351** (33.420)	-68.652* (36.502)	-43.676 (28.999)	-56.852* (29.941)	
Market overlap with non-coopetitors	-3.568 (466.481)	-4.627 (3295.116)	-3.705 (575.883)	-3.743 (653.328)	-3.732 (516.946)	-3.494 (358.071)	-3.849 (665.011)	-4.102 (1089.977)	
Geographic overlap with non-coopetitors	0.118 (1.625)	-0.490 (1.643)	0.156 (1.653)	-0.610 (1.579)	-0.902 (1.496)	-0.468 (1.523)	-2.062 (1.618)	-1.547 (1.656)	
Technological overlap with coopetitors	0.668*** (0.199)	0.467** (0.219)	0.556** (0.236)	0.659*** (0.186)	0.547*** (0.210)	0.673*** (0.229)	0.845*** (0.243)	0.348 (0.243)	
Technological overlap with coopetitors ²	-1.168*** (0.444)	-0.953** (0.474)	-1.111** (0.498)	-1.276*** (0.426)	-1.146** (0.446)	-1.380*** (0.481)	-1.585*** (0.531)	-0.760* (0.418)	
Market overlap with coopetitors	0.697** (0.288)	0.923*** (0.303)	0.879*** (0.304)	0.474* (0.273)	0.635** (0.282)	0.481 (0.299)	0.826*** (0.286)	1.089*** (0.277)	
Geographic overlap with coopetitors	0.094 (0.132)	-0.193 (0.217)	-0.187 (0.218)	0.031 (0.128)	-0.0154 (0.215)	0.061 (0.225)	-0.072 (0.133)	-0.457** (0.210)	
Technological overlap × Market overlap (with coopetitors)	1.012*** (0.307)		0.761** (0.348)	0.987*** (0.288)		0.661** (0.318)	1.671*** (0.416)		

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Table 3 (continued)

	Breakthrough inventions (95th percentile)			Breakthrough inventions (five-year lag)			Breakthrough inventions (citation weighted)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
Technological overlap ² × Market overlap (with cooperitors)	−2.297*** (0.690)		−1.607** (0.803)	−2.316*** (0.660)		−1.613** (0.758)	−3.619*** (0.875)		
Technological overlap × Geographic overlap (with cooperitors)		0.707** (0.276)	0.562* (0.312)		0.459* (0.268)	0.129 (0.319)		0.755** (0.297)	
Technological overlap ² × Geographic overlap (with cooperitors)		−1.375*** (0.481)	−0.995* (0.563)		−1.123** (0.457)	−0.440 (0.555)		−1.412*** (0.529)	
Patent class dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Constant	0.540 (2.049)	2.352 (2.166)	1.004 (2.131)	0.561 (2.268)	4.114 (2.578)	2.803 (2.629)	−1.819 (1.867)	−1.416 (1.867)	
Log likelihood	−337.195	−337.753	−335.465	−333.841	−334.666	−332.418	−548.925	−553.037	
Wald/Likelihood ratio Chi-sq.	119.430***	106.380***	120.720***	163.360***	156.310***	164.720***	145.570***	131.620***	
Market overlap (text mining)									
	(9)	(10)	(11)	(12)	(13)	(14)	(15)		
R&D intensity	0.281*** (0.062)	1.560*** (0.420)	1.486*** (0.420)	1.576*** (0.418)	0.018 (0.075)	−0.005 (0.072)	0.038 (0.069)		
Firm size	0.347*** (0.107)	1.059** (0.427)	1.006** (0.424)	1.042** (0.427)	−0.475* (0.267)	−0.523* (0.267)	−0.470* (0.281)		
Cooperitors	2.044 (2.454)	22.089* (12.348)	20.302 (12.348)	20.924* (12.370)	6.655*** (2.144)	5.467*** (2.105)	6.405*** (2.199)		
Cooperitors ²	−1.329 (1.081)	−10.853** (5.451)	−10.095* (5.436)	−10.421* (5.443)	−3.395*** (0.989)	−2.934*** (0.954)	−3.303*** (1.015)		
Non-cooperitors	−0.165 (0.514)	1.305 (2.664)	1.151 (2.665)	1.332 (2.650)	−0.620 (0.434)	−0.931** (0.449)	−0.782* (0.433)		
Non-cooperitors ²	0.288 (0.300)	1.118 (1.420)	1.279 (1.414)	1.121 (1.411)	0.503** (0.254)	0.746*** (0.257)	0.583** (0.268)		
Knowledge stock	−0.892*** (0.252)	2.932** (1.324)	2.912** (1.338)	2.990** (1.318)	0.0379 (0.259)	0.038 (0.260)	0.0434 (0.256)		
Technological diversity	0.057 (0.043)	0.425 (0.286)	0.466 (0.288)	0.417 (0.285)	0.089** (0.045)	0.098** (0.044)	0.078* (0.043)		
Recombinant novelty	0.536*** (0.152)	2.388*** (0.792)	2.245*** (0.792)	2.283*** (0.790)	0.472** (0.199)	0.482** (0.185)	0.385** (0.168)		
Self-citation	0.400 (0.301)	−1.597 (1.856)	−0.851 (1.843)	−1.309 (1.854)	0.309 (0.297)	0.490 (0.312)	0.406 (0.312)		
Past knowledge spillover	1.303 (0.911)	3.307 (4.249)	2.521 (4.277)	2.971 (4.241)	−0.058 (1.609)	−0.435 (1.351)	1.655* (1.000)		
Asia	−1.347 (0.835)	−9.879*** (3.126)	−10.130*** (3.086)	−10.051*** (3.089)	0.785 (1.769)	1.219 (1.744)	1.118 (1.811)		

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Table 3 (continued)

	Breakthrough inventions (citation weighted)	Tobit model	Market overlap (text mining)				
	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Europe	-0.592 (1.304)	-18.666*** (4.486)	-19.345*** (4.487)	-18.706*** (4.448)	0.086 (2.228)	0.629 (2.121)	3.943 (11.089)
Technological overlap with non-coopetitors	16.427** (8.128)	73.054* (40.035)	78.493* (40.226)	70.120* (39.911)	15.048 (9.363)	16.936* (8.950)	11.681 (8.118)
Technological overlap with non-coopetitors ²	-45.120 (28.640)	-155.145 (131.923)	-165.986 (131.919)	-145.000 (131.403)	-31.942 (34.920)	-39.140 (33.609)	-17.023 (30.238)
Market overlap with non-coopetitors	-3.594 (476.500)	-6.774 (163.011)	-7.833 (254.373)	-6.961 (153.176)	-4.096 (528.597)	-4.096 (978.461)	-3.981 (844.616)
Geographic overlap with non-coopetitors	-2.061 (1.629)	-8.509 (8.523)	-7.924 (8.446)	-8.451 (8.449)	-0.876 (1.802)	-0.916 (1.790)	-0.886 (1.846)
Technological overlap with coopetitors	0.709*** (0.274)	4.702*** (1.248)	4.376*** (1.258)	5.050*** (1.286)	0.902*** (0.241)	0.463** (0.218)	0.896*** (0.265)
Technological overlap with coopetitors ²	-1.438** (0.584)	-8.870*** (2.705)	-8.710*** (2.916)	-10.096*** (2.918)	-1.845*** (0.581)	-0.911* (0.467)	-1.902*** (0.600)
Market overlap with coopetitors	0.945*** (0.299)	0.448 (1.113)	1.312 (1.014)	0.618 (1.107)	0.080 (0.058)	0.063 (0.054)	0.084 (0.059)
Geographic overlap with coopetitors	-0.320 (0.214)	1.057 (0.826)	0.514 (0.980)	0.829 (0.992)	0.116 (0.138)	-0.048 (0.207)	-0.014 (0.208)
Technological overlap × Market overlap (with coopetitors)	1.512*** (0.446)	5.259*** (1.864)		4.302** (2.030)	1.126*** (0.414)		1.074** (0.545)
Technological overlap ² × Market overlap (with coopetitors)	-3.128*** (0.988)	-11.780*** (4.094)		-9.153* (4.751)	-2.508*** (0.890)		-2.381** (1.171)
Technological overlap × Geographic overlap (with coopetitors)	0.472 (0.344)		2.022* (1.186)	1.088 (1.301)		0.538** (0.268)	0.219 (0.280)
Technological overlap ² × Geographic overlap (with coopetitors)	-0.757 (0.636)		-4.897** (2.165)	-2.609 (2.501)		-1.031** (0.456)	-0.355 (0.515)
Patent class dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-1.780 (1.855)	-60.447 (41.156)	-62.959 (85.870)	-60.193 (42.587)	3.453 (2.564)	4.357* (2.597)	3.486 (2.620)
Log likelihood	-547.851	-475.600	-477.256	-474.982	-288.532	-290.448	-287.884
Wald/Likelihood ratio Chi-sq.	143.880***	35.190***	30.670***	31.440***	102.170***	98.350***	108.020***

Note: $n = 2582$. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are in parentheses.

different products.⁷ Similar to prior studies on content similarity (Piezunka and Dahlander, 2015), we measured market overlap by using text-mining analysis based on each firm's description of products from the Orbis database. We first removed all punctuation, space and non-alphabetic characters before mining the text, and changed each word to its root form (e.g., “building” and “builds” become “build”). We then used a bag of words to represent each firm's description of products. We built a firm-product word matrix (i.e., A). Two firms are more similar in products if they share more words in the description of products. We developed an $A \times A$ matrix, in which each cell is the cosine similarity between two firms. We need the subsets of the data to calculate the sample firms' market overlap with coopeititors and calculated $R \times A \times A$ matrix where R denotes the coopeitition relationship matrix which indicates whether two firms are coopeititors (i.e., value 1 denotes that two firms are coopeititors). Finally, we used the row sum of the $R \times A \times A$ matrix to get a measure of a focal firm's market overlap with coopeititors. In sum, we calculated content similarity of text between coopeititors. We created a new measurement of market overlap by multiplying the content similarity by the SIC similarity. Therefore, we have measured market overlap with coopeititors by firm type, SIC codes, and product description. The results were consistent with our main findings (see Table 3).

Sixth, we also checked for a potential three-way interaction effect of technological, market and geographical overlap on breakthrough inventions. We first divided our sample based on high and low levels of geographical (market) overlap according to the mean or median, and then conducted split sample analyses for a model with a two-way interaction effect of technological overlap and market (geographical) overlap. However, we did not find significant differences across the split samples based on either market overlap or geographical overlap. Therefore, we did not find indications for a three-way interaction effect.

Seventh, a focal firm's overlap with coopeititors may be endogenously determined, as firms, which are technologically successful, may attract similar or distinct coopeititors, or omitted variables may simultaneously influence the choice of coopeititors and breakthrough inventions. To address the endogeneity of technological overlap, we use instrumental variables in a two-stage least squares (2SLS) regression. We identified two instrumental variables — *rival's alliances* and *ITC policy*. We used rival's alliances as it is less likely to influence breakthrough inventions directly but is more likely to influence the possibility of collaborating with competitors (Ryu et al., 2018), calculated as the number of alliances belonged to solar PV firms co-located in the same country or region where the focal firm is. The federal solar Investment Tax Credit (ITC) in 2006 was one of the most important policies supporting the deployment of solar energy in the U.S. The ITC was implemented by the U.S. Energy Policy Act (P.L. 109-58) with effect from January 1, 2006. It provided a 30% tax credit for solar PV systems specifically on residential and commercial properties placed in service between January 1, 2006 and December 31, 2007. The ITC commercial guide indicates that a solar PV system is eligible for the 30% tax credit if it is located in the U.S. and used by a taxpayer subject to U.S. income taxes. This tax reduction policy significantly reduced the costs and prices of solar PV systems for residential and commercial properties, boosting their installation rates and therefore the entries of solar PV firms into this area (Byrne and Kurdgelashvili, 2011). Due to its success, the ITC was extended in 2006, 2008 and 2015, till the end of 2023. According to statistics of the Solar Energy Industries Association (SEIA), the ITC has helped annual solar installation to grow by over 1600% (a compound annual growth rate of 76%) since 2006, making the solar PV industry one of the fastest-growing industries in the U.S. As the ITC can trigger new entries of solar PV firms to a specific area, it may increase the technological overlap with coopeititors if a focal firm is focused on technologies related to the area. However, the tax reduction benefits from the ITC should not directly affect a focal firm's technological activity. Based on this exogenous shock, we construct a binary variable equal to 1 if (i) a focal firm had branches in the U.S. and (ii) the U.S. branches were established after 2006, and 0 otherwise. We used geographic density and ITC policy as the instruments for technological overlap with coopeititors. Following Stock et al. (2002), an under-identification test indicated that our instruments are not weak (Anderson CC = 16.881, $p < 0.01$; Cragg-Donald F = 8.499). We further conducted an overidentification test and found that our instruments are valid (Sargan J = 1.840, $p = 0.174$). The 2SLS regression results for the hypotheses are presented in Table 4, providing robust results.

Finally, we conducted an *ex post* validation test of our theoretical mechanism about knowledge leakage risks associated with technological overlap with coopeititors. To the best of our knowledge, there is no prior work that has operationalized knowledge leakage in the coopeitition context. We created a proxy of knowledge leakage risks by counting the number of cross-citations made by a focal firm's coopeititors to the focal firm's patents in the subsequent three years (i.e., year $t + 1$ to $t + 3$). We then conducted a *t*-test to examine the difference in this proxy of knowledge leakage risks between two groups of firms with high vs. low technological overlap with coopeititors defined by the mean of our sample. The *t*-test results showed that firms with high technological overlap with coopeititors, on average, have significantly greater knowledge leakage risks than firms with low technological overlap with coopeititors (mean = 0.070 vs. 0.006; $t = 2.048$, $p < 0.05$), supporting our theoretical arguments.

Discussion and implications

In this study, we investigate the impact of a focal firm's technological, market and geographical overlap with coopeititors on its ability to generate breakthrough inventions. Our findings show an inverted U-shaped relationship between a focal firm's technological overlap with coopeititors and its breakthrough inventions. Moreover, we find consistent evidence that higher market overlap steepens this inverted U-shaped relationship. Although we also find a significant moderation effect for geographical overlap, this latter effect disappears when simultaneously considering the moderation effect of market overlap. Below, we first discuss the implications of our findings for coopeitition research. Subsequently, we touch upon the managerial implications of our findings. Finally, we point to the core limitations of our research and suggest interesting avenues for future research.

⁷ We thank one anonymous reviewer who suggested this point.

Table 4
Endogeneity test.

	First stage	Second stage			
	(1)	(2)	(3)	(4)	(5)
R&D intensity	0.002 (0.002)	0.011 (0.071)	0.070 (0.059)	0.023 (0.072)	0.082 (0.075)
Firm size	−0.001 (0.002)	−0.438 (0.297)	−0.091 (0.234)	−0.390 (0.324)	−0.101 (0.320)
Coopetitors	0.018 (0.047)	5.299** (2.239)	4.739** (2.215)	4.815** (2.282)	4.261* (2.381)
Coopetitors ²	−0.011 (0.020)	−2.848*** (1.014)	−2.644*** (1.016)	−2.676*** (1.033)	−2.466** (1.081)
Non-coopetitors	−0.001 (0.009)	−0.696* (0.409)	−0.838** (0.387)	−0.710* (0.413)	−0.835** (0.412)
Non-coopetitors ²	−0.004 (0.005)	0.624** (0.249)	0.641*** (0.243)	0.619** (0.255)	0.637** (0.255)
Knowledge stock	0.006 (0.006)	0.041 (0.257)	0.004 (0.225)	0.139 (0.270)	0.101 (0.260)
Technological diversity	−0.002 (0.001)	0.098** (0.043)	0.075* (0.041)	0.090** (0.044)	0.065 (0.045)
Recombinant novelty	−0.001 (0.002)	0.528*** (0.183)	0.466*** (0.167)	0.489*** (0.184)	0.375** (0.178)
Self-citation	−0.029*** (0.009)	0.354 (0.304)	0.169 (0.274)	0.335 (0.304)	0.235 (0.310)
Past knowledge spillover	−0.007 (0.025)	−0.620 (1.119)	−0.401 (1.146)	−0.580 (1.183)	1.488 (0.986)
Asia		−0.010 (1.865)	−1.618 (1.604)	−0.268 (2.004)	−1.470 (2.006)
Europe		−0.763 (2.069)	−2.113 (1.752)	−0.930 (2.188)	0.871 (6.460)
Technological overlap with non-coopetitors	0.203 (0.127)	19.673** (9.541)	16.270* (8.858)	16.146* (9.562)	11.737 (9.410)
Technological overlap with non-coopetitors ²	−0.377 (0.429)	−58.024 (37.223)	−53.440 (34.977)	−45.796 (37.198)	−32.251 (36.575)
Market overlap with non-coopetitors	0.001 (0.005)	−4.319 (1.739)	−4.676 (4.141)	−3.797 (576.020)	−4.271 (1.824)
Geographic overlap with non-coopetitors	−0.015 (0.024)	−0.645 (1.680)	−0.451 (1.577)	−0.841 (1.661)	−0.980 (1.718)
Technological overlap with coopetitors		1.964*** (0.669)	3.005*** (0.745)	1.926** (0.844)	2.903*** (1.002)
Technological overlap with coopetitors ²		−1.565** (0.733)	−3.581*** (1.043)	−1.790** (0.823)	−3.568*** (1.216)
Market overlap with coopetitors	0.001 (0.005)	0.267 (0.304)	0.306 (0.309)	0.362 (0.333)	0.523 (0.341)
Geographic overlap with coopetitors	−0.005 (0.005)	0.168 (0.137)	0.067 (0.134)	0.016 (0.231)	−0.014 (0.241)
Technological overlap × Market overlap (with coopetitors)			2.475** (1.136)		2.227* (1.189)
Technological overlap ² × Market overlap (with coopetitors)			−4.147** (1.688)		−3.750** (1.786)
Technological overlap × Geographic overlap (with coopetitors)				1.307 (1.092)	1.100 (1.132)
Technological overlap ² × Geographic overlap (with coopetitors)				−1.424* (0.843)	−1.166 (0.840)
Rivals' alliance	0.016*** (0.004)				
ITC policy	−0.019** (0.008)				
Patent class dummies	Yes	Yes	Yes	Yes	Yes
Constant	−0.029 (0.050)	3.968 (2.782)	−0.127 (2.029)	3.848 (2.798)	1.760 (2.690)
R ²	0.123				
F	1.930***				
Log likelihood		−297.530	−289.010	−289.800	−287.450
Likelihood ratio test			17.040***	15.460***	20.160***
Wald Chi-sq.		94.190***	107.030***	101.660***	110.570***

Note: $n = 2582$. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Standard errors are in parentheses.

Theoretical implications

Our study contributes to the coopetition literature in several important ways. Whereas prior research has often conceptualized coopetitors as a rather homogenous group, the heterogeneity among coopetitors is rarely recognized (Park et al., 2014a, 2014b). We advance our understanding of the heterogeneity of coopetitors by unveiling different and intertwined dimensions of overlap among coopetitors. In such a conceptualization, the level of coopetition can substantially vary depending on technological, market and geographical overlap between a focal firm and its coopetitors. Moreover, we show that these different dimensions are not independent, but rather imply complex interactions, jointly shaping focal firms' ability to generate breakthrough inventions. While past research has started considering the direct effects of these dimensions (Park et al., 2014a, 2014b), it is important for future research to understand the nuanced interdependencies between these dimensions, collectively influencing coopetition outcomes as one dimension may amplify or hinder the impact of another. Overall, this paper implies that a firm's portfolio of coopetitors cannot be conceptualized as a homogeneous group of actors. Instead, it is important to make an explicit distinction between different dimensions and consider the potential interactions among them.

This study also enriches the ongoing debate on the tension between knowledge acquisition and knowledge leakage in extant coopetition research (e.g., Estrada et al., 2016; Ritala et al., 2015). Knowledge acquisition from and knowledge leakage to coopetitors pose a strategic dilemma when firms collaborate with competitors (Ritala et al., 2015). Therefore, co-existence of knowledge acquisition opportunities and knowledge leakage risks is an important characteristic of coopetition. Considering the knowledge acquisition opportunities without accounting for the knowledge leakage risks cannot grasp the holistic picture of coopetition and its impact on technological performance. We demonstrate that firms have agency in shaping the actual interplay between knowledge acquisition and knowledge leakage by paying careful attention to different dimensions of overlap when engaging in coopetition. Firms can actively manage the tension between knowledge acquisition and knowledge leakage in coopetition by collaborating with coopetitors that have appropriate levels of technological, market and geographical overlap with them.

In the broader literature on interfirm collaboration, a research stream is emerging that pays particular attention to the impact of geographical factors on the formation (McCann et al., 2016), governance (Ryu et al., 2018), and performance implications (Faems et al., 2019) of collaborative relationships. In our research, we consistently observed that, when controlling for the moderating effect of market overlap, the moderating effect of geographical overlap became insignificant. This finding suggests that, in the setting of coopetition, the moderating role of geographical overlap between a focal firm and its coopetitors is less pronounced than we expected. Companies, which are active in similar market domains, might cluster together, resulting in geographical overlap (Pouder and John, 1996). This positive correlation between market-related and geographical characteristics implies the risk that, when scholars do not control for market overlap in research on the impact of geographical factors on collaboration activities, the effect might actually not reflect the impact of geographical factors, but rather point to an impact of market-related factors. To avoid such issues, it is important for future research to take into account market-related factors when considering the implications of geographical factors on coopetition in particular and collaboration activities in general.

Managerial implications

Scholars refer to the substantive risks of collaborating with competitors as an explanation for firms' reluctance to engage in coopetition (e.g., Park and Russo, 1996). Acknowledging the heterogeneity of coopetitors in terms of technological, market and geographical overlap, our findings provide specific recommendations into how managers can maximize the knowledge acquisition opportunities of coopetition while minimizing knowledge leakage concerns. In particular, our data point to selecting coopetitors that have medium technological overlap and high market overlap as a productive approach in terms of generating breakthrough inventions. At the same time, our data show that collaborating with competitors that have a high market overlap is risky. In such a setting, a shift from medium to high technological overlap can have dramatic consequences, where knowledge recombination benefits of coopetition can swiftly evaporate. More risk-averse companies might therefore prefer coopetitors with lower market overlap. Although this might constrain to some extent the potential benefits of increasing technological overlap, it also reduces the risks that the increased technological overlap results into a learning race with devastating consequences for technological capabilities of the focal firm.

Although most of the observed firms only collaborated with one coopetitor in a particular year, some firms were engaged in a portfolio of coopetitors. This latter group of firms can also manage the aforementioned tension by changing or adjusting the composition of their coopetition portfolios. At the same time, we acknowledge that, for focal firms that have a portfolio of coopetitors, we only looked at the average level of overlap among the coopetitors. Managers could consider the variety of overlap among coopetitors in the portfolio. For instance, it would be interesting to explore and compare the technological performance of (i) a portfolio of two coopetitors where both coopetitors have medium technological overlap with the focal firm and (ii) a portfolio of two coopetitors where one coopetitor has low technological overlap with the focal firm and the other coopetitor has high technological overlap.

Limitations and future research

Despite its merits, this study also has some limitations, which hold promise for future work. First, although focusing on a particular industry allowed us to generate fine-grained data on coopetitors and their heterogeneity, it restricts the generalizability of our findings (Haleblian et al., 2006). Second, whereas we relied on knowledge acquisition and leakage arguments in our theorizing, the nature of our ability to explicitly measure these mechanisms. Although our robustness check provides the first indication that higher

technological overlap indeed creates higher risks of knowledge leakage, more fine-grained research on the interplay between knowledge acquisition and knowledge leakage is necessary. Our measures of technological, market and geographical overlap also have some limitations. For example, we rely on patent classes to indicate technological domains, which do not always reflect firms' technological architecture. Complementing secondary data with more primary data on this topic is a fruitful avenue for future research. Finally, by focusing on technological, market and geographical overlap, we mainly theorized how the selection of particular coopetitors influences a focal firm's ability to address associated knowledge acquisition opportunities and knowledge leakage risks. However, existing research provides evidence that such issues can also be actively managed by implementing particular structural or relational governance mechanisms (Elfenbein and Zenger, 2017; Estrada et al., 2016; Lavie, 2007). In other words, a focal firm could counteract potential risks of a certain partner in terms of technological, market and geographical overlap, by introducing particular governance mechanisms. In-depth research on active management of coopetitors therefore is a fruitful avenue for future research. In addition, our results shed some light on the impact of technological, market and geographical overlap with non-coopetitors that is different from the impact of technological, market and geographical overlap with coopetitors. This is also an interesting avenue for future research, which potentially bridges coopetition and general alliance research.

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Appendix A. An example of calculating geographical overlap

We provide an example of how to calculate market overlap with coopetitors. For example, the focal firm A has three branch locations: Country 1, 2 and 3. Its coopetitor firm B has two branch locations: Country 1 and 4. Two vectors of branch locations for firm A and firm B can be created as $l_A (1,1,1,0)$ and $l_B (1,0,0,1)$, respectively. Based on Equation (3), the market overlap between firms A and B is:

$$l_A \cdot l_B / \sqrt{(l_A \cdot l_A)(l_B \cdot l_B)} = (1 \times 1 + 1 \times 0 + 1 \times 0 + 0 \times 1) / \sqrt{(1 + 1 + 1 + 0) \times (1 + 0 + 0 + 1)} = 1 / \sqrt{6} \approx 0.408$$

Appendix B. Testing the shift of turning point

To formally test the up and down shift of the turning point when the moderator changes, we used “nlcom” command in Stata to assess whether Equation (5) as a whole is significantly different from zero (Haans et al., 2016).

If $Y = \beta_0 + \beta_1 X + \beta_2 X^2 + \beta_3 XM + \beta_4 X^2 M + \beta_5 M$,

that is $Y = (\beta_2 + \beta_4 M)X^2 + (\beta_1 + \beta_3 M)X + (\beta_0 + \beta_5)$, then

$$\begin{aligned} \frac{\delta Y^*}{\delta M} &= \beta_5 - \frac{(\beta_1 + \beta_3 M)^2}{4(\beta_2 + \beta_4 M)} \\ &= \beta_5 - \frac{8\beta_3(\beta_1 + \beta_3 M)(\beta_2 + \beta_4 M) - 4\beta_4(\beta_1 + \beta_3 M)^2}{16(\beta_2 + \beta_4 M)^2} \\ &= \beta_5 - \frac{(\beta_1 + \beta_3 M)(2\beta_2\beta_3 + \beta_3\beta_4 M - \beta_1\beta_4)}{4(\beta_2 + \beta_4 M)^2} \quad (5). \end{aligned}$$

This test reports z statistic to indicate whether the turning point significantly move up or down when the moderator increases.

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