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Ties that matter: The impact of alliance partner knowledge recombination novelty on knowledge utilization in R&D alliances

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ABSTRACT

Whereas extant alliance research tends to consider the knowledge pool of partner firms as a set of independent components, we highlight that alliance partners' components are interconnected. In particular, we introduce the concept of alliance partner knowledge recombination novelty – i.e., the extent to which an alliance partner has created component ties that no other firm within the industry has created – and hypothesize that it has an inverted U-shaped relationship with the focal firm's utilization of the alliance partner's knowledge. We also expect this relationship to be moderated by the focal firm's own knowledge recombination novelty. Analyzing 313 R&D alliance dyads of 70 firms in the fuel cell industry, we find support for the hypothesized inverted U-shaped relationship between an alliance partner's knowledge recombination novelty and the focal firm's knowledge utilization from the alliance partner. However, we do not find support for a moderation effect of the focal firm's knowledge recombination novelty. Based on these findings, we demonstrate the importance of framing alliance partner knowledge pools as sets of interconnected components, where alliance partners' history of knowledge recombination shapes the focal firm's knowledge utilization rates.

1. Introduction

R&D alliances – i.e., collaborative arrangements between two or more independent organizations in which resources are pooled in order to develop new technologies (Hagedoorn, 2002) – are important mechanisms for accessing external knowledge (Gomes-Casseres et al., 2006; Mowery et al., 1996; Rosenkopf and Almeida, 2003). Alliance scholars (e.g., Kavusan et al., 2016; Mowery et al., 1996; Schildt et al., 2012) therefore examine which particular characteristics of alliance partners' knowledge pool influence the focal firm's utilization of alliance partners' knowledge. They show that, when alliance partners have larger and more distant knowledge pools, the focal firm is more likely to utilize alliance partners' knowledge. At the same time, they point to potential limitations in the focal firm's ability to absorb knowledge from such knowledge pools (e.g., Kavusan et al., 2016; Schildt et al., 2012; Subramanian et al., 2018).

Whereas this literature stream provides important insights into the relationship between particular characteristics of alliance partners' knowledge pools and the knowledge recombination capabilities of the focal firm, we challenge how these scholars conceptualize the knowledge pool of alliance partners. We highlight that alliance scholars tend to characterize the knowledge pool of alliance partners as a set of independent components, ignoring alliance partners' history of recombining these components. This lack of attention to how alliance partners' components are connected is surprising as knowledge recombination scholars (Dibiaggio et al., 2014; Yayavaram and Ahuja, 2008; Wang et al., 2014) increasingly emphasize the relevance of looking at the nature of ties between components. Within a firm's knowledge pool, components are often tied to each other due to firms' prior knowledge recombination activities (Dibiaggio et al., 2014; Yayavaram and Ahuja, 2008). Moreover, the nature of ties between components in the knowledge pool has important performance implications (Dibiaggio et al., 2014; Yayavaram and Ahuja, 2008; Yayavaram and Chen, 2015).

Even though knowledge recombination literature has extensively studied the implications of ties between components within a firm's internal knowledge pool, it has largely ignored inter-firm collaborative contexts such as alliances. The study of Yayavaram et al. (2018) is a notable exception, showing that the nature of the ties between components in the knowledge pool of potential alliance partners is a characteristic that influences the likelihood of alliance formation. We, however, expect that how components are connected in the knowledge

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pool of alliance partners not only influences alliance formation, but can also significantly shape the extent to which the focal firm utilizes knowledge from alliance partners after the alliance is formed. In this paper, we therefore test the relationship between alliance partner knowledge recombination novelty – i.e., the extent to which an alliance partner has created component ties that no other firm within the industry has created – and the focal firm's knowledge utilization from this particular alliance partner.

We theorize that the presence of unique ties between components in the knowledge pool of an alliance partner is associated with an increase in the perceived value of its knowledge pool and, consequently, to an increase in knowledge utilization by the focal firm. At the same time, we expect that such knowledge recombination novelty can be a source of technological complexity that hampers the ability of the focal firm to absorb and subsequently utilize knowledge of the alliance partner. Bringing these different mechanisms together, we hypothesize an inverted U-shaped relationship between alliance partner knowledge recombination novelty and the focal firm's knowledge utilization from this alliance partner. In addition, we expect this relationship to be moderated by the knowledge recombination novelty of the focal firm.

To empirically test our predictions, we use data on 313 R&D alliance dyads of 70 focal firms in the fuel cell industry over a period of 15 years (1993-2007). In line with prior studies, we use patent citations to track knowledge utilization (e.g., Gomes-Casseres et al., 2006; Mowery et al., 1996; Rosenkopf and Almeida, 2003) and identify component ties by looking at the co-occurrence of IPC codes on patents (e.g., Dibiaggio et al., 2014; Verhoeven et al., 2016). Analyzing these data, we find that the alliance partner's knowledge recombination novelty has the predicted inverted U-shaped relationship with the focal firm's knowledge utilization from this alliance partner. In post-hoc analyses, we also find evidence that this relationship is mainly driven by the uniqueness of knowledge ties and not by the uniqueness of the components that constitute the knowledge ties. At the same time, we do not find evidence that the focal firm's knowledge recombination novelty moderates this relationship.

Jointly, these findings have important implications for our theoretical understanding of R&D alliances and on how they influence knowledge recombination at the firm level. They highlight the importance of moving away from conceptualizing alliance partner knowledge pools as a set of independent components. We propose that alliance partner knowledge pools represent a set of interdependent components, where the nature of ties between components shapes the recombinant potential for the focal firm. In doing so, we demonstrate the importance of applying state-of-the-art insights from knowledge recombination literature to alliance research to gain a deeper understanding of why certain alliances perform better than others. Our results also point to knowledge recombination novelty as a potential isolating mechanism, which can help firms to reduce the risk of losing learning races within R&D alliances.

2. Theoretical background

2.1. R&D alliances, knowledge recombination, and firm performance

Alliances can help firms to access novel knowledge that complements their own knowledge pool (Rosenkopf and Almeida, 2003; Savino et al., 2017). In the fuel cell industry, for instance, automotive firms initially did not have sufficient knowledge of electrochemistry, a discipline that became of high relevance with the emergence of fuel cell-powered electric motors. To address this knowledge gap, these firms engaged in alliances with dedicated fuel cell firms to learn the intricacies of electrochemistry and its implications for the design of fuel cell-based automotive vehicles. Both Daimler and Ford, for instance, formed an alliance with Ballard Power Systems, a Canadian fuel cell manufacturer, to improve the design of their fuel cell vehicles.

After having accessed knowledge from their alliance partners, firms can recombine it with their own knowledge, resulting in the generation of novel or even breakthrough inventions (Ahuja and Lampert, 2001). The ability of firms to benefit from alliances in terms of knowledge recombination hinges on characteristics of the alliance partner's knowledge pool (Savino et al., 2017). A first important characteristic is the size of the alliance partner's knowledge pool. The larger the knowledge pool of the alliance partner, the larger the number of components to which the focal firm has access, which in turn increases the likelihood that it can use the alliance partner's knowledge in knowledge recombination activities (Ravichandran and Giura, 2019; Schilling and Phelps, 2007). A second important characteristic of the alliance partner's knowledge pool is knowledge pool distance – i.e., the extent to which alliance partners' components belong to technological fields that are different from the technological fields in which the focal firm is active. More distant alliance knowledge pools increase the ability of the focal firm to access unfamiliar components (e.g., Kavusan et al., 2016; Mowery et al., 1996; Schildt et al., 2012), which subsequently allows for richer and more valuable knowledge recombination activities (Rosenkopf and Nerkar, 2001). Beyond a certain level of alliance partner knowledge distance, however, the focal firm might no longer have the cognitive abilities and appropriate routines to effectively absorb such components (Sampson, 2007; Subramanian et al., 2018). Instead, trying to absorb highly distant components from alliance partners can lead to information overload and diseconomies of scale in knowledge recombination efforts (Faems et al., 2020; Lane and Lubatkin, 1998), which triggers additional costs that can hamper or even outweigh potential knowledge recombination benefits.

In sum, extant alliance research provides important insights into which characteristics of an alliance partner's knowledge pool can shape the ability of the focal firm to utilize the alliance partner's knowledge. However, when conceptualizing and operationalizing the knowledge pool of alliance partners, these scholars tend to frame it as a set of independent components, ignoring potential ties among them. Below, we discuss recent research from the knowledge recombination literature that highlights the relevance of considering ties between components when defining and operationalizing knowledge pools.

2.2. Ties between components and recombinant value

Knowledge recombination studies (e.g., Dibiaggio et al., 2014; Yayavaram and Ahuja, 2008; Wang et al., 2014) emphasize that, next to considering characteristics of components within firms' knowledge pools, it is important to look at how these components are tied to each other. They provide three arguments that support the need to consider ties between components within knowledge pools.

First, components are highly malleable, implying that they can be recombined in numerous ways to build new inventions (Fleming, 2001; Hargadon and Sutton, 1997; Wang et al., 2014). For example, the polymer Polytetrafluoroethylene (PTFE) – better known by the brand name Teflon – is used to develop special coatings for non-stick frying pans, but also lubricants for various types of equipment. The notion that components are malleable constitutes the foundation for Weitzman's (1998) influential idea-based growth model. In this model, he proposes that limits to technological growth depend not so much on the introduction of new components, but rather on the ability of inventors to reuse existing components in novel ways. At the same time, components cannot be recombined ad infinitum. There are inherent limits to the number of different combinations in which components can be reused before they reach the point of recombinant exhaustion (Fleming, 2001; Wang et al., 2014). Considering the notion of malleability at the firm level, studies show that two firms with the same set of components may generate entirely different combinations using them (Dibiaggio et al., 2014; Yayavaram and Ahuja, 2008). Nesta and Dibiaggio (2003), for instance, find that, despite convergence in the technological origins of components used by biotech firms, considerable divergence is present in the actual usage of these components in knowledge recombination.

Second, components become tied to each other when they are used together to generate new inventions. This insight is based on modularity literature, which typically depicts inventions as complex systems of components that are linked together in specific ways (Fleming and Sorenson, 2001; Ghosh et al., 2014; Henderson and Clark, 1990). For an invention to come into existence, the underlying components need to be considerably adapted to each other (Hargadon and Sutton, 1997; Henderson and Clark, 1990). When building a fuel cell-powered laptop, for instance, the fuel cell system has to be adapted in such a way that operating temperatures remain low and uniform in order to avoid damaging the other components within the combination. This implies that, when two components A and B are used together in a new combination, the characteristics and functionalities of component A become intertwined with those of component B, i.e., the components become 'tied'. These ties create idiosyncrasies in firms' understanding of component functionalities. For example, whereas Mitsubishi Heavy Industries recombined fuel reformers within large-scale fuel cell power plants, Delphi and BMW recombined fuel reformers within fuel cell-driven Auxiliary Power Units (APU). As a result, their understanding of how fuel reformers function and how they can be applied to develop new inventions is clearly different.

Third, ties between components, which arise from prior knowledge recombination, can be a source of value on their own. In particular, they represent signals of the existence of potential synergies between two particular components, which can be further explored and probed to generate new inventions (Dibiaggio et al., 2014; Guan and Liu, 2016; Wang et al., 2014). At the same time, ties between components can also imply important challenges in the knowledge recombination process. Fleming and Sorenson (2001) report that recombining highly interdependent components (i.e., changes in one component affect how other components function) leads to inventions with lower value due to the inherent complexity and uncertainty involved with the adaptation processes associated to such inventions. Moreover, inventions that recombine highly interdependent components are difficult to access by actors that were not involved in the original creation of the invention (Sorenson et al., 2006). Yayavaram and Ahuja (2008) argue that firms with knowledge pools that have high levels of integration (i.e., each component is tied to numerous other components) have difficulties to create useful new inventions due to the large number of interdependencies that have to be considered between components. In a similar vein, Guan and Liu (2016) find that highly-integrated knowledge pools tend to reinforce firms' predispositions to exploit knowledge from familiar technological fields, but they do not influence their explorative efforts.

In sum, knowledge recombination scholars argue that (i) due to the malleable nature of components, firms may generate very different combinations even when using the same set of components, (ii) components become tied when they are jointly used in knowledge recombination, changing firms' understanding of how these components can be applied in new inventions, and (iii) the nature of these ties in the knowledge pool has important implications for subsequent knowledge recombination activities. In this study, we apply these insights in the context of R&D alliances, theorizing on how the nature of ties between components within the knowledge pool of an alliance partner influences the focal firm's knowledge utilization from the alliance partner. In particular, we focus our attention on alliance partner knowledge recombination novelty, which we define as the extent to which the alliance partner has created component ties that no other firm within the industry has created. We look at component ties that are new-to-the-industry as this makes the 'uniqueness' of the alliance partner's knowledge recombination capabilities most salient. Moreover, this level of analysis has been used in numerous knowledge recombination studies that examine component tie novelty (e.g., Dahlin and Behrens, 2005; Jung and Lee, 2016).

In the context of R&D alliances, the difference between low and high knowledge recombination novelty is best illustrated using a hypothetical example. In Figure 1, we depict two different alliance partner knowledge pools. Each circle represents a component. The letters represent the technological fields to which the components pertain. The solid lines indicate non-unique knowledge ties, whereas the dashed lines represent unique knowledge ties. The two alliance partner knowledge pools have the same quantity of components (six components) and the same distribution of knowledge across technological fields. However, we observe that, using the same components, the ties that are generated are considerably different. For example, alliance partner 1 has created a new-to-the-industry tie between components A and B, whereas alliance partner 2 has only created ties that exist elsewhere in the industry. According to our definition, this implies that the knowledge pool of alliance partner 1 has higher knowledge recombination novelty than the knowledge pool of alliance partner 2. In the next section, we hypothesize on how such differences in alliance partner knowledge recombination novelty influence the focal firm's knowledge utilization from this alliance partner.

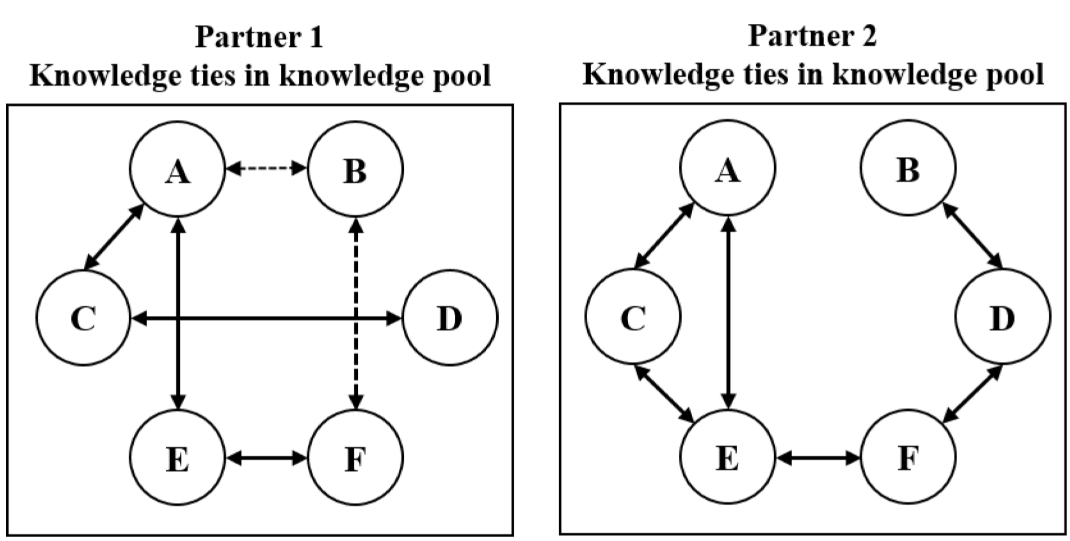

Fig. 1. Example of alliance partner knowledge recombination novelty

3. Hypothesis development

3.1. Alliance partner knowledge recombination novelty and focal firm knowledge utilization

Extant alliance research (e.g., Kavusan et al., 2016; Lane and Lubatkin, 1998; Larsson et al., 1998) points to two forces that shape the extent to which a focal firm utilizes knowledge from an alliance partner. The first is the value of available learning opportunities – i.e., the degree to which the knowledge possessed by the alliance partner is perceived as valuable by the focal firm and, thus, worthwhile to build upon in future inventions. The second is the retrievability of knowledge – i.e., the degree to which the focal firm is able to develop an adequate understanding of the alliance partner's knowledge, such that it can recombine it into new inventions. We stress that the value and retrievability of an alliance partner's knowledge pool not only depend on the individual characteristics of its components, but are also shaped by the nature of the ties among its components.

Our theoretical reasoning builds on the premise that the presence of unique knowledge ties in the alliance partner's knowledge pool can motivate the focal firm to learn more intensively from the alliance partner and subsequently utilize its knowledge. Within R&D alliances, alliance partners learn about each other's knowledge through cooperative activities (Faems et al., 2007; Hamel, 1991). Once the focal firm has a sufficient understanding of the knowledge of the partner, it can subsequently utilize this knowledge in its own inventive activities. However, the motivation to learn from a particular alliance partner can vary substantially (Larsson et al., 1998). We argue that the focal firm is more interested in learning from an alliance partner, if this alliance partner has demonstrated a capability to create ties between components in ways that are unique in the industry. When the alliance partner is the only firm in the industry to have recombined two particular components to build an invention, it indicates that this alliance partner has unique recombinant capabilities (Hargadon and Sutton, 1997). This increases the motivation of the focal firm to learn from this particular alliance partner, absorb its knowledge, and utilize it in subsequent knowledge recombination activities. In contrast, when an alliance partner does not have unique knowledge ties, the focal firm will be less motivated to learn from the alliance partner, which is associated with lower knowledge utilization rates. In other words, more unique ties increase the perceived value of an alliance partner's knowledge pool, increasing the motivation of the focal firm to learn from this particular alliance partner and utilize its knowledge in knowledge recombination activities (see upward-going solid line in the left panel in Figure 2).

At the same time, we expect that the alliance partner's knowledge recombination novelty creates knowledge retrievability challenges for the focal firm. Knowledge on how to adjust components in order to integrate them into new combinations is highly tacit (Hargadon and Sutton, 1997; Henderson and Clark, 1990) and, consequently, difficult to transfer across organizational boundaries (Kogut and Zander, 1992; Sorenson et al., 2006; Szulanski, 1996). This issue is exacerbated in the case of an alliance partner that has knowledge ties that are new-to-the-industry, since the knowledge involved with creating such ties resides exclusively within this partner. Consequently, developing an understanding of an alliance partner's unique knowledge tie is expected to be a complex and time-consuming process for the focal firm.

It is likely that the retrievability challenges associated with unique knowledge ties also affect the extent to which other knowledge of the alliance partner can be retrieved. This is because the alliance partner's understanding of how individual components function, and how they should be applied in knowledge recombination, hinges on the characteristics of all other knowledge present in the knowledge pool. Due to these interdependencies, an individual knowledge tie cannot be isolated from the knowledge pool (Ghosh et al., 2014; Yayavaram and Ahuja, 2008). To exemplify this, consider how, in Figure 1, alliance partner 1's understanding of how component E functions not only hinges on its prior recombination with components A and F, but also, indirectly, on how component A was uniquely recombined with component B. In this example, the nature of the tie between components E and A is, thus, partly shaped by component A's tie with component B.

Furthermore, we expect that these retrievability challenges become exponentially stronger when the propensity of unique ties in the alliance partner's knowledge pool is higher. Specifically, the larger the propensity of unique knowledge ties in the alliance partner's knowledge pool, the higher the number of unique knowledge ties that has to be considered simultaneously by the focal firm before a sufficiently deep understanding of the alliance partner's knowledge can be obtained. The exponentially increasing solid line in the middle panel in Figure 2 represents this retrievability mechanism.

To summarize, we expect that, the higher the propensity of unique knowledge ties in the knowledge pool of the alliance partner, the more valuable the focal firm perceives the knowledge pool to be, increasing its motivation to absorb and utilize knowledge from the alliance partner. At the same time, an increase in the propensity of unique knowledge ties in the knowledge pool of the alliance partner increases retrievability challenges for the focal firm, hampering its ability to actually utilize knowledge from this alliance partner. Moreover, these retrievability challenges increase in a non-linear way. As Haans et al. (2016) describe, and as shown by the solid line in the right panel in Figure 2, this combination of a linear positive effect and an exponential negative effect results in an inverted U-shaped relationship. We therefore hypothesize:

H1. *The alliance partner's knowledge recombination novelty has an inverted U-shaped relationship with the focal firm's knowledge utilization from the alliance partner.*

3.2. The moderating effect of the focal firm's knowledge recombination novelty

We argue that the relationship between alliance partner knowledge recombination novelty and a focal firm's knowledge utilization can be moderated by the focal firm's own knowledge recombination novelty in

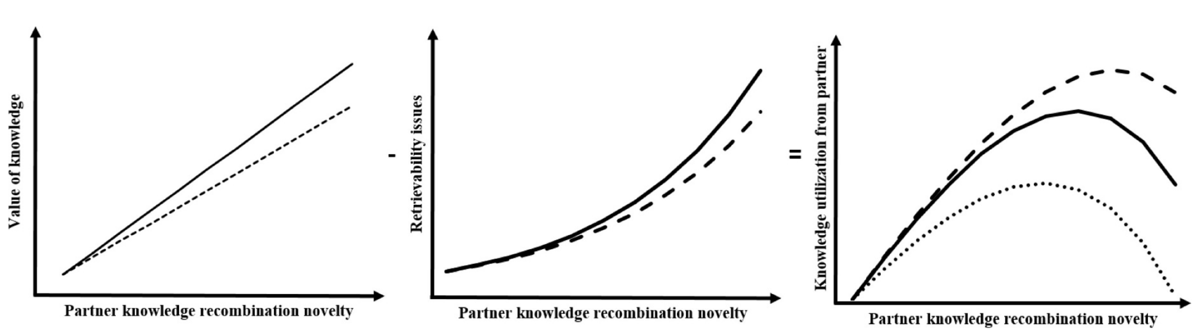

Fig. 2. Theoretical mechanisms for hypothesis 1 and 2

two different ways. First, we highlight that the focal firm's knowledge recombination novelty can increase its ability to deal with the aforementioned retrievability challenges. Second, we expect that the focal firm's knowledge recombination novelty might also reduce its motivation to take advantage of the alliance partner's knowledge recombination novelty.

3.2.1. Impact on ability to address retrievability challenges

We expect that the strength of retrievability challenges associated with alliance partner knowledge recombination novelty depends on the focal firm's own experience with recombining components in unique ways. When the focal firm has a history of recombining components in unique ways, it has valuable experience in understanding and dealing with idiosyncratic ties among components. Prior knowledge recombination efforts are stored in the firm's organizational memory as experiences and lessons that can later be called back upon to inform and guide new knowledge recombination activities (Cattani, 2005; Hargadon and Sutton, 1997). This follows the familiar notion that "capabilities are built through experience" (Eggers, 2012, p. 318).

The main advantage of experience with creating unique ties among components is that firms learn how to disentangle component combinations more effectively. When firms repeatedly recombine components in highly novel ways, they develop an understanding of how components should be understood as constituents of large complex systems. They also develop a generic understanding on how to create ties between components that do not exist elsewhere (Hargadon, 2002; Hargadon and Sutton, 1997). Through repeatedly creating unique knowledge ties, the tasks and interactions underlying such recombination efforts are routinized within the firm (Grant, 1996; Hargadon, 2002; Hargadon and Sutton, 1997), allowing for their subsequent redeployment in new knowledge recombination activities. We therefore argue that, when the focal firm has developed the capability to generate unique ties between components, such capability helps in better understanding how other firms have recombined components in unique ways. This experience effect is likely to reduce the strength of the retrievability mechanism associated with alliance partner's knowledge recombination novelty, as represented by the dashed line in the middle panel of Figure 2.

3.2.2. Impact on motivation to access and absorb knowledge

While its own knowledge recombination novelty might provide a focal firm with useful experience to better retrieve knowledge in the alliance partner's knowledge pool, it can also reduce its motivation to access and absorb the knowledge of the alliance partner. Individuals in firms are often positively biased towards the value of their own knowledge, and negatively biased towards external sources of knowledge (Grigoriou and Rothaermel, 2017; Katz and Allen, 1982; Srivastava and Gnyawali, 2011). These biases typically become more pronounced when the value of firms' own knowledge is higher and when internal resources are already proficient (Hussinger and Wastyn, 2016; Srivastava and Gnyawali, 2011). Such firms might perceive venturing outside their organizational boundaries to find unique knowledge as unnecessarily risky and costly activities (Ahuja and Lampert, 2001; Srivastava and Gnyawali, 2011). In our context, we expect that, when a focal firm has already generated numerous unique ties within its own knowledge pool, this reduces the perceived value of unique knowledge ties of an alliance partner, reducing the motivation of the focal firm to spend resources to retrieve the alliance partner's knowledge. This effect is likely to reduce the strength of the positive mechanism associated with the alliance partner's knowledge recombination novelty, as represented by the dashed line in the left panel of Figure 2.

3.2.3. Net moderating effect of focal firms' knowledge recombination novelty

We expect these two potential moderating effects to co-exist, such that focal firms with high knowledge recombination novelty are more capable of overcoming the retrievability challenges that are associated with high alliance partner recombination novelty, but simultaneously less motivated to access and absorb knowledge from alliance partners with high recombination novelty. A priori, three mutually exclusive net outcomes are possible depending on the relative strength of these two effects: (1) if the positive 'ability' effect is stronger than the negative 'motivation' effect, the inflection point of the inverted U-shaped relationship between alliance partner knowledge recombination novelty and the focal firm's knowledge utilization from this alliance partner would shift upwards and to the right (the dashed line in the right panel in Figure 2), (2) if the positive 'ability' effect is weaker than the negative 'motivation' effect, the inflection point of the inverted U-shaped relationship between alliance partner knowledge recombination novelty and the focal firm's knowledge utilization from this alliance partner would shift downwards and to the left (the dotted line in the right panel in Figure 2), (3) if the positive 'ability' effect and negative 'motivation' effect cancel each other out, then the inflection point of the inverted U-shaped relationship between alliance partner knowledge recombination novelty and the focal firm's knowledge utilization from this alliance partner does not shift (consistent with the solid line in the right panel in Figure 2). From a theoretical point of view, it is ambiguous which of the three outcomes to expect. We therefore do not formulate an explicit hypothesis regarding the nature of the net moderation effect of the focal firm's knowledge recombination novelty on the relationship between alliance partner knowledge recombination novelty and the focal firm's knowledge utilization from this alliance partner.

4. Methods

4.1. Empirical setting

We tested our predictions using data on the fuel cell R&D alliances of 70 firms in the period 1993-2007[1]. Fuel cells are electrochemical devices that produce electricity through a chemical reaction between hydrogen and oxygen. The first use of fully-operational fuel cell systems dates back to the early 1960's, when NASA used them to provide electricity and potable water to space crafts in the Apollo program (Sharaf and Orhan, 2014). In the 1970's and 80's, fuel cell development slowed down because of the apparent commercial infeasibility of the technology. However, in the early 1990's, several important breakthrough inventions in the design of polymer-electrolyte fuel cells (PEFC) led firms to reinvest in the development of fuel cell technology

[1] The focal sample of 70 firms was constructed in different steps. We first compiled a list of the top 200 patent applicants in the fuel cell industry. For these 200 firms, we collected ownership data, aggregating all patents of subsidiaries in which these firms had a controlling interest to the parent-firm level. For the ownership data of these parent firms, we used the most recent data available at the time of data collection from Bureau van Dijk's Orbis database. This information was complemented with data regarding mergers and acquisitions from the SDC Platinum Mergers and Acquisitions database. We also looked for potential name changes and aliases of firms, using data from the Orbis database. To obtain harmonized names of patent applicants, we relied on the EEE-PPAT (ECOOM-EUROSTAT-EPO PATSTAT Person Augmented Table) data from ECOOM. After removing firms with missing data (i.e., the firm did not form fuel cell R&D alliances with other firms between 1993 and 2007, had incomplete ownership data, had only alliance partners with zero fuel cell patents, or did not have data on consolidated revenues), we retained a sample of 85 focal firms. Finally, 15 focal firms were excluded from the analyses because they had no within-unit variance in the dependent variable (i.e., they never cited any alliance partner).

(Perry and Fuller, 2002). In subsequent years, firms started considering fuel cells as alternative sources of energy for numerous vehicles and devices, ranging from automotive vehicles and ships, to laptops and cellphones. As a result, the field saw numerous new entrants from different industries as well as the emergence of dedicated fuel cell firms.

The fuel cell industry has many characteristics that make it an ideal setting for studying R&D alliances and their relationship with firms' knowledge recombination activities. First, as a corollary of intense technological developments in the past three decades, patenting activity in fuel cell technology is consistently high, ranking among the highest in clean energy technologies (Albino et al., 2014). As a result, firms have left behind an observable trail of their inventive activities, which we can use to infer the characteristics of their knowledge recombination activities. Second, since there are many different types of firms that develop fuel cell technology, including automotive manufacturers (such as Daimler, General Motors, and Toyota), electronics firms (such as Panasonic, Samsung Electronics, and Toshiba), and dedicated fuel cell system producers (such as Ballard Power Systems, FuelCell Energy, and Hydrogenics), variance in knowledge recombination activities is ensured. Third, due to the interdisciplinary nature of fuel cell technology, where knowledge from different fields such as electrochemistry, thermofluids, material sciences, and physics needs to be combined, firms in this industry have a high tendency to participate in alliances (Hellman and van den Hoed, 2007; Vasudeva and Anand, 2011).

4.2. Patent data

To measure the knowledge recombination activities of firms, we collected data on the worldwide patenting activities of the firms in our sample from the PATSTAT database (Autumn 2013 version). To retrieve fuel cell patents, we collected all patents filed by firms with the International Patent Classification (IPC) code H01M8 (which is titled 'Fuel cells; Manufacture thereof'). In contrast to other technologies, which tend to be dispersed across different IPC codes, fuel cell technology is largely concentrated within this single IPC code (Tanner, 2014; Vasudeva and Anand, 2011). In line with recent patent studies (Bakker et al., 2016; de Rassenfosse et al., 2013; Kok et al., 2019), we aggregate patent applications to the patent family level, using the European Patent Office's DOCDB patent family categorization[2]. The DOCDB patent family captures all patent applications filed at any patent office in the world that cover the same technical content (i.e., the same underlying invention) (Albrecht et al., 2010). Relying on patent families helps to overcome the home-country bias of single patent office applications (de Rassenfosse et al., 2013). This bias arises because firms tend to solely file patents to their local patent office. For example, many European firms file their patents at the EPO and not at the USPTO. As a result, solely relying on USPTO patent applications would considerably underestimate the knowledge recombination activities of firms outside North-America (de Rassenfosse et al., 2013). This bias is especially problematic in the fuel cell industry, as many prominent players in this field are Asian (e.g., Asahi Glass, Honda, Samsung Electronics) or European (e.g., Air Liquide, Renault, Siemens) firms. An additional important advantage of using patent families is that it captures a broader set of backward citations (Albrecht et al., 2010). Since we use information from backward citations to track knowledge utilization, this is an important advantage of using patent families[3]. To capture the date that is closest to the actual creation of the invention, we used the priority date of the patent family (i.e., the filing date of the first patent application to protect the underlying invention at any patent office in the world). Moreover, when measuring knowledge pool characteristics of the focal firm and the alliance partner, we applied a five-year time window, implying that we only considered patents to be part of the knowledge pool if they were filed between t-5 and t = 0. For example, the patents that are part of a firm's knowledge pool in 2000 are those with a priority year between 1995 and 2000.

To identify the technological fields from which recombined components in inventions originate, we inspected the IPC codes listed on fuel cell patents. IPC codes are assigned to patents to facilitate patent examiners' search activities. As a result, they tend to be rather objective measures of the invention's technological content (Gruber et al., 2013). Each IPC code associated to a patent reflects a heterogeneous and distinct body of technological knowledge used to develop the underlying invention (Dibiaggio et al., 2014; Gruber et al., 2013), allowing us to detect which components are recombined into new inventions. Moreover, when two IPC codes are co-listed on a patent, this represents the generation of a new tie or reinforcement of an existing tie between these components (Dibiaggio et al., 2014). The IPC code system is hierarchical (i.e., lower levels represent subdivisions of higher levels), such that the first IPC code digit indicates the highest level of abstraction (e.g., H refers to 'Electricity' while G refers to 'Physics'). Subsequent digits increase the level of granularity. To capture the technological field to which an invention pertains, we use the IPC code level referred to as the main group. For example, C08J5 (i.e., 'Manufacture of articles or shaped materials containing macromolecular substances') and H02J7 (i.e., 'Circuit arrangements for charging or depolarizing batteries or for supplying loads from batteries') are main groups that often appear on fuel cell patents.

4.3. Alliance data

We used the LexisNexis database to identify R&D alliances in the fuel cell industry. We used this database since there is strong evidence that other databases, such as Thompson Reuters' SDC Platinum Joint Venture and Strategic Alliances database, considerably underestimate the number of existing alliances (Lavie, 2007)[4]. The LexisNexis database compiles press releases from different sources, including newspapers, trade journals, and wire transcripts. We employed a broad set of keywords to detect fuel cell R&D alliances[5,6] and manually screened over 50,000 press releases. We searched for all fuel cell R&D alliances formed before 2008. Our selection criteria for R&D alliances mirrored

[2] This means that we aggregated the information contained in individual patent applications with IPC code H01M8 and at least one firm applicant to the DOCDB patent family level (i.e., patent office, applicant name, IPC codes, number of inventors). Therefore, the patent-based measures are forward-looking, in the sense that information from future patent applications is used to infer characteristics of the patent family in its priority year.

[3] We emphasize that, following the methodology described by Bakker et al. (2016) and Nakamura et al. (2015), the backward citations of all individual patent applications within each patent family were aggregated to the patent family level. In recent versions of PATSTAT, this information can be found in table TLS228. For example, consider two patents A and B that belong to patent family 1. If patent A cites patents C and D, and patent B cites patents D and E, then patent family 1's backward citations are C, D, and E. We also corrected for patent family membership at the backward citation-level in such a way that, if patent family 1's cited patents D and E that actually pertain to the same patent family, they are not counted twice.

[4] To verify this evidence, we searched in the SDC database for all alliances in which the deal text mentioned the keyword "fuel cell". In the period 1993-2007, for our 70 sample focal firms, we detected 92 alliance announcements (of any type, including supply, marketing, distribution, etc.) in SDC. In contrast, we identified 393 ongoing R&D alliances in the same period when we searched in LexisNexis.

[5] We did not specifically search for non-R&D alliances because (i) the focus of our study is on technological activities and (ii) the language used to describe non-R&D alliances is highly idiosyncratic, especially for supply and distribution alliances. Hence, our sample only contains alliances with an R&D element (Hagedoorn, 2002).

[6] The set of keywords used in the search procedure is available from the authors upon request.

the definition of Hagedoorn (2002)[7]. Following earlier studies (e.g., Ahuja, 2000; Phelps, 2010), multi-partner R&D alliances were transformed into dyads. To give an example, the following press release extract identifies an R&D alliance between DuPont Fluoroproducts and H Power Corp:

*H Power Corp., a leading fuel cell development company, today announced it has formed a joint development agreement with DuPont Fluoroproducts aimed at developing direct methanol fuel cells (DMFC) for portable and mobile applications. Under the agreement, the two companies will work together to develop direct methanol fuel cell products in the range of 100 to 1000 watts, initially targeted to mobile applications, such as scooters, bicycles and golf carts. This technology could also be applied to consumer products such as power tools and other battery replacement applications. (*Business Wire, 2001*)*

Whereas numerous studies assume a fixed lifespan for alliances (e.g., Schilling and Phelps, 2007; Srivastava and Gnyawali, 2011; Vasudeva and Anand, 2011), we instead tracked alliances over time to more precisely identify their starting and termination dates and have a more accurate estimate of their duration (Ahuja, 2000; Lavie, 2007; Phelps, 2010)[8]. This is an important methodological step, given the substantial heterogeneity in the lifespan of alliances (Deeds and Rothermael, 2003).

4.4. Variables

4.4.1. Dependent variable

To measure the focal firm's knowledge utilization from an alliance partner, we follow earlier alliance studies (Gomes-Casseres et al., 2006; Mowery et al., 1996; Rosenkopf and Almeida, 2003) and examine backward citations of patents. Backward citations are a proxy for the prior technological knowledge upon which an invention builds and have therefore been used to track inter-firm knowledge utilization (Jaffe et al., 1993; Jaffe and de Rassenfosse, 2017). As Belenzon (2012, p. 267) notes “A citation from patent B to an antecedent patent A indicates that patent A contains a piece of knowledge on which patent B builds”. To compute the dependent variable, we count the total number of fuel cell citations that the focal firm made to an alliance partner[9]. This variable is lagged by one year since we assume that it takes time for the focal firm to absorb and use knowledge from its alliance partner.

Some studies claim that backward citations are rather indirect proxies of knowledge flows (e.g., Alcacer and Gittelman, 2006; Criscuolo and Verspagen, 2008) because (i) citations are not only added by the applicant, but also by third parties such as patent examiners and (ii) citations are often added to patents for strategic or legal reasons. In contrast, other studies, using information from inventor surveys, provide evidence for the close link between knowledge flows and patent citations (e.g., Duguet and MacGarvie, 2005; Jaffe et al., 2000). We perform two actions to alleviate potential biases associated with backward citation data. First, by aggregating patent citations to the patent family-level, we can effectively triangulate the information from different patent examiners from different patent offices, allowing us to mitigate issues such as the bias of patent examiners to cite patents that are geographically proximate (see, e.g., Criscuolo and Verspagen, 2008). Second, we control for the citation strategies of the focal firm by including control variables for (i) its rate of internal backward citations, (ii) its average age of backward citations, and (iii) its distribution of patents across the three major patent offices (USPTO, EPO, JPO).

4.4.2. Independent variable

To operationalize *Knowledge recombination novelty*, we inspect the IPC codes that were listed on the patents filed by the firm (Verhoeven et al., 2016)[10]. We construct this variable in two steps. First, we create a list of the IPC code dyads present on fuel cell patents filed by all firms in the industry between t-5 and t = 0. Second, we examine whether the IPC code dyads that were listed on a firm's patents within its knowledge pool were also present on other patents of firms in the industry. If one firm applied for all the patents on which a particular IPC code dyad is listed, then this constitutes a unique knowledge tie for that particular firm. To normalize our measure, we divide the total number of unique knowledge ties by the total number of knowledge ties in the firm's knowledge pool.

4.4.3. Control variables

We include two control variables that are related to the alliance portfolio of the focal firm. We control for the total number of alliance partners of the focal firm in the current year (*Alliance portfolio size)* (Deeds and Hill, 1996; Wassmer, 2010). It is likely that, in large alliance portfolios, the attention of the focal firm is diverted to other alliance partners, lowering knowledge utilization of the alliance partner in the focal dyad. Moreover, given the different nature of knowledge provided by research organizations, we control for the share of organizations within the alliance portfolio that are universities, research institutes, and government laboratories (*Research organization partners*) (Faems et al., 2005; Mora-Valentin et al., 2004).

At the alliance dyad level, we follow Gomes-Casseres et al. (2006) and control for the number of concurrent R&D alliances between the focal firm and the alliance partner (*Concurrent alliances*). We also control for the tenure of the alliance, calculated as the time that elapsed since the (current) ongoing tie between the focal firm and the alliance partner was initiated (*Alliance tenure*)[11]. This is an important control variable as trust and relational quality between alliance partners tend to be developed over time (Dyer and Singh, 1998), influencing knowledge utilization outcomes (Schildt et al., 2012). Multi-partner alliances – i.e., alliances in which more than two alliance partners are involved – can increase the motivation to engage in free-riding behavior and hamper coordination (Das and Teng, 2002). Therefore, we include a control variable that captures whether the alliance dyad is part of a multi-partner alliance (*Multi-partner*). Since equity arrangements in an R&D alliance may curb opportunistic behavior and consequently influence knowledge transfer (Kogut, 1988), we include a control variable for

[7] Consistent with the emerging nature of fuel cell technology, there were several collaborations in which the only aim was to trial, validate or demonstrate the technology. We consistently excluded these from our sample because they were (i) typically challenging to track over time, (ii) positioned relatively downstream (i.e., only involving non-R&D active end-users as partners, such as electric services providers), and (iii) typically of very short duration, with some lasting periods as short as one week. Moreover, we noticed that such alliances were typically reported separately from joint development alliances, indicative of their inherently different nature.

[8] When termination of the alliance was not formally announced, we followed Ahuja (2000) and either (i) utilized the expected tenure of the alliance or (ii) tracked the ongoing status of the alliance through subsequent press releases. Moreover, when the termination date could not be approximated, we assumed that the alliance was terminated in the year subsequent to the starting year, which is consistent with the relatively short tenure of the majority of R&D alliances (Ahuja, 2000).

[9] We only include citations from fuel cell patents of the focal firm to fuel cell patents of the alliance partner because (i) this ensures that the knowledge flows that we capture are related to the fuel cell alliance activity and (ii) core explanatory variables are based on IPC codes listed on the fuel cell patents of the focal firm and the alliance partner.

[10] Fleming et al. (2007), using United States Patent Classification (USPC) codes, consider a dyad to be unique when it appears for the first time on a patent filed at the USPTO. Our approach differs from theirs, as we only consider IPC code dyads that are listed on fuel cell patents (i.e., patents that list IPC code H01M8). This is to ensure that the IPC code dyad is, in fact, related to fuel cell technology.

[11] For example, if two firms have two separate ongoing alliances in 2002, one of which was initiated in 1998 and the other in 2000, then this control variable takes a value of 4 in the year 2002 for this firm-partner dyad.

whether the alliance is organized as a joint venture (*Joint venture*). The presence of government funding often entails that an extensive contractual framework is present and that the alliance faces external control (Busom and Fernández-Ribas, 2008), which helps aligning the actions of alliance partners and reducing opportunistic behavior. Therefore, we include a control variable that captures whether the alliance is government-funded (*Government-funded*). We identified the presence of government funding in the news articles in LexisNexis that referred to the alliance. Geographical distance can hamper knowledge transfer between alliance partners (Faems et al., 2020). Therefore, we include a control variable defined at the parent firm level that captures whether the alliance partner is from a different country than the one where the focal firm is located (*International alliance partner*). We also control for industry overlap between the focal firm and the alliance partner, based on two-digit SIC codes (*Industry overlap*). Specifically, at the parent firm level, if the focal firm and the partner belonged to the same two-digit SIC code, this variable took a value of one and a value of zero otherwise. This variable is a proxy for the objectives of the alliance since high industry overlap between alliance partners is indicative of alliances targeting scale benefits, while low industry overlap is indicative of alliances targeting technological diversification (Jiang et al., 2010).

We also include in our models several variables that measure attributes of the knowledge pool of the alliance partner. We emphasize that a five-year time window is used when measuring the attributes of the knowledge pool of the alliance partner. We control for the size of the alliance partner's knowledge pool by counting the total number of IPC codes used by the alliance partner on its fuel cell patents (*Alliance partner knowledge quantity)*. We control for the diversity of the alliance partner's knowledge pool, by computing the Herfindahl index of the distribution of IPC codes listed on the alliance partner's fuel cell patents (*Alliance partner knowledge diversity*). We also control for the average age of the components in the alliance partner's knowledge pool, measured as the average number of years elapsed since each component became part of the knowledge pool of the alliance partner (*Alliance partner knowledge age*). We adopt the measure developed by Yayavaram and Chen (2015) to control for the overall complexity of the alliance partner's knowledge pool (*Alliance partner knowledge complexity*). To create this measure, we looked at all DOCDB patent families on which a particular IPC code had been listed up until the current year (i.e., no time window is applied). We first needed to calculate the ease of recombination of each individual IPC code. To do so, we divided the number of unique IPC codes the IPC code has been co-listed with on a patent family before by the number of patent families on which the IPC code has been listed on before. Subsequently, each IPC code's ease of recombination was weighted by its proportion in the alliance partner's knowledge pool. For example, if the alliance partner's knowledge pool contains three IPC codes with an ease of recombination of respectively 0.05, 0.02, and 0.1 that have been used by the firm four, three, and two times, then the alliance partner's knowledge pool complexity equals: $(\frac{4}{9} \times 0.05) + (\frac{3}{9} \times 0.02) + (\frac{2}{9} \times 0.1) = 0.051$. High values of this measure correspond to knowledge pools with components that, on average, can be more easily combined with components from other technological fields. We also control for the level of usage of components in the alliance partner's knowledge pool by calculating the average number of ties of each component in the knowledge pool (*Alliance partner knowledge reuse*). We include a variable that captures the knowledge distance between the knowledge pool of the focal firm and the alliance partner (*Alliance partner knowledge distance)* by calculating the measure of knowledge distance developed by Jaffe (1986) and used by numerous alliance studies (e.g., Sampson, 2007; Subramanian et al., 2018)[12]. To capture the extent to which the alliance partner's knowledge is also used by other firms in their inventive efforts, which could reflect the competitive intensity of knowledge utilization (Katila and Chen, 2008), we count how many fuel cell citations were made to the alliance partner's fuel cell patents at t + 1 by other firms (we exclude citations from the focal firm and the alliance partner itself) (*Knowledge utilization by other firms)*. We also control for the number of fuel cell citations that the focal firm made to the alliance partner's fuel cell patents up until the current year in order to account for potential path-dependencies in the knowledge utilization patterns of the focal firm. We split this variable up into two parts: (i) the sum of fuel cell citations made by the focal firm to the partner's fuel cell patents up until one year before the start of the alliance (*Knowledge utilization before alliance*) and (ii) the sum of fuel cell citations made by the focal firm to the partner's fuel cell patents between the starting year of the alliance up until the current year (*Knowledge utilization during alliance*). We do not apply a time window when measuring these two variables.

We control for a number of focal firm characteristics. In line with the variables at the alliance partner level, we include variables measuring the focal firm's knowledge pool size (*Firm knowledge quantity*), diversity (*Firm knowledge diversity*), age (*Firm knowledge age*), complexity (*Firm knowledge complexity*), and knowledge usage (*Firm knowledge reuse*). We include the total number of external fuel cell backward citations of the focal firm at t + 1 (*Firm total external knowledge utilization*) to account for the overall tendency of the firm to use external knowledge in its knowledge recombination activities. We control for the average number of inventors listed on the focal firms' fuel cell patents (*Firm internal social network*) to account for the intensity of collaboration among inventors within the focal firm's internal social network. We include a variable measuring the focal firm's share of internal fuel cell backward citations in order to control for the focal firm's tendency to rely on its own knowledge (*Firm internal knowledge focus*). We capture the focal firm's focus on old rather than recent knowledge, by calculating the average age of its fuel cell backward citations (*Firm old knowledge focus*). We control for the focal firm's focus on different patent offices to control for any between-patent office heterogeneity that might affect patent citation behavior (Bakker et al., 2016; de Rassenfosse et al., 2013). In particular, we introduce three control variables that measure the share of fuel cell patent families in the focal firm's knowledge pool in which at least one patent application within the patent family was filed at the USPTO, EPO, or JPO (*Firm USPTO patents, Firm EPO patents, Firm JPO patents*). To capture the overall size of the focal firm, we collected additional data from Compustat, LexisNexis, Factiva, and annual reports on the consolidated revenues of the focal firms in the years included in our sample (*Firm turnover*). This control variable is divided by 1,000,000 to improve legibility. Finally, all models include dummies for each focal firm and year of observation.

4.5. Analytical method

The unit of analysis is the firm-partner dyad (Gomes-Casseres et al., 2006; Schildt et al., 2012). We constructed our sample in two steps. First, for each focal firm in our sample, we identified all the partners with which it had been involved in a fuel cell R&D alliance between 1993 and 2007. Second, for the identified firm-partner dyads, we created an observation for each year in which they were involved in an alliance. This means that, if focal firm *i* and partner *j* initiated an alliance in 1998 that lasted until 2003, this resulted in 6 observations. We use negative binomial regressions to analyze our data, since the dependent variable only takes non-negative integer values and is overdispersed (Hausman et al., 1984). In negative binomial regressions, observations are omitted when there is no within-unit variance in the

[12] Our main results remained stable when we used an alternative measure for knowledge distance, which consists of calculating the Euclidean distance between the distribution of IPC codes listed on the patents of the focal firm and its

(*footnote continued*)
alliance partner (e.g., Ahuja, 2000; Rosenkopf and Almeida, 2003).

dependent variable. Since, in our analyses, we include dummies for each focal firm, this implies that observations of focal firms that never cited any alliance partner (i.e., the dependent variable for the observations of this focal firm always equals zero) were excluded. The final sample therefore includes 1623 firm-partner-year observations, associated to 70 focal firms.

To account for non-independencies between dyads, we cluster the standard errors in two dimensions: (i) the dyad, where observations of the same dyad are grouped together[13]; and (ii) the partner, where observations that involve the same partner are grouped together. The multi-way cluster-robust standard errors, obtained using the Stata routined developed by Kleinbaum et al. (2013), are based on the algorithm by Cameron et al. (2011).

4.6. Results

4.6.1. Descriptive statistics

Table 1 shows the descriptive statistics and correlation matrix. We observe that in the average firm-partner dyad year, the focal firm cites 3.27 patents from the partner and 17.5% of alliance partner knowledge ties are new-to-the-industry. This latter value suggests that the creation of unique knowledge ties is not a rare event in the context of the fuel cell industry. Moreover, we observe that the average tenure of the alliance dyad is 2.95 years, with a maximum of 20 years. To verify whether our data suffer from issues of multicollinearity, we compute variance inflation factor (VIF) values, and find that average VIF values are below the common threshold values of five and ten (Mason and Perreault, 1991).

4.6.2. Regression results

Table 2 shows the regression results. Model 1 is the baseline model, which only includes the control variables. In line with our expectations, we find that a focal firm's higher propensity for having unique knowledge ties is associated with higher citation rates to alliance partners (Model 1: $\beta_{\text{Firm knowledge recombination novelty}} = 2.165$, $p < 0.001$). In terms of knowledge pool characteristics of the alliance partner, we observe that more complex (Model 1: $\beta_{\text{Alliance partner knowledge complexity}} = -9.307$, $p < 0.05$) and distant (Model 1: $\beta_{\text{Alliance partner knowledge distance}} = -6.394$, $p < 0.001$) knowledge pools are associated with fewer citations from the focal firm. In contrast, knowledge pools in which components have been extensively reused on average have a positive and statistically significant association with the number of citations from the focal firm to the alliance partner's patents (Model 1: $\beta_{\text{Alliance partner knowledge reuse}} = 0.071$, $p < 0.001$).

Model 3 includes the variable *Alliance partner knowledge recombination novelty* and its squared term and allows testing Hypothesis 1. The results show a statistically significant and positive linear coefficient for alliance partner knowledge recombination novelty (Model 3: $\beta_{\text{Alliance partner knowledge recombination novelty}} = 4.941$, $p < 0.001$) and a statistically significant and negative quadratic coefficient for alliance partner knowledge recombination novelty (Model 3: $\beta_{\text{Alliance partner knowledge recombination novelty squared}} = -7.934$, $p < 0.001$). To verify the existence of an inverted U-shaped relationship, we follow the procedure described by Lind and Mehlum (2010) and Haans et al. (2016). We confirm that (i) the slope of alliance partner knowledge recombination novelty before the inflection point is positive and statistically significant, and the slope of alliance partner knowledge recombination novelty after the inflection point is negative and statistically significant and (ii) the 95% Fieller confidence interval of the inflection point (which is located at a value of 0.31, or, approximately one standard deviation above the mean) is within the range of observable data points ([0.227, 0.429]). Hence, we find support for Hypothesis 1. This relationship is depicted in Figure 3. The predicted count of citations from the focal firm to the partner equals 3.55 when knowledge recombination novelty is 0 (i.e., the partner's knowledge pool contains no unique ties) and 7.67 when knowledge recombination novelty takes a value of 0.31 at the inflection point of the inverted U-shaped relationship. Hence, alliance partner knowledge recombination novelty is associated with a considerable difference in the rate of knowledge utilization from a partner. Model 5 allows us to test the interaction between the focal firm's knowledge recombination novelty and the alliance partner's knowledge recombination novelty. The results show that this interaction is statistically non-significant.

4.7. Additional analyses

4.7.1. Self-selection bias

The firm's decision to form an alliance is likely to be non-random (de Faria et al., 2010). In particular, firms are likely to self-select into specific alliances based on characteristics that are unobservable but which may affect the outcomes of the alliance. To attenuate this potential issue, we follow extant research (e.g., Acharya and Pollock, 2013; Funk, 2014) and use a Heckman two-stage correction for self-selection (Heckman, 1979). In the first stage, we estimate the probability of an alliance between the focal firm and the alliance partner to exist in a particular year using a probit regression (in this context, the dependent variable is a binary variable indicating the existence of an alliance between the focal firm and the alliance partner in a given year). The first stage has to include an instrumental variable that is associated with selection into the main sample (i.e., alliance formation), but is not associated with the outcome of the second stage (i.e., knowledge utilization from an alliance partner). Using the predicted values from the first stage, a correction factor is computed, referred to as the inverse Mills ratio, which is entered as an additional control variable in the second stage. The inclusion of the inverse Mills ratio in the main equation helps attenuating self-selection issues.

In order to obtain the population of realized and unrealized alliance dyads for the first stage probit regression, we follow Yayavaram et al. (2018) and create a list of all firms that have been involved in a fuel cell R&D alliance before 2008. We then use this list to create a set of unrealized dyads for each year in which the focal firms in our sample had ongoing R&D alliances. For example, we match 315 firms to Toyota in 2005, of which four firms had an actual partnership with Toyota in that year. These 315 firms were those that had formed at least one R&D fuel cell alliance before 2008 and had at least one fuel cell patent with knowledge ties in the knowledge pool, implying that they represent a meaningful ‘at risk’ set of potential R&D alliance partners. This procedure yields a total of 144,968 observations, of which 1623 represent realized dyads.

The instrumental variable that we use in the first stage probit regression is membership in the U.S. Fuel Cell Council (USFCC). The USFCC was one of the largest trade associations in the fuel cell industry (in 2010, it merged with the National Hydrogen Association to form the Fuel Cell and Hydrogen Energy Association). Its core mission was to address barriers hindering the widespread commercialization of fuel cell and hydrogen technologies. To this end, the USFCC conducted a wide range of activities, such as helping to set standards and benchmarks, lobbying for government support, and educating the public about fuel cell and hydrogen technologies. The USFCC included firms from different parts of the supply chain (e.g., system integrators and subsystem producers). Moreover, it was a truly international association, where close to one third of its members had their headquarters outside the US. Theoretically, we expect that two firms that are part of the same trade association are more likely to be involved in an R&D alliance. Managers of firms involved in trade associations interact more

[13] We note that, when a focal firm *i* collaborates with a partner *j* that is also part of our sample of 70 focal firms, this results in the same dyad being observed twice but in a different configuration. Such observations are likely to be non-independent, which is why we cluster the standard errors on the dyad (i.e., *i-j* and *j-i* are one group).

Table 1
Descriptive statistics and correlation matrix

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	Knowledge utilization from partner	1.00																
2	Alliance partner knowledge recombination novelty	-0.05	1.00															
3	Firm knowledge recombination novelty	-0.06	0.09	1.00														
4	Alliance portfolio size	-0.11	0.06	-0.05	1.00													
5	Research organization partners	0.02	0.08	0.14	0.25	1.00												
6	Concurrent alliances	0.05	-0.02	-0.05	0.01	0.01	1.00											
7	Alliance tenure	0.16	0.05	-0.03	-0.01	-0.07	0.19	1.00										
8	Multi-partner	-0.08	-0.05	-0.04	0.11	0.14	0.25	-0.11	1.00									
9	Joint venture	0.02	0.04	0.05	-0.07	-0.12	0.22	0.27	-0.06	1.00								
10	Government-funded	-0.14	0.05	0.08	0.18	0.28	0.07	-0.18	0.41	-0.20	1.00							
11	International alliance partner	-0.10	0.09	0.06	0.15	-0.12	0.03	0.23	0.00	0.15	-0.14	1.00						
12	Industry overlap	0.18	-0.08	-0.12	-0.06	-0.08	-0.02	0.09	-0.03	-0.01	-0.19	0.09	1.00					
13	Alliance partner knowledge quantity	0.33	-0.08	-0.09	-0.10	-0.09	0.06	0.12	-0.06	-0.04	-0.12	-0.06	0.20	1.00				
14	Alliance partner knowledge diversity	-0.07	0.33	0.05	0.17	0.10	0.00	-0.15	0.07	-0.03	0.17	0.01	-0.15	-0.04	1.00			
15	Alliance partner knowledge age	0.00	-0.10	0.04	0.07	0.13	0.01	0.15	0.07	-0.01	0.21	0.01	-0.10	0.01	0.05	1.00		
16	Alliance partner knowledge complexity	-0.09	0.29	0.08	0.01	-0.01	-0.04	-0.12	-0.03	0.04	0.03	0.13	-0.06	-0.11	0.37	-0.07	1.00	
17	Alliance partner knowledge reuse	0.18	0.12	-0.06	-0.01	-0.05	0.06	0.01	0.00	-0.03	-0.02	-0.01	0.00	0.50	0.42	0.10	0.14	1.00
18	Alliance partner knowledge distance	-0.25	0.11	0.11	0.12	0.08	-0.14	-0.29	0.09	-0.11	0.28	0.00	-0.21	-0.25	0.24	-0.02	0.39	-0.09
19	Knowledge utilization from other firms	0.34	-0.10	-0.06	-0.15	-0.13	0.12	0.15	-0.05	0.06	-0.16	0.03	0.14	0.76	-0.03	0.02	-0.09	0.48
20	Knowledge utilization before alliance	0.26	-0.05	-0.05	-0.06	0.06	0.02	0.05	-0.08	0.05	0.06	-0.05	0.06	0.16	-0.01	0.12	-0.08	0.11
21	Knowledge utilization during alliance	0.64	-0.05	-0.07	-0.09	-0.03	0.11	0.49	-0.10	0.14	-0.14	0.00	0.11	0.36	-0.11	0.08	-0.13	0.15
22	Firm knowledge quantity	0.53	-0.06	-0.14	-0.05	0.07	0.04	0.09	-0.10	-0.05	-0.15	-0.05	0.18	0.08	-0.03	0.02	-0.07	0.05
23	Firm knowledge diversity	-0.07	0.02	0.34	0.14	0.15	-0.05	-0.20	0.07	-0.07	0.18	0.05	-0.13	-0.05	0.13	0.05	0.08	-0.02
24	Firm knowledge age	-0.08	0.04	-0.10	0.23	0.15	0.01	0.19	0.06	-0.03	0.19	-0.01	-0.14	0.05	0.08	0.30	-0.09	0.01
25	Firm knowledge complexity	-0.09	0.09	0.36	0.08	0.03	-0.07	-0.16	0.01	0.05	0.06	0.13	-0.10	-0.10	0.05	-0.11	0.14	-0.08
26	Firm knowledge reuse	0.25	-0.07	0.19	0.03	0.07	-0.01	-0.06	-0.03	-0.03	-0.05	0.02	-0.03	0.03	-0.01	0.00	-0.01	0.01
27	Firm total external knowledge utilization	0.64	-0.06	-0.08	0.02	0.08	0.02	0.05	-0.14	-0.02	-0.18	-0.03	0.21	0.05	-0.02	-0.06	-0.04	0.02
28	Firm internal social network	-0.08	-0.08	0.11	0.07	0.10	-0.01	-0.18	0.13	-0.11	0.11	-0.14	-0.15	-0.03	0.07	0.07	-0.07	0.05
29	Firm internal knowledge focus	0.05	0.09	-0.14	0.22	0.19	0.01	0.13	0.04	0.05	0.03	0.03	0.00	0.00	-0.03	-0.01	-0.01	-0.03
30	Firm old knowledge focus	-0.15	0.13	0.06	0.23	0.05	-0.01	0.09	0.00	0.02	0.13	0.08	-0.09	-0.17	0.00	-0.06	0.09	-0.16
31	Firm USPTO patents	-0.17	0.17	0.16	0.38	0.17	-0.02	0.02	0.03	0.04	0.22	0.19	-0.04	-0.15	0.11	-0.01	0.20	-0.05
32	Firm EPO patents	-0.19	0.12	0.22	0.18	0.12	-0.08	-0.06	0.14	-0.03	0.28	0.27	-0.15	-0.22	0.13	0.04	0.17	-0.15
33	Firm JPO patents	0.25	-0.12	-0.20	-0.47	-0.18	0.01	0.02	-0.06	0.00	-0.22	-0.32	0.01	0.20	-0.19	-0.07	-0.14	0.12
34	Firm turnover	0.20	-0.01	-0.02	0.01	0.03	-0.01	0.03	-0.03	0.10	-0.13	0.14	0.16	-0.02	-0.02	0.03	0.01	-0.06
	Mean	3.27	0.17	0.18	8.47	0.13	1.10	2.95	0.48	0.09	0.29	0.61	0.26	344.54	0.79	2.06	0.09	10.97
	Standard deviation	10.41	0.14	0.12	6.07	0.16	0.33	3.36	0.50	0.29	0.45	0.49	0.44	857.75	0.12	0.99	0.02	6.69
	Minimum	0.00	0.00	0.00	1.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	2.00	0.19	0.00	0.03	1.00
	Maximum	158.00	0.86	0.83	27.00	0.75	3.00	20.00	1.00	1.00	1.00	1.00	1.00	9322.00	0.97	5.00	0.23	54.82

(continued on next page)

Table 1 (*continued*)

	Variables	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34
1	Knowledge utilization from partner																	
2	Alliance partner knowledge recombination novelty																	
3	Firm knowledge recombination novelty																	
4	Alliance portfolio size																	
5	Research organization partners																	
6	Concurrent alliances																	
7	Alliance tenure																	
8	Multi-partner																	
9	Joint venture																	
10	Government-funded																	
11	International alliance partner																	
12	Industry overlap																	
13	Alliance partner knowledge quantity																	
14	Alliance partner knowledge diversity																	
15	Alliance partner knowledge age																	
16	Alliance partner knowledge complexity																	
17	Alliance partner knowledge reuse																	
18	Alliance partner knowledge distance	1.00																
19	Knowledge utilization from other firms	-0.32	1.00															
20	Knowledge utilization before alliance	-0.21	0.25	1.00														
21	Knowledge utilization during alliance	-0.28	0.34	0.34	1.00													
22	Firm knowledge quantity	-0.20	0.05	0.33	0.51	1.00												
23	Firm knowledge diversity	0.24	-0.05	-0.10	-0.15	-0.06	1.00											
24	Firm knowledge age	-0.04	-0.06	0.12	0.05	0.02	0.01	1.00										
25	Firm knowledge complexity	0.30	-0.05	-0.13	-0.16	-0.12	0.54	-0.17	1.00									
26	Firm knowledge reuse	0.00	0.03	0.16	0.19	0.54	0.42	0.03	0.32	1.00								
27	Firm total external knowledge utilization	-0.17	0.04	0.23	0.38	0.76	-0.01	-0.14	-0.02	0.44	1.00							
28	Firm internal social network	0.06	-0.01	0.01	-0.11	-0.09	0.31	0.06	0.08	0.15	-0.11	1.00						
29	Firm internal knowledge focus	-0.08	-0.06	0.05	0.11	0.15	0.01	0.28	-0.06	0.22	0.14	-0.04	1.00					
30	Firm old knowledge focus	0.13	-0.20	-0.17	-0.11	-0.24	-0.06	0.00	0.21	-0.27	-0.16	-0.10	-0.04	1.00				
31	Firm USPTO patents	0.33	-0.16	-0.13	-0.16	-0.26	0.18	0.01	0.29	-0.12	-0.09	-0.14	0.14	0.39	1.00			
32	Firm EPO patents	0.41	-0.20	-0.19	-0.21	-0.29	0.45	0.00	0.35	-0.03	-0.23	0.24	0.00	0.30	0.42	1.00		
33	Firm JPO patents	-0.29	0.20	0.19	0.20	0.33	-0.13	-0.11	-0.21	0.17	0.20	-0.04	-0.04	-0.31	-0.54	-0.48	1.00	
34	Firm turnover	-0.02	-0.01	0.04	0.18	0.32	0.10	-0.12	0.12	0.17	0.41	-0.17	0.01	-0.15	0.05	-0.01	-0.05	1.00
	Mean	0.18	121.34	3.24	13.33	448.67	0.80	2.04	0.09	12.24	152.60	2.96	0.15	6.72	0.51	0.37	0.34	48339.77
	Standard deviation	0.16	214.76	10.15	40.13	886.23	0.11	0.82	0.01	5.87	285.17	0.62	0.11	1.56	0.32	0.28	0.38	65807.47
	Minimum	0.00	0.00	0.00	0.00	2.00	0.19	0.00	0.04	1.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	2.97
	Maximum	0.76	1371.00	159.00	592.00	9322.00	0.95	5.00	0.20	32.18	2852.00	5.33	1.00	17.00	1.00	1.00	1.00	356000.00

N = 1623

Table 2
Estimating focal firm's knowledge utilization from alliance partner

	(1)	(2)	(3)	(4)	(5)
Alliance portfolio characteristics					
Alliance portfolio size	-0.038	-0.038	-0.039*	-0.038*	-0.038*
	[0.020]	[0.020]	[0.019]	[0.019]	[0.019]
Research organization partners	0.201	0.166	0.148	0.147	0.145
	[0.413]	[0.400]	[0.393]	[0.393]	[0.394]
Dyadic characteristics					
Concurrent alliances	0.191	0.193	0.211	0.201	0.201
	[0.159]	[0.162]	[0.162]	[0.165]	[0.164]
Alliance tenure	0.037	0.035	0.027	0.029	0.028
	[0.030]	[0.031]	[0.030]	[0.030]	[0.030]
Multi-partner	-0.139	-0.119	-0.089	-0.096	-0.096
	[0.149]	[0.151]	[0.149]	[0.149]	[0.149]
Joint venture	-0.166	-0.160	-0.213	-0.209	-0.202
	[0.308]	[0.305]	[0.301]	[0.303]	[0.304]
Government-funded	-0.293	-0.297	-0.299	-0.301	-0.294
	[0.164]	[0.164]	[0.171]	[0.174]	[0.170]
International alliance partner	-0.663***	-0.668***	-0.718***	-0.722***	-0.720***
	[0.177]	[0.181]	[0.173]	[0.173]	[0.174]
Industry overlap	-0.054	-0.052	-0.038	-0.043	-0.043
	[0.164]	[0.162]	[0.160]	[0.160]	[0.161]
Alliance partner characteristics					
Alliance partner knowledge quantity	-0.000	-0.000	-0.000	-0.000	-0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Alliance partner knowledge diversity	0.023	-0.215	-0.943	-0.930	-0.955
	[1.050]	[1.066]	[1.061]	[1.056]	[1.053]
Alliance partner knowledge age	0.025	0.034	0.027	0.031	0.032
	[0.103]	[0.102]	[0.100]	[0.100]	[0.101]
Alliance partner knowledge complexity	-9.307*	-9.731*	-9.630*	-9.544*	-9.145*
	[4.124]	[4.164]	[4.247]	[4.237]	[4.234]
Alliance partner knowledge reuse	0.071***	0.069***	0.075***	0.075***	0.075***
	[0.015]	[0.015]	[0.014]	[0.014]	[0.014]
Alliance partner knowledge distance	-6.394***	-6.319***	-6.023***	-6.032***	-6.032***
	[0.806]	[0.804]	[0.785]	[0.783]	[0.784]
Knowledge utilization from other firms	0.002***	0.002***	0.002***	0.002***	0.002***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Knowledge utilization before alliance	0.012	0.012	0.011	0.011	0.011
	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]
Knowledge utilization during alliance	0.007**	0.007**	0.007***	0.007***	0.007**
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
Focal firm characteristics					
Firm knowledge quantity	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Firm knowledge diversity	-2.032*	-2.036*	-1.861	-1.836	-1.782
	[1.026]	[1.032]	[0.979]	[0.979]	[0.988]
Firm knowledge age	-0.353**	-0.360**	-0.362**	-0.360**	-0.362**
	[0.133]	[0.135]	[0.135]	[0.136]	[0.134]
Firm knowledge complexity	16.794*	16.349*	14.909	14.629	14.594
	[7.997]	[7.949]	[7.909]	[8.211]	[8.102]
Firm knowledge reuse	0.022	0.023	0.026	0.028	0.027
	[0.026]	[0.026]	[0.024]	[0.024]	[0.024]
Firm total external knowledge utilization	0.002***	0.002***	0.002***	0.002***	0.002***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Firm internal social network	-0.138	-0.131	-0.113	-0.116	-0.119
	[0.178]	[0.179]	[0.175]	[0.174]	[0.175]
Firm internal knowledge focus	-0.776	-0.829	-0.854	-0.895	-0.920
	[1.688]	[1.700]	[1.724]	[1.748]	[1.732]
Firm old knowledge focus	-0.162*	-0.162*	-0.148	-0.146	-0.147
	[0.080]	[0.080]	[0.079]	[0.080]	[0.079]
Firm USPTO patents	0.358	0.406	0.248	0.246	0.280
	[0.860]	[0.866]	[0.841]	[0.846]	[0.841]
Firm EPO patents	1.083	1.046	1.155*	1.183*	1.184*
	[0.565]	[0.564]	[0.549]	[0.546]	[0.548]
Firm JPO patents	-0.140	-0.147	-0.285	-0.275	-0.295
	[0.918]	[0.925]	[0.922]	[0.913]	[0.905]
Firm turnover	0.000*	0.000*	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Firm knowledge recombination novelty	2.165***	2.199***	2.174**	1.013	0.118
	[0.655]	[0.661]	[0.665]	[0.978]	[1.490]
Hypotheses testing					
Alliance partner knowledge recombination novelty		0.714	4.941***	3.986*	2.221
		[0.745]	[1.436]	[1.565]	[2.638]
Alliance partner knowledge recombination novelty squared			-7.934***	-8.207***	-4.402
			[2.314]	[2.390]	[5.033]
Alliance partner knowledge recombination novelty × Firm knowledge recombination novelty				5.508	14.957
				[4.219]	[13.184]

(*continued on next page*)

Table 2 (*continued*)

	(1)	(2)	(3)	(4)	(5)
Alliance partner knowledge recombination novelty squared × Firm knowledge recombination novelty					-19.688 [25.457]
Firm and year effects					
Focal firm dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Obs.	1623	1623	1623	1623	1623
Pseudo R^2	0.224	0.225	0.228	0.228	0.228
Log-likelihood	-2244.788	-2243.532	-2234.626	-2233.800	-2233.436

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Multi-way cluster-robust standard errors at the dyad- and partner-level between brackets.

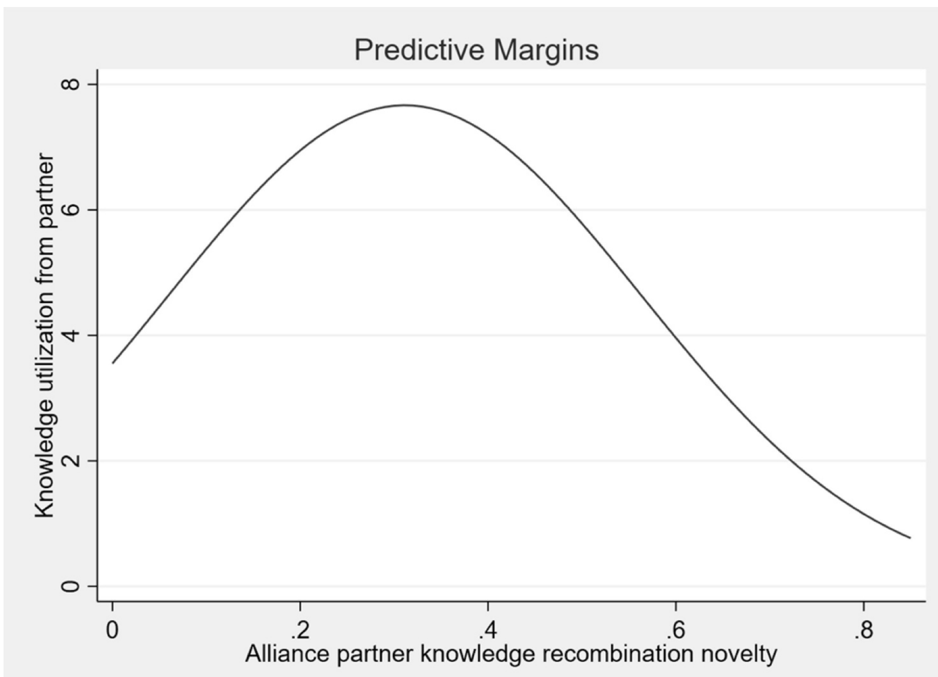

Fig. 3. Relationship between alliance partner knowledge recombination novelty and focal firm's knowledge utilization from alliance partner

frequently, discovering potential opportunities to collaborate in an alliance. Rosenkopf et al. (2001), using a sample of firms in the cellular industry, already demonstrated that mutual membership in technical committees increases the likelihood of R&D alliance formation between firms. At the same time, it is unlikely that mutual trade association membership is strongly associated with knowledge utilization from a firm, with whom the focal firm has an ongoing R&D alliance. As argued by Rosenkopf et al. (2001), when two partners are already in an alliance, the additional information that they might obtain about each other through technical committees is relatively superficial and largely redundant. Hence, alliances are stronger links for exchanging knowledge and information between firms than technical committees. In our context, we therefore argue that, for ongoing R&D alliances (as is the case in the second stage regressions) the added value of joint trade association membership in terms of additional information exchange is likely to be limited. We dynamically track membership in the USFCC from its inception in 1998 until 2007 (the final year in our sample). The corresponding variable takes a value of one when the focal firm and the (un)allied firm in the dyad are both members of the USFCC at t-1, and zero otherwise.

In Models 6 and 7 in Table 3, we present the results from the first-stage probit regressions[14]. In line with our expectations, we observe that membership in the USFCC has a positive and statistically significant association with alliance dyad existence (Model 7: $\beta_{\text{USFCC membership}} = 0.305$, $p < 0.001$). Moreover, we observe that the pseudo R-squared value increases considerably with the inclusion of this variable. From Model 7, we compute the inverse Mills ratio, which is subsequently included in the second-stage negative binomial regression models as an additional control variable. The inverse Mills ratio is only weakly correlated with our core independent variables: alliance partner knowledge recombination novelty (r = -0.02) and focal firm knowledge recombination novelty (r = 0.04). In models 8 and 9, we observe that

[14] Explanatory variables that are contingent upon the existence of an alliance cannot be included in the first stage (Ryu et al., 2018). That is, the variables 'alliance tenure', 'joint venture', 'government-funded', 'multi-partner', 'concurrent alliances', 'knowledge utilization during alliance', 'knowledge utilization before alliance', cannot be created for firm dyads that are not involved in an alliance. Hence and in line with the procedure followed by prior alliance research (e.g., Ryu et al., 2018), we report models in which alliance-contingent variables are excluded in the first stage probit regressions.

Table 3
Additional analyses

	Attenuating self-selection bias issues				Unique ties (non-unique components)		Unique ties (unique components)		Unique ties (new to focal firm)		Unique ties (new to portfolio)	
	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Alliance portfolio characteristics												
Alliance portfolio size	0.038***	0.037***	-0.065*	-0.065*	-0.040*	-0.039*	-0.045*	-0.044*	-0.037	-0.037	-0.027	-0.032
	[0.005]	[0.005]	[0.031]	[0.031]	[0.019]	[0.019]	[0.020]	[0.021]	[0.020]	[0.020]	[0.024]	[0.025]
Research organization partners	-0.379***	-0.397***	0.397	0.407	0.285	0.244	0.301	0.288	0.225	0.252	0.737	0.873
	[0.115]	[0.118]	[0.421]	[0.424]	[0.402]	[0.396]	[0.426]	[0.425]	[0.417]	[0.414]	[0.657]	[0.693]
Dyadic characteristics												
Concurrent alliances			0.237	0.228	0.181	0.224	0.210	0.220	0.199	0.181	0.136	0.071
			[0.156]	[0.158]	[0.162]	[0.173]	[0.161]	[0.167]	[0.161]	[0.161]	[0.181]	[0.178]
Alliance tenure			0.024	0.025	0.034	0.033	0.033	0.035	0.032	0.030	0.034	0.034
			[0.030]	[0.030]	[0.030]	[0.030]	[0.031]	[0.032]	[0.030]	[0.030]	[0.037]	[0.037]
Multi-partner			-0.097	-0.104	-0.113	-0.113	-0.114	-0.128	-0.128	-0.138	-0.097	-0.111
			[0.148]	[0.148]	[0.149]	[0.150]	[0.147]	[0.148]	[0.154]	[0.152]	[0.177]	[0.174]
Joint venture			-0.233	-0.223	-0.230	-0.250	-0.178	-0.182	-0.201	-0.156	-0.148	-0.069
			[0.299]	[0.301]	[0.299]	[0.301]	[0.309]	[0.306]	[0.306]	[0.307]	[0.325]	[0.333]
Government-funded			-0.316	-0.313	-0.273	-0.287	-0.287	-0.296	-0.247	-0.231	-0.189	-0.129
			[0.169]	[0.169]	[0.170]	[0.169]	[0.165]	[0.162]	[0.165]	[0.164]	[0.171]	[0.168]
International alliance partner	-0.393***	-0.368***	-0.479	-0.467	-0.672***	-0.674***	-0.690***	-0.687***	-0.665***	-0.663***	-0.692***	-0.677***
	[0.073]	[0.073]	[0.268]	[0.269]	[0.175]	[0.178]	[0.187]	[0.189]	[0.170]	[0.170]	[0.190]	[0.188]
Industry overlap	0.184*	0.188*	-0.134	-0.145	-0.039	-0.019	-0.045	-0.044	-0.031	-0.028	0.032	0.028
	[0.086]	[0.087]	[0.199]	[0.201]	[0.162]	[0.162]	[0.161]	[0.163]	[0.164]	[0.166]	[0.179]	[0.179]
Alliance partner characteristics												
Alliance partner knowledge quantity	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Alliance partner knowledge diversity	0.656**	0.575*	-1.332	-1.365	-0.677	-0.654	-0.168	-0.145	-0.475	-0.401	-0.797	-0.588
	[0.255]	[0.248]	[1.141]	[1.141]	[1.119]	[1.134]	[1.033]	[1.030]	[1.071]	[1.053]	[1.142]	[1.120]
Alliance partner knowledge age	-0.002	-0.007	0.033	0.039	0.040	0.041	0.036	0.043	0.003	0.002	-0.015	-0.025
	[0.020]	[0.019]	[0.102]	[0.103]	[0.102]	[0.102]	[0.099]	[0.100]	[0.104]	[0.105]	[0.113]	[0.111]
Alliance partner knowledge complexity	1.490	1.510	-10.883*	-10.461*	-7.750	-8.606*	-9.740*	-9.548*	-8.891*	-8.712*	-7.904	-7.764
	[0.853]	[0.845]	[4.838]	[4.812]	[4.134]	[4.168]	[4.216]	[4.134]	[4.208]	[4.157]	[4.425]	[4.329]
Alliance partner knowledge reuse	0.010	0.009	0.069***	0.068***	0.075***	0.076***	0.070***	0.070***	0.071***	0.071***	0.075***	0.074***
	[0.005]	[0.005]	[0.014]	[0.014]	[0.015]	[0.014]	[0.015]	[0.015]	[0.014]	[0.014]	[0.016]	[0.015]
Alliance partner knowledge distance	-1.531***	-1.463***	-5.018***	-4.973***	-6.131***	-6.080***	-6.162***	-6.151***	-6.015***	-6.089***	-6.377***	-6.469***
	[0.223]	[0.221]	[1.236]	[1.255]	[0.797]	[0.801]	[0.843]	[0.843]	[0.791]	[0.799]	[0.915]	[0.914]
Knowledge utilization from other firms	0.001*	0.001*	0.001	0.001	0.001***	0.001***	0.002***	0.002***	0.002***	0.002***	0.002*	0.002*
	[0.000]	[0.000]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]
Knowledge utilization (until current year)	0.003	0.002										
	[0.001]	[0.001]										
Knowledge utilization before alliance			0.009	0.009	0.012	0.013	0.012	0.012	0.012	0.011	0.010	0.009
			[0.008]	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]	[0.008]	[0.009]	[0.010]
Knowledge utilization during alliance			0.005*	0.005	0.006**	0.006**	0.007**	0.007**	0.006**	0.007**	0.007**	0.007**
			[0.003]	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.003]	[0.003]
Focal firm characteristics												
Firm knowledge quantity	-0.000	-0.000	-0.000**	-0.000**	-0.000**	-0.000**	-0.000***	-0.000***	-0.000**	-0.000**	-0.000*	-0.000**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Firm knowledge diversity	-0.018	-0.052	-1.764	-1.676	-1.877	-1.772	-1.112	-0.972	-2.340*	-2.395*	-1.566	-1.281
	[0.272]	[0.275]	[0.991]	[1.000]	[1.020]	[1.005]	[0.997]	[0.996]	[1.060]	[1.043]	[1.180]	[1.270]
Firm knowledge age	-0.014	-0.014	-0.351**	-0.350**	-0.384**	-0.388**	-0.379**	-0.392**	-0.340*	-0.338*	-0.241	-0.204
	[0.028]	[0.027]	[0.135]	[0.134]	[0.128]	[0.129]	[0.134]	[0.133]	[0.135]	[0.134]	[0.143]	[0.162]
Firm knowledge complexity	3.173*	2.999*	12.725	12.278	17.386*	16.576*	16.049*	16.311*	18.115*	19.299**	19.998*	18.430
	[1.264]	[1.259]	[8.059]	[8.238]	[8.834]	[8.427]	[7.699]	[7.330]	[7.424]	[6.787]	[9.706]	[10.403]
Firm knowledge reuse	0.008	0.009	0.021	0.022	0.015	0.017	0.038	0.035	0.017	0.020	0.024	0.037
	[0.006]	[0.006]	[0.026]	[0.026]	[0.025]	[0.024]	[0.023]	[0.023]	[0.025]	[0.026]	[0.024]	[0.025]

(*continued on next page*)

Table 3 (*continued*)

	Attenuating self-selection bias issues				Unique ties (non-unique components)		Unique ties (unique components)		Unique ties (new to focal firm)		Unique ties (new to portfolio)	
	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Firm total external knowledge utilization	0.000	0.000	0.002***	0.002***	0.001***	0.001***	0.002***	0.002***	0.002***	0.001***	0.001***	0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Firm internal social network	0.060	0.065	-0.156	-0.165	-0.171	-0.165	-0.166	-0.166	-0.144	-0.149	-0.002	-0.021
	[0.039]	[0.040]	[0.175]	[0.175]	[0.170]	[0.167]	[0.178]	[0.178]	[0.177]	[0.178]	[0.180]	[0.185]
Firm internal knowledge focus	0.164	0.230	-0.921	-0.993	-0.988	-0.861	-1.600	-1.635	-1.093	-1.284	-4.243*	-4.530*
	[0.280]	[0.280]	[1.716]	[1.726]	[1.724]	[1.729]	[1.784]	[1.788]	[1.678]	[1.689]	[2.111]	[2.114]
Firm old knowledge focus	-0.007	-0.006	-0.147	-0.146	-0.145	-0.149	-0.155	-0.155	-0.155	-0.158*	-0.236***	-0.255***
	[0.015]	[0.015]	[0.079]	[0.079]	[0.079]	[0.078]	[0.083]	[0.082]	[0.080]	[0.078]	[0.068]	[0.070]
Firm USPTO patents	0.256	0.241	0.088	0.113	0.206	0.070	0.455	0.488	0.303	0.350	0.076	-0.032
	[0.166]	[0.167]	[0.868]	[0.867]	[0.854]	[0.812]	[0.862]	[0.870]	[0.848]	[0.844]	[0.894]	[0.942]
Firm EPO patents	-0.040	-0.049	1.190*	1.223*	1.118*	0.984	1.031	0.996	1.227*	1.245*	0.272	0.434
	[0.141]	[0.141]	[0.541]	[0.540]	[0.555]	[0.565]	[0.531]	[0.538]	[0.562]	[0.569]	[0.626]	[0.647]
Firm JPO patents	0.068	0.146	-0.236	-0.244	-0.379	-0.292	-0.497	-0.510	-0.368	-0.372	-0.975	-1.070
	[0.154]	[0.157]	[0.934]	[0.917]	[0.869]	[0.899]	[0.893]	[0.873]	[0.961]	[0.966]	[0.771]	[0.861]
Firm turnover	0.000	0.000	0.000	0.000	0.000	0.000	0.000*	0.000*	0.000*	0.000*	0.000**	0.000**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Firm knowledge recombination novelty	0.029	0.065	2.164**	0.033	3.535***	7.480**	1.083	-0.218	2.101**	-1.799	2.002**	-1.829
	[0.199]	[0.202]	[0.660]	[1.516]	[0.947]	[2.345]	[0.920]	[1.270]	[0.644]	[3.120]	[0.641]	[3.442]
Hypotheses testing												
Alliance partner knowledge recombination novelty	0.012	-0.011	4.974***	2.193	6.091**	12.180*	2.523	0.395	3.544**	2.239	4.577***	4.466*
	[0.156]	[0.160]	[1.436]	[2.628]	[2.350]	[4.755]	[2.045]	[2.221]	[1.270]	[2.479]	[1.284]	[2.254]
Alliance partner knowledge recombination novelty squared			-7.995***	-4.477	-18.539**	-29.963*	-3.485	2.842	-3.080*	-2.629	-4.305***	-5.786**
			[2.325]	[5.006]	[7.171]	[15.059]	[4.013]	[4.765]	[1.242]	[2.266]	[1.282]	[1.913]
Alliance partner knowledge recombination novelty × Firm knowledge recombination novelty				-19.707		-50.055		26.899		6.890		2.649
				[25.409]		[28.527]		[16.391]		[10.165]		[11.234]
Alliance partner knowledge recombination novelty squared × Firm knowledge recombination novelty				15.303		92.822		-79.804		-2.377		5.431
				[13.297]		[89.778]		[43.967]		[8.690]		[8.646]
Self-selection variables												
Mutual USFCC membership		0.305***										
		[0.079]										
Inverse Mills ratio			-0.737	-0.777								
			[0.761]	[0.767]								
Firm and year effects												
Focal firm dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	144968	144968	1623	1623	1623	1623	1623	1623	1623	1623	1345	1345
Pseudo R^2	0.132	0.136	0.228	0.229	0.227	0.228	0.224	0.224	0.226	0.227	0.227	0.229
Log-likelihood	-7731.996	-7693.548	-2233.680	-2232.387	-2238.119	-2234.210	-2245.998	-2244.807	-2239.378	-2238.179	-1815.813	-1811.091

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Multi-way cluster-robust standard errors at the dyad- and partner-level between brackets between brackets.

our main results remain stable when including the inverse Mills ratio as an additional control variable.

4.7.2. Alternative operationalizations of knowledge recombination novelty

To better understand what drives the relationship between the alliance partner's knowledge recombination novelty and the focal firm's knowledge utilization from this alliance partner, we conduct additional analyses in which we operationalize unique knowledge ties in alternative ways[15]. First, we divide unique knowledge ties into two distinct groups: (i) unique knowledge ties based on components that are non-unique and (ii) unique knowledge ties in which at least one of two constituent components is unique. A component is considered to be unique when all the firm fuel cell patents with a particular IPC code were filled by the same firm. We find that 11.6% of knowledge ties in the alliance partner's knowledge pool are unique ties between components that are non-unique, and that 5.9% of ties in the alliance partner's knowledge pool are unique ties where at least one component is unique. Our analyses, shown in Table 3, indicate that there is an inverted U-shaped relationship between alliance partner knowledge recombination novelty (non-unique components) and the focal firm's knowledge utilization from this partner (Model 10), but that this relationship is statistically non-significant for alliance partner knowledge recombination novelty (unique components) (Model 12). These findings suggest that the relationship found in our main analysis between an alliance partner's knowledge recombination novelty and the focal firm's knowledge utilization from the alliance partner is driven by the existence of unique knowledge ties and not by the existence of unique components. This supports our contention that, next to component-level characteristics, heterogeneity in ties between components is also associated with differences in knowledge utilization in R&D alliances.

Second, we test variables that only include (i) ties in the alliance partner's knowledge pool that do not appear in the focal firm's knowledge pool and (ii) ties in the alliance partner's knowledge pool that do not appear in the knowledge pool of the focal firm or any of its other partners (for this analysis, we restrict the sample to observations where the focal firm has more than one firm partner in a given year). We find that there is an inverted U-shaped relationship between these two different types of knowledge recombination novelty and the focal firm's knowledge utilization from the alliance partner (Models 14 and 16 in Table 3). Hence, our results do not seem to be driven by our specific operationalization of knowledge recombination novelty.

4.7.3. Sensitivity checks

We conduct several sensitivity checks to verify the stability of our main results[16]. First, we exclude extreme observations of the dependent variable (i.e., values that exceed the 99th percentile). Second, we extend the time lag for the dependent variable to 2 years, that is, we consider how characteristics of the firm-partner dyad at $t=0$ correlate with knowledge utilization from the alliance partner by the focal firm at $t+2$. Third, we change the memory decay window from 5 to 10 years for knowledge pool characteristics of the firm and alliance partner. Fourth, we test whether the main results are robust to the inclusion of quadratic terms for alliance partner knowledge quantity, diversity, and distance. Our main results remain stable in all these alternative model specifications.

Fifth, to examine whether our results are driven by dynamics in the focal firm's alliance portfolio: (i) we interact alliance portfolio size with the knowledge recombination novelty of the partner in the focal dyad (and find no statistically significant interaction effect) and (ii) we restrict the sample to observations where the focal firm has more than one firm partner in a given year and rerun the analyses including a control variable for the average knowledge recombination novelty of the other partner(s) in the alliance portfolio (and find that our main results remain stable).

Sixth, we examine to what extent the partner's knowledge recombination novelty has a different impact on the focal firm's utilization of unique knowledge ties, familiar knowledge ties (i.e., knowledge ties that are already in the focal firm's knowledge pool), and knowledge ties that are new to the firm (but non-unique for the partner). The results show an inverted U-shaped relationship between alliance partner knowledge recombination novelty and both the utilization of unique knowledge ties and the utilization of familiar knowledge ties. This supports our contention that unique knowledge ties in the alliance partner's knowledge pool also affect the utilization and retrieval of other knowledge ties (i.e., familiar knowledge ties), in line with the arguments developed in our first hypothesis. However, the results demonstrate that the utilization of partner's new-to-the-firm knowledge ties is not affected by the presence of unique knowledge ties in the partner's knowledge pool: alliance partner knowledge recombination novelty neither increases nor decreases the utilization of such knowledge ties. In terms of interpretation, these results further confirm that, when an alliance partner has some knowledge recombination novelty, the knowledge pool of this partner is likely to attract the attention of the focal firm. Moreover, the results provide first indications that the focal firm is mainly interested in (i) alliance partner's knowledge ties that are proximate to the focal firm (i.e., learning about and utilizing knowledge ties that are also present in its own knowledge pool) or (ii) alliance partner's knowledge ties that are very distant from the focal firm (i.e., learning about and utilizing knowledge ties that are new to the industry). At the same time, alliance partner's knowledge ties that are new-to-the-focal-firm seem to lack the necessary uniqueness or familiarity to be attractive sources of knowledge for the focal firm.

5. Discussion

Shifting the conceptual lens from the component level to the ties among components within the knowledge pool of an alliance partner, we studied the relationship between alliance partner knowledge recombination novelty and the focal firm's utilization of knowledge from this alliance partner. We found support for our hypothesis that alliance partner knowledge recombination novelty has an inverted U-shaped relationship with the focal firm's knowledge utilization from the alliance partner. The results also show that the focal firm's own knowledge recombination novelty (i.e., the focal firm's experience with generating unique knowledge ties) does not significantly moderate the relationship between alliance partner's knowledge recombination novelty and the focal firm's knowledge utilization from the alliance partner. There are two possible explanations for this non-finding. First, it might be the case that the focal firm's knowledge recombination novelty improves its ability to disentangle unique knowledge ties of alliance partners but that this positive mechanism is canceled out by the focal firm's reduced motivation to access knowledge from alliance partners with high knowledge recombination novelty. Second, we acknowledge the possibility that this non-finding emerges because the two anticipated forces are too weak to change the shape of the relationship between alliance partner knowledge recombination novelty and the focal firm's knowledge utilization from this partner[17]. However, despite the lack of statistical significance for this moderation effect, we do observe a direct positive effect of focal firm knowledge recombination novelty on knowledge utilization from the alliance partner. Thus, a focal firm's experience with creating unique knowledge ties increases access and utilization of the alliance partner's knowledge, but this does not vary

[15] We thank the anonymous reviewers for suggesting these additional analyses.

[16] We do not report these results in the paper for the sake of brevity. They are available from the authors upon request.

[17] We thank an anonymous reviewer for pointing out this alternative explanation for our findings.

depending on the alliance partner's level of knowledge recombination novelty.

5.1. Theoretical implications

The alliance literature has a long tradition of studying knowledge recombination across organizational boundaries (e.g., Sampson, 2007; Schilling and Phelps, 2007). However, it tends to frame knowledge pools as collections of atomistic components, ignoring the ties between them. At the same time, the knowledge recombination literature highlights the importance of ties between components (Dibiaggio et al., 2014; Yayavaram and Ahuja, 2008; Wang et al., 2014). However, this literature stream tends to confine its theorizing to within-firm contexts, largely ignoring knowledge recombination across organizational boundaries. In this paper, we contribute to bridging these two different but complementary literature streams, examining the relationship between alliance partner's knowledge recombination novelty and the focal firm's knowledge utilization from the alliance partner.

Our results indicate that, by solely focusing on original component attributes and ignoring heterogeneity in ties between alliance partners' components, alliance research might have underestimated the learning potential of alliance partner knowledge pools. We provide first evidence that, even when component-level attributes of alliance partners' knowledge pool are held constant, important differences in the knowledge recombination implications of alliances emerge due to heterogeneity in ties between components of alliance partners. Shifting attention to the alliance partner's component ties, we also manage to identify and theorize on novel mechanisms that can hamper the focal firm's ability to learn from alliance partners. In particular, we conceptually argue and empirically demonstrate that an extensive number of unique ties within the alliance partner knowledge pool can create substantial technological complexity, hampering the ability of the focal firm to retrieve knowledge from the alliance partner. In sum, by considering ties between the components of alliance partners, we discover additional learning opportunities and retrievability challenges that remain invisible when exclusively considering the original component attributes of alliance partners.

At the same time, our findings add to the knowledge recombination literature by increasing our understanding of the implications of heterogeneity in knowledge ties between firms. Extant knowledge recombination literature highlights that such heterogeneity in knowledge ties can explain why certain firms can achieve considerable inventive value whereas others cannot (Dibiaggio et al., 2014; Guan and Liu, 2016; Yayavaram and Ahuja, 2008). However, our results clearly show that heterogeneity in knowledge ties has implications that go beyond the boundary of the firm. For one, we see that, when an alliance partner has unique knowledge ties, firms are more motivated to access and utilize knowledge from that partner. Moreover, we found a positive direct effect between the focal firm's knowledge recombination novelty and its utilization of partner's knowledge, showing that the internal capability to develop unique knowledge ties influences the ability to absorb external knowledge from alliance partners. Together, these findings suggest that the nature of ties between components is an important characteristic that explains differences in the motivation and ability of alliance partners to engage in inter-organizational knowledge transfer and recombination processes.

We see ample opportunities to further bridge the alliance and knowledge recombination literature, applying existing knowledge recombination concepts in the context of alliances. Whereas we focused on the presence of unique knowledge ties as a core characteristic of the knowledge pool of firms participating in alliances, prior knowledge recombination studies have highlighted several other relevant dimensions such as the level of complementary and substitutability between components (Dibiaggio et al., 2014), the extent to which structural holes exist between components within the knowledge pool (Guan and Liu, 2016; Wang et al., 2014), or the level of complexity of the knowledge pool (Yayavaram and Chen, 2015). Examining these knowledge pool structure characteristics in the context of R&D alliances can further increase our understanding of when and how focal firms can benefit from their alliance partners' knowledge pool when engaging in knowledge recombination.

5.2. Managerial Implications

Firms need to carefully approach the management of strategic alliances (Ireland et al., 2002) to make sure that their benefits (i.e., superior access to knowledge of other firms) outweigh their liabilities (i.e., unintended outflows of knowledge). In worst cases, firms can end up at the losing end of a learning race, where alliance partners are able to learn extensively from them, whereas they fail to learn from the alliance partners. In such circumstances, interdependences between alliance partners become unbalanced, increasing the likelihood of alliance dissolution and creating a significant competitive disadvantage for the partner that loses the learning race (Hamel, 1991; Khanna et al., 1998). Prior research (e.g., Alvarez and Barney, 2001; Faems et al., 2010) has provided valuable insights into how firms can avoid losing learning races by generating constant streams of new inventions or by formulating particular contractual governance structures.

Our findings suggest an additional strategy to avoid losing learning races. In particular, we point to building an internal knowledge pool with numerous unique knowledge ties as an interesting and relevant option. Our findings suggest that, when firms have built-up an extensive set of unique knowledge ties, such high levels of knowledge recombination novelty are likely to trigger retrievability challenges for the alliance partner, reducing the risk of unintended knowledge spillovers. At the same time, the positive direct effect of focal firms' knowledge recombination novelty on alliance partner knowledge utilization shows that the ability to absorb knowledge from the alliance partner increases. In sum, our findings suggest that an internal knowledge pool with high knowledge recombination novelty can simultaneously function as (i) an isolating mechanism, reducing the risk of unintended knowledge spillovers to alliance partners and (ii) a condition that fosters knowledge absorption from alliance partners.

5.3. Limitations and future research

This study has several limitations, which also represent interesting starting points for future research. First, the fuel cell industry was an interesting setting for our study as it is characterized by substantial heterogeneity in terms of the type of firms involved. However, it would be interesting to examine the influence of unique knowledge ties within an industry in which firms are more homogeneous in terms of technological background, such as the biotech industry. Since firms are more likely to recombine knowledge in similar ways in such a setting, it is possible that firms will be better able to overcome the retrievability challenges associated with unique knowledge ties.

Second, we relied on rich archival data, combining hand-collected alliance data with data on the worldwide patenting activities of firms, to test our hypotheses. Whereas these data allow for a rather objective assessment of how particular alliance partner knowledge characteristics influence focal firms' knowledge utilization, they provide limited empirical insights into the underlying processes. In-depth qualitative research, delving deeper into the actual processes of accessing and utilizing alliance partner's knowledge, might therefore represent an interesting complement for our study, clarifying the underlying processes connecting unique knowledge ties of alliance partners to the focal firm's utilization of knowledge from these alliance partners.

Third, we examined the influence of knowledge recombination novelty within the context of R&D alliances, identifying it as an important factor that creates heterogeneity in the performance of R&D alliances. However, next to R&D alliances, firms also use other strategies, such as acquisitions (Ahuja and Katila, 2001), hiring inventors and entrepreneurs (Distel et al., 2019, Palomeras and Melero, 2010), and closely observing the actions of competitors (Ernst, 1997; Operti and Carnabuci, 2014; Moreira and Tae, 2019), to access knowledge from other firms. We encourage future research to examine how knowledge recombination novelty influences knowledge utilization in the context of these different strategies, creating new insights into the role of knowledge ties in driving firm performance. One potential hypothesis is that, for 'weaker' knowledge transfer strategies, retrievability issues will be more prominent compared to R&D alliances (Villalonga and McGahan, 2005). This would imply that, in those settings, the inflection point of the inverted U-shaped relationship between knowledge recombination novelty and the focal firm's utilization rate would occur earlier.

Fourth, in this study we zoomed in on the relationship between characteristics of an alliance partner and knowledge utilization by the focal firm at the alliance dyad level. However, it would also be interesting to conduct empirical studies in which the explicit aim is to examine how characteristics of other alliance dyads influence knowledge utilization outcomes in a focal alliance dyad. For instance, future studies could examine how the participation of a focal firm in multiple alliances influences the extent to which it utilizes knowledge within a particular alliance dyad. In this way, new insights into the dual management of individual alliances and alliance networks can potentially be generated (Wassmer, 2010).

Despite these limitations, we think that this study has provided important insights into the knowledge recombination implications of ties between components in R&D alliances. Moreover, we hope that our findings can motivate scholars to further explore the ties between components in internal and external knowledge pools and their impact on knowledge utilization within different collaborative settings.

CRediT authorship contribution statement

Holmer Kok: Conceptualization, Writing - original draft, Writing - review & editing, Methodology, Formal analysis, Investigation. **Dries Faems:** Conceptualization, Writing - original draft, Writing - review & editing. **Pedro de Faria:** Conceptualization, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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