To Complete a Puzzle, You Need to Put the Right Pieces in the Right Place

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Exploring Knowledge Recombination and the Creation of New Inventions

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Exploring Knowledge Recombination and the Creation of New Inventions

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Chapter 1. General Introduction

"Combinatory play seems to be the essential feature in productive thought" - Albert Einstein

Knowledge recombination is considered a main engine of technological growth (Carnabuci & Bruggeman, 2009; Schumpeter, 1934; Weitzman, 1998). In this process, new inventions originate from recombining existing knowledge components or reconfiguring existing combinations of components (Fleming, 2001; Galunic & Rodan, 1998; Henderson & Clark, 1990). Numerous important inventions originated from knowledge recombination, such as Ford's mass production techniques (Hargadon, 2002), Hewlett-Packard's inkjet printing technology (Fleming, 2002), the first amplifier circuit (Arthur & Polak, 2006), valuable polymers at 3M (Boh, Evaristo, & Ouderkirk, 2014), highly-efficient fuel cell systems (Sharaf & Orhan, 2014), and many more. The notion that every new technology, product or idea emerges from knowledge recombination processes is conceptually and empirically useful: it provides us with a framework to understand when and how valuable new inventions are generated. It is also inherently intriguing since it implies that most inputs and tools to generate new inventions are already available, they just need to be used in the right way.

Knowledge recombination plays a central role in the conceptual and/or empirical framework of seminal studies in different fields. At the firm-level, scholars rely on knowledge recombination to examine the benefits of different extramural knowledge sourcing strategies (Savino, Petruzzelli, & Albino, 2017; Van de Vrande, 2013). Indeed, scholars argue that foreign market presence (e.g. Berry, 2014; Kafouros, Buckley, & Clegg, 2012; Singh, 2008), entry into new technological domains (e.g. Furr & Snow, 2014; George, Kotha, & Zheng, 2008; Kotha, Zheng, & George, 2011), strategic alliances (e.g. Davis & Eisenhardt, 2011; Lahiri & Narayanan, 2013; Phelps, 2010), mergers and acquisitions (e.g. Ahuja & Katila, 2001; Makri, Hitt, & Lane, 2010; Valentini, 2012), corporate venture capital investments (e.g. Wadhwa & Kotha, 2006; Wadhwa, Phelps, & Kotha, 2016), and employee mobility (e.g. Tzabbar, 2009) provide access to novel complementary component knowledge, creating opportunities for valuable knowledge recombination (Fleming, 2002). At the team-level, scholars have used knowledge recombination insights to examine how teams should be configured in a way that maximizes the quality and quantity of new inventions (e.g. Bercovitz & Feldma, 2011; Taylor & Greve, 2006; Wang, Van de Vrande, & Jansen, 2017), focusing for instance on the presence of generalists in the team (Melero & Palomeras, 2015). Similarly, at the individual-level, scholars have argued that inventors develop certain abilities that allow them to generate more valuable component combinations than others (e.g. Boh *et al.,* 2014; Fleming, Mingo, & Chen, 2007; Gruber, Harhoff, & Hoisl, 2013).

Clearly, knowledge recombination has been widely-adopted as a mechanism to explain variance in inventive output. Despite this, we observed that the majority of studies have treated knowledge recombination rather superficially in conceptual and empirical terms, sticking to tenets of knowledge recombination that are already well-established. The problem with this research approach is that, by sticking to the well-trodden path, most studies make few efforts to advance our current understanding of knowledge recombination. At the same time, examining the core literature on knowledge recombination, in which fundamental aspects of this concept are studied in-depth (e.g. Fleming, 2001; Yayavaram & Ahuja, 2008; Wang *et al.,* 2014), we quickly learn that knowledge recombination is still poorly understood in many important areas (Savino *et al.,* 2017). Our main research objective in this dissertation is therefore to substantially advance our understanding of knowledge recombination, creating new insights about the origins of new inventions.

To fulfill this research objective, we conduct three empirical projects on knowledge recombination in the fuel cell industry, developing research questions that help us to venture beyond what we already know about this concept. In chapter 2, challenging the widely-held assumption that components' recombinant value is pre-determined at creation, we join an emerging research stream on knowledge reuse trajectories and argue that a component's contemporary recombinant value largely depends on how recently it was reused. In chapter 3, arguing that knowledge pool size and diversity are not the only drivers of knowledge recombination in R&D alliances, we explore the knowledge recombination benefits and liabilities of alliance partners' knowledge pool applicability. In chapter 4, questioning the implicit assumption that going-together always outperforms going-alone in terms of generating high-quality technological solutions, we argue that idiosyncratic combinative capabilities play a pivotal role in helping organizations reap the knowledge recombination benefits of going-together. To explain this research approach in more detail, we provide an overview of the three empirical projects in the following section (see Figure 1.1).

Figure 1.1. Overview of dissertation

	Chapter 2 Recombinant lag and the technological value of inventions	**Chapter 3 Knowledge pool applicability in R&D alliances**	**Chapter 4 Going-together in challenge-based R&D projects**
Core research gap	Recency of component reuse influences components' recombinant value	Knowledge pool applicability of alliance partners drives interfirm recombination	Only organizations with particular abilities can realize recombination benefits of going-together
Core knowledge recombination insight	Components' recombinant value changes over time through reuse	Components differ in terms of applicability	Potential recombinant opportunities are not always equal to realized recombinant opportunities
Outcome variable	Value of new combination	Recombination of partners' component knowledge	Value of new combination
Main data	Fuel cell patents Wind energy patents (1959-2007)	Fuel cell patents Fuel cell R&D alliances (1993-2007)	Challenge-based R&D projects on hydrogen and fuel cell technologies (2003-2016)

1.1. Overview of three empirical projects

1.1.1. Project 1: Recombinant Lag and the Value of Inventions

In chapter 2, we present the results of the first project. In this project, we study how attributes of recombined components influence the technological value of new inventions (Capaldo, Lavie, & Petruzzelli, 2017; Li, Vanhaverbeke, & Schoenmakers, 2008). Knowledge recombination research has traditionally focused on original attributes of components (Phene, Fladmoe-Lindquist, & Marsh, 2006; Miller, Fern, & Cardinal, 2007; Rosenkopf & Nerkar, 2001) – i.e. attributes that were embedded into the component at the time of creation. From this perspective, a component's recombinant value is largely pre-determined at creation. An emerging stream of research on knowledge reuse trajectories, however, relaxes this assumption, and argues that components' recombinant value may change considerably over time through component reuse – i.e. the integration of components into new combinations (Fleming, 2001; Katila & Chen, 2008; Yang, Phelps, & Steensma, 2010). Using organizational learning theory (Argote & Miron-Spektor, 2011), they argue that each instance of reuse produces, what we refer to as, reuse information flows – i.e. information flows that are generated when components are reused in different combinations (Katila & Chen, 2008). Inventors can access these reuse information flows in order to improve their understanding of how particular components should be applied most effectively in new combinations (Fleming, 2001; Katila & Chen, 2008).

Research on knowledge reuse trajectories has extensively focused on the frequency of reuse, arguing that the magnitude of reuse information flows influences the recombinant value of components (Fleming, 2001; Katila & Ahuja, 2002). Contributing to this emerging stream of research, our specific research objective in the first project is to examine the largely neglected temporal dimension of reuse, introducing the concept of recombinant lag – i.e. the time that recombined components have remained unused. We hypothesize that recent reuse triggers a rejuvenation effect, embedding the component in the state-of-the-art of technology by creating information about its most up-to-date applications in knowledge recombination. Consequently, we expect that recent reuse improves inventors' ability to generate inventions with higher technological value. Moreover, we explore whether this main relationship is moderated by the frequency at which recombined components were previously reused. These expectations are explored using data on 21,117 patent families from the fuel cell industry pertaining to 139 consolidated firm applicants. Additional data from a post-hoc exploratory analysis are also used, including an inspection of fuel cell literature, an interview with a fuel cell expert, and additional patent data from the wind energy industry.

1.1.2. Project 2: Knowledge Pool Applicability in R&D Alliances

In chapter 3, we present the results of the second project on the topic of knowledge recombination within interfirm R&D alliances. R&D alliances are often conceived as learning vehicles which firms can use to access novel component knowledge from other firms (Rosenkopf & Almeida, 2003). Alliance scholars claim that, by collaborating with external partners that possess larger and more technologically diverse knowledge pools, the focal firm gains new opportunities to generate component combinations (Fleming, 2001; Phelps, 2010; Schilling & Phelps, 2007). However, inspecting recent knowledge recombination literature (e.g. Dibiaggio, Nasiriyar, & Nesta, 2014; Wang *et al.,* 2014), we notice that, next to quantity and diversity, the applicability of components is also regarded as an important driver of knowledge recombination activities. Alliance research, however, tends to ignore variance in components' level of applicability. Therefore, we introduce the concept of knowledge pool applicability – i.e. the extent to which components situated in the knowledge pool can be used in different application domains, studying its impact on the focal firm's intensity of partner-specific recombination.

From the focal firm's perspective, we expect that it is highly beneficial to collaborate with a partner that has higher knowledge pool applicability, at least up until a certain point. In particular, by collaborating with such a partner, the focal firm gains considerable flexibility in its pursuit of recombination opportunities (Yayavaram & Ahuja, 2008). At the same time, beyond a certain threshold value, we expect that the partner's knowledge pool applicability will reduce the focal firm's partner-specific recombination, since there are significant learning complexities associated with very widely-applicable component knowledge (Hargadon & Sutton, 1997). Next to the partner's knowledge pool applicability, we also consider the knowledge recombination implications of the focal firm's own knowledge pool applicability. We hypothesize that, equipped with prior experience building widely-applicable component knowledge, the focal firm is able to more flexibly and effectively engaging in knowledge recombination within the partner's knowledge pool, increasing its intensity of partner-specific recombination. We explore these two expectations using a highly unique dataset on the R&D alliances of 88 consolidated focal firms in the fuel cell industry over a 15-year time period (1993-2007), using patent citations to track knowledge recombination between the focal firm and its partners within 461 R&D alliance dyads.

1.1.3. Project 3: Going-together in Challenge-Based R&D Projects

In chapter 4, we present the results of the third project in which we examine the difference in problem-solving performance between going-together and going-alone strategies in challenge-based R&D projects. In recent years, numerous large-scale government-funded programs aimed at addressing society's greatest challenges, such as climate change, have been initiated (Howard-Grenville, Buckle, Hoskins, & George, 2014; Olsen, Sofka, & Grimpe, 2016). Within the scope of these programs, different types of organizations participate in challenge-based R&D projects to solve extant technological problems within a specific field. In grand challenges literature, there seems to be an implicit assumption that going-together strategies, in which the focal organization formally involves partners in the project, always outperform going-alone strategies in terms of generating high-quality technological solutions. The underlying mechanism is that going-together creates important knowledge recombination opportunities, as it allows merging partners' heterogeneous knowledge pool to generate new technological solutions (Das & Teng, 2000).

In this project, using insights from the knowledge-based view (Galunic & Rodan, 1998; Kogut & Zander, 1992), we argue that organizations require unique abilities to identify, retrieve, and recombine partners' component knowledge in order to reap the knowledge recombination benefits of going-together (Zahra & George, 2002). To explore this contention, we first formulate a baseline hypothesis in which we expect that going-together, on average, yields higher problem-solving performance than going-alone. In the three subsequent hypotheses, we argue that three distinct characteristics of the focal organization – institutional background, internal knowledge pool size, and challenge-based R&D project portfolio size – influence the size of the problem-solving performance gap between going-together and going-alone. To study these hypotheses, we analyse a highly unique dataset comprising detailed project-level information on 414 challenge-based R&D projects within the U.S. Department of Energy's Hydrogen and Fuel Cells Program over a 14-year time period (2003-2016).

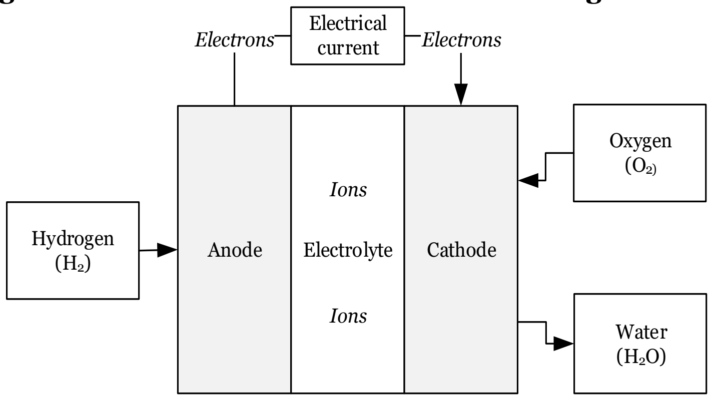
1.2. Empirical setting: The fuel cell industry

In the following section, we present some details regarding the fuel cell industry, which is the empirical setting of this dissertation. In particular, since we rely extensively on examples from the fuel cell industry in each empirical project, we first provide a short explanation of what a basic fuel cell system looks like. Subsequently, we discuss three factors that motivated our choice for this industry as the focal empirical setting of this dissertation.

1.2.1. Basic overview of fuel cell system

In its most basic form, a single fuel cell comprises an anode, a cathode, and an electrolyte sandwiched in-between (see Figure 1.2) (Steele & Heinzel, 2001). In a fuel cell, hydrogen molecules enter at the anode, where they are catalytically separated into negatively charged electrons and positively charged protons (i.e. hydrogen ions) by a platinum catalyst. The separated electrons travel from the anode side of the fuel cell to the cathode side through an external wire to generate an electrical current. The protons travel from the anode side of the fuel cell to the cathode side by permeating through the electrolyte (which is typically made of a solid polymer membrane or a solid oxide). Oxygen molecules enter at the cathode side of the fuel cell, where they react with the electrons and protons, creating potable water as a residual at the cathode side. As such, a fuel cell can generate electricity for as long as reactants (i.e. hydrogen and oxygen) are supplied to it, with water and heat as its residuals.

Figure 1.2. Basic chemical reaction inside single fuel cell



Since a single fuel cell typically does not generate enough voltage, multiple fuel cells are usually combined, creating a so-called 'fuel cell stack'. Special techniques have been developed over the years to stack fuel cells effectively, ensuring that reactants are distributed evenly across the single fuel cells, operating temperatures remain uniform, and no gases leak from the stack. The fuel cell stack is situated at the heart of the fuel cell system, as this is where the electrochemical reaction takes place that generates electricity. However, a fuel cell stack, in and of itself, does not constitute a fuel cell system. Instead, a fully-integrated fuel cell system usually comprises other crucial subsystems. Importantly, hydrogen tanks (to store pure hydrogen that is supplied to the fuel cell stack) or fuel reformers (to reform a hydrocarbon or alcohol fuel into reformate hydrogen that can be used in the fuel cell) are generally integrated with the fuel cell stack, such that reactants can be readily fed into the stack. In turn, the oxygen that is supplied to the fuel cell usually simply comes from the air (for example, in many fuel cell cars, there are inlets at the frontside of the car that allow oxygen to easily travel to the fuel cell stack). Moreover, other balance-of-plant components, such as fans (to circulate oxygen and/or cool down the fuel cell system), sensors (e.g. to detect impurities in hydrogen fuel), and heat exchangers (e.g. to cool the fuel cell stack, to feed heat from the fuel cell stack to the fuel reformer) are often used to support the overall functioning of the fuel cell system (Sharaf & Orhan, 2014). The compiled fuel cell system can be integrated into larger systems, such as large- and small-scale power plants, light-duty vehicles, heavy-duty vehicles, airplanes, boats, unmanned aerial vehicles (UAV), etc. As such, using hydrogen and oxygen from the air, fuel cell systems can generate electricity which can power a wide array of devices.

1.2.2. Motivation to study the fuel cell industry

We chose the fuel cell industry as the empirical setting of this dissertation for three principal reasons: (i) importance of interorganizational collaboration, (ii) availability of rich archival quantitative data, and (iii) diversity of organizations involved. First, since we study interorganizational collaboration activities in chapters 3 and 4, we needed to find an industry in which these activities are prevalent and consequential. In the fuel cell industry, interorganizational collaboration is seen as crucial for generating improved fuel cell technologies (Hellman & Van den Hoed, 2007). Not only are resources and capabilities heterogeneously distributed amongst organizations, there is also much uncertainty about the future of the technology, requiring organizations to actively engage in interorganizational collaboration to keep pace (Schilling, 2015). The necessity of interorganizational collaboration for developing valuable fuel cell technologies was also emphasized by several leading industry practitioners. For example, Carlos Ghosn (then COO of Nissan) stated that: “There is no one car company working on fuel cells on its own [...] This is a very complex technology, there are a lot of technical challenges to be overcome (The Daily Yomiuri (Tokyo), 1999)”. Similar opinions were voiced by Matthew Fronk, technical director of the fuel cell program of Delphi Automotive Systems/General Motors between 1990 and 2009, when discussing Delphi’s collaboration with Exxon and ARCO: “Building an integrated gasoline fuel processor and fuel cell system presents formidable technical challenges [...] our joint research initiative brings together expertise in automotive technology, electric propulsion systems, and fuel processing to address technical issues involved in converting liquid fuels to hydrogen in a compact, vehicle-scale reformer. (PR Newswire, 1997)".

Second, quantitative archival data is extensively available about fuel cell and associated hydrogen technologies. Organizations in the fuel cell industry invest considerably in patenting newly-created inventions, leaving behind a trail of inventive activities that we can easily track. In fact, for many years, patenting activities in fuel cell technology ranked among the highest in clean energy technologies (Albino, Ardito, Dangelico, & Petruzzelli, 2014). Since we rely on patent data to track knowledge recombination activities in chapters 2 and 3, this aspect of fuel cell inventive activities was instrumental to our decision to examine the fuel cell industry. Similarly, data on interorganizational collaborative activities in the fuel cell industry is widely-available. R&D alliance activities between fuel cell organizations have been extensively documented, ensuring that we can track interorganizational collaboration patterns over long periods of time. This is important, as we need to pinpoint the starting and ending date of R&D alliances as accurately as possible for the second project. Similarly, data on challenge-based R&D projects, which we study in the third project, is easy to access. Other data for this empirical project, such as the configuration and problem-solving performance of challenge-based R&D projects, is also easy to retrieve. Hence, for the three projects in this dissertation, we are able to use extremely rich quantitative data to explore our research questions.

Third, an important advantage of studying the fuel cell industry is the sheer diversity of organizations involved in this industry (Hellman & Van den Hoed, 2007). Some of the largest automotive (e.g. Toyota, Honda, Daimler, Renault, General Motors, Ford), chemical (e.g. 3M, BASF, Dow Chemical, Showa Denko), oil & gas (e.g. Shell, ExxonMobil, Air Products & Chemicals, Osaka Gas), heavy equipment (e.g. IHI, Mitsubishi Heavy Industries), electronics (e.g. Samsung Electronics, Toshiba, Panasonic), ceramics (e.g. Toto, Corning), and rare metal (e.g. Engelhard, Johnson Matthey) firms have (had) a strong stake in fuel cell technology. Besides this, numerous dedicated fuel cell manufacturers (e.g. Plug Power, Ballard Power Systems, Fuelcell Energy, Hydrogenics) have been responsible for important advances in the technology. Universities and research institutes are also heavily invested in fuel cell technology, with prominent U.S. (e.g. Stanford University, Gas Technology Institute, Georgia Tech) and European (e.g. Jülich Research Centre, Energy Research Centre of the Netherlands, Alternative Energies and Atomic Energy Commission) research organizations playing an important role in driving technological change in fuel cells. Altogether, the diversity of players in the fuel cell industry ensures sufficient variance in the capabilities and resources of organizations that we study in each project, allowing us to adequately test our hypotheses.

Chapter 2. Dusting off the Knowledge Shelves

The Impact of Recombinant Lag on the Technological Value of Inventions

Abstract: Whereas knowledge recombination research tends to focus on original knowledge component attributes and their recombinant value implications, we contribute to an emerging literature stream on knowledge reuse trajectories, investigating the temporal dimension of reuse by introducing the concept of recombinant lag – i.e. the time that components have remained unused. Relying on organizational learning theory, we emphasize that it is not only important to consider the frequency of reuse, but also the recency of reuse. Our core argument is that recent reuse of knowledge components can trigger a rejuvenation effect that influences the value of resulting inventions. Analyzing 21,117 fuel cell patent families, we find an unexpected U-shaped relationship between recombinant lag and the value of inventions, which is moderated by frequency of reuse. Conducting post-hoc exploratory data analyses, we advance the concept of dormant components – i.e. valuable components that have remained unused prolongedly, as a potential explanation for this unexpected U-shaped pattern. Moreover, collecting and analyzing data on a second sample in the wind energy industry, we provide first indications for the generalizability of these unexpected findings. We contribute to a richer understanding of knowledge reuse trajectories, highlighting that, next to the magnitude of reuse information flows – i.e. information flows that are generated when components are reused, the timing of creation of these information flows shapes the value of subsequent recombination activities. We also contribute to extant research on the temporal dimension of knowledge recombination, pointing to recombinant lag as an important aspect next to component age.

This chapter was written together with Dries Faems and Pedro de Faria. Earlier versions of this chapter have been presented at the *Strategic Management Society Annual International Conference* in Denver (2015), *Annual Meeting of the Academy of Management* in Anaheim (2016), and in research seminars at *University of Groningen* (2015) and *Tilburg University* (2017). A manuscript based on this chapter is conditionally accepted for publication in the *Journal of Management*.

2.1. Introduction

Inventions originate from the recombination of existing components[1] (Fleming, 2001). The technological value of new inventions therefore hinges on attributes of recombined components, such as the technological field, geographical location, organizational context and temporal context from which they originate (e.g. Nerkar, 2003; Phene *et al.,* 2006; Rosenkopf & Nerkar, 2001). Whereas knowledge recombination research has focused on how the recombinant value of components is driven by their original attributes – i.e. attributes that were embedded into the component at the time of creation, this value is not necessarily pre-determined at creation (e.g. Fleming, 2001; Wang *et al.,* 2014). Instead, components go through a unique trajectory over time, which influences their recombinant value. Recently, some studies have started examining how components' recombinant value changes over time (e.g. Belenzon, 2012; Fleming, 2001; Yang *et al.,* 2010), focusing on how the frequency of reuse of components – i.e. the number of times a component was previously reused in a combination – shapes recombinant value (e.g. Boh *et al.,* 2014; Fleming, 2001; Katila & Ahuja, 2002). These scholars argue that each instance of component reuse produces new information flows about the component, which can improve subsequent recombination activities (Katila & Chen, 2008).

This emerging stream of literature on reuse trajectories, however, tends to ignore the temporal dimension of component reuse, neglecting that components differ in terms of when they were last reused[2]. This is surprising as two components created at the same time may go through different reuse trajectories over time, where one may have been last reused 10 years ago, and the other only 1 year ago. We therefore argue that, to increase our theoretical understanding of how knowledge reuse trajectories influence components' recombinant value, it is not only important to look at their frequency of reuse, but also essential to look at when this reuse occurred. To capture the temporal dimension of reuse, we introduce the

[1] In the context of this study, components refer to the "fundamental bits of knowledge or matter that inventors might use to build inventions" (Fleming & Sorenson, 2004: 910).
[2] An exception is Capaldo et al. (2017) who looked in a robustness check at the time elapsed since the last instance of reuse by the firm. However, they position the recency of component reuse as an alternative measure of component age. In contrast, we see the recency of component reuse as a distinct dimension of time that has a different effect from component age.

concept of recombinant lag – i.e. the time that recombined components have remained unused – and empirically test its impact on the technological value of resulting inventions[3].

Using organizational learning theory insights (Argote & Miron-Spektor, 2011), we argue that recent reuse of knowledge components allows for the creation of information flows about the contemporary applications of the component in knowledge recombination. Such rejuvenation effect subsequently increases the value of resulting inventions. As components remain unused for longer periods, however, we expect this rejuvenation mechanism to reduce in strength in a non-linear way. Therefore, we hypothesize a non-linear negative relationship between recombinant lag and technological value of resulting inventions. We also predict that frequency of reuse moderates this relationship in such a way that the value-enhancing mechanism of rejuvenation becomes stronger when a component was frequently reused.

To test the hypotheses, we rely on a sample of 21,117 patent families in the fuel cell industry. Our analyses point to an unexpected U-shaped relationship between recombinant lag and the technological value of inventions. In addition, we observe that, for this fuel cell sample, this relationship mainly manifests itself when the frequency of reuse is low. Based on additional analyses – i.e. screening of raw data, exploration of fuel cell journals, an interview with a fuel cell expert, and additional tests in the wind energy industry, we explain this unexpected pattern by pointing to the existence of dormant components – i.e. valuable components that have remained unused for prolonged periods. Moreover, we provide first indications for the generalizability of this unexpected pattern, confirming the U-shaped relationship for an additional sample in the wind energy industry.

This study adds to the knowledge recombination literature in two important ways. First, we contribute to an emerging stream of literature on knowledge reuse trajectories and their impact on recombinant value of components. In particular, we theorize on the different mechanisms underlying frequency and recency of reuse and empirically demonstrate their impact on the technological value of

[3] Following earlier studies, we examine to what extent the recombination of particular components increases the technological value of resulting inventions, which we conceptualize as the number of times that these inventions serve as inputs for subsequent recombination efforts (Fleming, 2001; Rosenkopf & Nerkar, 2001).

inventions. Second, we contribute to a richer perspective on the temporal dimension of knowledge recombination. We show that it is not only important to consider when a component was created (i.e. component age), but also when it was last used to create new inventions. In terms of managerial implications, we highlight that the reevaluation of existing knowledge stocks may play an important role in the implementation of knowledge creation strategies.

2.2. Theoretical background

In this section, we discuss how extant knowledge recombination literature relies on knowledge search concepts to study how original attributes of components shape their recombinant value. Subsequently, we discuss an emerging stream within knowledge recombination literature that shifts focus from original component attributes to knowledge reuse trajectories as drivers of recombinant value. Finally, we point to the need to explicitly consider the temporal dimension of component reuse, introducing the concept of recombinant lag.

2.2.1. Original component attributes and recombinant value

In the early 1990's, inventors from Mitsubishi Electric Corporation and Kansai Electric Power Company recombined existing component knowledge on (i) fuel reformers and (ii) electrodes in order to generate highly efficient fuel cell systems in which the exothermic heat produced by the fuel cell could directly be used to fasten the endothermic reforming process (Ohtsuki, Seki, Miyazaki, & Sasaki, 1995). This example illustrates how new inventions originate from processes of knowledge recombination in which inventors seek out existing components and recombine them in novel ways (Fleming, 2001). Since recombined components largely determine how a new invention functions, the value and usefulness of a new invention hinges on the attributes of the recombined components (Capaldo *et al.,* 2017; Li *et al.*, 2008). Relying on knowledge search theory (Stuart & Podolny, 1996), existing research has mainly focused on original attributes of components, assuming that attributes that are embedded in components at the time of creation determine the value that can be realized from using them in recombination. Following this theoretical perspective, scholars have pointed to two important underlying mechanisms affecting the value of inventions that result from the recombination of components: novelty and retrievability (Miller *et al.,* 2007; Phene *et al.,* 2006; Rosenkopf & McGrath, 2011). Whereas novelty refers to the extent to which the component is new to the focal inventor or context (Rosenkopf & McGrath, 2011), retrievability signifies the extent to which the component can be absorbed into the focal inventor's knowledge pool (Miller *et al.,* 2007; Phene *et al.,* 2006). Relying on these insights, scholars have examined how the origins of recombined components in terms of technological field (e.g. Nemet & Johnson, 2012; Rosenkopf & Nerkar, 2001), geographical region (e.g. Ahuja & Katila, 2004; Phene *et al.,* 2006), organizational context (e.g. Miller *et al.,* 2007), and temporal context (e.g. Capaldo *et al.,* 2017; Katila, 2002; Nerkar, 2003) influence the value of resulting inventions.

2.2.2. Component reuse, learning opportunities and knowledge recombination

Whereas existing knowledge recombination research mainly investigates original attributes of components as drivers of recombinant value, some scholars have started shifting attention to how the recombinant value of components is also driven by their reuse over time (Belenzon, 2012; Fleming, 2001; Wang *et al.,* 2014). These scholars assume that components are highly malleable (Hargadon & Sutton, 1997; Wang *et al.,* 2014), and can be reused in numerous and diverse ways (Dibiaggio *et al.,* 2014; Fleming, 2001; Hargadon & Sutton, 1997; Yayavaram & Ahuja, 2008) by different inventors situated in different organizations (Belenzon, 2012; Yang *et al.,* 2010) at different points in time (Katila & Chen, 2008).

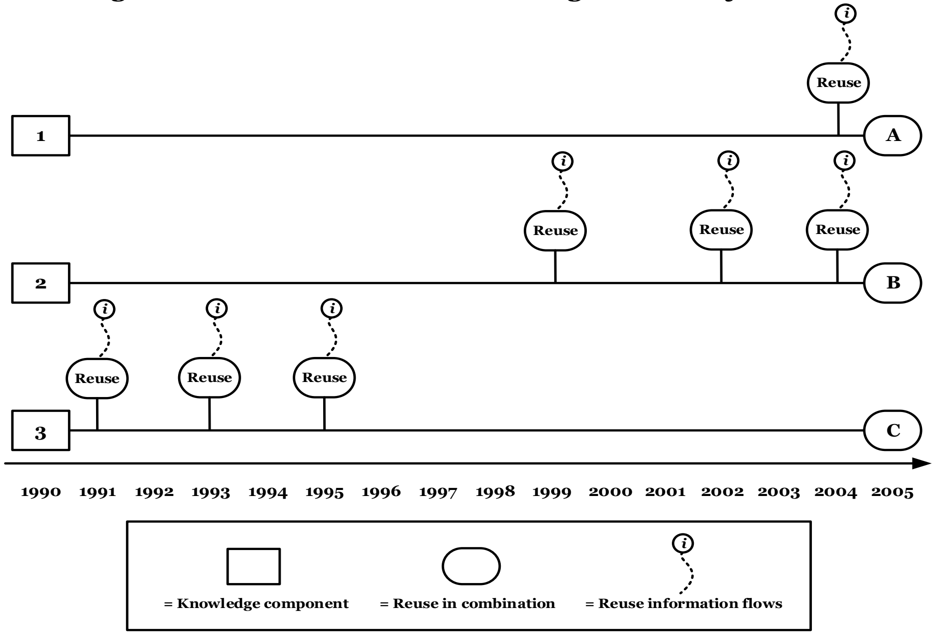
Relying on insights from organizational learning theory (Argote & Miron-Spektor, 2011), they frame component reuse as a learning process by which new information flows are generated that allow inventors to guide and improve their own recombination activities (Katila & Chen, 2008). Through each instance of reuse, new information is produced about how the component behaves in a new combination (Yang *et al.,* 2010). We label this release of new information through the reuse of a component as reuse information flows. Through these reuse information flows, inventors may obtain an improved understanding of the technological specificities underlying this component. To acquire such information flows, inventors may disassemble combinations in which components were reused, gaining important information about the interconnections that exist between constituent components (Hargadon & Sutton, 1997; Sorenson, Rivkin, & Fleming, 2006; Zander & Kogut, 1995). Several studies provide evidence to support these learning dynamics (Katila & Chen, 2008), showing how inventors learn from prior recombination efforts by acquiring technologies for reverse-engineering (Zander & Kogut, 1995) or by closely inspecting patent documents and scientific publications (Murray & O'Mahony, 2007; Yang *et al.,* 2010). For example, inventors often acquire and subsequently test fuel cell stacks for prolonged periods of time, obtaining an understanding of how each individual component that comprises the fuel cell stack (such as electrolytes, electrodes, bipolar plates) contributes to the overall performance of the combination.

2.2.3. Frequency and recency of component reuse

Pointing to the importance of knowledge reuse trajectories, scholars have primarily focused on the frequency of reuse. They have mainly argued that the frequency of component reuse is positively related to the value of inventions (Boh *et al.,* 2014; Dibiaggio *et al.,* 2014; Fleming, 2001). As instances of reuse provide important opportunities to obtain a richer understanding of components' specificities, frequently reused components tend to be more reliable and well-understood in knowledge recombination (Fleming, 2001; Katila & Ahuja, 2002; Wang *et al.,* 2014). Effectively, the higher the number of prior instances of reuse, the higher the number of reuse information flows and learning opportunities that are available (Yang *et al.,* 2010).

In this study, we argue that, next to its frequency, component reuse also varies in terms of its recombinant lag, which we define as the time that recombined components have remained unused. To illustrate the notion of recombinant lag, consider Figure 2.1, where we compare three components that were created in 1990 and which are recombined in an invention in 2005. Having as reference point the recombination that occurred in 2005, components 1, 2, and 3 have similar component age (i.e. 15 years). Moreover, we see that, before 2005, component 1 has been reused once, whereas component 2 and 3 have been reused three times. Although the frequency of reuse of component 2 and 3 is similar, the recombinant lag of component 2 is equal to one (i.e. component 2 was last reused in 2004), whereas the recombinant lag of component 3 is ten. In the next section, we theorize on how these differences in recombinant lag are likely to influence the technological value of resulting inventions.

Figure 2.1. Three different knowledge reuse trajectories



2.3. Hypotheses

In this section, we hypothesize how recombinant lag influences the value of knowledge recombination. Our core argument is that a recent instance of reuse creates reuse information flows that can be used by potential inventors to learn how to apply the component in contemporary knowledge recombination and to create inventions with higher technological value. At the same time, we expect this rejuvenation mechanism to lose strength in a non-linear way. Moreover, we theorize that the strength of this rejuvenation mechanism is contingent upon the frequency of reuse of components.

2.3.1. Recombinant lag and the technological value of inventions

Organizational learning scholars have long acknowledged that the value of learning opportunities associated to information flows is dependent on the particular temporal context during which they occur (e.g. Argote & Miron-Spektor, 2011; Eggers, 2012). Building on these insights, we argue that, next to considering the magnitude of reuse information flows (i.e. frequency of component reuse), it is also important to look at when reuse information flows are generated (i.e. recency of component reuse). Specifically, we argue that recent reuse of a component implies the generation of reuse information flows, which are embedded in the state-of-the-art of technology. Recent reuse of a component thus creates learning opportunities that allow inventors to infer how to apply the component in contemporary knowledge recombination activities, essentially 'rejuvenating' the component's recombinant potential. Effectively, the way components are recombined into new inventions changes over time in line with the evolution of technological paradigms (Dosi, 1982). If we draw a parallel to cooking, we can see knowledge components as food ingredients which are combined and cooked in a particular way in order to prepare a meal (Petruzzelli & Savino, 2014). Culinary preferences change based on newly-acquired tastes and trends in the market, making it necessary to integrate certain ingredients into meals in different ways over time. In the same way, the more recent the last instance of reuse of a component, the more modern and up-to-date the ways in which the component was recombined. As a result, more valuable reuse information flows are generated. Tapping into these reuse information flows, recently reused components become more suitable to inventors for addressing present-day technological problems and opportunities.

To give an example of the importance of recent reuse, consider the case of fuel reformers in the fuel cell industry. Fuel reformers are typically used in fuel cell systems to extract hydrogen from a hydrocarbon (such as gasoline) or an alcohol fuel (such as methane), to be subsequently used as the reactant in the fuel cell. During the 1980's and 1990's, fuel reformer components were often used to design new fuel reformer systems for large-scale fuel cell power plants. In the early 2000's, however, it was expected that the existing oil and gas infrastructure could be used for fuel cell vehicles (known as FCV). Inventors at firms such as Shell and ExxonMobil therefore started recombining existing component knowledge of fuel reformers in order to develop on-board fuel reformer systems that could be installed inside FCVs. A fuel cell expert we interviewed described these as "small chemical plants under the hood". Consequently, fuel reformer components that had been used in combinations for fuel cell plants decades before were now being reapplied in FCVs in radically different ways. By accessing these recently-produced reuse information flows, inventors were able to infer the most up-to-date applications of fuel reformer components, generating ultimately more useful inventions as a result.

However, given the generally rapid pace of technological change (Fabrizio, 2009; Stuart & Podolny, 1996), it is likely that the rejuvenation effect depreciates in a non-linear way. We expect that the difference in technological value between an invention with a recombinant lag of 1 year and an invention with a recombinant lag of 4 years is likely to be substantial as the learning opportunities of 1-year old reuse information flows are likely to be much higher than 4-year old reuse information flows. In contrast, the difference in technological value between an invention with a recombinant lag of 4 year and an invention with a recombinant lag of 7 years is likely to be less outspoken as the learning opportunities of 4-year old and 7-year old reuse information flows are likely to be more similar.

In sum, we expect that, for components with a high recombinant lag, reuse information flows will provide less useful opportunities to learn how to apply the component in contemporary knowledge recombination compared to components with a low recombinant lag. Consequently, we expect the technological value of inventions that result from the recombination of components with a high recombinant lag to be lower than the technological value of inventions resulting from components with a low recombinant lag. However, because we expect the most recent instances of reuse to provide substantially more useful reuse information flows to inventors than relatively less recent ones, we predict a non-linear relationship between recombinant lag and technological value. In particular, we expect the negative effect of moving from low to medium recombinant lag to be more outspoken than the negative effect of moving from medium to high recombinant lag. We therefore hypothesize:

Hypothesis 1: The recombinant lag of components used in knowledge recombination has a negative and diminishing impact on the technological value of resulting inventions

2.3.2. The moderating effect of the frequency of reuse

Components do not only differ in terms of their recency of reuse, but also in terms of how frequently they have been reused. Jointly considering these two dimensions of component reuse, we expect that the frequency of reuse amplifies the rejuvenation effect associated with low recombinant lag.

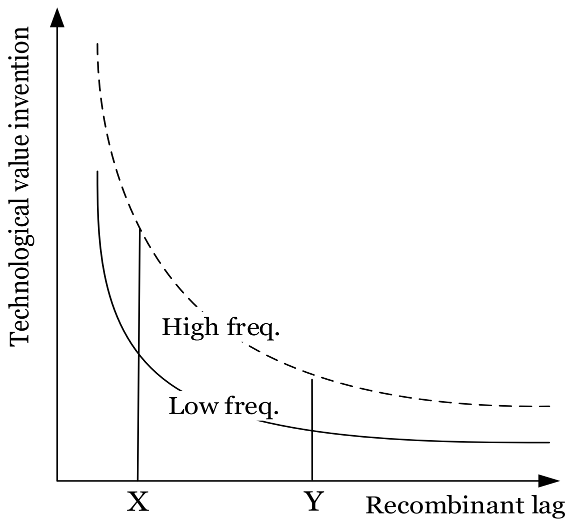
A core tenet of organizational learning theory is that learning opportunities that are less ambiguous tend to be more useful (Argote & Miron-Spektor, 2011; Bohn, 1995; Lampel, Shamsie, & Shapira, 2009). Relying on these insights, we argue that reuse information flows from a recent instance of component reuse are less ambiguous (and, therefore, more useful) when numerous prior combinations are available in which the component was also reused. In particular, when frequency of reuse is higher, ambiguity regarding the unique features of the most recent and contemporary application of the component will be substantially reduced. When a component was reused more frequently, the inventor can access numerous reuse information flows regarding the component's prior instances of reuse, and use these to contrast how the component's most recent instance of reuse deviates from older ones (e.g. in Figure 2.1, component 2's most recent recombination in 2004 can be contrasted with its recombinations in 2002 and 1999).

Going back to our previous example: before they were reused in FCVs, fuel reformer components had already been used extensively in combinations targeted at fuel cell power plants, producing sizeable reuse information flows. Later, when inventors started developing on-board fuel reformers, the recent reuse of fuel reformer components in FCVs could easily be contrasted with prior reuse in fuel cell plants. Consequently, this allowed inventors to better understand how recombination of fuel reformer components in FCVs differed from recombination in fuel cell plants.

Higher frequency of reuse is thus expected to enhance the rejuvenation effect of recombinant lag. However, we argue that the strength of this moderation effect will depend on the level of recombinant lag. In particular, as we argued in the previous section, the rejuvenation effect of recombinant lag is likely to reduce in strength in a non-linear way as recombinant lag increases. Therefore, at higher values of recombinant lag, higher frequency of reuse will only slightly raise the impact of recombinant lag on the technological value of inventions. To clarify our reasoning, we depict this hypothesized moderating relationship in Figure 2.2. Here, we observe that, when recombinant lag has a value of X, the difference in impact between high and low frequency of reuse is considerably large. This is because, through higher frequency of reuse, the rejuvenation effect of recent reuse is amplified. However, moving towards a value of recombinant lag of Y, we observe that the difference between low and high frequency of reuse becomes smaller. At such high values of recombinant lag, the rejuvenation effect is nearly dissipated, making the moderating effect of higher frequency of reuse negligible. In other words, the convex relationship between recombinant lag and technological value of invention is expected to become steeper when the frequency of reuse is higher. Therefore, we hypothesize:

Hypothesis 2: The frequency of reuse of components used in knowledge recombination moderates the relationship between components' recombinant lag and the technological value of resulting inventions in such a way that the relationship becomes steeper for higher frequency of reuse.

Figure 2.2. Frequency of reuse and recombinant lag



2.4. Methodology

2.4.1. Empirical context

To test our hypotheses, we collected data on inventions related to fuel cell technology. We studied the patent family applications of the 200 firms with the highest number of patent applications in this industry. Invented in 1839 by William Grove, fuel cells produce electricity through a chemical reaction that combines a fuel (usually hydrogen) with an oxidizing agent (usually oxygen). This technology witnessed its first practical application in the 1960's when it was used by NASA in the Space Program to provide electricity (and drinking water) to spacecrafts (Perry & Fuller, 2002). In subsequent decades, the potential of this technology has been exploited in distributed energy generation, automobiles, and portable electronic devices (Sharaf & Orhan, 2014).

The fuel cell industry is suitable for testing our hypotheses for several reasons. First, given the long technological lineage of fuel cell technology, components used in fuel cell inventions vary substantially in terms of when they were created and when they were last used. Second, knowledge recombination as a means to generate new inventions is pervasive in the fuel cell industry. In fact, the successful integration of disparate components into coherent combinations is often heralded as the foundation of success of new fuel cell technologies (Sharaf & Orhan, 2014). Third, we use patent data to track inventions, and studies have shown that patenting propensities in fuel cell technology are among the highest in clean energy technologies (Albino *et al.,* 2014).

2.4.2. Data

Patent data. To study fuel cell inventions, we relied on patent data retrieved from the October 2013 version of the PATSTAT database[4]. In line with recent studies (e.g. Bakker, Verhoeven, Zhang, & Van Looy, 2016), we used patent families to identify inventions and knowledge recombination. To delineate patent families, we used the European Patent Office worldwide bibliographic database

[4] Some authors have expressed concerns about the use of patent data to study inventions, arguing that some firms tend to rely more on alternative appropriation mechanisms (Arundel & Kabla, 1998; de Faria & Sofka, 2010). Nevertheless, given the fact that we sampled from an industry in which patenting propensity rates are generally elevated, these concerns are alleviated (Arundel & Kabla, 1998).

(DOCDB) patent family definition. The DOCDB patent family captures all patent applications related to the same invention but filed at different patent offices (Albrecht, Bosma, Dinter, Ernst, Ginkel, & Versloot-Spoelstra, 2010). Effectively, a patent applicant seeking protection for an invention in more than one juridical region has to file a new patent application in each separate region (e.g. the USPTO for the U.S. and the JPO for Japan). These different patent applications from different patent offices collectively comprise more information about the invention than if only one single patent office is considered (Nakamura, Suzuki, Kajikawa, & Osawa, 2015). Therefore, we collected patent applications from all patent offices in the world, and aggregated these to the patent-family level. To capture the date that is closest to ideation of the invention, we looked at the priority date (i.e. the first time that the applicant sought patent protection for its invention at a patent office) of the patent family. The use of patent families to denote inventive activities has a number of advantages over the use of single patent office applications (Bakker *et al.,* 2016; de Rassenfosse, Dernis, Guellec, Picci, & van Pottelsberghe de la Potterie, 2013; Martínez, 2011). First, it captures a wider array of inventions since it does not limit itself to one patent office (Bakker *et al.,* 2016). Second, it overcomes the home-country bias of single patent office applications (Criscuolo, 2006; de Rassenfosse *et al.,* 2013). Third, studying patent families provides a more complete coverage of backward citations than single patent office applications (Albrecht *et al.,* 2010; Nakamura *et al.,* 2015).

Following earlier research, we studied patents' backward citations to examine the components that are recombined to create new inventions (Jaffe & de Rassenfosse, 2017; Phene *et al.,* 2006; Rosenkopf & Nerkar, 2001)[5]. Since we studied patent families, we aggregated all backward citations at the patent family-level (see for an example: Nakamura *et al.,* 2015). We collected all patent family applications filed by firms in IPC class H01M8 (titled 'Fuel Cells; Manufacture thereof') which corresponds to fuel cell technology (Tanner, 2014). Our data collection procedure allowed us to identify a total of 21,117 patent family

[5] We recognize that patent citations included by patent examiners may bias some of our results (Alcacer & Gittelman, 2006). However, we are confident that our findings are not driven by this data limitation. As Sorenson et al. (2006: 1001) note: "At worst, if examiners add citations that do not reflect true knowledge flows and do so in an unbiased way, this should only add noise, increasing the difficulty of finding statistical support for our hypothesis".

applications. These patent family applications were retrieved after removing (i) patent families that were not filed by the firms that we consolidated, (ii) patent families with incomplete backward citation information and (iii) patent families filed after 2007.

Firm ownership data. To ensure that the examined patents captured the full extent of the firms' inventive activities, we aggregated the subsidiaries of the 200 firms with the highest number of patent applications in the fuel cell industry at the parent firm-level (Ahuja & Lampert, 2001; Nerkar, 2003). It was necessary to consolidate patenting activities at the parent firm-level in order to identify which patent citations were internal (i.e. citations between patents from the same applicant) and which were not.

We identified all subsidiaries in which each of these 200 firms had a controlling interest. In order to do so, we relied on the most recent ownership data available for these firms in Bureau van Dijk's Orbis Database. We subsequently matched the names of these subsidiaries to those available in the patent database[6]. Some of the firms in the top 200 were subsidiaries of other firms in the top 200, therefore their patent applications were aggregated at the parent firm-level. Other firms had incomplete ownership data due to, for example, bankruptcy, and therefore were not included in the analysis. As a result, our final group of firms included 139 firms.

2.4.3. Variables

Dependent variable. To measure the *Technological value* of inventions, we relied on forward citations (i.e. citations made to the patent family). Forward citations have often been used to capture the technological value of patented inventions (Ahuja & Lampert, 2001; Fleming, 2001; Jaffe & de Rassenfosse, 2017). Forward citations correlate positively with the economic value of patents (Hall, Jaffe, & Trajtenberg, 2005) and technology improvement rates (Benson & Magee, 2015). A high citation count indicates that a patented invention is frequently used

[6] We made efforts to connect the subsidiaries to their respective parent firms by inspecting potential name changes and other names that firms were known as (also available in the Orbis Database). Moreover, we collected data on mergers and acquisitions of the firms in our sample (retrieved from the SDC Platinum Mergers and Acquisitions Database). We also cross-checked ambiguous cases using the LexisNexis Academic Database. Finally, when necessary, we also inspected the address that was listed on the patent application of the applicant (provided that they were available). Harmonized applicant names were obtained through the EEE-PPAT, provided by ECOOM.

as an input for new patented inventions. Since older patents may receive more citations because they have been in existence for longer (Fleming, 2001; Nemet & Johnson, 2012), we applied a fixed four-year window to forward citations. In other words, irrespective of the year in which the patent was filed, we counted the number of forward citations that was made to this patent within the first four years after it was filed (e.g. for a patent filed in 2000, we counted the number of forward citations made to this patent up until 2004). In line with prior research (e.g. Miller *et al.,* 2007), we excluded internal forward citations.

Independent variables. To measure *Recombinant lag*[7], we considered the forward citations made to patents that were cited by the focal patent. Katila and Chen (2008: 606) already noted that "because one of the requirements for patenting is novelty, each time an existing patent is cited as an antecedent for a new patent, it is used in a different context than before. Thus each repeat use of a citation serves as a distinct source for learning." Hence, the use of patent citations to track reuse and learning opportunities generated therefrom is highly suitable. For each patent cited by the focal patent, we calculated how many years elapsed between the priority year of the focal patent and the priority year of the last citation that was made to the cited patent. For example, in Figure 2.3 we have patent C that cites patent A, which was filed in 1995 and was last cited by patent B in 1997. The number of years elapsed between the creation of the focal patent (i.e. 2002) and the last citation that was made to patent A by patent B (i.e. 1997) is 5, which represents the recombinant lag of patent A for patent C. When a focal patent cites a patent, which had not been cited before, the recombinant lag equals the number of years elapsed between the priority year of the focal patent and the priority year of the cited patent. In Figure 2.3, the recombinant lag of patent A for patent B is therefore 2.

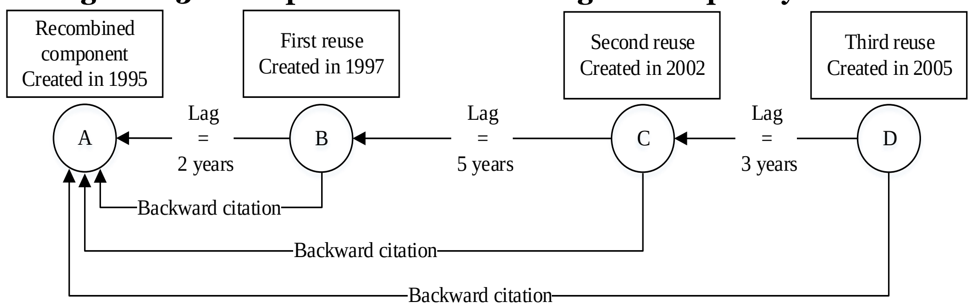
For each patent, we took the median value of recombinant lag of its backward citations (Nerkar, 2003). We took the median value of recombinant lag to more aptly capture the typical time that recombined components had remained

[7] Capaldo et al. (2017) tested the impact of a similar measure in one of their robustness checks. Whereas we examine the time that a patent has not been cited by *anyone*, they examined whether the time that elapsed since the last citation *by the firm* has a similar effect on the value of a patent as the age of a patent citation. We computed the same measure in a robustness check. We found that this measure had a very high correlation with age (0.85). Moreover, its impact on the value of a patent was similar to that of component age (i.e. strictly negative and linear).

unused. Relying on the median value of a variable is also warranted when the distribution of the variable is skewed. In our case, the distribution of recombinant lag was skewed to the right, indicating that most components had remained unused for short periods of time (i.e. 58 percent of backward citations had a recombinant lag of 1).

To measure *Frequency of reuse*, we examined how often the patents cited by the focal patent family were themselves cited by other patents (Hohberger, 2017; Miller *et al.,* 2007). In this way, we could assess to what extent an invention recombines components that were frequently used in other combinations. For example, in Figure 2.3, patent A was cited once before being cited by patent C. The frequency of reuse of patent A for patent C is therefore 1. Similarly, patent A was cited twice before being cited by patent D. The frequency of reuse of patent A for patent D is therefore 2. For each patent, we took the average value of frequency of reuse of its backward citations.

Figure 2.3. Example of recombinant lag and frequency of reuse



Control variables. Following prior research on the technological value of inventions, we included several control variables in the models. We controlled for several attributes of recombined components. It is expected that recombination of older components yields a negative impact on the technological value of inventions (Benson & Magee, 2015; Fabrizio, 2009; Nerkar, 2003; Schoenmakers & Duysters, 2010). We control for this by including the variable *Component age,* which is measured by the median number of years that elapsed between the priority year of the focal patent family and the priority years of the backward citations (Nerkar, 2003). Inventions that recombine a larger number of components tend to be more valuable (Kelley, Ali, & Zahra, 2013). To control for this fact, we included the variable *Number of components,* which is measured by counting the number of backward citations of the patent family. Moreover, inventions that rely strongly on internal components tend to be less valuable (Kim, Song, & Nerkar, 2012; Rosenkopf & Nerkar, 2001). The variable *Internal components* controls for this fact and is calculated by dividing the number of internal backward citations by the total number of backward citations of the patent family. The technological diversity of recombined components may further influence the technological value of resulting inventions (Kelley *et al.,* 2013). We computed the variable *Technological breadth* using the measure developed by Gruber et al. (2013), which calculates technological breadth at the backward citation-level on the basis of IPC codes (we used the subclass level).

We also controlled for attributes of the focal patented invention. Single inventors tend to generate inventions with poorer outcomes than teams of inventors (Singh & Fleming, 2010). Hence, to control for these effects, we included the variable *Team size* which counts the number of inventors that are listed on the patent family application. Moreover, earlier research found that the number of patent authorities in which a patent was filed correlates with the value of the invention (Harhoff, Scherer, & Vopel, 2003). Hence, the number of patent offices in which a patent was filed may be indicative of the quality of the underlying invention. We included the variable *Patent offices* which counts the number of unique patent offices in which patents in the patent family were filed. Finally, since granted patents have passed patent examiners' evaluation of patentability, their technological value is generally higher. To control for this fact, we included the binary variable *Patent granted* which takes a value of 1 if at least one patent in the patent family had been granted.

2.4.4. Analytical method

Our unit of analysis is the patent family. In total, we analyzed 21117 patent families filed by 139 unique applicants over the time period 1959-2007. Each patent family was only observed once, in the year corresponding to its priority date. As our dependent variable is an overdispersed count variable (i.e. the standard deviation of the variable exceeds the mean), we used negative binomial regressions to test our hypotheses (Hausman, Hall, & Griliches, 1984). This method of analysis has also been employed by prior research using patent data (e.g. Fleming, 2001; Nemet & Johnson, 2012; Rosenkopf & Nerkar, 2001). To control for variance associated with the year of creation of the patent family, we included year dummies in all models. Moreover, to hold constant characteristics of the applicant of the patent (i.e. the focal firm), we included firm dummies in all models. Finally, to control for heteroskedasticity, we included robust standard errors in all models.

2.4.5. Results

Descriptive statistics. Table 2.1 shows the descriptive statistics and correlation matrix. On average, the patents in our sample receive 2.48 citations in the first four years after creation. Moreover, we find that 38.5 percent of these patents receive no forward citations in the first four years after creation. The patents in our sample typically have a recombinant lag of 1.72 years, suggesting that most inventions rely on components that have remained unused for relatively short periods of time. Finally, our descriptive statistics indicate that the patents in our sample typically cite patents that were, on average, previously cited 6.96 times by other patents.

To check for potential multicollinearity problems, we consider the variance inflation factors (VIF) and the condition numbers of our models. The VIF analysis shows a maximum value of 1.45 and an average value of 1.20 for all variables, well below the threshold value of 10 (Mason & Perreault, 1991). Moreover, the condition numbers remain below the threshold value of 30 at 9.95 (Mason & Perrault, 1991). Consequently, we are confident that multicollinearity is not an issue in our models.

Table 2.1. Descriptive statistics and correlation matrix

	Variables	1	2	3	4	5	6	7	8	9	10
1	Technological value	1									
2	Recombinant lag	-0.09	1								
3	Frequency of reuse	0.12	-0.20	1							
4	Component age	0.02	0.45	0.20	1						
5	Number of components	0.30	-0.13	0.22	0.08	1					
6	Internal components	-0.06	-0.07	-0.04	-0.16	-0.06	1				
7	Technological breadth	0.10	-0.05	0.12	0.04	0.22	-0.05	1			
8	Team size	0.07	-0.01	0.01	-0.01	0.06	-0.02	0.03	1		
9	Patent offices	0.30	-0.11	0.15	0.04	0.37	-0.03	0.14	0.04	1	
10	Patent granted	0.19	-0.06	0.09	0.04	0.22	0.02	0.09	0.03	0.26	1
	Mean	2.48	1.72	6.96	5.42	9.05	0.16	0.65	2.99	2.41	0.72
	SD	4.23	1.77	8.08	3.94	9.53	0.22	0.36	1.96	2.01	0.45
	Min	0	0	0	0	1	0	0	1	1	0
	Max	85	58	327.88	58	179	1	1	22	19	1

Regression Results. Table 2.2 presents the results of the negative binomial regressions. Model 1 is the baseline model which only includes the control variables. Overall, the control variables have the expected signs and have a statistically significant effect on the technological value of inventions. In line with prior research (e.g. Nerkar, 2003; Schoenmakers & Duysters, 2010), we find that the age of recombined components has the expected negative and statistically significant effect on the technological value of inventions (Model 1: $\beta_{\text{Component age}} = -0.021$, $p < 0.001$). The number of recombined components has a positive and statistically significant effect on the technological value of inventions (Model 1: $\beta_{\text{Number of components}} = 0.017$, $p < 0.001$), suggesting that inventions that recombine many different components are more technologically valuable (Kelley *et al.,* 2013). The invention's reliance on internally-generated components has a negative and statistically significant effect on the technological value of the invention (Model 1: $\beta_{\text{Internal components}} = -0.340$ $p < 0.001$), indicating that strong reliance on internal components may inhibit the ability of others to build upon the newly-created invention (Kim *et al.,* 2012). The results also suggest that fuel cell inventions benefit from relying on technologically broad components (e.g. Kelley *et al.,* 2013), as indicated by the positive and statistically significant effect of technological breadth on the technological value of inventions (Model 1: $\beta_{\text{Technological breadth}} = 0.146$, $p < 0.001$).

The size of the team that contributed to the invention has a positive and statistically significant effect on the technological value of inventions (Model 1: $\beta_{\text{Team size}} = 0.026$, $p < 0.001$), supporting the notion that larger teams of inventors may be better able to resolve technological problems (Singh & Fleming, 2010). The number of unique patent authorities in which the patent was filed has a positive and statistically significant effect on the technological value of inventions (Model 1: $\beta_{\text{Patent offices}} = 0.113$, $p < 0.001$), providing evidence that a broader scope of patent protection may be indicative of the quality of an invention (Harhoff *et al.,* 2003). Finally, inventions which meet patent examiners' patentability evaluation tend to be more technologically valuable (Model 1: $\beta_{\text{Patent granted}} = 0.220$, $p < 0.001$).

In model 3 we test Hypothesis 1. We find a negative and statistically significant effect of recombinant lag on the technological value of inventions (Model 3: $\beta_{\text{Recombinant lag}} = -0.097$, $p < 0.001$) and a positive and statistically significant quadratic effect (Model 3: $\beta_{\text{Recombinant lag squared}} = 0.003$, $p < 0.001$), indicating the existence of a non-linear relationship between recombinant lag and the technological value of inventions. We execute several tests to examine whether this is the relationship that we hypothesized (i.e. negative and with diminishing marginal effects) (Haans, Pieters, & He, 2016; Karim, 2009; Lind & Mehlum, 2010). We find that: (i) the linear coefficient is negative and statistically significant and the quadratic coefficient is positive and statistically significant, (ii) the 95 percent Fieller confidence interval of the inflection point is within the range of observable points ([13.19, 28.00]), (iii) the slope before the inflection point is negative and statistically significant at the minimum value of recombinant lag ($p < 0.001$) and the slope after the inflection point is positive and statistically significant at the maximum value of recombinant lag ($p < 0.001$), and (iv) the linear and quadratic coefficients of recombinant lag are jointly statistically significant ($Chi^2 = 71.50$, $p < 0.001$). This means that, instead of the predicted negative relationship with diminishing marginal effects, we actually find a U-shaped relationship between recombinant lag and the technological value of inventions. Figure 2.4 plots this relationship and shows that the inflection point occurs at a value of recombinant lag of 17.2, implying an inflection point at relatively high levels of recombinant lag. Thus, although negative value implications of recombinant lag are clearly present for the initial range of values of recombinant lag, we do not find full support for Hypothesis 1.

In model 5 we test Hypothesis 2. We find a statistically significant interaction between the frequency of reuse of components and recombinant lag on the technological value of inventions (Model 5: $\beta_{\text{Recombinant lag} \times \text{Frequency of reuse}} = 0.007$, $p < 0.05$; Model 5: $\beta_{\text{Recombinant lag squared} \times \text{Frequency of reuse}} = -0.001$, $p < 0.01$). In Figure 2.5, we show that the upward slope of the U-shaped relationship between recombinant lag and technological value mainly emerges when frequency of reuse is low. Below, we first discuss our robustness checks. Subsequently, we present additional analyses and data to explain this unexpected U-shaped relationship.

Figure 2.4. Recombinant lag and technological value of invention

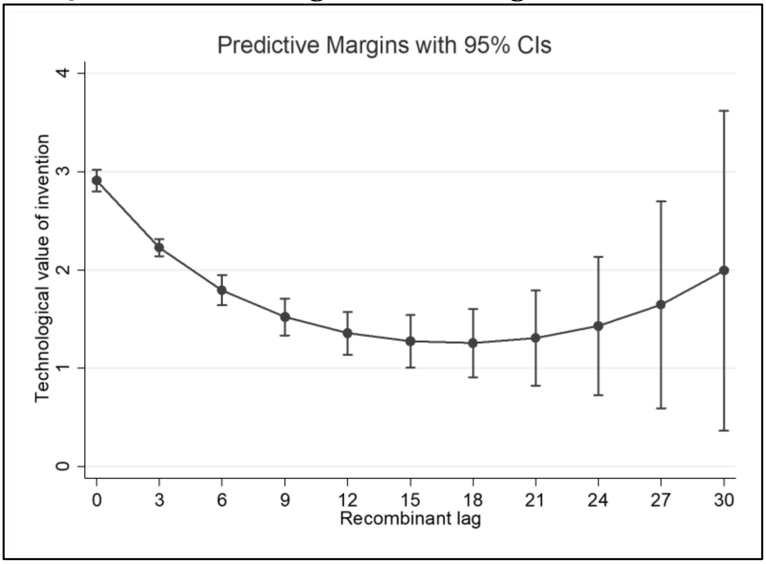


Figure 2.5. Interaction recombinant lag and frequency of reuse

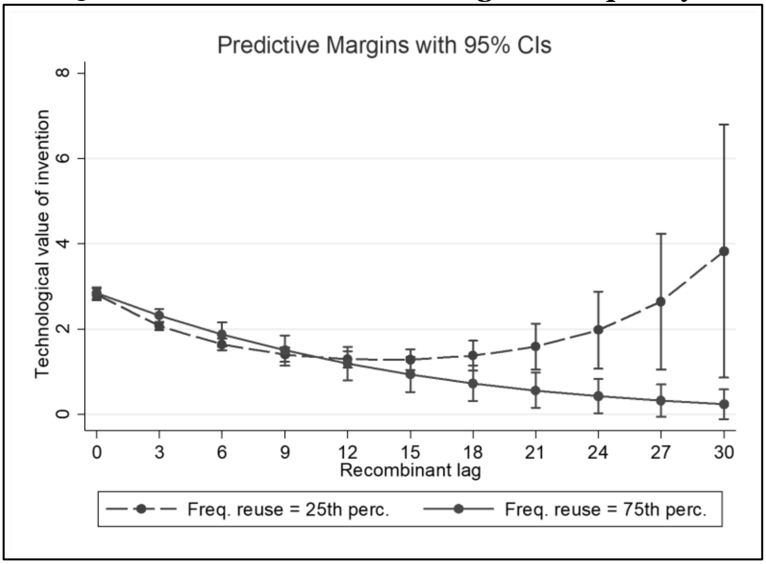


Table 2.2. Negative binomial regression results

DV: Technological value of invention	1	2	3	4	5
Component age	-0.02***	-0.01***	-0.01**	-0.01**	-0.01***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Number of components	0.02***	0.02***	0.02***	0.02***	0.02***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Internal components	-0.34***	-0.35***	-0.35***	-0.35***	-0.35***
	[0.05]	[0.05]	[0.05]	[0.05]	[0.05]
Technological breadth	0.15***	0.15***	0.15***	0.15***	0.15***
	[0.03]	[0.03]	[0.03]	[0.03]	[0.03]
Team size	0.03***	0.03***	0.03***	0.03***	0.03***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Patent offices	0.11***	0.11***	0.11***	0.11***	0.11***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Patent grant	0.22***	0.22***	0.21***	0.21***	0.21***
	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
Frequency of reuse	0.01***	0.01***	0.01***	0.01***	0.00
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Recombinant lag		-0.06***	-0.10***	-0.10***	-0.13***
		[0.01]	[0.01]	[0.01]	[0.02]
Recombinant lag squared			0.00***	0.00***	0.01***
			[0.00]	[0.00]	[0.00]
Recombinant lag × Frequency of reuse				-0.00	0.01*
				[0.00]	[0.00]
Recombinant lag squared × Frequency of reuse					-0.00**
					[0.00]
Firm dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Observations	21117	21117	21117	21117	21117
Pseudo R^2	0.118	0.119	0.119	0.119	0.119
AIC	76248.10	76175.56	76147.40	76149.40	76140.12
BIC	77807.84	77743.26	77723.05	77733.00	77731.68
Log Likelihood	-37928.05	-37890.78	-37875.70	-37875.70	-37870.06
Wald chi^2	11516.31***	11589.89***	11632.16***	11634.81***	11646.36***

† $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. Robust standard errors between brackets.

Robustness checks. To assess the robustness of our findings, we run several additional model specifications (see Table 2.3). First, we test whether component age also has a non-linear relationship with the technological value of inventions (model 6). We find no statistical evidence of a non-linear relationship between the age of recombined components and the technological value of inventions. In contrast to recombinant lag, age appears to have a strictly negative linear relationship with the technological value of inventions, which is in line with the prior work of Nerkar (2003). Second, in models 7 and 8, we exclude patent families with a single backward citation (representing 4.58 percent of the sample), since these may not reflect knowledge recombination processes (i.e. only one component is used to build a new invention). The main results remain unchanged. Third, in models 9 and 10, we exclude all patent families created before 1990, since fuel cell technological development principally took off after this year (Perry & Fuller, 2002; Sharaf & Orhan, 2014). Results remain largely unaffected.

Table 2.3. Robustness checks

DV: Technological value of invention	6	7	8	9	10	11	12	13	14	15
Component age	-0.01*	-0.01***	-0.01***	-0.01***	-0.01***	-0.01*	-0.01**	-0.01***	-0.01**	-0.01**
	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Number of components	0.02***	0.02***	0.02***	0.02***	0.02***	0.01***	0.01***	0.02***	0.02***	0.01***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Internal components	-0.35***	-0.35***	-0.35***	-0.37***	-0.37***	-0.26***	-0.25***			
	[0.05]	[0.05]	[0.05]	[0.05]	[0.05]	[0.04]	[0.04]			
Technological breadth	0.15***	0.14***	0.14***	0.12***	0.12***	0.13***	0.13***	0.25**	0.25***	0.27***
	[0.03]	[0.03]	[0.03]	[0.03]	[0.03]	[0.03]	[0.03]	[0.08]	[0.08]	[0.08]
Team size	0.03***	0.03***	0.03***	0.03***	0.03***	0.02***	0.02***	0.04**	0.03*	0.03*
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]
Patent offices	0.11***	0.11***	0.11***	0.11***	0.11***	0.10***	0.10***	0.05***	0.05***	0.05***
	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]
Patent grant	0.22***	0.20***	0.20***	0.16***	0.16***	0.18***	0.18***	0.27***	0.27***	0.25***
	[0.02]	[0.02]	[0.02]	[0.03]	[0.03]	[0.02]	[0.02]	[0.05]	[0.05]	[0.05]
Frequency of reuse	0.01***	0.01***	-0.00	0.01***	0.00	0.01***	-0.00	0.04***	0.05***	0.04***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]
Recombinant lag	-0.06***	-0.10***	-0.15***	-0.10***	-0.12***	-0.09***	-0.13***	-0.07***	-0.07***	-0.11***
	[0.01]	[0.01]	[0.02]	[0.02]	[0.02]	[0.01]	[0.02]	[0.01]	[0.02]	[0.02]
Recombinant lag squared		0.00***	0.01***	0.00**	0.01***	0.00***	0.01***	0.00***	0.00**	0.00**
		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Recombinant lag × Frequency of reuse			0.01**		0.01+		0.01***		-0.01*	-0.00
			[0.00]		[0.00]		[0.00]		[0.00]	[0.01]
Recombinant lag squared × Frequency of reuse			-0.00***		-0.00*		-0.00***		0.00**	0.00
			[0.00]		[0.00]		[0.00]		[0.00]	[0.00]
Component age squared	0.00									
	[0.00]									
Firm dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21117	20150	20150	19164	19164	20119	20119	3674	3674	3554
Pseudo R^2	0.119	0.118	0.119	0.119	0.119	0.097	0.098	0.073	0.073	0.073
AIC	76176.64	73696.49	73686.45	70662.48	70660.60	65969.82	65957.05	18213.05	18209.22	17687.52
BIC	77752.29	75262.86	75268.64	71967.37	71981.22	67535.89	67538.93	18523.50	18532.09	17934.55
Log Likelihood	-37890.32	-36650.24	-36643.22	-35165.24	-35162.30	-32786.91	-32778.52	-9056.53	-9052.61	-8803.76
Wald chi^2	11594.05***	11124.52***	11142.48***	10631.71***	10638.41***	8683.21***	8714.80***	2963.14***	2984.11***	1462.46***

† p < .10, * p < .05, ** p < .01, *** p < .001. Robust standard errors between brackets.

Fourth, in models 11 and 12, we exclude inventions with very high technological value (i.e. above 95th percentile) which corresponds to patents that receive more than 10 external forward citations within the fixed four-year window. Results remain highly stable.

We also execute several additional analyses, which we do not report in Table 2.3 for the sake of brevity, but which are available upon request: (i) we recalculate recombinant lag by taking the mean value of recombinant lag of the backward citations of the patent family, (ii) we run the analyses excluding component age as a control variable, (iii) we increase the fixed window of external forward citations to 5 years, and (iv) we rerun the analyses, excluding patents created before 1980. In all four cases, the main results remain highly stable.

2.4.6. Post-hoc exploratory data analysis

Whereas we hypothesized a negative relationship with diminishing returns between recombinant lag and the technological value of inventions, we actually detected a robust U-shaped relationship. To make sense of this unexpected finding, we performed four steps. First, we reexamined our data, trying to identify inventions that drove this unexpected relationship. Subsequently, we delved into fuel cell technology literature and conducted an interview with a fuel cell technology expert to better understand why some inventions contributed to this unexpected relationship. Third, we conducted additional tests on a sample of inventions in the wind industry to explore the generalizability of our unexpected findings. Finally, we connected the additional information that emerged out of these analyses to existing knowledge recombination literature.

Data examination. As Figure 2.4 illustrates, the inflection point of the U-shaped curve is situated at relatively high levels of recombinant lag. In an attempt to understand what drives this U-shaped curve, we screened inventions beyond the inflection point of the curve, representing a small group of 49 inventions with a recombinant lag of at least 17 years. Screening these inventions, we observed that, in accordance with our hypothesis, 26 of them had received zero forward citations within the first four years of creation. However, we also identified a group of 23 inventions for which, following our hypothesis, we had expected very limited technological value, but which actually had considerable technological value (i.e.

on average these inventions received 1.83 external forward citations within the first four years of creation). These data suggest that the upward slope of our unexpected U-shaped relationship was driven by a limited number of observations with high levels of recombinant lag and higher-than-expected technological value.

Sense making. To understand why, in some exceptional cases, high recombinant lag is associated with considerable technological value, we reexamined the context of our study. In particular, we inspected issues of leading fuel cell technology journals (e.g. *Fuel Cells Bulletin*), and read several review articles on fuel cell technology (e.g. Sharaf & Orhan, 2014; Steele & Heinzel, 2001). In addition, we arranged an interview with a fuel cell expert who has published extensively in fuel cell-oriented journals and was responsible for coordinating several large Dutch- and European-level fuel cell programs.

Based on these data sources, we found strong indications that the cyclical nature of technology development can explain why some components with extreme recombinant lag are associated to inventions with considerable technological value. In the fuel cell literature, it is emphasized that, in line with other industries, fuel cell technology has experienced several cycles of technological development, where periods of revived interest and intense technological development are followed by periods of relative technological stability (Tushman & Anderson, 1986). These cycles of technological development are principally triggered by the emergence of new application fields for the technology, such as consumer electronic products for fuel cells in the early 2000's (Sharaf & Orhan, 2014). These new application domains often emerge following important technological breakthroughs in the primary technology, as similarly argued by Tushman and Anderson (1986). According to the interviewed fuel cell expert, one of the most notable technological cycles in fuel cell technology began in the 1960's when NASA placed fuel cells on board of their spacecrafts in order to generate electricity and provide drinking water. During this decade, polymer-electrolyte fuel cells (PEFC), developed by General Electric, competed against alkaline fuel cells (AFC), created by Pratt & Whitney. Due to the comparatively lower energy efficiency of PEFCs, NASA ended up selecting AFCs for most space missions, effectively putting PEFC development on the back burner. It was not until the early 1990's, following important improvements that increased the energy efficiency of PEFCs and reduced platinum loading requirements for the catalyst (Prater, 1990), that interest in this technology was revived (Sharaf & Orhan, 2014). Following these technological improvements, automotive manufacturers recognized the potential of PEFC technology for the propulsion of automotive vehicles.

Additional analyses in wind energy industry. We conducted an additional test to examine whether the U-shaped relationship between recombinant lag and technological value is generalizable to other industries. In particular, we collected additional data from the wind energy industry. This industry is an interesting setting for checking the generalizability of our unexpected findings. On the one hand, the fuel cell and wind energy industry are similar, as firms in these two industries principally focus their technological activities on improving the cost-efficiency of the technology (i.e. kWh/$ rates) (Blanco, 2009; Sharaf & Orhan, 2014). On the other hand, an important difference between the two industries is that they experienced very different technology cycles in terms of duration, frequency, and intensity (Kaldellis & Zafirakis, 2011; Perry & Fuller, 2002).

The wind energy patent families were retrieved using IPC code F03D (titled 'Wind motors') (Popp, Hascic, & Medhi, 2011). To ensure comparability, we examine the same time period as the fuel cell industry analysis (1959-2007). This produced a sample of 3,674 patent families[8]. For this wind industry sample, we also find the unexpected U-shaped relationship between recombinant lag and the technological value of inventions (model 13 in Table 2.3)[9]. Notably, the inflection point of this relationship is situated at a higher level in the wind energy sample (recombinant lag of 26.6 years compared to 17.2 years in the fuel cell sample). Moreover, in the wind energy sample, we find a negative, rather than positive, interaction effect between frequency of reuse and recombinant lag (model 14). This interaction effect, however, was not robust to several model specifications. For

[8] Note that this data is unconsolidated, meaning that no distinction is made between internal and external citations.

[9] In model 13 of Table 2.3, The linear coefficient is negative and statistically significant ($\beta_{\text{Recombinant lag}}$ = -0.075, $p < 0.001$) and the quadratic coefficient is positive and statistically significant ($\beta_{\text{Recombinant lag squared}}$ = 0.001, $p < 0.001$), the 95 percent Fieller confidence interval of the inflection point is within the range of observable points ([20.34, 44.78]), the left part of the slope is negative and statistically significant at the minimum value of recombinant lag ($p < 0.001$) and the right part of the slope is positive and statistically significant at the maximum value of recombinant lag ($p < 0.01$), and the linear and quadratic coefficients of recombinant lag are jointly statistically significant ($Chi^2 = 34.57$ $p < 0.001$).

instance, in model 15, we show the results for the sample in which patents created before 1980 are excluded, indicating a statistically non-significant interaction effect between frequency of reuse and recombinant lag.

Connection to literature. Based on our review of the fuel cell literature, interview with the fuel cell expert, and additional tests in the wind energy industry, we found strong indications to suggest that inventions with extremely high recombinant lag might rely upon components that have remained unused since a previous technological cycle. This suggests that components that have remained unused since a previous cycle may only become valuable when a new technology cycle emerges. Because they remain unused or 'dormant' for such extensive periods, we subsequently refer to these components as dormant components. The fact that components that have remained unused for a long time may still be valuable, is comparable to the concept of 'shelved knowledge' advanced by Garud and Nayyar (1994). They argue that, due to time lags in technological and market developments, some knowledge should be shelved, maintained, and then reactivated at a later point in time when complementary resources have emerged. Thus, they propose that some knowledge pieces remain unused for prolonged periods, not because they contain less value, but rather due to missing complementary resources or because they emerged ahead of their time (Garud & Nayyar, 1994). Applying these insights, we hence find strong indications that the upward slope of the U-shaped relationship between recombinant lag and the technological value of inventions can be explained by the existence of dormant components – i.e. valuable components that have remained unused for prolonged periods (Garud & Nayyar, 1994).

2.5. Discussion and conclusion

This study explores the relation between recombinant lag – i.e. the time that components in knowledge recombination have remained unused – and the technological value of inventions. Whereas existing studies on knowledge reuse trajectories have mostly focused on the frequency of reuse of components, this study shows that the technological value of inventions is also substantially driven by the recency of component reuse. The core finding of this study is the U-shaped relationship between recombinant lag and technological value, which we identified in two different industries. In this section, we first discuss the implications of our findings for the knowledge recombination literature. Subsequently, we discuss the practical implications of our findings. Finally, we discuss the core limitations of our study and suggest interesting avenues for future research.

2.5.1. Implications for knowledge recombination literature

Recency and frequency of reuse. In this study, we deviate from the majority of knowledge recombination research by shifting attention from the original attributes of knowledge components to how they are actually reused over time. We argue that knowledge components should not be considered as pieces of knowledge with a value that is fully determined at the origin. Instead, we follow an emerging stream of literature on reuse trajectories (Fleming, 2001; Katila & Chen, 2008; Yang *et al.,* 2010), emphasizing that components experience a history of reuse, which influences their recombinant value over time. At the same time, we contribute to this latter literature stream, illuminating that, next to the frequency of reuse, it is also important to consider the recency of reuse. Theoretically, we apply insights from organizational learning theory and emphasize that recency of reuse entails the generation of reuse information flows that are embedded in the state-of-the-art of technology, reflecting a rejuvenation effect. This is clearly different from frequency of reuse, which mostly captures the magnitude of available reuse information flows, and thus the amount of available learning opportunities. In our empirical analysis, we indeed find strong evidence of this rejuvenation effect, showing that the most recent instances of reuse yield inventions with the highest technological value.

At the same time, we unexpectedly observe that recombining components with extremely high recombinant lag may lead to considerable technological value. After conducting several additional analyses into this unexpected relationship, we found strong suggestions that these components reflect dormant component knowledge – i.e. valuable components that have remained inactive for prolonged periods. Thus, according to our findings, when recombinant lag is low, associated reuse information flows are valuable because they are embedded in the state-of-the-art of technology. But, according to our findings, value can also be associated with high recombinant lag and, thus, a last instance of reuse that occurred a long time ago. This implies that reuse information flows associated with a temporally distant last instance of reuse may contain valuable information about how to apply a component in recombination. Based on the findings of our post-hoc exploratory data analyses, a potential explanation might be that, when generated, these reuse information flows represented information about the component's applications in recombination that was too far ahead of its time (Garud & Nayyar, 1994). Given inventors' inability to leverage these reuse information flows when they were generated, these particular reuse information flows were 'frozen' for the time being. Years later, during the emergence of a new technology cycle, inventors could 'defrost', interpret, and exploit these reuse information flows, leading to a value-enhancing recombination of the component.

To summarize: our findings make an important contribution to knowledge reuse trajectories literature, illuminating the importance of component rejuvenation or the generation of reuse information flows that are embedded within the state-of-the-art of technology. At the same time, we highlight that, when reuse information flows were generated a long time ago, they can represent information that was simply too far ahead of its time, implying opportunities for value-adding recombination when new technological cycles have emerged. Jointly, the findings provide a better understanding of how time and reuse information flows shape learning opportunities for knowledge recombination.

Recombinant lag and component age. Emphasizing the temporal dimension of knowledge recombination, scholars have paid a lot of attention to component age (e.g. Katila, 2002; Nerkar, 2003). These studies tend to assume, explicitly or implicitly, that components inevitably become more widely-reused as they get older (e.g. Ahuja & Lampert, 2001; Heeley & Jacobs, 2008; Kelley *et al.,* 2013). As a result, they tend to ignore that there is actually much variation in terms of when and how frequently components are reused (Capaldo *et al.,* 2017). We contribute to our understanding of the temporal dimension of knowledge recombination by showing that component age and recombinant lag are distinct concepts, which influence components' recombinant value in different ways. From a theoretical point of view, recombinant lag implies a theoretical mechanism – i.e. the rejuvenation of recombinant potential of a component – that the age of a component does not capture. From an empirical perspective, our results consistently show that, controlling for age, recombinant lag significantly influences the recombinant value of components. In sum, our results indicate that, despite the importance of component age in driving knowledge recombination value (as our empirical results confirm), it does not fully capture the impact of the temporal dimension of knowledge components on their recombinant value. Instead, we identify recombinant lag as an additional temporal dimension of knowledge recombination, emphasizing that it is not only important to account for when a component was created, but also to examine when a component has been reused.

2.5.2. Implications for practitioners

Our findings carry important implications for practitioners. First, they imply that important learning opportunities become available when components were reused recently in knowledge recombination. When reuse occurs recently, the value of a component may be significantly enhanced because of access to additional up-to-date learning opportunities. For policy makers, these findings imply additional proof for the importance of transparency and information disclosure in new technology production. By allowing for information about new inventions to disseminate more quickly and accurately to other inventors, subsequent production of new inventions will be more valuable.

Second, our findings unexpectedly show that, beyond a certain tipping point, higher levels of recombinant lag can be positively associated with the technological value of inventions. Through several post-hoc exploratory data analyses, we found strong indications to suggest that this relationship was driven by dormant components – i.e. valuable components that have remained unused for prolonged periods. Thus, our findings suggest that the existing knowledge stock should be maintained and closely monitored over time. Concomitantly, the existing knowledge stock should be continually reevaluated – i.e. dusting off the shelves – in order to detect these potentially valuable knowledge components and their reuse information flows.

2.5.3. Limitations and future research

Generalizability and industry-specific conditions. Although we made substantial efforts in exploring the generalizability of our finding by collecting data on an additional industry, we acknowledge that there are limitations to the generalizability of our findings. Comparing the results of the two samples (i.e. fuel cell sample and wind energy sample), we found a robust U-shaped relationship between recombinant lag and technological value. At the same time, we also observed that the exact nature of this relationship and the conditions under which it manifests most strongly differed across the two industries. We found that the inflection point of this U-shaped relationship was situated at a higher value of recombinant lag for the wind energy sample than the fuel cell sample. Moreover, whereas we found a robust interaction effect of frequency of reuse for the fuel cell sample, such a robust interaction effect remained absent in the wind energy sample. These interesting differences point to the need to further study the impact of industry-specific characteristics on the impact of reuse trajectories on technological value of inventions. We highlight two industry-specific conditions that could serve as an interesting starting point in this respect.

First, to explain the emergence of dormant components, we pointed to the nature of technology cycles in an industry. As prior research indicates, although most industries face various technology cycles during their evolution (Tushman & Anderson, 1986), the nature of these cycles, in terms of length and duration, differs across industries. This might explain why, in the wind energy industry, the inflection point beyond which recombinant lag positively influences technological value is situated at a higher level than in fuel cells. Second, when technological change in an industry occurs in a more punctuated, rather than incremental, manner (Tushman & Anderson, 1986), the value of recombinant lag might differ. For example, when technological change is punctuated, the recombinant value of a relatively less recent instance of reuse will be very minimal, as the reuse information flows contained therein will largely misrepresent the current state-of-the-art of technology. In contrast, in the absence of such technological punctuation, the state-of-the-art of technology is likely to be more stable, implying that rejuvenation effects might also emerge for components with relatively high recombinant lag. Jointly, we therefore encourage future studies to further explore the impact of and interaction between recombinant lag and frequency of reuse in a wide variety of different technological settings, which have different characteristics in terms of technological cycles and the absence/presence of technological shocks.

Original component attributes and component reuse. In this study, we moved away attention from the original attributes of knowledge components to their reuse trajectories. In this way, we were able to demonstrate that, next to component age, also the recency of reuse is an important temporal dimension that influences the value of resulting inventions. A next step to expand our understanding of knowledge recombination could be to examine the interaction between original component attributes and knowledge reuse trajectories. Future studies could examine, for instance, whether certain components have original attributes that impede the disentanglement of combinations in which these components are integrated. Components with certain technological characteristics embedded in them at creation may, for example, be more difficult to physically detach from a combination in which they are reused. In fuel cells, for instance, the recombination of a particular fuel mixture, as opposed to a physical piece of hardware such as a seal, may result in combinations which are more difficult to take apart (Fleming & Sorenson, 2001), impeding the creation of useful reuse information flows. In other words, original attributes of the component might restrict the learning experience of inventors when such a component is reused. We therefore encourage future research to delve deeper into the interplay between original attributes of knowledge components and their reuse over time.

Antecedents of recombining dormant components. Using patent data, we were able to examine the value of components on a large scale, using methods and measures validated by previous studies. However, these data did not allow fine-grained analyses of how and why particular components are utilized in knowledge recombination. Nevertheless, research on the antecedents of knowledge recombination is much-needed (Carnabuci & Operti, 2013). Therefore, we particularly urge future studies to conduct in-depth qualitative studies on the recombination and primary characteristics of valuable dormant components. These studies would carry important managerial implications, as they would help firms identify more precisely which components should be reconsidered for knowledge recombination.

Chapter 3. Exploring Knowledge Recombination in R&D Alliances

Why Knowledge Pool Applicability Matters

Abstract: Knowledge applicability is a core driver of knowledge recombination activities. Extant research on the knowledge recombination implications of R&D alliances, however, tends to ignore the issue of knowledge applicability. Instead, it focuses on the size and diversity of the partner's knowledge pool. In this study, we address this gap, shifting attention to knowledge pool applicability – i.e. the extent to which components in the knowledge pool can be used in different application domains – and examining its implications for knowledge recombination activities in R&D alliances. We expect that both the partner's and the focal firm's knowledge pool applicability significantly impact firm's partner-specific knowledge recombination. Analysing 461 R&D alliance dyads of 88 firms in the fuel cell industry, our findings indicate that partner's knowledge pool applicability has an inverted U-shaped relationship with firms' partner-specific knowledge recombination. Surprisingly, we find that the knowledge pool applicability of the focal firm has a U-shaped relationship with its partner-specific recombination. Bringing forward the concept of knowledge pool applicability, this study contributes to a richer theoretical understanding of the knowledge recombination implications of R&D alliances.

This chapter was written together with Dries Faems and Pedro de Faria. Earlier versions of this chapter have been presented at the *Annual Meeting of the Academy of Management* in Atlanta (2017), *Strategic Management Society Annual International Conference* in Houston (2017), and at research seminars at the *University of Groningen* (2017), *École Polytechnique Fédérale De Lausanne* (2016), and *Stockholm School of Economics* (2017). A manuscript based on this chapter is currently under review for publication.

3.1. Introduction

R&D alliances are valuable mechanisms for firms to expand their knowledge pool, generating new opportunities for knowledge recombination across different knowledge components (e.g. Lahiri & Narayanan, 2013; Schilling & Phelps, 2007; Srivastava & Gnyawali, 2011). At the same time, not being able to effectively use partners' knowledge triggers the risk of ending up at the losing end of learning races, threatening the competitive position of firms (Hamel, 1991; Khanna, Gulati, & Nohria, 1998). Scholars have therefore started exploring the ability of firms to recombine knowledge from alliance partners. Existing research mainly focuses on the size and diversity of the partner's component knowledge pool as key drivers of knowledge recombination activities (e.g. Lahiri & Narayanan, 2013; Phelps, 2010; Schilling & Phelps, 2007). In this study, we complement this prior research by focusing on knowledge pool applicability as a crucial aspect to explain variance in knowledge recombination from alliance partners.

Knowledge recombination literature argues that components vary in terms of where they can be applied (Hargadon & Sutton, 1997; Wang *et al.,* 2014; Yayavaram & Ahuja, 2008). Some components are highly malleable and can be used in different application domains, whereas other components may be substantially constrained in their range of applications (Dibiaggio *et al.,* 2014; Hargadon & Sutton, 1997). For instance, in the fuel cell industry, which is the empirical setting of this study, some inventions can be used in multiple application domains, such as fuel cell stacks and fuel reformers, whereas the applicability of other inventions may be restricted to one single domain. Based on these insights, we argue that, next to size (i.e. number of components) and diversity (i.e. diversity of technology domains in which components are situated), knowledge pools can also be characterized in terms of their applicability or the extent to which single components within them have different application domains.

The notion that components vary in their applicability is largely neglected in existing research on alliances and their knowledge recombination implications. However, we theorize that knowledge pool applicability substantially influences the focal firm's partner-specific knowledge recombination or the extent to which the focal firm relies on knowledge from a particular partner when generating inventions. In particular, we hypothesize (i) an inverted U-shaped relationship between the partner's knowledge pool applicability and the focal firm's partner-specific recombination and (ii) a positive relationship between the focal firm's knowledge pool applicability and the focal firm's partner-specific recombination.

To empirically test our hypotheses, we collected unique data on 461 R&D alliance dyads of 88 focal firms in the fuel cell technological field and combined this with data on their worldwide fuel cell patenting activities. Our analyses show that, controlling for other characteristics of the partner's knowledge pool, partner's knowledge pool applicability has an inverted U-shaped relationship with firms' recombination of partner's components. Moreover, instead of the hypothesized linear positive relationship, we find a U-shaped relationship between the focal firm's internal knowledge pool applicability and partner-specific knowledge recombination.

These findings contribute to a richer theoretical understanding of the knowledge recombination implications of R&D alliances in two fundamental ways. First, we show the importance of applicability as a core characteristic of knowledge pools that influences knowledge recombination activities in the setting of R&D alliances. Existing studies have theoretically framed the knowledge pool of alliance partners on an aggregate level, arguing that components create value relative to other components present in the knowledge pool. We argue, however, that a closer examination of the components inside the knowledge pool may reveal that a lot of components do not actually have the assumed broad scope of applicability normally associated with large and diverse knowledge pools (e.g. Lahiri & Narayanan, 2013). Second, we develop novel theoretical arguments regarding firms' idiosyncratic abilities to engage in knowledge recombination in R&D alliances. Prior research tends to conceptually intertwine the focal firm's ability to identify and absorb component knowledge with its ability to actually recombine this component knowledge (e.g. Gilsing, Nooteboom, Vanhaverbeke, Duysters, & van den Oord, 2008; Rosenkopf & Almeida, 2003; Vasudeva, Zaheer, & Hernandez, 2013). We underline the fact that identification and transfer of component knowledge are necessary but not sufficient conditions for knowledge recombination to occur. Instead, firms need to be able to envision novel applications for components, in order to use them in knowledge recombination. In sum, this study underlines the importance of taking an in-depth knowledge recombination perspective to studying the performance implications of R&D alliances.

3.2. Theory

3.2.1 Knowledge recombination in the alliance context: state of the art

Knowledge recombination plays a central role in explaining performance differences across R&D alliances (e.g. Phelps, 2010; Schilling & Phelps, 2007; Wuyts & Dutta, 2014). In order to stimulate the creation of new inventions through knowledge recombination activities, firms have to enrich the contents of their own knowledge pool with novel components accessed from alliance partners (Fleming, 2001; Rosenkopf & Almeida, 2003; Savino *et al.,* 2017). Alliance scholars have prominently argued that, when the partners' knowledge pool contains more components, the focal firm is able to realize a larger set of new combinations (e.g. Lahiri & Narayanan, 2013; Schilling & Phelps, 2007).

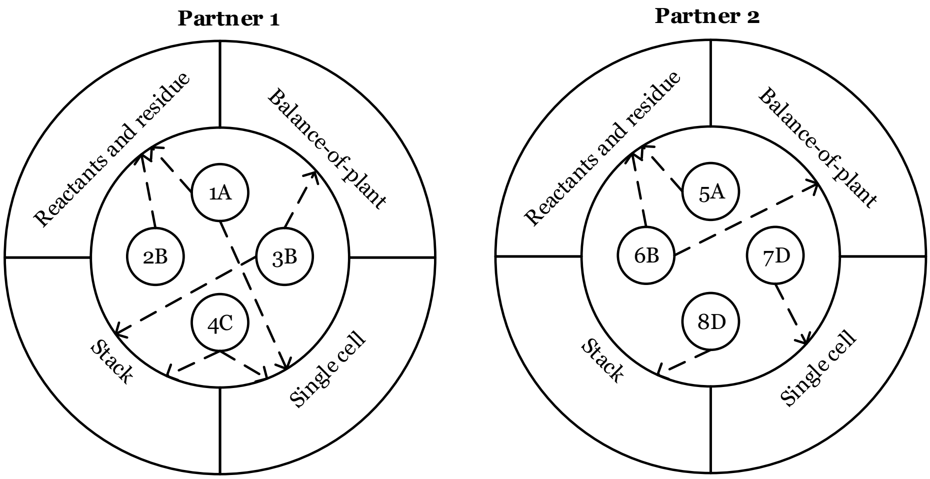
Scanning recent alliance literature, however, we observe a clear shift from focusing on the size of the partner's knowledge pool toward examining the diversity of the partner's knowledge pool (e.g. Phelps, 2010; Srivastava & Gnyawali, 2011; Wuyts & Dutta, 2014). Alliance scholars have argued that components accessed from alliance partners differ in terms of their usefulness and ease of retrievability (e.g. Gomes-Casseres, Jaffe, & Hagedoorn, 2006; Nooteboom, Vanhaverbeke, Duysters, Gilsing, & Van den Oord, 2007; Vasudeva & Anand, 2011). Accessing components from diverse technological domains allows generating more novel combinations (Phelps, 2010; Subramanian & Soh, 2017), that tend to be more valuable (Srivastava & Gnyawali, 2011; Rosenkopf & Nerkar, 2001; Wuyts & Dutta, 2014). At the same time, components from different technological domains tend to be more difficult to understand and apply in knowledge recombination (Phene *et al.,* 2006; Nooteboom *et al.,* 2007; Vasudeva & Anand, 2011). Hence, access to a diverse knowledge pool from a partner may involve substantial benefits and challenges, influencing the focal firm's ability to generate new technologies

(Nooteboom *et al.,* 2007; Phelps, 2010; Srivastava & Gnyawali, 2011; Subramanian & Soh, 2017; Wuyts & Dutta, 2014).

Thus, existing alliance literature has mostly focused on the size and diversity of partners' knowledge pool, arguing that they might influence the performance implications of R&D alliances. However, examining recent knowledge recombination literature, we observe that scholars have argued that more factors influence knowledge recombination than merely the diversity and number of available components (e.g. Dibiaggio *et al.,* 2014; Wang *et al.,* 2014; Yayavaram & Ahuja, 2008). In particular, what emerges from this literature is that components also vary in terms of where and how they can be applied in knowledge recombination. On the one hand, it has been argued that some components can be used in knowledge recombination across different settings, such as different industries (Hargadon & Sutton, 1997), countries (Petruzzelli & Savino, 2014) or technological generations (Furr & Snow, 2014), allowing firms to economize substantially on cognitive resources (Baker & Nelson, 2005; Wang *et al.,* 2014). Moreover, knowledge recombination scholars found that components that can easily be applied in different combinations also tend to enhance experimentation by the focal firm, since it becomes easier to mix-and-match components, enhancing exploratory innovation (Dibiaggio *et al.,* 2014; Guan & Liu, 2016; Wang *et al.,* 2014). On the other hand, however, when components can too easily be mixed-and-matched, it becomes costly to determine the optimal way in which to apply the components (Yayavaram & Ahuja, 2008). Jointly, these findings all point into the same direction: next to knowledge pool diversity and size, components in the knowledge pool may also vary in terms of where and how they may be applied in knowledge recombination.

To tackle this issue in the R&D alliance context, we introduce the concept of knowledge pool applicability, which denotes the extent to which components in the knowledge pool can be used in different application domains. In this way, we attempt to capture the extent to which components in the knowledge pool can flexibly be used in different recombination efforts. To make the concept of knowledge pool applicability more concrete, consider the example in Figure 3.1. In this figure, we show two partners from the fuel cell industry with the same knowledge pool size (i.e. four components, as denoted by the smaller circles) and diversity (i.e. same distribution of technological domains, where domain A may refer to hydrogen and domain D may refer to ceramic compounds). Moreover, we indicate that each component has one or more potential application domains (corresponding to the four main subsystems of a fuel cell system, in which new fuel cell inventions may be applied). Hence, although partners 1 and 2 both have a component pertaining to hydrogen (i.e. components 1 and 5), partner 1 is able to apply this component in two domains, whereas partner 2 is only able to do so in one domain. Partner 1 may, for example, have component knowledge of the composition of hydrogen that could be integrated into the design of the single cell, or to improve the performance of the fuel reformer. Thus, even when the knowledge pool size and diversity of two alternative alliance partners is the same, we show that their knowledge pool applicability may still differ substantially, potentially impacting recombination opportunities available to the focal firm.

Figure 3.1. Knowledge pool size, diversity, applicability



To summarize, knowledge recombination literature has shown that the extent of applicability of components is an important determinant of knowledge recombination activities. However, this has been largely neglected in alliance research, where the focus has instead been on the partners' knowledge pool size and diversity. In this study, we address this research gap by focusing on the knowledge pool applicability of the partner and focal firm, arguing that this dimension of the knowledge pool may substantially affect knowledge recombination activities in R&D alliances. In the following section, we developed two hypotheses connecting knowledge pool applicability to the focal firm's partner-specific recombination.

3.3. Hypotheses development

3.3.1. Partner's knowledge pool applicability

In the R&D alliance setting, we expect that a partner's knowledge pool applicability will positively impact the focal firm's partner-specific recombination. Specifically, partners with higher knowledge pool applicability are able to generate a larger number of combinations on the basis of a given set of components. Consequently, when collaborating with a partner with high knowledge pool applicability, the components that the focal firm learns to use from this partner tend to be more widely-applicable (Boh *et al.,* 2014; Wang *et al.,* 2014). Instead of being constrained to one single application, the focal firm gains flexibility in terms of where and how to apply the accessed components, greatly facilitating the generation of new combinations on the basis of a partner's components (Hargadon & Sutton, 1997; Wang *et al.,* 2014). The obtained flexibility can optimize the allocation of resources to the R&D alliances, ensuring that attempted efforts to learn how to recombine a partner's components bear fruit (Wang *et al.,* 2014). For example, in Figure 3.1, even if the focal firm is unable to learn how to apply partner 1's component 4 in the single cell domain, it may still be able to recombine this component in the stack domain. Such flexibility is, however, generally not present in partner 2's knowledge pool, severely restricting the focal firm's pursuit of recombination opportunities.

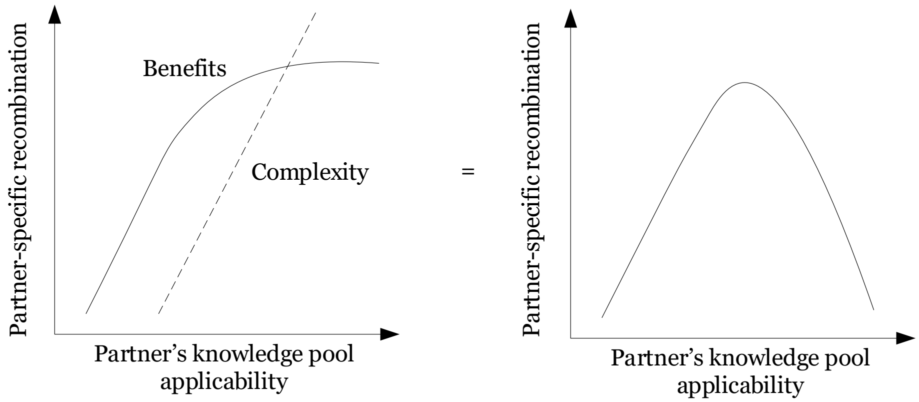
Beyond a certain point, we expect, however, that the benefits of a partner's knowledge pool applicability will taper off and diminish in magnitude. A key tenet in knowledge recombination literature is that, although in theory all components in the environment could be considered for recombination, firms' resource and cognitive constraints severely narrow down the number of combinations that can eventually be realized based on these components (Carnabuci & Bruggeman, 2009; Fleming & Sorenson, 2001; Olsson & Frey, 2002). As a consequence, the number of potential recombination opportunities generally outweighs the number of realized recombination opportunities (Strumsky & Lobo, 2015; Zahra & George, 2002). In line with this reasoning, alliance scholars found evidence to suggest that firms often face constraints in terms of fully realizing partner's recombination opportunities (Bos, Faems, & Noseleit, 2017; Cohen & Levinthal, 1990; Deeds & Hill, 1996; Vasudeva & Anand, 2011). Thus, we argue that, even if the partner's components can be applied in many different ways, the focal firm will only be able to identify and realize a fraction of the recombination opportunities associated with these components. In other words, the benefits accruing from higher partner knowledge pool applicability will become less outspoken beyond a certain threshold value.

In addition to diminishing marginal benefits of partner's knowledge pool applicability, we also expect certain challenges to emerge alongside with partner's knowledge pool applicability. The various applications for which a component can be used tend to be highly similar (Hargadon & Sutton, 1997), because they are strongly based on the same fundamental technological principles. For this reason, when the partner's components are very widely-applicable, firms may find it highly challenging to distinguish one component's application from another, rendering learning processes less effective and more cumbersome. Effectively, when partner's knowledge pool applicability is high, the focal firm will spend a lot of time trying to optimally allocate its attention and learning efforts in the partner's knowledge pool (Ghosh, Martin, Pennings, & Wezel, 2014; Katila & Ahuja, 2002; Yayavaram & Ahuja, 2008), as it becomes more difficult to identify which components' applications are most worthwhile to pursue. Thus, due to increased learning complexities (Fleming & Sorenson, 2001; Leiponen & Helfat, 2010), the focal firm's attention and resources may be detracted from actual knowledge recombination efforts towards determining the optimal way to recombine a partner's components, reducing the focal firm's partner-specific recombination.

Figure 3.2 summarizes our arguments. In this figure, we show that the benefits arising from a partner's knowledge pool applicability eventually level off, due to limited resource availability that constrain the full realization of a partner' potential recombination opportunities. At the same time, important challenges associated with identifying valuable recombination opportunities may emerge beyond a certain value of a partner's knowledge pool applicability. Hence, beyond a certain point, we expect the disadvantages of partner's knowledge pool applicability to rise faster than the benefits, shaping an inverted U-shaped relationship between partner's knowledge pool applicability and the focal firm's partner-specific recombination (Haans *et al.,* 2016). We hypothesize:

H1: The partner's knowledge pool applicability has an inverted U-shaped relationship with the focal firm's partner-specific recombination

Figure 3.2. Theoretical mechanisms underlying Hypothesis 1



3.3.2. Focal firm's knowledge pool applicability

In R&D alliances, firms often face difficulties accessing and recombining a partner's components (Faems, Janssens, & Van Looy, 2007; Gomes-Casseres *et al.,* 2006; Hamel, 1991). Many partners' components remain untapped in knowledge recombination, because firms perceive that the components' recombinant potential has already been exhausted or they are simply unable to use the components in any meaningful way (Ahuja & Katila, 2004; Fleming, 2001). Faced with such constraints, most firms are unable to fully utilize the component knowledge that may be accessed from an alliance partner, increasing the gap between the potential and realized recombination opportunities arising from the R&D alliance (Wuyts & Dutta, 2014; Zahra & George, 2002). We expect, however, that focal firms with higher knowledge pool applicability are able to bring the realization of combinatorial opportunities closer to its potential level through two principal mechanisms: (i) flexibility and (ii) effectiveness of knowledge recombination.

First, following the notion that "capabilities are built through experience" (Eggers, 2012: 318), we argue that by building widely-applicable component knowledge, firms develop a greater comprehension of how component knowledge, in general, can be flexibly applied in different ways. This provides them with the ability to better leverage available component knowledge (Lewin, Massini, & Peeters, 2011; Wuyts & Dutta, 2014). Hence, these firms experience more flexibility in terms of which of the partner's components they may consider for knowledge recombination, being able to envision and realize more applications for a given component. Indeed, as argued by Henderson (1995), technological limits of components tend to be mostly present in the mind of inventors, rather than being grounded in actual technological limits. In other words, whereas one firm may quickly run into exhaustion of recombinant potential of a component, another firm may be able to elevate the recombinant potential of a component to a higher level. This means that, when provided with access to a component set of, for example, five components, a focal firm with higher knowledge pool applicability may be able to envision four different uses for these components, whereas a focal firm with low knowledge pool applicability may only be able to envision two of such uses.

Second, whereas firms with low knowledge pool applicability may pursue costly trial-and-error processes trying to generate new combinations on the basis of a particular set of components, firms with high knowledge pool applicability may have a better understanding of where to locate their attention. This is because the latter type of firm, having prior experience developing component knowledge with multiple applications, has a better understanding of where the limits of a component's recombinant potential lie, avoiding ultimately fruitless recombination efforts in the partner's knowledge pool (Nemet & Johnson, 2012). Hence, leveraging these unique capabilities, firms with higher knowledge pool applicability will be able to deploy resources towards the utilization of a partner's components more effectively, making fuller use of a partner's component knowledge pool, whilst using fewer resources in the process.

We also expect the benefits of higher internal knowledge pool applicability to consistently outweigh the costs of applying these capabilities in R&D alliances.

Capabilities emerging concomitantly with building internal knowledge pool applicability have already been assimilated and embedded into the firm's routines (Cohen & Levinthal, 1990; Lewin *et al.,* 2011; Wuyts & Dutta, 2014). Therefore, the various applications of these capabilities are well-understood, with a deep understanding of how to align available recombination opportunities with capabilities to realize these opportunities. Hence, the application of these recombination capabilities is more certain and less prone to mistakes (Katila & Ahuja, 2002). This makes it far more likely that sufficient resources are available to make full use of these recombination capabilities in order to better leverage a partner's component knowledge pool. Hence, we expect a strictly positive relationship between the firm's internal knowledge pool applicability and its partner component recombination because (i) higher internal knowledge pool applicability allows to more flexibly and effectively leverage the partner's knowledge pool and (ii) costs associated with applying capabilities emerging from internal knowledge pool applicability are negligible:

H2: The focal firm's knowledge pool applicability has a positive relationship with the focal firm's partner-specific recombination.

3.4. Methodology

3.4.1. Sample and data collection

Empirical context. We tested our hypotheses using data from the fuel cell technological field. Fuel cells are electrochemical devices that produce electricity through a chemical reaction between hydrogen and oxygen. We focused on the fuel cell R&D alliances of 88 firms in the period 1993-2007. These 88 firms were retrieved after compiling a list of the top 200 patent applicants in the fuel cell technological field and removing (i) firms with incomplete ownership data and (ii) firms that did not form any fuel cell R&D alliance during the time period of this study[1].

[1] We were able to collect complete ownership data for 139 parent firms. We aggregated all patents of subsidiaries in which these firms had a controlling interest to the parent-firm level. To collect ownership data of these parent firms, we used Bureau van Dijk's ORBIS database. Moreover, we complemented this with data on executed mergers and acquisitions, retrieved from the SDC Platinum Mergers and Acquisitions database. We also corrected for potential name changes and aliases of firms, using data

The fuel cell technological field is highly comparable to other technological fields in which R&D alliances have been studied, such as pharmaceuticals (e.g. Bos *et al.,* 2017; Wuyts & Dutta, 2014), semiconductors (e.g. Srivastava & Gnyawali, 2011), and telecommunications (e.g. Phelps, 2010). First, patenting propensities are elevated in the fuel cell technological field and rank among the highest in clean energy technologies (Albino *et al.,* 2014). Second, knowledge resources and capabilities are highly heterogeneously distributed in the fuel cell technological field (Hellman & van den Hoed, 2007; Vasudeva & Anand, 2011), creating a greater need to form R&D alliances (Harrison, Hitt, Hoskisson, & Ireland, 2001). Third, the environment in which fuel cell firms operate is highly uncertain and dynamic (Hellman & van den Hoed, 2007; Verbong, Geels, & Raven, 2008), increasing firms' tendencies to form strategic alliances (Schilling, 2015).

Patent data. To obtain a proxy for the knowledge recombination activities of firms, we collected data on worldwide patenting activities of the firms in our sample from the PATSTAT database (Autumn 2013 version). Consistent with prior studies, patents represent the knowledge components in a firm's knowledge pool (Ahuja & Katila, 2001). To retrieve fuel cell patents, we collected all patents filed in IPC class H01M8 which corresponds to fuel cell technology (Tanner, 2014). We aggregated these patent applications to the patent family level (following the European Patent Office's DOCDB definition). A DOCDB patent family captures all patent applications related to the same invention but filed at different patent offices (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, for example, North-American firms have a much higher likelihood to file a patent at the USPTO rather than at, for example, the EPO or JPO. As a result, solely relying on USPTO patent applications considerably underestimates the knowledge recombination activities of firms outside North-America (de Rassenfosse *et al.,* 2013). This bias is especially problematic in the fuel cell technological field, as many prominent players in this field are Asian (e.g. Toyota, Honda, Nissan, Hitachi, Panasonic, Toshiba, Samsung Electronics, Asahi

from the ORBIS database. Subsequently, of these 139 firms, we retained 88 firms which had engaged in at least one R&D fuel cell alliance between 1993 and 2007. Harmonized patent applicant names were obtained through EEE-PPAT (ECOOM-EUROSTAT-EPO PATSTAT Person Augmented Table) from ECOOM.

Glass) or European (e.g. Daimler, Siemens, BASF, Shell, Renault) firms (Vasudeva, 2009). An additional important advantage of using patent families is that it captures a broader and more complete set of backward citations (Albrecht *et al.,* 2010).

Alliance data. To collect the alliance data, we identified R&D alliances in the LexisNexis database. We used this method because there is considerable evidence that other databases, such as Thompson Reuters' SDC Platinum Joint Venture and Strategic Alliances database (Schilling, 2009), severely underestimate the number of alliances formed (Lavie, 2007; Lavie & Rosenkopf, 2006)[2]. The LexisNexis database compiles press releases from different sources, including newspapers, trade journals, wire transcripts, etc. We employed a broad set of keywords to detect fuel cell R&D alliances[3,4], manually screening over 50,000 press releases. To give an example, the following press release extract identifies an R&D alliance between Nuvera Fuel Cells and TotalFinaElf:

> *Nuvera Fuel Cells, Inc., a leading global designer and developer of fuel cell and fuel processing technology today announced it has entered into an agreement with TotalFinaElf, one of the world's leading oil companies, to study the effects of gasoline on fuel processors and fuel cell stacks designed for the automotive industry* (PR Newswire, 2003)

We searched for all fuel cell R&D alliances formed before 2008.The first fuel cell R&D alliance that we detected, between Westinghouse Electric and Energy Research Corporation, started in 1978[5]. We included all fuel cell R&D alliances in which at least one firm was involved. Moreover, we also included fuel cell R&D alliances that were part of wider government-funded projects, such as the United

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[2] To verify this, we conducted a broad search in the SDC database for all alliances in which the deal text mentioned the keyword "fuel cell" in the period 1978-2007. This search produced a total of 126 alliances, comprising not only R&D alliances, but also other types of alliances (e.g. marketing, supply). In contrast, during the same time period, we detected 849 R&D alliances in the fuel cell industry using the LexisNexis database. Similarly, Lavie and Rosenkopf (2006) reported that only 25% of alliances in their dataset were detected in the SDC database.

[3] 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 (Schilling, 2009), especially for supply and distribution alliances. Hence, our sample only contains alliances with an R&D element (Hagedoorn, 2002).

[4] The set of employed keywords is available from the authors on request.

[5]Although we focus on the 1993-2007 period, we also searched for R&D alliance data for the 1978-1992 period, in order to capture alliances which had started before 1993, but were still ongoing in 1993.

States Department of Energy's (DOE) *Hydrogen and Fuel Cells Program*. Finally, multi-partner R&D alliances were transformed into dyads, following earlier studies (e.g. Phelps, 2010).

Whereas numerous studies assume a fixed lifespan for alliances, ranging from one to five years (e.g. Schilling & Phelps, 2007; Srivastava & Gnyawali, 2011; Vasudeva & Anand, 2011), often within the same industry, we tracked alliances over time to approximate their starting and termination dates (Ahuja, 2000; Hashai, Kafouros, & Buckley, 2018; Lavie, 2007; Phelps, 2010). This is an important methodological step, given that there exists substantial heterogeneity in the lifespan of alliances (Deeds & Rothermael, 2003). Moreover, as emphasized by Wassmer (2010), alliance research should attempt to only focus on ongoing partnerships since, otherwise, statistical inferences are drawn about partnerships that do not actually exist anymore. When termination of the alliance was not formally announced, we followed Ahuja (2000) and utilized either (i) the expected tenure of the alliance or (ii) tracked the ongoing status of the alliance through subsequent press releases. In case a termination date could not be approximated, we followed Ahuja (2000) and assumed that the alliance was terminated in the year subsequent to the starting year.

3.4.2. Variables

Dependent variable. To measure *partner-specific recombination*, we followed earlier knowledge recombination (Katila, 2002; Phene *et al.,* 2006; Rosenkopf & Nerkar, 2001) and alliance (Frankort, 2016; Gomes-Casseres *et al.,* 2006; Mowery, Oxley, & Silverman, 1996; Rosenkopf & Almeida, 2003; Schildt, Keil, & Maula, 2012; Subramanian, Bo, & Kah-Hin, 2018; Vasudeva & Anand, 2011) literature and used backward citations of patents. Backward citations reflect the prior technological knowledge upon which an invention builds and can thus be used to denote the components that are recombined to generate a new invention (Katila, 2002; Phene *et al.,* 2006; Jaffe & de Rassenfosse, 2017). Although some studies argue that backward citations are a rather noisy indicator of knowledge flows (e.g. Alcacer & Gittelman, 2006), others provide reasonable evidence for the equivalence between patent citations and knowledge flows (e.g. Duguet & MacGarvie, 2005; Jaffe, Trajtenberg, & Fogarty, 2000). To compute the dependent variable, we counted the total number of fuel cell citations that focal firm *i* made to a partner *j* in a given year[6]. In order to correct for differences in firm scale, following Phelps (2010), we compute the share of citations made by focal firm *i* to a partner *j* in year *t*:

$$\text{Focal firm's partner-specific recombination}_{ijt} = \frac{\text{Fuel cell citations to partner}_{ijt}}{\text{Total fuel cell citations}_{it}}$$

Independent variable. In order to capture *knowledge pool applicability*, we inspected the International Patent Classification (IPC) codes listed on fuel cell patent applications. IPC codes are principally assigned to patents to facilitate patent examiner's search activities, and reflect the technological content of an invention (Strumsky & Lobo, 2015). Prior innovation studies have similarly employed IPC codes as a categorization tool to localize patents into specific technological domains (e.g. Kapoor & Adner, 2012; Phelps, 2010). IPC codes are classified in a hierarchical manner (i.e. lower levels represent subdivisions of higher levels), such that the first digit indicates the highest level of abstraction (e.g. H refers to 'Electricity' while G refers to 'Physics'), and subsequent digits increase the level of granularity (Benner & Waldfogel, 2008). To illustrate this hierarchical construction, we show an example of subgroup H01M8/24 in Figure 3.3.

Figure 3.3. Hierarchical construction of IPC code H01M8/24

Section	H	Electricity
Class	H01	Basic electric elements
Subclass	H01M	Processes or means, e.g. batteries, for the direct conversion of chemical into electrical energy
Main group	H01M8	Fuel cells; Manufacture thereof
Subgroup	H01M8/24	Grouping of fuel cells, e.g. stacking of fuel cells

[6] Following the methodology described by Bakker et al. (2016) and Nakamura et al. (2015), we aggregated all single patent office applications within a patent family to the patent family level to obtain a more precise account of the components that were recombined to generate the invention. 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. Naturally, we also correct for patent family membership at the backward citation-level in such a way that, if patent family 1's cited patents D and E actually pertain to the same patent family, they are not counted twice.

Whereas higher IPC levels (such as the subclass, or, four-digit IPC code) can be used to gain an understanding of the broadness of technological fields that firms use to build inventions (Leten, Belderbos, & Van Looy, 2016), they tend to not be precise enough to denote the actual domains within which new inventions can be applied (Thompson & Fox-Kean, 2005). Instead, in order to determine the application domains of patents within a particular technological field (for fuel cell patents, main group H01M8), it is useful to look at the application domains nested within this field (for fuel cells, subgroups H01M8/02-H01M8/24). Here, an application domain is thus a subset of a technological field within which a particular invention can be applied. We identified four main application domains of fuel cell inventions[7,8]; namely: The single cell, stacking techniques, reactant production and residue treatment, and balance-of-plant aspects of fuel cell systems (EG&G Technical Services, 2004; Sharaf & Orhan, 2014). To capture these four applications domains, we used subgroups H01M8/02, H01M8/04, H01M8/06, and H01M8/24 (see Table 3.1 for a description of these subgroups)[9]. Effectively, from the IPC codes listed on a patent, we inferred that, when a firm generates a new invention that describes a technological solution to a problem that spans

[7] While our measure is somewhat conservative, in the sense that it focuses solely on the fuel cell technological domain as a potential location for application of inventions, we verified, through examination of fuel cell articles (e.g. EG&G Technical Services, 2004; Sharaf & Orhan, 2014; Steele & Heinzel, 2001), that these four application domains are indeed most relevant to fuel cell technology. Moreover, looking at the citation scope of fuel cell patents, we observe that this is a highly insular technological domain (George *et al.,* 2008), in which technologies draw, and are applied, mostly within the same technological domain (i.e. close to 75% of all backward citations of fuel cell patents go to other fuel cell patents). Finally, we only examine R&D alliances that are specifically targeted at fuel cell technology, meaning that the four application domains are likely to be the most relevant ones in this context.

[8] There are 12 subgroups within main group H01M8 that can be used to identify the aspects of fuel cell technology that are addressed by the fuel cell patent. Eight of these subgroups (i.e. H01M8/08-H01M8/22) are used to categorize the patent as pertaining to the design of a specific type of fuel cell. Fuel cell types can (principally) be distinguished on the basis of the electrolyte inside the cell (Steele & Heinzel, 2001). For example, H01M8/10 refers to the design of fuel cells with a solid electrolyte (e.g. polymer exchange membrane fuel cells) and H01M8/12 refers to the design of fuel cells with a solid oxide electrolyte (e.g. solid oxide fuel cells). The remaining four subgroups (i.e. H01M8/02, H01M8/04, H01M8/06, and H01M8/24) can be used to detect the application domains of fuel cell inventions. For each IPC subgroup, we examined hundreds of patent documents to verify their correspondence to a particular application domain. We further validated this correspondence by comparing the distribution of firms' patents across different application domains with press releases and firm documents describing their fuel cell technological activities.

[9] Out of all the patents in the sample, 90% of the patents had at least one of the four IPC subgroups listed on them (Table 3.1). For the remaining patents (10% of the sample), we examined patterns of co-occurrence of IPC subgroups (i.e. Breschi, Lissoni, & Malerba, 2003; Dibiaggio *et al.,* 2014) in order to categorize each subgroup into the subsystem with which it was most likely associated (e.g. subgroup C08J5/22, which refers to manufacturing films, membranes, or diaphragms made of macromolecular substances, co-occurred 99% of the time with subgroup H01M8/02, suggesting a strong association with the single cell).

multiple application domains, the firm demonstrates an understanding of how this invention can potentially be applied to each of these domains, in new knowledge recombination efforts (Boh *et al.,* 2014).

Having classified each patent into its corresponding application domain(s), we subsequently calculated the average number of application domains that were listed on each patent, and then aggregated this to the firm-level. For example, in Figure 3.1, partner 1 has 4 patents in its knowledge pool, three of which have two potential application domains, and one has one potential application domain. In this case, knowledge pool applicability takes a value of $\frac{(3\times2)+(1\times1)}{4} = 1.75$. Similarly, partner 2's knowledge pool applicability equals $\frac{(1\times2)+(3\times1)}{4} = 1.25$.

Table 3.1. Application domains in the fuel cell technological field

Application domain	Description	IPC subgroup
Single cell	This application domain relates to elements inside the fuel cell. This includes the design of gas diffusion layers, electrolytes, electrodes, etc.	H01M8/02
Balance-of-plant	This application domain relates auxiliary equipment of fuel cells. This includes the design of heat exchangers, air pumps, controlling systems etc.	H01M8/04
Producing reactants / treating residues	This application domain relates to producing reactants (e.g. hydrogen) and treating residues. This includes fuel reforming, hydrogen purification, hydrogen supply, etc.	H01M8/06
Stacking techniques	This application domain relates to stacking of fuel cells. This includes compression techniques of single cells, composition of stacks, etc.	H01M8/24

Control variables. We controlled for relevant attributes of the R&D alliance. Since trust and relational assets between partners are often developed over time (Dyer and Singh, 1998), we controlled for the age of the alliance, calculated as the time that elapsed since the (current) ongoing tie between the firm and the partner was initiated (*Age alliance*)[10]. Since equity arrangements in an R&D alliance may curb opportunistic behavior (Kogut, 1988), we included a control

[10] We looked at the age of the tie, rather than the alliance itself, because some dyads in our sample had multiple ongoing alliances at the same time (which we also control for). For example, Toshiba and UTC initiated a joint venture alliance in 1985, and a separate joint venture in 2001, both of which were terminated in 2004.

variable that takes a value of 1 when the alliance is a joint venture (*Joint venture*). We included a control variable that takes a value of 1 when the alliance is part of a government-funded program (*Government-funded*). Multi-partner alliances - i.e. alliances in which more than two partners are involved - can influence the behavior of any participating organization, inciting, in some cases, free-riding behavior (Das & Teng, 2002). Therefore, we included a control variable that takes a value of 1 when the alliance is a multi-partner alliance (*Multi-partner*). Knowledge recombination in R&D alliances with foreign partners may be strongly influenced by, for example, cultural differences between the firm and the partner (Lavie & Miller, 2008). Therefore, we included a control variable that takes a value of 1 when the partner is non-domestic (*International*). Finally, we controlled for the number of concurrent alliances ongoing between the firm and the partner (*Concurrent alliances*) (Gomes-Casseres *et al.,* 2006).

We also controlled for several alliance portfolio-level characteristics of the focal firm (Faems, Van Looy, & Debackere, 2005; Wassmer, 2010). Having a high number of technology collaborators may detract attention from the partner, potentially reducing the focal firm's partner-specific recombination. We therefore controlled for the number of technologically active fuel cell technology partners of the firm in the current year (*Inventive partners*) (Deeds & Hill, 1996; Wassmer, 2010). Technologically active fuel cell technology partners are firm partners which have filed at least one fuel cell patent in the past five years. In a similar way, we controlled for the number of non-technologically active fuel cell technology partners of the firm in the current year (*Non-inventive partners).* Moreover, we controlled for the number of upstream partners (i.e. universities, research institutes, and government laboratories) of the firm in the current year (*Upstream partners*) (Faems *et al.,* 2005).

We also controlled for several attributes of the knowledge pool of the firm and the partner. We controlled for the size of knowledge pool of the focal firm (*Firm knowledge pool size*) and the partner (*Partner knowledge pool size)* by computing a cumulative count of patents filed in the past five years [t-6, t-1]. These two variables were divided by 1000, to improve readability of the results. Furthermore, we controlled for the total number of backward citations made by the firm in a given year (*Total recombination*). We also divided this variable by 1000, to improve readability of the results. Importantly, we also controlled for the number of fuel cell citations that the firm made to the partner's patent stock in the past five years (*Past partner-specific recombination*) to control for any path-dependent effects (Gomes-Casseres *et al.,* 2006). We controlled for the focal firm's (*Firm knowledge pool diversity*) and partner's knowledge pool diversity (*Partner knowledge pool diversity*). Following earlier studies (e.g. Phelps, 2010; Sampson, 2007; Subramanian & Soh, 2017), we aggregated all IPC codes (at the main group level) of a firm's patents to the firm-level, and subsequently calculated the distribution among them relying on the widely-used Herfindahl index. Moreover, using IPC main group codes, we subsequently measured overlap in component knowledge (*Knowledge pool distance*), between the firm and the partner, by relying on the widely-used measure of technological distance introduced by Jaffe (1986) and used in numerous alliance studies (e.g. Sampson, 2007; Van de Vrande, 2013). The measure ranges between 0 and 1, where a value of 0 indicates full overlap and a value of 1 indicates no overlap in any technological domain. We controlled for potential coordination costs associated with conducting internal R&D and building new component knowledge and capabilities, by calculating the average number of inventors listed on the focal firm's patents (*Internal coordination costs*) (Grigoriou & Rothaermel, 2017). Moreover, we also controlled for the focal firm's experience with recombining internal components (*Internal component reliance*), dividing the number of internal backward citations by the total number of backward citations, and with older components (*Old component reliance)*, calculating the average age of backward citations of a focal firm's patents (Wuyts & Dutta, 2014). We also controlled for the focal firm's focus on particular patent offices, in order to control for any between-patent office heterogeneity that might affect patent citation behavior (Bakker *et al.,* 2016). Specifically, we included three control variables representing the share of patents in the focal firm's knowledge pool that were filed in each of the three main patent offices (i.e. EPO, JPO, USPTO).

3.4.3. Analytical method

The 88 focal firms were engaged in 461 R&D alliance dyads between 1993 and 2007. In the analyses, we focused on firm-partner dyads, where the firm and the partner need to be technologically active (i.e. they must have filed at least 1 fuel cell patent in the past five years) firms (i.e. we do not include upstream partners such as universities). Since most alliances lasted for longer than one year, and many of them were multi-partner alliances, this resulted in a total of 1691 firm-partner year observation. Each observation stands for a specific firm-partner dyad in a year in which it has an ongoing partnership. Following Gomes-Casseres et al. (2006), the citation output of a firm to an alliance partner in the next year is a function of the characteristics of the respective firm-partner dyad in the current year.

We relied on Generalized Estimating Equations (GEE) in order to test our hypotheses (Baum, 2008; Phelps, 2010). GEE models are especially fit for analyzing models in which the dependent variable appears as a fraction or proportion (i.e. the share of citations made to a partner by the firm) (Baum, 2008). Moreover, these specifications allow to substantially correct for non-independence across similar observations over a period of time (Hardin, Hilbe, & Hilbe, 2012). We applied an exchangeable correlation structure, to correct for correlation amongst observations from the same focal firm, and included robust standard errors in order to alleviate issues of heteroskedasticity (Hardin *et al.,* 2012). Furthermore, due to the distribution of our dependent variable, we used a binomial family and logit link function (Baum, 2008; Phelps, 2010). To control for variance over time, we included year dummies in each model. Finally, we lead the dependent variable by one year to reduce concerns of reverse causality.

3.4.4. Results

Descriptive statistics. Table 3.2 presents the descriptive statistics and correlation matrix. The average focal firm makes 1.9% of its citations to a partner in a given year. The average alliance tie has a lifespan of 2.88 years, in line with earlier studies (e.g. Phelps, 2010). The knowledge pool applicability of the focal firm and partner are well-distributed, with an average of 1.44 and 1.47 respectively, a minimum value of 1, and a maximum of 3. None of the pair-wise correlations are above 0.7. Moreover, VIF values, based on OLS regression, in all models are well-below the threshold value of 10, with an average value of 1.59 and a maximum value of 2.64 (Mason & Perreault, 1991). Therefore, we are confident that multicollinearity issues are not present in our models.

Table 3.2. Descriptive statistics and correlation matrix

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
1	Partner-specific recombination	1																								
2	Age alliance	0.16	1																							
3	Joint venture	0.08	0.23	1																						
4	Government-funded	-0.11	-0.11	-0.10	1																					
5	Multi-partner	-0.04	-0.10	-0.05	0.37	1																				
6	International	-0.09	0.23	0.15	-0.09	0.01	1																			
7	Concurrent alliances	0.05	0.19	0.26	0.08	0.21	0.01	1																		
8	Inventors	-0.16	0.01	0.02	0.02	0.09	0.18	0.02	1																	
9	Non-inventors	-0.12	0.01	-0.04	0.25	0.15	0.26	-0.01	0.30	1																
10	Upstream partners	-0.15	0.01	-0.06	0.27	0.12	0.02	0.00	0.38	0.24	1															
11	Firm knowledge pool size	0.00	0.11	-0.03	-0.12	-0.09	-0.07	0.08	0.02	-0.16	0.01	1														
12	Partner knowledge pool size	0.34	0.15	-0.01	-0.11	-0.06	-0.06	0.11	-0.06	-0.11	-0.06	0.09	1													
13	Total recombination	-0.03	0.06	0.00	-0.16	-0.15	-0.04	0.07	0.15	-0.12	0.06	0.66	0.04	1												
14	Past partner-specific recombination	0.29	0.34	0.06	-0.09	-0.06	-0.04	0.17	0.00	-0.11	-0.02	0.55	0.43	0.38	1											
15	Firm knowledge pool diversity	-0.10	-0.12	-0.06	0.09	0.00	0.03	-0.04	0.14	0.01	0.17	-0.07	-0.02	0.03	-0.05	1										
16	Partner knowledge pool diversity	0.02	-0.03	-0.04	0.01	-0.07	0.00	-0.05	0.03	-0.02	0.06	-0.03	0.02	0.00	0.01	0.14	1									
17	Knowledge pool distance	-0.22	-0.27	-0.10	0.20	0.03	-0.01	-0.15	-0.01	0.14	0.04	-0.21	-0.25	-0.16	-0.29	0.22	0.23	1								
18	Internal component reliance	-0.02	0.12	0.03	0.07	0.06	-0.06	-0.01	0.23	-0.04	0.12	0.15	0.04	0.13	0.10	0.09	-0.07	-0.12	1							
19	Old component reliance	-0.05	-0.06	0.04	0.18	0.04	0.12	-0.03	0.17	0.23	0.15	-0.26	-0.15	-0.17	-0.17	0.21	0.04	0.18	-0.04	1						
20	JPO patents	0.21	0.00	-0.02	-0.20	-0.09	-0.35	0.03	-0.35	-0.40	-0.33	0.32	0.18	0.18	0.18	-0.11	-0.07	-0.26	0.06	-0.33	1.00					
21	EPO patents	-0.09	-0.02	0.02	0.23	0.12	0.31	-0.07	0.10	0.32	0.18	-0.30	-0.21	-0.21	-0.20	0.32	0.08	0.40	-0.10	0.49	-0.48	1				
22	USPTO patents	-0.14	0.03	0.01	0.25	0.05	0.22	-0.03	0.31	0.42	0.28	-0.27	-0.13	-0.06	-0.13	0.12	0.08	0.32	0.08	0.36	-0.55	0.49	1			
23	Internal coordination costs	-0.04	-0.17	-0.02	0.08	0.08	-0.05	-0.05	0.12	0.03	0.07	-0.09	-0.04	-0.09	-0.07	0.29	0.06	0.12	-0.09	0.22	-0.06	0.28	-0.07	1		
24	Partner knowledge pool applicability	0.00	0.05	-0.03	0.04	-0.02	0.18	0.01	-0.06	0.00	0.03	-0.06	-0.04	-0.07	0.01	0.08	-0.19	-0.15	-0.03	0.03	-0.08	0.09	0.00	0.02	1	
25	Firm knowledge pool applicability	-0.09	0.06	-0.04	0.02	-0.05	0.17	-0.03	0.25	0.31	0.16	-0.09	-0.06	0.01	-0.04	-0.17	0.03	0.01	0.01	0.20	-0.32	0.19	0.41	0.08	0.00	1
	Mean	0.02	2.88	0.08	0.28	0.51	0.62	1.12	4.8	1.86	1.14	0.17	0.13	0.19	9.64	0.79	0.76	0.18	0.12	8.82	0.35	0.39	0.52	2.95	1.44	1.47
	SD	0.05	3.32	0.27	0.45	0.50	0.49	0.34	3.27	2.38	1.65	0.36	0.33	0.38	26.49	0.13	0.19	0.16	0.08	2.18	0.38	0.30	0.33	0.69	0.32	0.28
	Min	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	2	0	0	0	1	1	1
	Max	0.60	20	1	1	1	1	3	15	13	8	3.85	3.85	3.74	354	0.96	0.97	0.76	0.50	25	1	1	1	5.57	3	3

Regression results. In Table 3.3, we present the results of the GEE regressions. Among the dyad characteristics, and consistent with expectations (Sampson, 2007), we find evidence that alliance dyads that are part of a joint venture lead to more recombination of a partner's components by the focal firm (Model 1: $\beta_{\text{Joint venture}} =$ 0.440, $p < .05$). Moreover, focal firms tend to recombine components of partners from different countries less often (Model 1: $\beta_{\text{International}} = -0.474$, $p < 0.01$) as expected (Gomes-Casseres *et al.,* 2006). In terms of alliance portfolio characteristics, we find that if the focal firm is engaged in R&D alliances with many other inventive partners, this has a negative and statistically significant influence on the intensity of partner-specific knowledge recombination (Model 1: $\beta_{\text{Inventors}} = -0.100$, $p < 0.01$), but the effect of non-inventive and upstream partners is statistically non-significant. Among the knowledge pool characteristics of the focal firm and the partner, we notice that partner's knowledge pool diversity positively influences partner- specific recombination (Model 1: $\beta_{\text{Partner knowledge pool diversity}} = 1.589$, $p < 0.01$), whereas knowledge pool distance decreases it (Model 1: $\beta_{\text{Knowledge pool distance}} = -4.807$, $p < 0.001$).

In model 4, we test Hypothesis 1 following the procedure described by Haans et al. (2016) for testing curvilinear relationships. We find that the linear effect of a partner's knowledge pool applicability is positive and statistically significant (Model 4: $\beta_{\text{Partner knowledge pool applicability}} = 8.347$, $p < 0.001$), whereas the quadratic term is negative and statistically significant (Model 4: $\beta_{\text{Partner knowledge pool applicability squared}} = -2.574$, $p < 0.01$). We plot this relationship in Figure 3.4. The plot shows an inflection point at a value of 1.62, which is within one standard deviation of the mean, and therefore well within the range of observable points. Furthermore, the slope before the inflection point is positive and statistically significant ($p < 0.001$) and the slope after the inflection point is negative and statistically significant ($p < 0.01$). Moreover, the 95 percent Fieller confidence interval of the inflection point is within the range of observable points ([1.50,1.86]). We also find that the linear and quadratic coefficients of partner's knowledge pool applicability are jointly statistically significant ($Chi^2 = 13.82$, $p < 0.001$). Hence, we find support for Hypothesis 1.

In model 5 we test Hypothesis 2. We find that the linear effect of the firm's knowledge pool applicability has a statistically non-significant impact on the firm's partner-specific recombination. However, when we further assess whether this relationship is instead driven by curvilinear effects, we surprisingly find that the linear effect of firm's knowledge pool applicability is negative and statistically significant (Model 6: $\beta_{\text{Firm knowledge pool applicability}} = -5.547$, $p < 0.001$), whereas the quadratic term is positive and statistically significant (Model 6: $\beta_{\text{Firm knowledge pool applicability squared}} = 1.603$, $p < 0.001$). The curve, as displayed in Figure 3.5, has an inflection point at a value of 1.73, which is within one standard deviation of the mean, and therefore well within the range of observable points. Furthermore, the slope before the inflection point is negative and statistically significant ($p < 0.001$), whereas the slope after the inflection point is positive and statistically significant ($p < 0.001$). Moreover, the 95 percent Fieller confidence interval of the inflection point is within the range of observable points ([1.53,1.88]. We also find that the linear and quadratic coefficients of the focal firm's knowledge pool applicability are jointly statistically significant ($Chi^2 = 42.98$, $p < 0.001$). Hence, rather than a linear and positive relationship, we detect a U-shaped relationship between the focal firm's knowledge pool applicability and the firm's partner-specific knowledge recombination. In model 7, we jointly introduce the quadratic terms of knowledge pool applicability of the partner and focal firm, and find robust results.

Figure 3.4. Main effect of partner knowledge pool applicability

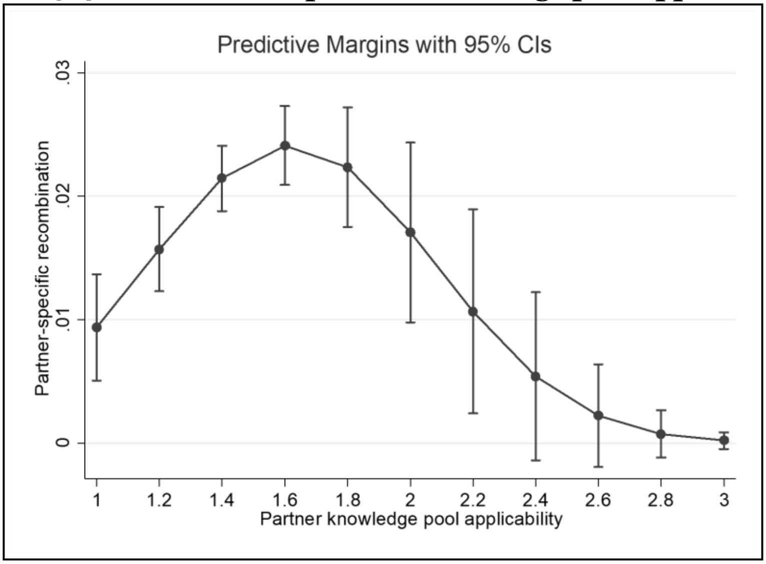

Figure 3.5. Main effect of focal firm knowledge pool applicability

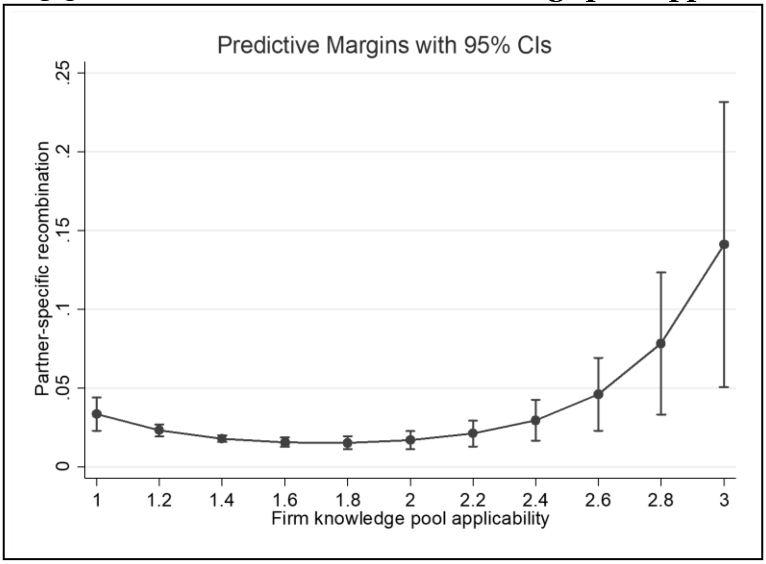

Table 3.3. GEE results

DV: Partner-specific recombination	1	2	3	4	5	6
Age alliance	0.03	0.03	0.03	0.03	0.03†	0.03†
	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
Joint venture	0.44*	0.50*	0.44*	0.47*	0.43*	0.46*
	[0.21]	[0.22]	[0.22]	[0.23]	[0.22]	[0.23]
Government-funded	-0.23	-0.28	-0.29	-0.29	-0.32	-0.32
	[0.24]	[0.24]	[0.24]	[0.23]	[0.23]	[0.23]
Multi-partner	0.22	0.23	0.21	0.21	0.21	0.21
	[0.19]	[0.18]	[0.18]	[0.18]	[0.18]	[0.18]
International	-0.47**	-0.55**	-0.53**	-0.57***	-0.61***	-0.64***
	[0.17]	[0.17]	[0.17]	[0.16]	[0.17]	[0.16]
Concurrent alliances	-0.23	-0.24	-0.23	-0.24	-0.23	-0.24
	[0.20]	[0.20]	[0.20]	[0.20]	[0.20]	[0.20]
Inventors	-0.10**	-0.10**	-0.10**	-0.09*	-0.08*	-0.08*
	[0.03]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]
Non-inventors	0.02	0.03	0.03	0.03	0.04	0.04
	[0.03]	[0.03]	[0.03]	[0.03]	[0.03]	[0.03]
Upstream partners	-0.11	-0.11	-0.11	-0.10	-0.11†	-0.11
	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]
Firm knowledge pool size	-1.64**	-1.65**	-1.65**	-1.64**	-1.62**	-1.61**
	[0.56]	[0.57]	[0.56]	[0.60]	[0.50]	[0.54]
Partner knowledge pool size	0.32†	0.34†	0.33†	0.36*	0.31†	0.34*
	[0.17]	[0.18]	[0.18]	[0.17]	[0.17]	[0.17]
Total recombination	0.07	0.09	0.10	0.15	0.16	0.20
	[0.19]	[0.19]	[0.19]	[0.20]	[0.19]	[0.20]
Past partner-specific recombination	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Firm knowledge pool diversity	-0.48	-0.49	-0.72	-0.75	-0.67	-0.72
	[0.54]	[0.55]	[0.59]	[0.61]	[0.61]	[0.62]
Partner knowledge pool diversity	1.59**	1.75***	1.74***	1.59**	1.72***	1.57**
	[0.49]	[0.52]	[0.51]	[0.54]	[0.49]	[0.52]
Knowledge pool distance	-4.81***	-4.75***	-4.85***	-4.05***	-5.12***	-4.37***
	[0.74]	[0.75]	[0.79]	[0.81]	[0.82]	[0.83]
Internal component reliance	-0.16	-0.10	0.04	-0.15	-0.09	-0.27
	[0.85]	[0.86]	[0.87]	[0.90]	[0.88]	[0.91]
Old component reliance	0.07	0.07	0.07	0.07	0.07	0.07
	[0.05]	[0.05]	[0.05]	[0.05]	[0.05]	[0.05]
JPO patents	0.82**	0.84**	0.83**	0.73**	0.69*	0.61*
	[0.26]	[0.25]	[0.26]	[0.27]	[0.27]	[0.28]
EPO patents	1.22***	1.22***	1.23***	1.25***	1.08**	1.12**
	[0.32]	[0.33]	[0.32]	[0.34]	[0.34]	[0.35]
USPTO patents	-0.37	-0.36	-0.24	-0.38	-0.29	-0.40
	[0.30]	[0.29]	[0.30]	[0.28]	[0.30]	[0.29]
Internal coordination costs	0.00	-0.01	0.02	-0.01	-0.06	-0.08
	[0.13]	[0.13]	[0.13]	[0.13]	[0.13]	[0.13]
Partner knowledge pool applicability		0.41†	0.40†	8.35***	0.42†	7.70***
		[0.24]	[0.24]	[2.41]	[0.24]	[2.33]
Firm knowledge pool applicability			-0.36	-0.33	-5.55***	-5.25***
			[0.42]	[0.41]	[1.06]	[1.02]
Partner knowledge pool applicability squared				-2.57**		-2.36**
				[0.79]		[0.77]
Firm knowledge pool applicability squared					1.60***	1.51***
					[0.27]	[0.25]
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1691	1691	1691	1691	1691	1691
Wald chi²	1312.48	1297.41	1553.23	1612.86	1637.08	1895.41

† p < .10, * p < .05, ** p < .01, *** p < .001. Robust standard errors between brackets.

Robustness checks. We run several robustness checks to verify our main results[11]. First, we examine whether our results are driven by outliers in the dependent and independent variables. Winsorizing the dependent and two independent variables at the 1st and 99th percentile, our results remain highly stable[12].

Second, we apply different model specifications: (i) we use a count variable as the dependent variable (i.e. number of citations made by the focal firm to a partner) with GEE models (with a negative binomial family and link function, and an exchangeable correlation structure), (ii) we use logit models, where the dependent variable takes a value of 1 when the focal firm makes at least one citation to the partner, and (iii) following Phelps (2010), we log-odds transform the dependent variable, and run an OLS regression with focal firm and year dummies. In all three model specifications, the main results remain stable.

Third, we check for potential interaction effects between the knowledge pool applicability of the partner and focal firm (i.e. through a linear interaction and a quadratic interaction). Our results show no evidence of an interaction between the two variables, suggesting that the focal firm's knowledge pool applicability does not substitute or complement the partner's knowledge pool applicability.

Fourth, we exclude observations from all years before 1998. We chose this year as the cut-off point because, in 1998, DaimlerChrysler (now Daimler), Ford and Ballard Power Systems (a Canadian fuel cell manufacturer) formed a 1$bn joint venture to develop fuel cell systems for automotive vehicles. The formation of this joint venture is widely regarded as a turning point in the fuel cell technological field, as it was seen as a strong indicator of the commercial feasibility of fuel cell technology. Excluding these observations did not affect our main results.

Fifth, because we are dealing with a non-linear model (Hoetker, 2007; Williams, 2012), we compute the marginal effects (also referred to as partial effects) of the two quadratic relationships. Indeed, as stated by Wiersema and Bowen (2009, p. 682) "in an LDV [limited dependent variable] model, an explanatory variable's estimated coefficient can rarely be used to infer the true

[11] We do not report most of these analyses for the sake of brevity. They are, however, available from the authors upon request.
[12] Log-transforming the independent variables, consistent with Haans et al. (2016), did not influence our main results either.

nature of the relationship between the explanatory variable and the dependent variable." For partner's knowledge pool applicability, we detect that the marginal effects are positive and statistically significant ($p<0.05$) when the partner's knowledge pool applicability is in the range [1.00,1.50], statistically non-significant ($p>0.05$) in the range [1.51,1.80], negative and statistically significant ($p<0.05$) in the range [1.81,2.54], and statistically non-significant ($p>0.05$) in the range [2.55,3.00]. For the focal firm's knowledge pool applicability, we detect that the marginal effects are negative and statistically significant ($p<0.05$) when the focal firm's knowledge pool applicability is in the range [1.00,1.55], statistically non-significant ($p>0.05$) in the range [1.56,1.92], and positive and statistically significant ($p<0.05$) in the range [1.93, 3.00].

Finally, we exclude observations in which the firm made no citations in the next year. Using this alternative specification, the results remain highly stable. In sum, using these alternative models, our main results remain consistent: Hypothesis 1 finds strong support and Hypothesis 2 is not supported.

3.5. Discussion and conclusion

In this study, using a unique dataset of 88 focal firms engaged in 461 R&D alliance dyads in the fuel cell industry, we examined how the knowledge pool applicability of the partner and focal firm influence the focal firm's partner-specific recombination. We find that the partner's knowledge pool applicability has a robust inverted U-shaped relationship with the focal firm's recombination of partner's components. The results, however, do not provide support for Hypothesis 2. We find that the focal firm's knowledge pool applicability has a U-shaped relationship with its rate of partner-specific recombination, rather than the hypothesized linear and positive effect.

A potential explanation for this unexpected finding is that firms first need to develop a base-level of knowledge pool applicability, before they can benefit from the capabilities that emerge from it, in the R&D alliance context. Deploying these combinative capabilities in the R&D alliance, when understanding of how these capabilities should be aligned with available recombination opportunities is only minimal, can be costly, as the focal firm will often draw mistaken inferences about the applications of a partner's component knowledge, attempting to generate combinations that do not actually function well (Hargadon & Sutton, 1997; Nemet & Johnson, 2012). Hence, in the initial phase (i.e. from low to average internal knowledge pool applicability), firms may not yet enjoy the benefits of being able to apply these combinative capabilities to the recombination of partner's component knowledge (Darr, Argote, & Epple, 1995).

3.5.1. Theoretical implications

Alliance scholars have principally focused on the size and diversity of partner's knowledge pool as core drivers of knowledge recombination activities in R&D alliances (e.g. Lahiri & Narayanan, 2013; Schilling & Phelps, 2007; Wuyts & Dutta, 2014). In this study, we demonstrate that, even when the partner's knowledge pool size and diversity are held constant, numerous recombination opportunities may still emerge depending on the partner's knowledge pool applicability. Numerous alliance studies implicitly assume that diverse and large knowledge pools present numerous opportunities to engage in knowledge recombination (e.g. Lahiri & Narayanan, 2013; Gilsing *et al.,* 2008; Schilling & Phelps, 2007). However, we argue that numerous components can only be used in one very specific application domain, substantially reducing the range of combinations in which they can be applied. Hence, only considering the aggregate knowledge pool, in terms of how diverse or how large it is, in many cases obscures the fact that many components actually have a limited range of applications. We therefore encourage future research to account for knowledge pool applicability in their conceptual and empirical framework, when studying R&D alliances and their performance implications.

We also develop novel theoretical arguments regarding firms' idiosyncratic abilities to engage in knowledge recombination in the partner's knowledge pool. Existing alliance research tends to conceptually focus more on the absorption of component knowledge into the focal knowledge pool, often remaining relatively agnostic about the actual recombination of a partner's component knowledge (e.g. Rosenkopf & Almeida, 2003; Vasudeva & Anand, 2011; Gilsing *et al.,* 2008). However, we emphasize that even if a component is transferred into the knowledge pool, it is also important to look at whether the focal firm actually knows how to use this component in knowledge recombination (Zahra & George, 2002). Hence, it is important to look into factors that are likely to drive firm-specific abilities to engage in meaningful knowledge recombination (Wuyts & Dutta, 2014). To this end, we argued that combinative capabilities that emerge from building widely-applicable component knowledge allow the focal firm to have a better understanding of components' true recombinant potential, overcoming technological limits that other firms might have (Henderson, 1995). Moreover, these capabilities allow the focal firm to recognize when the recombinant potential of a component has reached its limit already, thus avoiding fruitless recombination efforts. We therefore point to the need to consider a more nuanced knowledge recombination perspective when examining the application of focal firms' internal capabilities in R&D alliances.

3.5.2. Limitations and future research

There are several limitations in this study, which can form a starting point for future research. First, in order to test our hypotheses, we chose an empirical setting which allowed us to easily operationalize the knowledge pool applicability of the focal firm and partner. Specifically, we examined the IPC subgroups that are listed on fuel cell patents, in order to determine a firm's knowledge pool applicability. In the fuel cell technological field, this approach was facilitated by the fact that there were only four major application domains for fuel cell inventions, and that there was a high correspondence between these four domains and the IPC subgroups of fuel cell patents. Although it is likely that this type of approach would work in other settings, we still encourage future studies to attempt to capture application domains in other settings.

Second, in this study we focused on technological application domains nested within a larger technological domain, capturing application domains which have immediate relevance to the context of this study (i.e. fuel cell-oriented R&D alliances). We encourage future studies to examine other types of application domains for knowledge components, such as other industries or countries (e.g. Hargadon & Sutton, 1997; Petruzzelli & Savino, 2014), developing potentially different theoretical insights than the ones discussed in this study.

Chapter 4. Does Going-Together Always Lead to Better Solutions?

An Exploration of Challenge-Based R&D Projects

Abstract: To tackle important grand societal challenges, government institutions initiate large-scale programs in which organizations participate in challenge-based R&D projects, aimed at solving extant technological problems within a specific field. The literature on grand challenges often implicitly assumes that organizations should formally involve partners in these projects – i.e. go-together – rather than proceeding independently – i.e. go-alone. They argue that the main advantage of going-together is that it increases the potential to generate high-quality technological solutions by merging partners' heterogeneous knowledge pool. In this study, we relax the assumption that going-together is always more productive than going-alone in terms of generating high-quality technological solutions – i.e. problem-solving performance. Specifically, we argue that that not every organization is able to translate potential into realized knowledge recombination opportunities. Firstly, we formulate a baseline hypothesis, in which we expect that problem-solving performance is higher, on average, when going-together than going-alone. Secondly, we hypothesize that the ability to translate potential into realized knowledge recombination opportunities when going-together is contingent upon the focal organization's institutional background, internal knowledge pool size, and challenge-based R&D project portfolio size. Analysing a unique sample of 414 challenge-based R&D projects within the Department of Energy's Hydrogen and Fuel Cells Program over a 14-year time period (2003-2016), we generally find support for our theoretical predictions. We contribute to the literature on grand challenges and open innovation by showing that the often-assumed performance edge of going-together over going-alone does not materialize for every organization. Based on these findings, we also encourage policy-makers to more carefully design grand societal challenge programs, and not treat going-together as some panacea for innovation.

This chapter was written together with Dries Faems and Pedro de Faria.

4.1. Introduction

Large-scale funding programs have been increasingly used by governments to stimulate the creation of innovative solutions aimed at tackling significant societal challenges such as climate change, demographic changes or smarter infrastructure (Howard-Grenville *et al.,* 2014; Olsen *et al.,* 2016). Within these programs, firms, universities and other organizations participate in challenge-based R&D projects, aimed at overcoming existing technological barriers within a particular technological field. Within these R&D projects, organizations strive to develop technological solutions with the objective of meeting certain technological targets by a certain point in time.

In line with the open innovation paradigm (Chesbrough, 2006), extant research on grand challenges strongly emphasizes the advantages of collaborative strategies to generate high-quality solutions for technological problems (Howard-Grenville *et al.,* 2014; Olsen *et al.,* 2016). The core argument within this paradigm is that collaboration allows organizations to access partners' heterogeneous knowledge, creating opportunities for synergistic knowledge recombination (e.g. Olsen *et al.,* 2016), resulting into solutions that the organization could not have generated individually. In other words, going-together in challenge-based R&D projects triggers unique knowledge recombination opportunities that are not available when going-alone. However, whereas research on grand challenges emphasizes these potential knowledge recombination opportunities, it remains surprisingly silent on organizations' ability to actually realize these opportunities. As a result, there seems to be an implicit assumption that going-together is always more productive in terms of generating high-quality technological solutions than going-alone. Relying on the established alliance literature, we, however, argue that realizing collaborative recombination opportunities may be highly challenging to some organizations. An exploration of when going-together leads to superior outcomes in challenge-based R&D projects therefore seems to be necessary.

The aim of this study is therefore to shed light on the conditions under which going-together substantially outperforms going-alone in challenge-based R&D projects in terms of generating high-quality solutions to extant technological problems. Using knowledge-based view (KBV) theoretical insights (Das & Teng, 2000; Galunic & Rodan, 1998; Kogut & Zander, 1992), we argue that not every organization has the ability to realize recombination opportunities emerging from going-together. Specifically, the benefits of going-together hinge on the focal organization's ability to identify, retrieve, and recombine components across different organizational boundaries, which can be challenging to certain organizations (Miller *et al.,* 2007; Rosenkopf & Nerkar, 2001; Zahra & George, 2002). In line with this contention, we argue that three characteristics of the focal organization influence the relative problem-solving performance – i.e. the ability to generate high-quality solutions to extant technological problems – of going-together compared to going-alone. First, we argue that focal organizations with different institutional backgrounds (i.e. firms and research organizations) possess certain characteristics that influence their ability to translate potential into realized knowledge recombination opportunities when going-together. In this respect, we expect that the positive performance gap between going-together and going-alone will be larger for research organizations than for firms, as we argue that research organizations tend to be more capable of recombining partners' component knowledge. Second, we posit that when the focal organization's internal knowledge pool is larger, its ability to identify and retrieve partners' valuable components will be higher (Cohen & Levinthal, 1990), increasing the positive performance gap between going-together and going-alone. Third, we expect that when the focal organization is concurrently engaged in a higher number of challenge-based R&D projects (i.e. larger R&D project portfolio), the performance gap between going-together and going-alone will decrease, because fewer resources will be available to realize recombination opportunities within single projects (Levinthal & Wu, 2010).

We investigate these expectations on 414 government-supported challenge-based R&D projects from the Hydrogen and Fuel Cells Program using unique data from the Department of Energy (DOE) over a 14-year time period (2003-2016). This database is particularly suitable to test our theoretical predictions since organizations within this program can opt to go-alone or go-together in challenge-based R&D projects. We operationalize this dichotomy by examining whether or not the project leader involves formal collaboration partners in the project. Moreover, in contrast to prior studies studying collaborative strategies, we do not infer project performance from organization-level performance, but rather capture problem-solving performance at the project-level, relying on objective and yearly project evaluations of expert peer reviewers.

Our findings indicate that going-together, on average, outperforms going-alone, suggesting that collaborative strategies indeed can provide unique knowledge recombination opportunities for solving particular R&D challenges. However, contrary to expectations, we find that the positive performance gap between going-together and going-alone is larger for firms than for research organizations, suggesting that, as leading entities, firms are more able to reap collaborative recombination opportunities in challenge-based R&D projects than research organizations. Moreover, in support of our theoretical arguments, we find that the positive performance gap between going-together and going-alone becomes larger when the focal organization has a larger internal knowledge pool. Finally, contrary to expectations, we find that the positive performance gap between going-together and going-alone initially widens as the focal organization's R&D project portfolio becomes larger. However, beyond a certain tipping point, the positive performance gap between going-together and going-alone decreases as the focal organization's R&D project portfolio becomes larger.

This study makes several important theoretical and practical contributions. Theoretically, we contribute to the literature on grand challenges and open innovation by underlining the fact that not every organization is able to fully reap the problem-solving benefits of going-together. In doing so, we provide a more nuanced perspective regarding the often-assumed benefits of going-together compared to going-alone in terms of generating valuable technological solutions. Our findings provide evidence that certain organizations – most notably research organizations and focal organizations with a small internal knowledge pool – are substantially less able to leverage collaborative knowledge recombination opportunities. These empirical findings also contribute to practice by pointing out that more careful consideration should be given to how challenge-based R&D projects are configured. Instead of treating going-together as a panacea for challenge-based R&D endeavors, it should be recognized that not all organizations are able to benefit from this problem-solving approach. Hence, we encourage policy-makers to more carefully design programs targeting societal grand challenges, paying careful attention to which type of organization is most capable of solving particular technological problems.

4.2. Theory and hypotheses

In this section, we discuss the relative problem-solving performance benefits of going-together compared to going-alone in challenge-based R&D projects. Challenge-based projects are projects in which a focal organization searches for high-quality technological solutions to extant critical technological problems (e.g. costs or durability of a particular material) within the framework of a grand societal challenge. To tackle these technological problems, focal organizations within challenge-based R&D projects can opt to go-together, involving formal partners to assist with problem-solving activities, or go-alone, conducting problem-solving activities without involvement of formal partners. In the following section, we formulate a baseline hypothesis in which we expect that problem-solving performance will be higher when the focal organization is going-together rather than going-alone. Subsequently, grounded in KBV insights, we explore three characteristics of the focal organization that might influence the size of the positive problem-solving performance gap between going-together and going-alone: (i) the institutional background of the focal organization, (ii) the focal organization's internal knowledge pool size, and (iii) the focal organization's R&D project portfolio size.

4.2.1. The knowledge recombination benefits of going-together

In challenge-based R&D projects, technological problems are addressed by recombining knowledge components into novel technological solutions (Galunic & Rodan, 1998; Fleming, 2001). Here, the adopted conceptualization of knowledge components comprises different "bits of knowledge or matter (Fleming & Sorenson, 2004: 910)" that can be used to develop new technological solutions. For example, the cost-efficiency of fuel cells was recently dramatically improved through a joint development effort between Ballard Power Systems and Nisshinbo Holdings, in which they created a non-platinum catalyst through recombining component knowledge of (i) carbon alloy materials, (ii) oxygen-reduction, and (iii) electrocatalysts (Banham *et al.,* 2017). The ability of the focal organization to generate useful technological solutions therefore depends largely on the availability of components. When too few components are available to generate interesting combinations, the focal organization runs the risk of being unable to adequately address technological problems at hand – i.e. the knowledge pool is dried-out (Fleming, 2001; Ahuja & Katila, 2004).

One means by which a focal organization can expand its component set is by participating in interorganizational collaboration (Grant & Baden-Fuller, 2004; Hamel, 1991; Rosenkopf & Almeida, 2003). Effectively, by merging various organizations' heterogenous knowledge pools, collaboration increases the set of available knowledge components that can be potentially used in new combinations and thereby makes it easier to find unique solutions to technological problems (Phelps, 2010). These complementary benefits exist because organizations develop technological competences in path-dependent and highly idiosyncratic ways (Nelson & Winter, 1982), implying that no two knowledge pools are ever completely identical (Yayavaram & Ahuja, 2008). Consequently, when merging the heterogeneous knowledge pools of partners, new combinations can be created that could not be developed by each partner independently (Das & Teng, 2000; Harrison *et al.,* 2001). By accessing the knowledge pool of other organizations via going-together, the focal organization will therefore be able to address extant technological problems more adequately, than when it is going-alone. Based on this theoretical mechanism, we formulate the following baseline hypothesis:

H1: Problem-solving performance is higher when the focal organization is going-together rather than going-alone

4.2.2. Organizations' abilities to realize potential recombination opportunities

Our baseline expectation is that going-together creates more potential recombination opportunities than going-alone, allowing focal organizations to solve extant technological problems more effectively when going-together compared to going-alone. Therefore, we assume that a larger positive problem-solving performance gap between going-together and going-alone indicates that the focal organization was able to translate the potential recombination opportunities of going-together into realized recombination opportunities to a larger extent. We expect, however, that the ability to realize these collaborative recombination opportunities is not equal for every organization. Even when organizations have access to the same set of components, there may be much variation in the extent to which they are able to use these components to develop valuable new technological solutions (Wuyts & Dutta, 2014; Zahra & George, 2002). In particular, organizations require abilities to identify valuable component knowledge in the partner's knowledge pool, retrieve it into the knowledge pool by developing a solid understanding of its technological characteristics, and, finally, develop high-quality solutions based thereupon by synergistically recombining it with other components (Fleming & Sorenson, 2001; Zahra & George, 2002). If they lack these abilities, focal organizations may either focus on the wrong components, be unable to retrieve the component knowledge, or be unable to realize valuable synergies based on the component, all of which may lead the focal organization to generate technological solutions of lower quality (Hargadon & Sutton, 1997; Nemet & Johnson, 2012).

Applying these insights, we argue that, in order to realize the potential recombination benefits of going-together, organizations should be able to identify, retrieve and recombine external components situated within partners' organizational boundaries (Grigoriou & Rothaermel, 2017; Lane & Lubatkin, 1998; Wuyts & Dutta, 2014). Organizational boundaries often present important barriers to extramural knowledge recombination, as they impede the focal organization's ability to retrieve accurate and complete information about external components (Galunic & Rodan, 1998; Miller *et al.,* 2007; Rosenkopf & Almeida, 2003; Sorenson *et al.,* 2006). Our baseline expectation is that going-together leads to higher problem-solving performance than going alone, by means of creating opportunities to access and exploit a larger and more diverse set of components to generate new technological solutions. Consequently, in case the organization is unable to span organizational boundaries in knowledge recombination, the problem-solving performance of going-together will be closer to that of going-alone (i.e. the available component set, in both situations, will be highly similar).

At the same time, certain organizations possess abilities to more effectively identify, retrieve and recombine external component knowledge than others (Bos *et al.,* 2017; Grigoriou & Rothaermel, 2017; Lane & Lubatkin, 1998; Wuyts & Dutta, 2014). In the following section, we follow these prior studies, and argue that three distinct characteristics of the focal organization are associated with these particular abilities. First, we expect that, since they are generally better able to identify, retrieve and recombine external component knowledge, research organizations have an edge over firms in terms of benefiting more from going-together compared to going-alone. Second, we expect that the larger the focal organization's internal knowledge pool, the larger the relative performance benefits of going-together compared to going-alone. Third, we argue that the focal organization's R&D project portfolio size (i.e. number of concurrent R&D projects) decreases the positive performance gap between going-together and going-alone.

Focal organization's institutional background. To translate potential into realized knowledge recombination benefits of going-together, organizations require abilities to identify, retrieve and recombine external component knowledge, creating synergies between partners' knowledge pool and their own (Das & Teng, 2000). These abilities, we argue, depend largely on the institutional role that the focal organization fulfills. Therefore, in this hypothesis we argue that research organizations are more able than firms to translate potential into realized recombination opportunities when going-together, impacting the relative problem-solving benefits of going-together compared to going-alone.

We expect that research organizations are highly capable of translating potential into realized recombination opportunities when going-together. This is principally because their institutional mission is to create and diffuse new scientific and technological knowledge (Cyert & Goodman, 1997), which (i) increases their appreciation of external knowledge and (ii) increases their willingness to actively collaborate and share knowledge with external parties. First, given their strong interest in diffusing new knowledge, research organizations are often strongly embedded within a broader research community. Indeed: "the central constituency for most university researchers lies outside the organization, in their professional reference group (Cyert & Goodman, 1997: 48)". Hence, research organizations are usually more outward- than inward-oriented (Trajtenberg, Henderson, Jaffe, 1997), concomitantly implying a higher level of receptiveness towards external knowledge. Second, as we know from research on social networks, knowledge diffuses more rapidly via collaboration networks (Fleming *et al.,* 2007). Therefore, it is expected that research organizations have strong incentives to collaborate and share their knowledge with partners. This increases the likelihood that knowledge diffuses more broadly and rapidly, which is advantageous for the research organization. Additionally, the research organization's willingness to share its own knowledge is likely to trigger reciprocal knowledge sharing on the partner's side, leading to higher synergistic knowledge recombination benefits (Das & Teng, 2000; Lane & Lubatkin, 1998).

In terms of appreciation of external knowledge and willingness to collaborate and share knowledge with partners, firms are very different from research organizations. Indeed, firms are profit-seeking organizations that tend to be more self-interested when engaging in knowledge sourcing, principally using it to create or sustain a competitive market position (Barney, 1991; Grant, 1996). As a corollary, firms usually prefer to be more self-reliant, relying principally on internal knowledge sources when possible (Srivastava & Gnyawali, 2011), as this minimizes the risks of exposing core technologies to external partners or becoming dependent for continuity on other organizations (Cassiman & Veugelers, 2002; Grimpe & Kaiser, 2010). Given this inward-orientation, firms also tend to suffer more often than research organizations from the not-invented-here syndrome (NIH) (Katz & Allen, 1982), whereby their receptivity towards external component knowledge is substantially lower than that of internal component knowledge (Fabrizio, 2009).

Taken together, we have two reasons to expect that research organizations will benefit relatively more from going-together than going-alone compared to firms: (i) research organizations have a higher appreciation of external component knowledge, implying that they will make more efforts to actively learn from external partners and (ii) it is more likely that, when research organizations collaborate with partners, knowledge is reciprocally shared, leading to the realization of synergistic benefits between partners' knowledge pools (Lane & Lubatkin, 1998)[1]. We hypothesize:

[1] For the sake of clarification, here we hypothesize that the relative problem-solving performance increase between going-together and going-alone is higher for research organizations than for firms. To illustrate this, consider a firm that has a performance of 200 when going-alone and 220 when going-together, and a research organization that has a performance of 100 when going-alone and 120 when

H2: The positive problem-solving performance gap between going-together and going-alone is larger for research organizations than for firms

Focal organization's internal knowledge pool. In this hypothesis, we argue that the size of the focal organization's internal knowledge pool – i.e. the quantity of technological solutions that the focal organization has successfully created within prior challenge-based R&D projects – influences the positive performance gap between going-together and going-alone. This influence is driven by two main theoretical mechanisms.

First, *ceteris paribus*, the larger the focal organization's internal knowledge pool, the more likely it is that the contents of this knowledge pool overlap with that of partners. As we know from prior studies (Lane & Lubatkin, 1998; Sampson, 2007), overlap in technological competences allows for easier communication between partners, improving the retrievability of components. That is, improved communication channels allow the focal organization to develop a more thorough understanding of components' recombination characteristics (Henderson & Clark, 1990; Sorenson *et al.,* 2006). Second, focal organizations with larger internal knowledge pools have more experience with creating high-quality solutions. Equipped with this experience, focal organizations are able to more rapidly and effectively identify valuable components in the partners' knowledge pool which they can subsequently use to create high-quality technological solutions (Henderson & Cockburn, 1994 Lewin *et al.,* 2011; Wuyts & Dutta, 2014). In this way, these focal organizations may circumvent a lot of the time-costly trial-and-error processes that lesser experienced focal organizations have to go through to achieve the same outcome (Katila & Ahuja, 2002; Fleming, 2002). Taken together, we hypothesize:

H3: The focal organization's internal knowledge pool size increases the positive performance gap between going-together and going-alone

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going-together. In this hypothesis, we argue that the relative problem-solving performance benefits of going-together compared to going-alone are higher for research organizations (i.e. difference between 120 and 100) than for firms (i.e. difference between 220 and 200). However, we are not comparing the difference in problem-solving performance between research organizations that go-together and firms that go-together (i.e. 120 versus 220).

Focal organization's R&D project portfolio. Numerous organizations participate in several challenge-based R&D project at the same time (Eggers, 2012; Henderson & Cockburn, 1996). Hence, single challenge-based R&D projects are often nested within a portfolio of challenge-based R&D projects at the organizational level. In this hypothesis, we argue that when the focal organization's portfolio of challenge-based R&D projects becomes larger, the positive problem-solving performance gap between going-together and going-alone will decrease.

By concurrently engaging in more challenge-based R&D projects, the focal organization's scarce resources are dispersed across a larger number of projects. As a result, the existing resource base of the focal organization is more likely to be overextended, leading to resource constraints at the project-level. This is especially problematic because resources that are used in challenge-based R&D projects tend to be non-scale free – i.e. their opportunity costs are positive (Levinthal & Wu, 2010). For example, the use of a fuel cell test facility in one project generally implies that other fuel cell projects cannot simultaneously make use of this same facility. The same holds for the allocation of human capital: R&D scientists can only be deployed in so many projects, before their productivity significantly declines. Thus, when the focal organization's challenge-based R&D project portfolio is larger, overextension of the focal organization's non-scale free R&D resources will considerably hamper knowledge recombination efforts at the project-level.

To translate potential into realized knowledge recombination opportunities when going-together, the focal organization needs to deploy a lot of resources in order effectively identify, retrieve, and recombine partners' external component knowledge. It follows that, if insufficient resources are available in going-together projects, the focal organization will be considerably less able to realize potential recombination opportunities. In support of this notion, numerous KBV studies (e.g. Bos *et al.,* 2017; Deeds & Hill, 1996; Laursen & Salter, 2006) show that organizations should concentrate R&D resources, rather than spread them too broadly, in order to benefit from extramural knowledge recombination. Taken together, we argue that when the focal organization's R&D project portfolio is larger, this will substantially reduce the realization of potential recombination opportunities in going-together projects, bringing their problem-solving performance closer to that of going-alone projects. Therefore, we formulate the following hypothesis:

H4: The focal organization's challenge-based R&D project portfolio size decreases the positive performance gap between going-together and going-alone

4.3. Methodology

4.3.1. Sample and data collection

Various government-supported programs have been initiated over the past few years in order to address important societal problems such as climate change, demographic changes, and smarter infrastructure (Olsen *et al.,* 2016). Government institutions generally issue calls for these programs, soliciting organizations to apply for various research projects that are targeted towards specific (technological) problems. These programs have the potential to make a big impact, as they allow coordinating and orchestrating various R&D efforts on a large scale. Indeed, in these programs, government institutions can align concerted R&D efforts by various parties with one another towards one common objective, potentially increasing the success rate of solving extant societal problems.

In this study, we specifically looked at challenge-based R&D projects that are part of the U.S. Department of Energy's (DOE) *Hydrogen and Fuel Cells Program* (HFCP hereafter)[2]. Hydrogen and fuel cell technologies form an increasingly prominent part of the United States' strategy to advance clean energy technologies and increase energy independence from oil. Fuel cell and associated hydrogen technologies are still in the early stage of commercialization, with numerous technical issues that still need to be addressed. Since the technology remains vastly uncommercialized, concerted government support is required in order to move the technology into the commercialization stage. The projects within this program tackle major issues hampering broad-scale fuel cell technology commercialization[3]. Hence, projects within this program are problem-oriented, as they are designed in

[2] The program was referred to as the Hydrogen, Fuel Cells, & Infrastructure Technologies Program between 2002-2009, the Fuel Cell Technologies Program between 2009 and 2012, and the Hydrogen and Fuel Cells Program since 2012.
[3] These (non-)technological issues are determined based upon, among other things, past programs' outputs as well as the advice of numerous national and international experts.

such a way that particular (technological) targets are met before a certain point in time. For instance, two of the 2020 technological targets set by the DOE for fuel cell power systems are (i) to increase their durability to 5,000 hours and (ii) decrease their cost efficiency to below 40$/kW (Satyapal, 2017). Hence, various projects within the fuel cell section of the HFCP focus on improving the durability and costs of fuel cell system components. Thus far, with an average annual budget of c.a. 180$mn, this program has contributed to important progress in fuel cell and hydrogen technologies, reducing the costs of fuel cell systems, increasing the durability of fuel cell stacks, increasing the mass density of hydrogen storage tanks, and generating ample patented inventions, commercial products, and new job opportunities (PNNL, 2017; Satyapal, 2017).

A unique feature of this data is that we can observe with high reliability the configuration of challenge-based R&D projects, in which focal organizations either go-alone or go-together. Specifically, in these projects, a project leader (i.e. the focal organization) is in charge of coordinating R&D activities, whilst also participating in them, to ensure that project objectives are met at a certain point in time. Importantly, the project leader may also enlist subcontractors in the project, which undertake R&D tasks within the project whilst reporting to the project leader. Using this information, we operationalize the dichotomy between go-together and go-alone by examining whether the project leader involves any subcontractors in the project. To track the configuration of projects over time, we examined project progress reports in the annual HFCP progress reports. All projects that are sponsored by the HFCP have to submit an abstract of the research they conducted during the past fiscal year, summarizing activities and progress made, which is subsequently made available online (https://www.hydrogen.energy.gov/). By inspecting these progress reports, we were able to track every project in this program over a long period of time, capturing the entire population of projects within this single program. The information contained in these abstracts is highly standardized, and could be retrieved for every year between 2003 and 2016. We used these progress reports to infer the identity of the project leader and potential subcontractors, and capture other relevant project-related information, such as the contract number associated with the project.

4.3.2. Variables

Dependent variable. To capture a project's performance, research on interorganizational collaboration often relies on (i) aggregated performance measures, such as an organization's net profit margin (e.g. Jiang, Tao, & Santoro, 2010) or (ii) project-level performance measures derived from surveys (e.g. Lane & Lubatkin, 1998; Cuypers, Ertug, Reuer, & Bensaou, 2017). Despite the merits of these two types of performance measures, they also have some important limitations. Notably, aggregated performance measures, like net profit margin, do not allow to isolate the performance effect of particular projects. Moreover, studies using surveys might suffer from common method bias. As we explain below, we deviate from these prior studies by using a performance indicator that is (i) measured at the project-level, providing a direct connection between the project's inputs and outputs, (ii) highly objective, because it is derived from anonymous peer reviewers with no conflicts of interest, and (iii) highly standardized across different projects.

The project's problem-solving performance data was retrieved from the HFCP Annual Merit Review (AMR) and Peer Evaluation reports, available on the DOE hydrogen website. Each year, the projects supported by the HFCP are evaluated through expert peer review[4] for three main reasons: (i) inform decision-making regarding funding of projects (e.g. should the project be discontinued, receive more/less funding in the following year), (ii) find ways to improve project performance and (iii) refocus program-wide objectives towards more productive ends (EERE, 2016). During the annual AMR meeting, projects are presented during workshops, allowing for peer reviewers to evaluate the project on its merits. Peer reviewers are additionally provided ahead of time with "an advance copy of the project summaries, reviewer instructions, evaluation forms for each project, an agenda, and an overall evaluation package specifically for that reviewer (EERE, 2016, p. 13)". The quality, objectivity and impartiality of reviewers is ensured through (i) only selecting reviewers with relevant experience in the field (based on, e.g. publication record and relevant degrees), (ii) anonymity of peer reviewers, and

[4] We note that not every project was evaluated on a yearly basis. In the EERE peer review guidelines (EERE, 2016), it is mentioned that some projects are excluded from peer evaluation if, for example, they had only very recently started or because they have already been retired.

(iii) not assigning reviewers to projects for which they might have a conflict of interest (EERE, 2016). The peer reviewers are asked to rate each project on a 4-point scale (1 being the lowest and 4 being the highest) along five dimensions: (i) Relevance to overall DOE objectives, (ii) approach to performing the research and development, (iii) technical accomplishments and progress toward project and DOE goals, (iv) technology transfer/collaborations with industry, universities and other laboratories, (v) approach to and relevance of proposed future research[5]. A final score is then derived by taking the weighted average of these five dimensions[6]. The DOE uses these overall project scores as a means to compare projects with each other, determining which projects perform well and which do not within the framework of the program. These evaluations are then collected and summarized in an evaluation report, referred to as the AMR evaluation report. The way in which performance was assessed over the years remained highly stable. The only noteworthy difference was that the weight of each dimension in the total score changed over the years. For example, the dimension related to technological accomplishments and progress received higher weights in later years (20% in 2003, 35% between 2004-2007, 40% between 2008-2012, and 45% between 2009-2016). We controlled for these shifts in importance attributed to different performance dimensions by including year dummies in all models.

Independent variables. To test the first hypothesis, we examined whether the project leader enlisted any subcontractors during the past fiscal year using data from the annual progress reports. If a subcontractor was listed in the project description, the variable *Going-together* took a value of 1, and a value of 0 if this was not the case (i.e. going-alone). To test the second hypothesis, we looked at whether the project leader listed on a project was a firm (=0) or a research organization (=1) (*Research organization*). In the latter category, we included

[5] Some minor variations occur. For example, American Recovery and Reinvestment Act (ARRA) projects were not evaluated for their future research directions. Similarly, technology validation and market transformation projects, in the years 2014-2016, were not evaluated on this dimension. We control for this through the inclusion of program section dummies.

[6] For example, in 2005, a project titled 'Complex Hydride Compounds with Enhanced Hydrogen Storage Capacity', led by United Technologies Research Center (UTRC), received a score of 3.5 for relevance to overall DOE objectives (20%), a 3.5 for approach to performing the research and development (20%), a 2.9 for technical accomplishments and progress toward project and DOE goals (35%), a 3.2 for technology transfer/collaborations with industry, universities and other laboratories (10%), and a 2.9 for approach to and relevance of proposed future relevance (15%), resulting in a final score of: (3.5*0.2)+(3.5*0.2)+(2.9*0.35)+(3.2*0.1)+(2.9*0.15) = 3.2.

universities as well as research institutes (Mora-Valentin, Montoro-Sanchez, & Guerras-Martin, 2004). To test the third hypothesis, we measured the project leader's internal knowledge pool size (*Internal knowledge pool size)* by inspecting the number of patents filed by the focal organization as part of projects that were supported by the HFCP (or one of its predecessors)[7]. We were able to identify these patents by examining the 2016 version of the *Pathways to Commercial Success* (PCS) report generated by the Pacific Northwest National Laboratory (PNNL) under contract of the DOE, and released to the public in October 2017 (PNNL, 2017)[8]. This report keeps detailed track of all patents, jobs, and commercial products that are generated resulting from support of the HFCP. It is important to note that only granted USPTO patents are recorded in this report, implying that we capture the size of the internal knowledge pool based on the generation of high-quality technological solutions. To infer when a particular patent was created, we used its priority date, rather than its publication date. To test the fourth hypothesis, we counted the number of concurrent R&D projects in which the project leader is engaged (*R&D project portfolio size)*. Specifically, we measured this variable by counting the number of R&D projects that were evaluated in the current fiscal year in which the focal organization was also involved as a leading entity.

Control variables. We controlled for several relevant project-level characteristics. First, we controlled for the age of the project (*Project age*). Given the learning benefits associated with undertaking problem-solving activities over longer periods of time (Darr *et al.,* 1995), it is expected that projects that have been ongoing for longer periods perform better. To calculate this variable, we subtracted the current year from the year in which the project was initiated (as mentioned on the contract corresponding to the project). We also used a dummy variable to control for whether a project was congressionally directed; that is, if it received funding from a source outside the DOE (C*ongressionally directed project*). The DOE has less influence on funding decisions regarding these projects. Therefore,

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[7] The HFCP was initiated in 2002, with first project evaluations provided in 2003 (i.e. the first year in our database). However, before this, various EERE-funded programs targeted towards improving fuel cell and hydrogen technologies were already undertaken. For example, within the Office of Transportation Technologies, the 'Transportation Fuel Cell Power Systems Program' resulted in several patented inventions which were included in the PCS report.
[8] We also verified this information using previous versions of this report that were released on a yearly basis between 2010 and 2016.

project participants have fewer incentives to actually perform well, since poorer performance will not be greatly reflected in the amount of funding the project receives. It is expected that larger projects perform better, given the higher availability of resources to effectuate problem-solving activities. Therefore, we controlled for the size of the project (*Project size*) by looking at the funds allocated to the project by the DOE, as reported by the project participants during the AMR workshops[9]. This variable was divided by 1,000,000 to improve legibility. We controlled for the cost-share percentage of project participants in the project (*Cost share*). In most projects, contracted organizations are required to use some of their own internal funds to support the project. For example, a project led by the company H2Gen Innovations Inc. on improving a hydrogen generation module (HGM), received DOE funds totaling 3,460,000$, with a contractor share of 1,890,000$ (i.e. 35% of total project funds). This variable is expected to positively influence project performance: the higher the contractors' cost-share, the higher their incentives to perform well, given that their own monetary investments are at stake. We included a control variable that takes a value of 1 when the project was discontinued, relying on data from the AMR evaluation report (*Project discontinued)*. We also controlled for the type of award attached to the project. In the sample, there were two broad types of awards: project grants and cooperative agreements. The main difference between the two types of awards is that, with cooperative agreements, government institutions are more involved in guiding and aiding R&D activities than with project grants. To control for this, we included a dummy variable that takes a value of 1 when the project is a cooperative agreement (*Cooperative agreement*). Some projects in the program were part of a hydrogen storage excellence center. Membership in such an excellence center confers various benefits to project participants, such as improved coordination with other projects within the same center, leading to potentially higher problem-solving performance.

[9] This information was validated using data from the U.S. government (available at www.usaspending.gov). To do this, we searched for all contract numbers that were attached to the projects in the HFCP. In case this information was not reported in the annual progress report (which it often was not), we used the Office of Scientific and Technical Information's (OSTI) SciTech Connect database, AMR workshop presentation slides (available on the DOE hydrogen website), or patents and academic publications that were published on the basis of the projects. Next to validating the size of project funds, it was also necessary to obtain contract numbers for each project in order to determine (i) whether a project was a cooperative agreement, project grant, contract, or government laboratory subcontract, (ii) identify which office (within the DOE) funded the project, (iii) and the starting date of the project.

Therefore, we included a dummy variable that takes a value of 1 when a project was part of such an excellence center (*Excellence center*), using information from the annual progress reports.

We further controlled for two relevant characteristics of the focal organization. To capture the go-alone and go-together experience of the focal organization, we counted the number of times (prior to the current year) that the focal organization had been enlisted as a project leader on a project in which no subcontractors were involved (*Going-alone experience*) and in which at least one subcontractor was involved (*Going-together experience*). We counted every project-year, rather than number of unique projects. The reason was that various projects involved subcontractors during a particular phase, but not prior or subsequent ones; hence, numerous projects were not uniquely organized using a going-together or going-alone strategy.

In all models, we further included dummies for (i) the program section within which the project fell (i.e. Hydrogen Storage; Hydrogen Production and Delivery; Fuel Cells; Systems Analysis; Safety, Codes, and Standards; Market Transformation; Technology Validation; American Recovery and Reinvestment Act; Manufacturing R&D), (ii) years (i.e. 2003-2016), (iii) the state-of-residence of the project leader, to control for geographical factors influencing problem-solving performance, and (iv) the office within the DOE from which funding was provided (i.e. although the majority of project funding comes from Office of Energy Efficiency and Renewable Energy (EERE), small contributions are also made by other offices such as the Office of Fossil Energy, the Office of Nuclear Energy, and the Office of Science).

4.3.3. Analytical method

The unit of analysis in this study is the project-year (e.g. a project that is evaluated three times, represents three separate observations). The full sample includes 1082 project-years spread across 414 unique R&D projects[10]. Despite the fact that the

[10] In our sampling strategy, we excluded challenge-based R&D projects which (i) were not led by a firm or research organization, (ii) fall within the 'education' section of the HFCP and therefore do not involve R&D activities, (iii) had not been ongoing sufficiently long enough to have been evaluated along all relevant dimensions (i.e. certain projects were already evaluated before achieving any substantial technological progress), (iv) only coordinated smaller sub-projects (e.g. EMTEC, through an award by the DOE, coordinated several smaller sub-projects, but did not take part in them), or (v) were supported through a contract or government laboratory subcontract, rather than an award from the DOE.

dependent variable is lower- and upper-bounded (between 1 and 4), we used an OLS regression method in order to test our hypotheses. Most of the values of the dependent variable are not cornered in the lower or upper bound of the data, and are normally distributed around the mean. This reduced the need to employ more complex non-linear regression methods, such as tobit. Moreover, results are easier to interpret using OLS regressions, given the more straightforward interpretation of regression coefficients (Wiersema & Bowen, 2009). To control for non-independence across observations from the same project, we clustered standard errors at the project level.

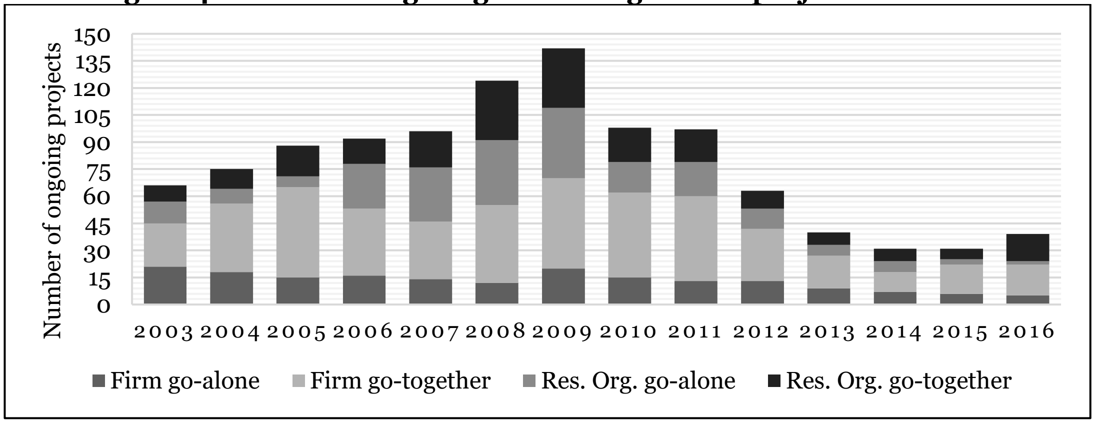
4.3.4. Results

Descriptive statistics. Table 4.1 presents the descriptive statistics and correlation matrix. In our sample, in most project-years (62.66%), the focal organization is going-together. We also observe that going-together is relatively more prevalent amongst firms (71.38% of project-years) compared to research organizations (49.89% of project-years). We plot these trends in Figure 4.1. The dependent variable, problem-solving performance, is normally distributed with a mean of 2.99, a standard deviation of 0.39, a minimum of 1.4, and a maximum of 3.8. The average internal knowledge pool has a size of 3.39. Moreover, in the average project-year, the project leader is involved in 1.71 concurrent R&D projects. Finally, the correlation matrix shows no evidence of multicollinearity. VIF analyses, based on OLS regression, support this, returning average (1.28) and maximum (1.56) values that are far below the advised threshold value of 10 (Mason & Perrault, 1991).

Table 4.1. Descriptive statistics and correlation matrix

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Problem-solving performance	1													
2	Go-together	0.08	1												
3	Research organization	0.10	0.02	1											
4	Internal knowledge pool size	0.21	0.14	0.30	1										
5	R&D project portfolio size	-0.32	0.07	-0.06	-0.05	1									
6	Project age	0.09	0.04	0.06	0.15	-0.09	1								
7	Cost share	-0.35	-0.09	-0.01	-0.05	-0.03	-0.16	1							
8	Project size	0.06	-0.02	-0.12	-0.11	-0.09	0.33	-0.13	1						
9	Project discontinued	0.12	0.35	-0.03	-0.08	0.00	0.09	-0.09	0.08	1					
10	Cooperative agreement	0.13	0.14	0.06	0.04	0.04	-0.05	-0.09	-0.06	0.35	1				
11	Congressionally directed project	-0.17	0.05	-0.27	-0.21	0.05	-0.04	0.16	0.21	0.07	-0.17	1			
12	Excellence center	0.16	0.07	0.15	0.23	-0.02	0.01	-0.08	-0.01	0.31	0.38	-0.21	1		
13	Go-alone experience	0.08	0.01	0.01	-0.02	-0.06	0.10	-0.04	-0.01	0.26	0.27	-0.11	0.28	1	
14	Go-together experience	0.07	-0.14	0.09	0.15	0.05	-0.09	0.01	-0.33	-0.22	0.19	-0.22	0.09	-0.02	1
	Mean	2.99	0.63	0.41	3.39	1.71	2.65	0.26	3.44	0.07	0.52	0.10	0.13	1.73	3.29
	SD	0.39	0.48	0.49	7.63	1.14	1.57	0.14	6.48	0.25	0.50	0.30	0.33	2.93	4.92
	Min	1.40	0	0	0	1	0	0	0.07	0	0	0	0	0	0
	Max	3.80	1	1	45	8	10	0.76	44.4	1	1	1	1	16	28

Figure 4.1. Number of go-together and go-alone projects over time



Regression results. In Table 4.2 we present the regression results. Projects that receive more funding tend to perform better (Model 1: $\beta_{\text{Project size}}$ = 0.009, $p < 0.001$). Moreover, projects that were subsequently discontinued tend to perform worse (Model 1: $\beta_{\text{Project discontinued}}$ = -0.445, $p < 0.001$). Congressionally-directed projects also tend to perform worse (Model 1: $\beta_{\text{Congressionally directed project}}$ = 0.401, $p < 0.001$). In line with our expectations, being part of an excellence center leads to higher problem-solving performance (Model 1: $\beta_{\text{Excellence center}}$ = 0.163, $p < 0.01$). The going-together experience of the focal organization has a negative influence on problem-solving performance (Model 1: $\beta_{\text{Go-together experience}}$ = -0.008, $p < 0.05$), while going-alone experience does not statistically significantly influence problem-solving performance. Notably, the project leader's internal knowledge pool size has a positive but only marginally statistically significant influence on problem-solving performance (Model 1: $\beta_{\text{Internal knowledge pool size}}$ = 0.004, $p < 0.1$).

In Model 2, we test Hypothesis 1. We find that going-together has a positive and marginally statistically significant influence on problem-solving performance (Model 2: $\beta_{\text{Go-together}}$ = 0.055, $p < 0.1$), supporting Hypothesis 1. Moreover, testing Hypothesis 2, we find a marginally statistically significant and negative interaction between going-together and research organization-led projects (Model 3: $\beta_{\text{Go-together} \times \text{Research organization}}$ = -0.103, $p < 0.1$). However, since the coefficient for the interaction only tells us that the overall interaction effect is statistically significant, we also computed partial effects and found that (i) firms that go-together have significantly higher problem-solving performance than firms that go-alone ($\frac{dy}{dx}$ = 0.099, $p<0.01$) and (ii) research organizations that go-together do not have statistically higher or lower problem-solving performance than research organizations that go-alone (see Figure 4.2).

For Hypothesis 3, we find a positive and statistically significant interaction between going-together and the focal organization's internal knowledge pool size (Model 4: $\beta_{\text{Go-together} \times \text{Internal knowledge pool size}}$ = 0.008, $p < 0.05$) (see Figure 4.3). To properly test Hypothesis 3, we test the difference in problem-solving performance between going-together and going-alone for different values of the focal organization's internal knowledge pool size (i.e. the difference between the dashed and solid line in Figure 4.3). We find that within a reasonable range ([4,45]) of values of internal knowledge pool size (i.e. 21.5% of the sample), the difference between going-together and going-alone is positive and statistically significant ($p < 0.05$), supporting Hypothesis 3.

Finally, we find a statistically non-significant interaction between the focal organization's R&D project portfolio size and going-together for Hypothesis 4. However, when testing whether this relationship is instead driven by curvilinear effects in model 7, we indeed find a statistically significant interaction (Model 7: $\beta_{\text{Go-together} \times \text{R\&D project portfolio size}} = 0.136$, $p < 0.05$; $\beta_{\text{Go-together} \times \text{R\&D project portfolio size squared}} = -0.022$, $p < 0.01$). This relationship is plotted in Figure 4.4. Subsequently, we computed partial effects to test the difference in problem-solving performance between going-together and going-alone at different values of R&D project portfolio size: (i) when the focal organization is engaged in one project, there is no statistical difference in problem-solving performance between going-together and going-alone, (ii) when the focal organization has 2 or 3 concurrent projects, there is a positive and statistically significant difference in problem-solving performance between going-together and going-alone ($p < 0.05$), (iii) when the focal organization has 4-7 concurrent projects, there is no statistically significant difference in problem-solving performance between going-together and going-alone, and (iv) when the focal organization has 8 projects, going-together performs statistically significantly worse than going-alone ($p < 0.05$). Thus, we find that (i) there seem to be benefits associated with a larger R&D project portfolio and (ii) there are indeed liabilities associated with a larger R&D project portfolio, but these only emerge when the R&D project portfolio is very large. Hence, we find partial support for Hypothesis 4.

Figure 4.2. Firm and research organization go-together performance

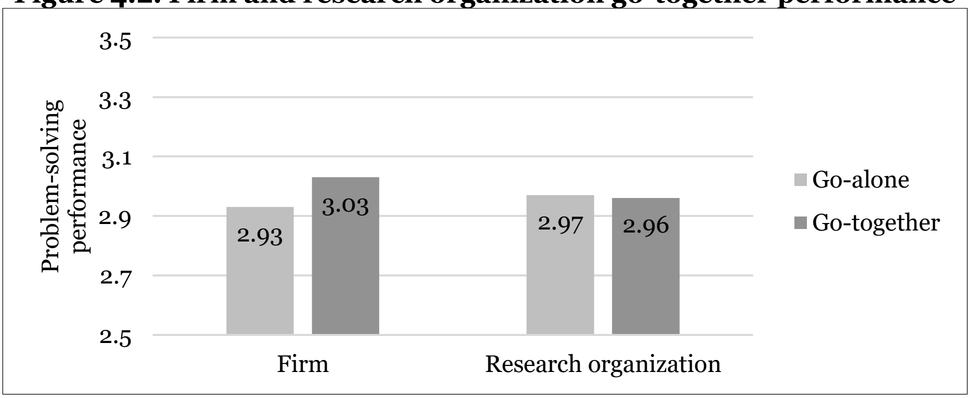


Figure 4.3. Interaction go-together and internal knowledge pool size

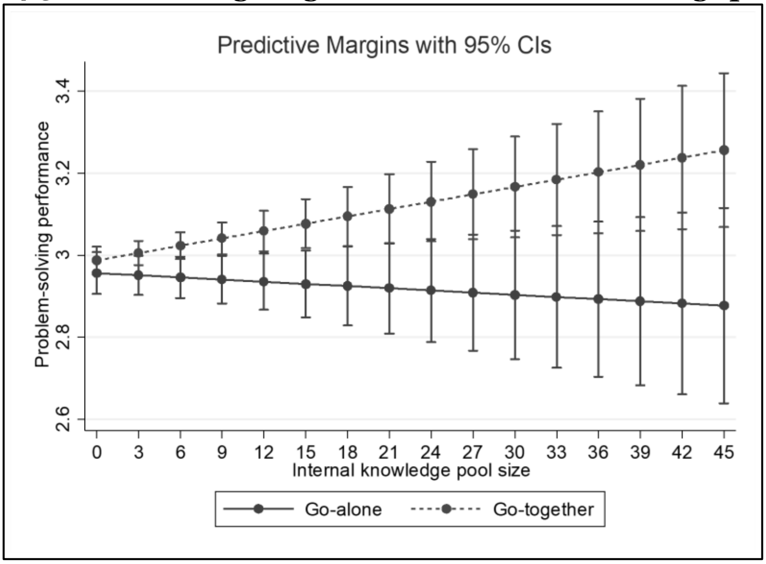


Figure 4.4. Interaction go-together and R&D project portfolio size

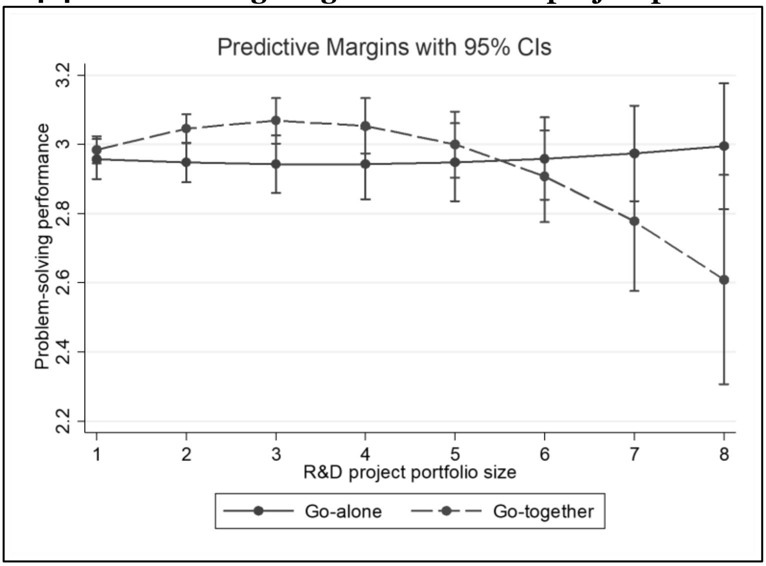


Table 4.2. Pooled OLS regression results

DV: Problem-solving performance	1	2	3	4	5	6	7	8
Project age	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Cost share	0.09	0.09	0.08	0.09	0.09	0.09	0.08	0.06
	[0.13]	[0.13]	[0.13]	[0.13]	[0.13]	[0.12]	[0.13]	[0.12]
Project size	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***	0.01***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Project discontinued	-0.45***	-0.45***	-0.44***	-0.44***	-0.45***	-0.44***	-0.43***	-0.43***
	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]
Cooperative agreement	0.01	0.01	0.01	-0.00	0.01	0.01	0.01	0.00
	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]	[0.04]
Congressionally directed project	-0.40***	-0.40***	-0.39***	-0.40***	-0.40***	-0.40***	-0.40***	-0.40***
	[0.06]	[0.06]	[0.06]	[0.06]	[0.06]	[0.06]	[0.06]	[0.06]
Excellence center	0.16**	0.19**	0.18**	0.20**	0.18**	0.18**	0.18**	0.19**
	[0.06]	[0.06]	[0.06]	[0.06]	[0.06]	[0.06]	[0.06]	[0.06]
Go-alone experience	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Go-together experience	-0.01*	-0.01*	-0.01*	-0.01*	-0.01*	-0.01**	-0.01**	-0.01**
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Research organization	-0.03	-0.02	0.03	-0.03	-0.02	-0.03	-0.03	0.02
	[0.04]	[0.04]	[0.06]	[0.04]	[0.04]	[0.04]	[0.04]	[0.06]
Internal knowledge pool size	0.00†	0.00†	0.00	-0.00	0.00†	0.00†	0.00†	-0.00
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
R&D project portfolio size	0.00	0.00	0.00	0.01	0.00	0.06	-0.02	0.00
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.04]	[0.04]	[0.05]
Go-together		0.06†	0.10**	0.03	0.05	0.06	-0.09	-0.03
		[0.03]	[0.04]	[0.03]	[0.05]	[0.05]	[0.08]	[0.08]
Go-together × Research organization			-0.10†					-0.10
			[0.06]					[0.06]
Go-together × Internal knowledge pool size				0.01*				0.01†
				[0.00]				[0.00]
Go-together × R&D project portfolio size					0.00	-0.00	0.14*	0.11†
					[0.02]	[0.02]	[0.06]	[0.06]
R&D project portfolio size squared						-0.01	0.00	0.00
						[0.00]	[0.01]	[0.01]
Go-together × R&D project portfolio size squared							-0.02**	-0.02*
							[0.01]	[0.01]
Fiscal year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-of-residence dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HFCP section dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DOE office dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1082	1082	1082	1082	1082	1082	1082	1082
R^2	0.42	0.43	0.43	0.43	0.43	0.43	0.43	0.44
Adjusted R^2	0.38	0.38	0.38	0.38	0.38	0.38	0.39	0.39

† $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. Standard errors clustered at project-level between brackets.

Robustness checks. We conduct several robustness checks in order to verify the stability of our findings. First, we reestimate our models using tobit regressions, and find highly stable results. Second, in Table 4.3, we split the sample up into (i) a group which only contains firm-led R&D projects, (ii) a group which only contains research organization-led R&D projects, (iii) a group which only contains R&D projects in which the focal organization is going-alone, and (iv) a group which only contains R&D projects in which the focal organization is going-together. Across all subsamples, we find results that confirm our main results. Third, we exclude projects in which the focal organization is a research institute, focusing solely on the difference in problem-solving performance between universities and firms. Results remain very similar. Fourth, we rerun the analyses including challenge-based projects that (i) fall within the 'education' section of the HFCP, (ii) are supported via a contract or a government laboratory subcontract, (iii) have not been ongoing long enough to be evaluated along all performance dimensions, and (iv) coordinated smaller sub-projects (see footnote 10), leaving the main results largely unchanged. Fifth, winsorizing at the 1st and 99th percentile the dependent variable and the independent variables capturing the focal organization's internal knowledge pool size and R&D project portfolio size, result remain stable.

Table 4.3. Subsample robustness checks

	Firm		Res. org.		Go-alone					Go-together				
DV: Problem-solving performance	9	10	11	12	13	14	15	16	17	18	19	20	21	22
Project age	0.00	0.01	0.01	0.01	-0.00	-0.01	-0.01	-0.01	-0.01	-0.00	0.00	0.00	0.00	0.01
	[0.01]	[0.01]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Cost share	0.14	0.15	-0.25	-0.24	0.08	0.16	0.17	0.17	0.17	0.33*	0.19	0.21	0.21	0.17
	[0.15]	[0.15]	[0.38]	[0.38]	[0.21]	[0.21]	[0.21]	[0.21]	[0.21]	[0.16]	[0.16]	[0.15]	[0.15]	[0.15]
Project size	0.01***	0.01***	0.02	0.02	0.01	0.01	0.01†	0.01†	0.01†	0.01***	0.01***	0.01*	0.01*	0.01*
	[0.00]	[0.00]	[0.02]	[0.02]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Project discontinued	-0.42***	-0.41***	-0.49***	-0.49***	-0.61***	-0.61***	-0.61***	-0.61***	-0.61***	-0.39***	-0.39***	-0.37***	-0.37***	-0.36***
	[0.07]	[0.07]	[0.05]	[0.05]	[0.07]	[0.07]	[0.07]	[0.07]	[0.07]	[0.05]	[0.06]	[0.05]	[0.05]	[0.05]
Cooperative agreement	0.04	0.03	-0.03	-0.03	0.03	0.03	0.02	0.02	0.02	-0.03	-0.03	-0.03	-0.03	-0.04
	[0.05]	[0.05]	[0.08]	[0.08]	[0.07]	[0.07]	[0.08]	[0.08]	[0.08]	[0.05]	[0.05]	[0.05]	[0.05]	[0.05]
Congressionally directed project	-0.34***	-0.33***	-0.47***	-0.47***	-0.53***	-0.53***	-0.53***	-0.54***	-0.54***	-0.38***	-0.37***	-0.37***	-0.37***	-0.38***
	[0.10]	[0.09]	[0.10]	[0.10]	[0.13]	[0.13]	[0.13]	[0.13]	[0.13]	[0.08]	[0.07]	[0.07]	[0.07]	[0.07]
Excellence center	0.09	0.13	0.15	0.15	0.03	0.02	0.03	0.03	0.03	0.29***	0.30***	0.29***	0.29***	0.29***
	[0.08]	[0.08]	[0.10]	[0.10]	[0.08]	[0.08]	[0.09]	[0.09]	[0.09]	[0.08]	[0.08]	[0.08]	[0.08]	[0.08]
Go-alone experience	0.01	0.01	-0.01	-0.01	-0.00	-0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00
	[0.01]	[0.01]	[0.02]	[0.02]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Go-together experience	-0.01*	-0.01*	-0.02†	-0.02†	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01†	-0.01*	-0.01*	-0.01**
	[0.00]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Go-together		0.10**		-0.02										
		[0.04]		[0.06]										
Research organization						0.09	0.09	0.09	0.09		-0.13**	-0.11*	-0.11*	-0.13**
						[0.08]	[0.08]	[0.08]	[0.08]		[0.04]	[0.04]	[0.04]	[0.04]
Internal knowledge pool size	0.00	0.00	0.01	0.01			-0.00	-0.00	-0.00			0.01**	0.01**	0.01**
	[0.00]	[0.00]	[0.01]	[0.01]			[0.00]	[0.00]	[0.00]			[0.00]	[0.00]	[0.00]
R&D project portfolio size	0.00	0.00	-0.00	-0.00				-0.00	0.00				-0.00	0.11*
	[0.01]	[0.01]	[0.04]	[0.04]				[0.02]	[0.05]				[0.02]	[0.05]
R&D project portfolio size squared									-0.00					-0.02**
									[0.01]					[0.01]
Fiscal year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-of-residence dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HFCP section dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DOE office dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	643	643	439	439	404	404	404	404	404	678	678	678	678	678
R^2	0.42	0.43	0.50	0.50	0.51	0.51	0.51	0.51	0.51	0.45	0.46	0.47	0.47	0.48
Adjusted R^2	0.35	0.36	0.41	0.41	0.42	0.42	0.42	0.42	0.42	0.38	0.39	0.41	0.40	0.41

† p < .10, * p < .05, ** p < .01, *** p < .001. Standard errors clustered at project-level between brackets.

4.4. Discussion and conclusion

Using data regarding 414 challenge-based R&D projects over a 14-year time-period (2003-2016), we examined the difference in problem-solving performance between going-together and going-alone. The findings indicate that (i) there is a marginally significant positive effect of going-together on problem-solving performance, (ii) there is a positive problem-solving performance gap between going-together and going-alone for firms but not for research organizations, (iii) the larger the focal organizations' internal knowledge pool, the larger the positive problem-solving performance gap between going-together and going-alone, and (iv) the focal organization's R&D project portfolio size initially increases the positive problem-solving performance gap between going-together and going-alone but, beyond a certain point, decreases it. These findings have important theoretical and practical contributions, which we discuss in the next section.

4.4.1. Theoretical implications for grand challenges literature

In this study, we deviated from prior grand challenges and open innovation studies, by relaxing the implicit assumption that going-together always outperforms going-alone in terms of generating high-quality solutions. We argued that not every organization is able to reap the unique knowledge recombination benefits of going-together to the same extent, since this problem-solving approach requires abilities to identify, retrieve and recombine component knowledge across organizational boundaries. Based on this, we argued that there are three characteristics of the focal organization that influence these abilities.

Focal organization's institutional background. We expected that, for research organizations, owing to their institutional mission of creating and diffusing new technological knowledge, the positive performance gap between going-together and going-alone would be larger than for firms. However, these expectations were not confirmed: we, instead, found strong evidence that firms are better able to reap the relative benefits of going-together compared to going-alone than research organizations. Perhaps this unexpected finding can be explained by the fact that firms are actually better at managing interorganizational partnerships than research organizations. Specifically, firms tend to govern and coordinate activities through active and frequent monitoring (Williamson, 1991), so as to ensure that their short-term goals can be met and that no delays are incurred (Cyert & Goodman, 1997). As such, it is likely that firms, as leading entities, regularly check up on partners to verify that they are doing what they are supposed to do within the framework of the project (Das, 2005). This implies that, when they go-together, firms will pay considerable attention to whether the partners' problem-solving activities are conducive to achieving the intended technological objectives, typically improving overall problem-solving performance (e.g. Sampson, 2007). In contrast, since research organizations tend to emphasize collegiality and democracy in governing activities (Manning, 2013), they might generally take a more laissez-faire attitude towards the problem-solving activities of external partners, being less attentive to whether they actually contribute to achieving the project's technological goals. This will, in turn, reduce the focal organization's ability to benefit substantially from going-together relative to going-alone.

This study contributes to the literature on challenge-based R&D project and open innovation in two ways. First, we contribute to these literatures by emphasizing the importance of partner management capabilities (Ireland, Hitt, & Vaidyanath, 2002; Majchrzak, Jarvenpaa, & Bagherzadeh, 2015). Our findings suggest that, despite the overall openness of research organizations towards external knowledge (Trajtenberg *et al.,* 1997), it is also pertinent that they, as leading entities, have the ability to manage interorganizational partnerships effectively. Otherwise, as our findings suggest, the collaborative knowledge recombination benefits of going-together will not be reaped. In contrast, our findings show a rather large difference in problem-solving performance between firms that go-together and those that go-alone. These findings suggest that firms have an advantage as leading entities in collaborative challenge-based R&D projects, possibly due to their superior ability to manage partners effectively, monitoring their activities and aligning them towards a common technological objective (Das, 2005). Second, we contribute to these literature streams by showing that there are important differences in problem-solving performance patterns between firms and research organizations. In particular, extant literature has principally focused on the firm as the focal actor, neglecting the important role of research organizations in engendering technological change. This is surprising, given the sheer number of challenge-based R&D projects that are undertaken by research organizations (i.e. 40% of project-years in our sample). Our findings show that this distinction is highly relevant, as the two types of organizations seem to engage in problem-solving activities rather differently. We therefore encourage future studies to consider the dichotomy between firms and research organizations more extensively in their conceptual and empirical framework.

The benefits of a large internal knowledge pool. As predicted, we found strong evidence to suggest that, the larger the focal organization's internal knowledge pool, the better its ability to translate potential into realized knowledge recombination opportunities when going-together (Zahra & George, 2002). This reflects an experience effect – i.e. organizations with larger internal knowledge pools have more experience identifying valuable component knowledge for recombination (Cohen & Levinthal, 1990) – and a retrieval effect – i.e. organizations with larger internal knowledge pools can more easily communicate with external partners, transferring component knowledge across organizational boundaries (Lane & Lubatkin, 1998; Mowery *et al.,* 1996; Sampson, 2007).

At the same time, we note that, in our sample, going-together only outperforms going-alone, in terms of problem-solving performance, when the focal organization has previously generated more than three unique high-quality solutions. This suggests that there are some boundary conditions to benefiting from prior technological experience (Argote & Miron-Spektor, 2011; Garud & Nayyar, 1994; Hargadon & Sutton, 1997). Recently, this discussion has reemerged, with studies questioning the benefits of prior technological experience (e.g. Anand, Mulotte, & Ren, 2016), especially in the context of knowledge recombination (e.g. Ghosh *et al.,* 2014). Contributing to this ongoing discussion, our findings suggest that organizations need to 'learn to learn' (Levinthal & March, 1993), pinpointing how the generation of new technological solutions can be leveraged as an asset to improve subsequent problem-solving activities. Thus, to optimally reap the benefits of a going-together problem-solving approach, it is pertinent that focal organizations have considerable experience generating high-quality solutions. In this way, extant technological problems can most adequately be addressed.

Benefits and liabilities of large R&D project portfolios. We expected that the positive performance gap between going-together and going-alone would decrease when the focal organization's R&D project portfolio becomes larger, as this would diminish the availability of non-scale free R&D resources required to benefit from going-together at the project-level (Levinthal & Wu, 2010). However, instead of these hypothesized liabilities, we found that there are initially benefits associated with a larger R&D project portfolio, in terms of increasing the problem-solving performance gap between going-together and going-alone. One explanation for this is that concurrent challenge-based R&D projects present alternative sources of information which can be tapped into in order to validate information or resolve uncertainties in other projects (Hargadon & Sutton, 1997; Henderson & Cockburn, 1996). When the challenge-based R&D project portfolio is larger, information pertaining to external components can be cross-validated with individuals involved in other projects, substantially alleviating ambiguities regarding the use of these components in new recombination efforts. In a way, therefore, concurrent challenge-based R&D projects can augment the absorptive capacity of the focal organization, allowing it to benefit more fully from going-together at the project-level. We do note, however, that when the R&D project portfolio is very large, resource constraints that hamper the realization of collaborative knowledge recombination opportunities do seem to emerge, substantially reducing the problem-solving performance gap between going-together and going-alone.

These findings suggest that the performance of single projects may be highly interlinked with that of other projects within the same organization. Hence, the focal organization should carefully consider how newly-engaged challenge-based R&D projects fit within the existing portfolio of projects, such that resource constraints are minimally experienced, and cross-validation benefits are maximally present. To achieve this, our findings suggest that focal organizations should have an intermediate number of concurrent challenge-based R&D projects, in line with what prior studies have found regarding the optimal size of alliance portfolios (Deeds & Hill, 1996; Wassmer, 2010).

4.4.2. Practical implications

Our findings have important policy implications for the configuration of challenge-based R&D projects for solving grand societal challenges. Whereas organizations are often encouraged to organize these challenge-based R&D projects in a collaborative way (Estrada, Faems, Cruz, & Santana, 2016; Olsen *et al.,* 2016), we find evidence to suggest that this is not necessarily conducive to higher problem-solving performance. In particular, although going-together increases the potential for valuable knowledge recombination, not every organization has the ability to fully realize these potential opportunities. Hence, we encourage policy-makers to more carefully design grand challenges programs, such that focal organizations that engage in challenge-based R&D projects employ problem-solving approaches which they are most befit to carry out (e.g. firms, per our findings, should preferably go-together rather than go-alone).

4.4.3. Limitations and future research

This study has several limitations which can serve as interesting starting points for future research. First, we used data on government-supported challenge-based R&D projects in order to examine the performance implications of going-alone and going-together. This setting was ideal for testing our hypotheses, as organizations can opt to go-alone or go-together within comparable R&D projects. Moreover, the distribution of go-alone and go-together projects was very equal in our sample. However, given the specificities of this setting, in terms of the types of problems to be solved, it is necessary that future research replicates our findings in other settings.

Second, we focused solely on the performance implications of going-together and going-alone, but we did not consider the antecedents for choosing either approach to organize challenge-based R&D projects (since this would fall outside the scope of this study). Future research should explore this topic, examining whether certain types of focal organizations are more inclined to opt for a go-together approach, or whether this is dependent on other factors, such as the availability of partners in geographical proximity (Phene & Tallman, 2014).

Chapter 5. General Discussion

The focal objective of this dissertation was to deepen our understanding of the concept of knowledge recombination. To this end, we conducted three empirical projects (chapter 2-4) in the fuel cell industry, addressing important research gaps in knowledge recombination literature. In this chapter, we first provide a short overview of the findings that emerged from the three projects. Second, we discuss our contributions to the initial research objective of this dissertation. Third, we provide a thought-provoking discussion of how our findings contribute to extant practice, paying special attention to open innovation and resource management strategies. Fourth, reflecting upon the empirical design of the three projects, we discuss the empirical contributions of this dissertation. Finally, we conclude with developing an agenda for future research on knowledge recombination.

5.1. Overview of findings

In chapter 2, we explored the influence of recombinant lag – i.e. the time that recombined components have remained unused – on the technological value of inventions. Our findings indicate that the relationship between recombinant lag and the technological value of inventions is more complex than initially anticipated. Across the two industries that we examined (i.e. fuel cell and wind energy), we found that recombinant lag has an unexpected U-shaped relationship with the technological value of inventions, signifying that low and high recombinant lag can both be associated with higher technological value. Moreover, with regards to the moderation effect of frequency of reuse on this main relationship, we found some interesting differences between the two industries. Whereas in fuel cells the U-shaped relationship between recombinant lag and the technological value of inventions mainly emerges when prior frequency of reuse is limited, in wind energy the moderation effect was not robust.

In chapter 3, we studied the impact of knowledge pool applicability – i.e. the extent to which components in the knowledge pool can be used in different application domains – on the focal firm's partner-specific recombination within R&D alliance dyads. Holding constant the partner's knowledge pool size, diversity, and distance, we found robust evidence that the partner's knowledge pool applicability has the expected inverted U-shaped relationship with the focal firm's partner-specific recombination. Unexpectedly, however, instead of a positive and linear relationship, a robust U-shaped relationship emerged between the focal firm's knowledge pool applicability and its partner-specific recombination.

In chapter 4, we studied the relative problem-solving performance benefits of going-together compared to going-alone in challenge-based R&D projects. In this chapter, we argued that not every organization is able to fully reap the knowledge recombination benefits of going-together. For our baseline hypothesis, we found evidence that going-together, on average, yields higher problem-solving performance than going-alone. At the same time, we found that there are certain characteristics of the focal organization that substantially influence the size of this positive problem-solving performance gap. First, in contrast to our expectations, we found that the problem-solving performance of firms is higher when going-together compared to going-alone, whereas this difference was not statistically significant for research organizations. Second, the findings indicated that the positive problem-solving performance gap between going-together and going-alone is larger for focal organizations with a greater internal knowledge pool. Finally, we unexpectedly found that a challenge-based R&D project portfolio of intermediate size is most conducive to a large positive problem-solving performance gap between going-together and going-alone.

5.2. Contributions to initial research objective

In this dissertation, our primary objective was to generate new insights into core aspects of knowledge recombination. To this end, we conducted three projects in which we ventured well beyond the traditional scope of knowledge recombination studies, generating insights that challenge many previously-held assumptions about knowledge recombination. In the following section, we provide an elaborate discussion of how this dissertation contributes to an improved understanding of knowledge recombination by generating new insights into (i) path-dependent effects that determine components' contemporary recombinant value, (ii) the applicability of components in the knowledge pool, and (iii) combinative capabilities in interorganizational collaboration settings.

5.2.1. Path-dependent knowledge reuse trajectories

A large body of research on knowledge recombination is concerned with identifying the origins of valuable inventions (Capaldo *et al.,* 2017; Kelley *et al.,* 2013; Schoenmakers & Duysters, 2010). This research principally focuses on the original attributes of components (e.g. Phene *et al.,* 2006; Miller *et al.,* 2007; Rosenkopf & Nerkar, 2001) – i.e. attributes that are embedded into components at the time of creation. As such, they adopt a theoretical perspective in which it is implicitly assumed that the recombinant value of knowledge components is largely pre-determined at creation. In contrast to this theoretical perspective, several recent studies have argued that a component's recombinant value is not necessarily pre-determined at creation, but may actually change considerably over time. These changes, they argue, principally occur via component reuse (Belenzon, 2012; Katila & Chen, 2008; Yang *et al.,* 2010). In particular, each time a component is reused, new reuse information flows are produced which inventors can access in order to improve the subsequent recombination of this component (Katila & Chen, 2008). Therefore, a component's current recombinant value is largely a function of how it has been reused in prior knowledge recombination efforts (Yayavaram & Ahuja, 2008). In other words, there are strong path-dependent effects in knowledge recombination that determine the contemporary recombinant value of components.

Our findings in chapter 2 underline the impact of these path-dependent component reuse effects. In this chapter, we deviated from prior research, which has principally examined the frequency of reuse (i.e. the magnitude of reuse information flows), by pointing to the timing of reuse – i.e. when was a component reused during its knowledge reuse trajectory – as a crucial determinant of a component's current recombinant value. Grounded in the notion that components are recombined in different ways over time (Dosi, 1982), we developed novel theoretical arguments suggesting that precisely when an instance of reuse occurs may largely influence the contents of generated reuse information flows. Relying on organizational learning theory (e.g. Argon & Miron-Spektor, 2011), we argued that, when a component was recently reused, its recombinant potential may be rejuvenated. That is, recent reuse allows inventors to access information about how components should be contemporarily applied in knowledge recombination, resulting in inventions that fit extant technological standards. In support of this argument, our empirical tests across two industries (i.e. fuel cell and wind energy) showed that low recombinant lag (i.e. recent reuse) is associated with the creation of valuable inventions,

In addition to this rejuvenation effect, we unexpectedly found that recombining components that were last reused a long time ago (i.e. high recombinant lag) may result in inventions with considerable technological value. Performing an extensive post-hoc exploratory analysis, we explained this alternative finding by arguing that reuse information flows attached to temporally distant instances of reuse may contain information about the component that was simply too far ahead of its time (Garud & Nayyar, 1994), subsequently becoming 'frozen' for prolonged periods. Decades later, however, during the emergence of a new technological cycle within an industry (Tushman & Anderson, 1986), inventors may be able to 'defrost' these reuse information flows, attach new meanings to them (Sonenshein, 2014), and subsequently leverage them to generate inventions with considerable technological value.

In sum, we emphasize that, in order to obtain a fuller understanding of a component's current recombinant value, it is not sufficient to only consider the attributes that are embedded into the component at creation. Instead, our findings in chapter 2 point out that the current recombinant value of a component is, to a large extent, determined by the path-dependent knowledge reuse trajectory through which it travelled from inception until the present. More specifically, we contribute to extant literature by emphasizing that even when two components were created at the same time, they may go through considerably different knowledge reuse trajectories over time, where not only the number of times they were reused (i.e. frequency of reuse) matters, but also the time that they have remained unused (i.e. recombinant lag). We therefore encourage future studies on knowledge recombination to account for the temporal dimension of component reuse, integrating recombinant lag into their conceptual and empirical framework.

5.2.2. Applicability of components in the knowledge pool

R&D scholars extensively examine the relation between partners' knowledge pool characteristics and the focal firm's internal knowledge recombination activities (e.g. Nooteboom *et al.,* 2007; Sampson, 2007; Phelps, 2010). Both conceptually and empirically, these studies tend to focus on aggregate characteristics of the partner's knowledge pool, such as its diversity or size. Hence, these studies analyze partners' knowledge pool holistically, rather than to isolate individual components that constitute the knowledge pool. Adopting this research approach, numerous alliance studies (e.g. Schilling & Phelps, 2007; Phelps, 2010; Wuyts & Dutta, 2014) assume that components situated within large and highly technologically diverse knowledge pools are more broadly applicable, creating various opportunities to generate new combinations (Ahuja & Katila, 2001; Fleming, 2002). However, findings have been rather inconsistent in this research area: whereas some studies detect a strictly positive influence of partners' technological diversity on the focal firm's knowledge recombination activities (e.g. Phelps, 2010; Subramanian & Soh, 2017), others find inverted U-shaped (e.g. Vasudeva & Anand, 2011) and U-shaped effects (e.g. Wuyts & Dutta, 2014). It therefore seems that our understanding of the knowledge recombination implications of component applicability within R&D alliances is currently incomplete.

In chapter 3, we made important progress towards resolving these extant inconsistencies. In particular, relying on recent knowledge recombination insights (e.g. Dibiaggio *et al.,* 2014; Wang *et al.,* 2014), we argued that individual components that constitute the knowledge pool may actually differ substantially in terms of applicability. In this chapter, we therefore shifted the theoretical lens from aggregate knowledge pool characteristics to individual components within the knowledge pool. More specifically, we focused on the knowledge pool applicability of R&D alliance partners – i.e. the extent to which individual components situated in the knowledge pool can be used in different application domains of a technological field. From the focal firm's perspective, we developed novel theoretical arguments regarding the knowledge recombination benefits and liabilities of collaborating with partners with higher knowledge pool applicability. We theorized an inverted U-shaped relationship between the partner's knowledge pool applicability and the focal firm's intensity of partner-specific recombination.

Here, the upward slope of the relationship is driven by the additional flexibility that the focal firm gain in terms of where and how it may apply components accessed from partners in knowledge recombination (Dibiaggio *et al.,* 2014; Wang *et al.,* 2014; Yayavaram & Ahuja, 2008), and the downward part of the slope mainly arises from learning complexities associated with overly-applicable component knowledge (Fleming & Sorenson, 2001; Hargadon & Sutton, 1997). In our empirical analyses, holding constant the size and diversity of the partner's knowledge pool, we found strong support for this hypothesis: a robust inverted U-shaped relationship between the partner's knowledge pool applicability and the focal firm's intensity of partner-specific knowledge recombination consistently emerged.

Taken together, chapter 3 demonstrates the importance of accounting for variance in the applicability of individual components within the knowledge pool of R&D alliance partners. Different from extant alliance research, which infers components' level of applicability from the size and technological diversity of partners' entire knowledge pool (e.g. Lahiri & Narayanan, 2013; Phelps, 2010; Schilling & Phelps, 2007), we make a strong case for digging deeper into partners' knowledge pool, examining whether individual components are, in fact, broadly applicable or not. Adopting a similar research approach, future research may be able to resolve important inconsistencies regarding the relationship between partners' knowledge pool diversity and the focal firm's internal knowledge recombination activities. Besides this, on a more general note, our study showed the value of adopting state-of-the-art knowledge recombination insights when examining the inventive benefits of R&D alliances, a research approach which is only rarely used in extant alliance research.

5.2.3. Combinative capabilities in interorganizational collaboration

Knowledge recombination studies often implicitly assume that components, to which the focal organization gains access via interorganizational collaboration, are directly connected to its inventive output. At the same time, it has been shown that, even when two organizations have access to the same set of components, there is typically much variation in terms of the quantity and quality of new combinations that they produce (Dibiaggio *et al.,* 2014; Yayavaram & Ahuja, 2008). These variations in inventive output arise from organizations' idiosyncratic abilities to identify valuable component knowledge in partners' knowledge pool, retrieve it by developing a solid understanding of its recombination characteristics, and subsequently use it in new recombination efforts to create new inventions (Fleming & Sorenson, 2001; Zahra & George, 2002). In this dissertation, we developed important new insights about these combinative capabilities (Kogut & Zander, 1992), examining how organizations leverage them in order to enhance the inventive benefits of interorganizational collaboration.

In chapter 3, we argued that focal firms with higher knowledge pool applicability, having prior experience creating component knowledge with broad applicability, can more intensively recombine the partner's components in R&D alliances. We argued that this experience can help firms overcome two barriers commonly blocking the recombination of alliance partners' component knowledge: (i) perceived exhaustion of recombinant potential and (ii) the pursuit of ultimately fruitless recombination opportunities. Tackling the former barrier, we argued that focal firms with higher knowledge pool applicability have, in general, a better understanding of how components can be recombined in different ways (Boh *et al.,* 2014). As such, these types of firms are able to elevate the recombinant potential of components in the partner's knowledge pool, envisioning a greater number of ways in which these components can be used in knowledge recombination (Boh *et al.,* 2014; Fleming, 2002; Henderson, 1995; Yang *et al.,* 2010). Moreover, tackling the latter barrier, we argued that experience with building widely-applicable component knowledge provides the focal firm with a better understanding of where the recombinant limits of components lie (Henderson, 1995; Yang *et al.,* 2010). Hence, while pursuing recombination opportunities in the partner's knowledge pool, these focal firms are able to quickly locate valuable components that provide opportunities to generate new combinations and not waste time on components which are "technological dead-ends" (Podolny & Stuart, 1995: 1225), bypassing time-costly trial-and-error activities in the process (Fleming, 2001; Katila & Ahuja, 2002). In line with these theoretical arguments, our findings showed that, beyond a certain threshold value, the focal firm's knowledge pool applicability is indeed positively associated with its intensity of partner-specific recombination.

In chapter 4, we further probed the usefulness of combinative capabilities, and compared the problem-solving performance of focal organizations that go-together or go-alone in challenge-based R&D projects. Prior studies on challenge-based R&D projects, following the open innovation paradigm (Chesbrough, 2006), often implicitly assume that going-together always outperforms going-alone in terms of generating high-quality technological solutions (e.g. Olsen *et al.,* 2016). These studies argue that, by going-together, focal organizations gain access to a potentially larger and more diverse set of components, allowing to create higher quality technological solutions (Das & Teng, 2000; Olsen *et al.,* 2016). In chapter 4, however, we pointed out that the extent to which these potential recombination opportunities can actually be realized depends on the ability of the focal organization to identify, retrieve, and recombine partners' components (Wuyts & Dutta, 2014; Zahra & George, 2002). Our findings strongly support this contention, and cast significant doubts over the purported advantages of going-together strategies to address extant societal challenges, indicating that, for many focal organizations, going-alone strategies often perform equally well in terms of problem-solving performance.

Jointly, in this dissertation we enriched our understanding of the value of combinative capabilities in interorganizational collaboration settings. We emphasized that, rather than to assume a direct connection between potential knowledge inputs accessed from partners and the focal organization's own inventive outputs, it is important to take into account that not all organizations are equally capable of leveraging the available set of components for knowledge recombination (Wuyts & Dutta, 2014; Zahra & George, 2002). In chapter 3, we conceptually focused on two known impediments to knowledge recombination, developing new theoretical arguments about how focal firms may develop abilities to successfully recombine the component knowledge of R&D alliance partners. In chapter 4, we found that strong combinative capabilities play a crucial role in translating potential into realized knowledge recombination opportunities when going-together in challenge-based R&D projects. The findings from chapter 4 are striking, as they imply that interorganizational collaboration, at least within the scope of challenge-based R&D projects, may not be a worthwhile strategy to pursue for focal organizations lacking the right combinative capabilities. For these types of focal organizations (most notably, research organizations and focal organizations with small internal knowledge pools), a going-alone strategy may be equally-beneficial when it comes to solving extant technological problems within a field.

5.3. Practical contributions

Next to theoretical contributions, the three empirical projects on knowledge recombination generated important practical contributions. These practical contributions fall into two categories, which we discuss in the following section: (i) open innovation strategies for new technology production and (ii) resource management strategies for knowledge recombination.

5.3.1. Open innovation strategies for new technology production

In line with the emerging open innovation paradigm (Chesbrough, 2006), academics and practitioners have called for more attention to collaboration across organizational boundaries, stimulating the exchange of heterogeneous resources and capabilities between different organizations (e.g. firms, universities, government institutions). We contribute to this emerging paradigm in important ways. In chapter 2, we found that available reuse information flows substantially influence the value of subsequent inventions. Especially when reuse information flows were recently produced, inventors become able to recombine associated components more effectively, leading to more valuable inventions as a result. Hence, we encourage policy-makers to push for more transparency in the production of new inventions, such that reuse information flows become more easily available to inventors. In this way, there may also be higher societal returns to investments into R&D, since the value-added benefits of new inventions do not singly remain within the confines of originating organizations (Ahuja, Lampert, & Novelli, 2013; Murray & O'Mahony, 2007; Yang *et al.,* 2010).

In chapters 3 and 4, we focused on how organizations use interorganizational collaboration activities to enhance their own knowledge recombination activities. Based on the extant literature (e.g. Gomes-Casseres *et al.,* 2006; Grant & Baden-Fuller, 2004; Mowery *et al.,* 1996), we argued that focal organizations often engage in interorganizational collaboration with the intention to access the component knowledge of other organizations. However, especially in the chapter 4, we found strong evidence to suggest that these benefits may not materialize for certain organizations. Hence, we encourage practitioners to carefully consider which organizations may actually be able to capture the knowledge recombination benefits of interorganizational collaboration. Especially when designing programs addressing grand societal challenges, a more careful consideration of organizations' ability to benefit from going-together strategies seems warranted.

5.3.2. Managing resources for knowledge recombination

In this dissertation, we consistently found that available resources, within and between organizations, should be carefully managed such that available knowledge recombination opportunities can be fully realized by the focal organization. In chapter 2, strong indications emerged that much technological value may be realized from recombining dormant components and accessing their associated reuse information flows. Therefore, we argue that the existing knowledge stock should continuously be reevaluated (Garud & Nayyar, 1994), such that these 'hidden gems' may be timely identified. For practitioners, this implies that they should more fully consider how previously generated resources may be managed such that they could have a long-lasting impact on organizations' ability to generate new value.

In chapter 3, we found, unexpectedly, that capabilities emerging from developing widely-applicable component knowledge initially decrease the focal firm's intensity of partner-specific recombination. In chapter 4, similar findings emerged, as we found that the internal knowledge pool size of the focal organization, initially, does not substantially increase the relative problem-solving performance benefits of going-together compared to going-alone. We explained these alternative findings by arguing that organizations need to 'learn to learn' (Levinthal & March, 1993); that is, they need to better understand how prior knowledge recombination outputs translate into capabilities that improve future knowledge recombination efforts (Ghosh *et al.,* 2014; Lewin *et al.,* 2011; Wuyts & Dutta, 2014). Thus, practitioners should carefully manage prior knowledge recombination activities and their associated inventive outputs (Anand *et al.,* 2016;

Ghosh *et al.,* 2014; Marsh & Stock, 2006), carefully considering how these prior experiences can be leveraged to improve knowledge recombination activities in interorganizational collaboration settings (Subramanian & Soh, 2017).

5.4. Empirical contributions

In this dissertation, we used state-of-the-art empirical methods to analyse rich quantitative data on the inventive activities of organizations in the fuel cell industry. In each project, we also introduced several innovations in the design of the empirical approach, which we discuss in the following section.

In chapter 2, we developed two major empirical contributions. First, following recent patent studies (e.g. Bakker *et al.,* 2016; de Rassenfosse *et al.,* 2013; Nakamura *et al.,* 2015), we collected patent applications related to fuel cell technology from every patent office in the world, and subsequently aggregated these single patent office applications to the patent family level (using the EPO's DOCDB definition). Studying patent families was particularly important in the fuel cell industry, as numerous prominent players in this industry are non-American firms that tend to patent extensively in their home region's patent office (e.g. Toyota at the JPO and Renault at the EPO). Moreover, we relied on patent citations to track knowledge recombination and reuse (Katila & Chen 2008; Yang *et al.,* 2010), and studies show that patent families provide a better account of patent citations than single patent office applications (Albrecht *et al.,* 2010; Bakker *et al.,* 2016; Nakamura *et al.,* 2015). In this way, we deviated from prior patent-based studies on knowledge recombination, which singly rely on patent applications from either the USPTO (e.g. Fleming, 2001; Miller *et al.,* 2007; Nemet & Johnson, 2012) or the EPO (e.g. Gruber *et al.,* 2013; Schoenmakers & Duysters, 2010). Second, in chapter 2, we had some concerns regarding the generalizability of our main findings from the fuel cell industry. Therefore, we collected additional data from a completely different industry (i.e. wind energy), in which we were able to confirm most, but not all, of our findings. In this way, we were able to further substantiate our contributions to the knowledge recombination literature (Bettis, Helfat, & Shaver, 2016).

In chapter 3, we made empirical contributions to studies on R&D alliances and patenting activities in general. First, we described how R&D alliance activities are heavily underestimated when relying on popular alliance databases, such as Thompson Reuters' SDC Platinum Joint Venture and Strategic Alliances database (Lavie, 2007; Lavie & Rosenkopf, 2006). To address this issue, we collected data on all fuel cell R&D alliances formed between 1978 and 2007 by examining close to 50,000 news articles within the LexisNexis database, following a handful of prior studies that have adopted a similar approach (e.g. Ahuja, 2000; Phelps, 2010; Vasudeva & Anand, 2011). Second, we tracked R&D alliances over time (Ahuja, 2000; Hashai *et al.,* 2018; Phelps, 2010), in order to estimate their starting and ending dates more precisely. This approach deviates from more conventional methods employed by alliance studies, in which a fixed lifespan (ranging from 2 to 5 years) is usually assumed for every alliance (e.g. Schilling & Phelps, 2007; Vasudeva & Anand 2011). Our approach is especially useful when we consider that there is actually much heterogeneity in the lifespans of alliances (Deeds & Rothaermel, 2003). For example, in our sample, we detected that some R&D alliances only lasted for one year, whereas others lasted for more than 15 years. Third, we conducted an in-depth examination of fuel cell patents' IPC codes to derive information about the applicability of knowledge components. Normally, patent IPC codes are aggregated at the firm-level, with little regard for the actual content of these codes. In this chapter, instead, we inspected several leading fuel cell review articles and news articles, and examined numerous patent documents, in order to identify the relevant application domains of fuel cell technology and their associated patent IPC codes.

Finally, in chapter 4, we used data from the U.S. Department of Energy's Hydrogen and Fuel Cells Program to examine the difference in problem-solving performance between focal organizations that go-together or go-alone in challenge-based R&D projects. Using this data, we developed several important empirical contributions. First, we adopted a performance metric that is (i) directly connected to the outputs of the project, (ii) provided by peer reviewers that are objective, anonymous, and experts in their respective fields, and (iii) comparable across projects. This performance indicator is arguably superior to the ones used by prior studies in which, for instance, firm-level performance data (e.g. net profit margin, stock market returns) is used to infer something about the outputs of particular collaborative projects (e.g. Jiang *et al.,* 2010; Sampson, 2007). Second, the challenge-based R&D projects that we examined, in which focal organizations go-alone or go-together, are highly comparable with one another, allowing us to tease out the problem-solving benefits of going-together strategies relative to going-alone strategies. Moreover, in our sample, we observed that these two R&D approaches are employed almost equally often by project leaders. Finally, we measured the focal organization's internal knowledge pool size, not by aggregating every single patent that the focal organization filed in the past, but instead by focusing on granted patents that were filed within the scope of the HFCP. In this way, our measure more accurately captured patents that were actually relevant to the particular challenge-based R&D projects that we studied.

5.5. Future research directions

In this section, we discuss several promising avenues for future research on knowledge recombination that emerged from our results in chapters 2-4. First, it is often argued that organizations need to use collaborative strategies in order to change the size, composition, and configuration of their own knowledge pool (Rosenkopf & Almeida, 2003). At the same time, in chapters 3 and 4, we already found strong indications that not every organization is actually able to access and recombine partners' external components very effectively. Future studies should build upon these findings, and examine to what extent organizations might be better off solely relying on internally available component knowledge to generate new inventions (Baker & Nelson, 2005; Miller *et al.,* 2007). As argued by recent knowledge recombination studies (e.g. Dibiaggio *et al.,* 2014; Yayavaram & Ahuja, 2008), some organizations are able to generate a considerable number of new inventions by reconfiguring existing component combinations within their own knowledge pool (Henderson & Clark, 1990). It would be interesting to compare the relative benefits of such inward-oriented strategies, with more outward-oriented strategies in which direct collaborations with other organizations are considered.

Second, in this dissertation, we consistently developed our theoretical arguments from the perspective of one focal entity (i.e. the focal inventor in chapter

2, the focal firm in chapter 3, and the focal organization in chapter 4). However, in many cases, such as when organizations collaborate in knowledge recombination, new combinations represent a recombination of different organizations' individual components. Hence, to enrich our understanding of how collaborative activities should be optimally configured, future research should study precisely whose components are actually utilized in collaborative knowledge recombination activities.

Third, future studies should examine which factors allow organizations to recombine components with specific attributes. We made some important progress in this area already, showing in chapter 3 that focal firms have different abilities that allow them to recombine alliance partners' knowledge components more intensively. Nevertheless, the body of research that focuses on these antecedents of knowledge recombination is still rather small (Carnabuci & Operti, 2013; Hohberger, 2014; Phelps, 2010), implying that there are still many 'low-hanging fruits' waiting to be picked in this research area. For example, an obvious extension of our project on recombinant lag would entail examining which factors stimulate organizations' ability to recombine components with different levels of recombinant lag and frequencies of reuse.

Finally, on the empirical front, it would be interesting to delve more deeply into non-patent-based measures of knowledge recombination. In our research, we relied extensively on patent citations (chapters 2 and 3) to track knowledge recombination. We recognized the many advantages of this method (e.g. the ability to assign components to particular originating firms, the ability to easily track knowledge recombination over time), but also acknowledged some limitations (e.g. bias created from examiner-added citations) (Jaffe & de Rassenfosse, 2017). Some qualitative studies on knowledge recombination already exist (e.g. Hargadon & Sutton, 1997; Fleming, 2002; Sonenshein, 2014), but large-scale quantitative research on knowledge recombination that does not principally rely on patent- or publication-based data is still largely missing (an exception is: Sidhu, Commandeur, & Volberda, 2007). At the very least, such quantitative research efforts would allow us to verify the generalizability of existing studies that use patent-based measures, of which there are now many (Laursen, 2012; Sidhu *et al.,* 2007).

5.6. Concluding thoughts

In this dissertation, we showed that the creation of new inventions is much like solving a puzzle: you need to put the right puzzle pieces (components) in the right place (combinative capabilities) in order to complete the puzzle (invention). In chapter 2, we showed that the recency of component reuse influences whether inventors are able to generate technological value from the recombination of particular components. This underlines the fact that knowledge recombination is a path-dependent process, in which a component's current usefulness in knowledge recombination cannot be understood separately from its historical knowledge reuse trajectory. Moreover, in chapter 3, we showed that components are highly malleable, with different application domains attached to them. Within the R&D alliance context, differences in component applicability may significantly impact opportunities of firms to engage in knowledge recombination. Finally, in chapter 4, we provided much-needed nuance to ongoing discussions regarding the benefits of collaborative knowledge recombination strategies. We found that organizations require adequate combinative capabilities in order to reap the knowledge recombination benefits of going-together. We hope that these findings provide interesting starting points for future academic research on knowledge recombination. Moreover, we are hopeful that our contributions to practice inspire practitioners and policy-makers alike to more carefully consider the pros and cons of various open innovation strategies, and the management of resources for new invention production.

Chapter 6. References

Ahuja, G. 2000. Collaboration networks, structural holes, and innovation: A longitudinal study. ***Administrative Science Quarterly***, 45: 425-455.

Ahuja, G., & Katila, R. 2001. Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. ***Strategic Management Journal***, 22: 197-220.

Ahuja, G., & Katila, R. 2004. Where do resources come from? The role of idiosyncratic situations. ***Strategic Management Journal***, 25: 887-907.

Ahuja, G., & Lampert, C. M. 2001. Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. ***Strategic Management Journal***, 22: 521-543.

Ahuja, G., Lampert, C. M., & Novelli, E. 2013. The second face of appropriability: Generative appropriability and its determinants. ***Academy of Management Review***, 38: 248-269.

Albino, V., Ardito, L., Dangelico, R. M., & Petruzzelli, A. M. 2014. Understanding the development trends of low-carbon energy technologies: A patent analysis. ***Applied Energy***, 135: 836-854.

Albrecht, M. A., Bosma, R., van Dinter, T., Ernst, J. L., van Ginkel, K., & Versloot-Spoelstra, F. 2010. Quality assurance in the EPO patent information resource. ***World Patent Information***, 32: 279-286.

Alcacer, J., & Gittelman, M. 2006. Patent citations as a measure of knowledge flows: The influence of examiner citations. ***The Review of Economics and Statistics***, 88: 774-779.

Anand, J., Mulotte, L., & Ren, C. R. 2016. Does experience imply learning? ***Strategic Management Journal***, 37: 1395-1412.

Argote, L., & Miron-Spektor, E. 2011. Organizational learning: From experience to knowledge. ***Organization Science,*** 22: 1123-1137.

Arthur, W. B., & Polak, W. 2006. The evolution of technology within a simple computer model. ***Complexity***, 11: 23-31.

Arundel, A., & Kabla, I. 1998. What percentage of innovations are patented? Empirical estimates for European firms. ***Research Policy,*** 27: 127-141.

Baker, T., & Nelson, R. E. 2005. Creating something from nothing: Resource construction through entrepreneurial bricolage. ***Administrative Science Quarterly***, 50: 329-366.

Bakker, J., Verhoeven, D., Zhang, L., & Van Looy, B. 2016. Patent citation indicators: One size fits all? ***Scientometrics***, 106: 187-211.

Banham, D., Kishimoto, T., Sato, T., Kobayashi, Y., Narizuka, K., Ozaki, J., Zhou, Y., Marquez, E., Bai, K., & Ye, S. 2017. New insights into non-precious metal catalyst layer designs for proton exchange membrane fuel cells: Improving performance and stability. ***Journal of Power Sources***, 344: 39-45.

Barney, J. 1991. Firm resources and sustained competitive advantage. ***Journal of Management***, 17: 99-120.

Baum, C. F. 2008. Stata tip 63: Modeling proportions. ***Stata Journal***, 8: 299-303.

Belenzon, S. 2012. Cumulative innovation and market value: Evidence from patent citations. ***The Economic Journal***, 122: 265-285.

Benner, M., & Waldfogel, J. 2008. Close to you? Bias and precision in patent-based measures of technological proximity. ***Research Policy***, 37: 1556-1567.

Benson, C. L., & Magee, C. L. 2015. Quantitative determination of technological improvement from patent data. ***PloS One***, 10: 1-23.

Bercovitz, J., & Feldman, M. 2011. The mechanisms of collaboration in inventive teams: Composition, social networks, and geography. ***Research Policy***, 40: 81-93.

Berry, H. 2014. Global integration and innovation: Multicountry knowledge generation within MNCs. ***Strategic Management Journal***, 35: 869-890.

Bettis, R. A., Helfat, C. E., & Shaver, J. M. 2016. The necessity, logic, and forms of replication. ***Strategic Management Journal***, 37: 2193-2203.

Blanco, M. I. 2009. The economics of wind energy. ***Renewable and Sustainable Energy Reviews***, 13: 1372-1382.

Boh, W. F., Evaristo, R., & Ouderkirk, A. 2014. Balancing breadth and depth of expertise for innovation: A 3M story. ***Research Policy***, 43: 349-366.

Bohn, R. E. 1995. Noise and learning in semiconductor manufacturing. ***Management Science***, 41: 31-42.

Bos, B., Faems, D., & Noseleit, F. 2017. Alliance concentration in multinational companies: Examining alliance portfolios, firm structure, and firm performance. ***Strategic Management Journal***. 38: 2298-2309.

Breschi, S., Lissoni, F., & Malerba, F. 2003. Knowledge-relatedness in firm technological diversification. ***Research Policy***, 32: 69-87.

Capaldo, A., Lavie, D., & Petruzzelli, A. M. 2017. Knowledge maturity and the scientific value of innovations: The roles of knowledge distance and adoption. ***Journal of Management***, 43: 503-533.

Carnabuci, G., & Bruggeman, J. 2009. Knowledge specialization, knowledge brokerage and the uneven growth of technology domains. ***Social Forces***, 88: 607-641.

Carnabuci, G., & Operti, E. 2013. Where do firms' recombinant capabilities come from? Intraorganizational networks, knowledge, and firms' ability to innovate through technological recombination. ***Strategic Management Journal***, 34: 1591-1613.

Cassiman, B., & Veugelers, R. 2002. R&D cooperation and spillovers: Some empirical evidence from Belgium. ***The American Economic Review***, 92: 1169-1184.

Chesbrough, H. W. 2006. ***Open innovation: The new imperative for creating and profiting from technology***. Boston, MA: Harvard Business Press.

Cohen, W.M. & Levinthal, D.A. 1990. Absorptive capacity: A new perspective on learning and innovation. ***Administrative Science Quarterly***, 35: 128-152.

Criscuolo, P. 2006. The 'home advantage' effect and patent families. A comparison of OECD triadic patents the USPTO and the EPO. ***Scientometrics***, 66: 23-41.

Cuypers, I. R., Ertug, G., Reuer, J. J., & Bensaou, B. 2017. Board representation in international joint ventures. ***Strategic Management Journal***, 38: 920-938.

Cyert, R. M., & Goodman, P. S. 1997. Creating effective university-industry alliances: An organizational learning perspective. ***Organizational Dynamics***, 25: 45-57.

Darr, E. D., Argote, L., & Epple, D. 1995. The acquisition, transfer, and depreciation of knowledge in service organizations: Productivity in franchises. ***Management Science***, 41: 1750-1762.

Das, T. K. 2005. Deceitful behaviors of alliance partners: Potential and prevention. ***Management Decision***, 43: 706-719.

Das, T. K., & Teng, B. S. 2000. A resource-based theory of strategic alliances. ***Journal of Management***, 26: 31-61.

Das, T. K., & Teng, B. S. 2002. Alliance constellations: A social exchange perspective. ***Academy of Management Review***, 27: 445-456.

Davis, J. P., & Eisenhardt, K. M. 2011. Rotating leadership and collaborative innovation recombination processes in symbiotic relationships. ***Administrative Science Quarterly***, 56: 159-201.

De Faria, P., & Sofka, W. 2010. Knowledge protection strategies of multinational firms—A cross country comparison. ***Research Policy***, 39: 956-968.

De Rassenfosse, G., Dernis, H., Guellec, D., Picci, L., & de van Pottelsberghe de la Potterie, B. 2013. The worldwide count of priority patents: A new indicator of inventive activity. ***Research Policy***, 42: 720-737.

Deeds, D. L., & Hill, C. W. 1996. Strategic alliances and the rate of new product development: An empirical study of entrepreneurial biotechnology firms. ***Journal of Business Venturing***, 11: 41-55.

Deeds, D. L., & Rothaermel, F. T. 2003. Honeymoons and liabilities: The relationship between age and performance in research and development alliances. ***Journal of Product Innovation Management***, 20: 468-484.

Dibiaggio, L., Nasiriyar, M., & Nesta, L. 2014. Substitutability and complementarity of technological knowledge and the inventive performance of semiconductor companies. ***Research Policy***, 43: 1582-1593.

Dosi, G. 1982. Technological paradigms and technological trajectories: A suggested interpretation of the determinants and directions of technical change. ***Research Policy***, 11: 147-162.

Duguet, E., & MacGarvie, M. 2005. How well do patent citations measure flows of technology? Evidence from French innovation surveys. ***Economics of Innovation and New Technology***, 14: 375-393.

Dyer, J. H., & Singh, H. 1998. The relational view: Cooperative strategy and sources of interorganizational competitive advantage. ***Academy of Management Review***, 23: 660-679.

EERE. 2016. Peer Review Guidance. https://www.energy.gov/sites/prod/files/2016/08/f33/EERE%20810%20-%20Peer%20Review%20Guidance.pdf [18 November 2017]

EG&G Technical Services, Inc. 2004. ***Fuel Cell Handbook*** (7th ed.). Morgantown, WV: US Department of Energy

Eggers, J. P. 2012. All experience is not created equal: Learning, adapting, and focusing in product portfolio management. ***Strategic Management Journal***, 33: 315-335.

Estrada, I., Faems, D., Cruz, N. M., & Santana, P. P. 2016. The role of interpartner dissimilarities in Industry-University alliances: Insights from a comparative case study. ***Research Policy***, 45: 2008-2022.

Fabrizio, K. R. 2009. Absorptive capacity and the search for innovation. ***Research Policy,*** 38: 255-267.

Faems, D., Janssens, M., & Van Looy, B. 2007. The initiation and evolution of interfirm knowledge transfer in R&D relationships. ***Organization Studies***, 28: 1699-1728.

Faems, D., Van Looy, B., & Debackere, K. 2005. Interorganizational collaboration and innovation: Toward a portfolio approach. ***Journal of Product Innovation Management***, 22: 238-250.

Fleming, L. 2001. Recombinant uncertainty in technological search. ***Management Science***, 47: 117-132.

Fleming, L. 2002. Finding the organizational sources of technological breakthroughs: The story of Hewlett-Packard's thermal ink-jet. ***Industrial and Corporate Change***, 11: 1059-1084.

Fleming, L., & Sorenson, O. 2001. Technology as a complex adaptive system: Evidence from patent data. ***Research Policy***, 30: 1019-1039.

Fleming, L., & Sorenson, O. 2004. Science as a map in technological search. ***Strategic Management Journal,*** 25: 909-928.

Fleming, L., Mingo, S., & Chen, D. 2007. Collaborative brokerage, generative creativity, and creative success. ***Administrative Science Quarterly***, 52: 443-475.

Frankort, H. T. 2016. When does knowledge acquisition in R&D alliances increase new product development? The moderating roles of technological relatedness and product-market competition. ***Research Policy***, 45: 291-302.

Furr, N. R., & Snow, D. C. 2014. Intergenerational hybrids: Spillbacks, spillforwards, and adapting to technology discontinuities. ***Organization Science***, 26: 475-493.

Galunic, C., & Rodan, S. 1998. Resource recombinations in the firm: Knowledge structures and the potential for Schumpeterian innovation. ***Strategic Management Journal,*** 19*:* 1193-1201.

Garud, R., & Nayyar, P. R. 1994. Transformative capacity: Continual structuring by intertemporal technology transfer. ***Strategic Management Journal,*** 15: 365-385.

George, G., Kotha, R., & Zheng, Y. 2008. Entry into insular domains: A longitudinal study of knowledge structuration and innovation in biotechnology firms. ***Journal of Management Studies***, 45: 1448-1474.

Ghosh, A., Martin, X., Pennings, J. M., & Wezel, F. C. 2014. Ambition is nothing without focus: Compensating for negative transfer of experience in R&D. ***Organization Science,*** 25*:* 572-590.

Gilsing, V., Nooteboom, B., Vanhaverbeke, W., Duysters, G., & van den Oord, A. 2008. Network embeddedness and the exploration of novel technologies: Technological distance, betweenness centrality and density. ***Research Policy***, 37: 1717-1731.

Gomes-Casseres, B., Hagedoorn, J., & Jaffe, A. B. 2006. Do alliances promote knowledge flows? ***Journal of Financial Economics***, 80: 5-33.

Grant, R. M. 1996. Toward a knowledge-based theory of the firm. ***Strategic Management Journal***, 17: 109-122.

Grant, R. M., & Baden-Fuller, C. 2004. A knowledge accessing theory of strategic alliances. ***Journal of Management Studies***, 41: 61-84.

Grigoriou, K., & Rothaermel, F. T. 2017. Organizing for knowledge generation: Internal knowledge networks and the contingent effect of external knowledge sourcing. ***Strategic Management Journal***, 38: 395-414.

Grimpe, C., & Kaiser, U. 2010. Balancing internal and external knowledge acquisition: The gains and pains from R&D outsourcing. ***Journal of Management Studies***, 47: 1483-1509.

Gruber, M., Harhoff, D., & Hoisl, K. 2013. Knowledge recombination across technological boundaries: Scientists vs. engineers. ***Management Science,*** 59: 837-851.

Guan, J., & Liu, N. 2016. Exploitative and exploratory innovations in knowledge network and collaboration network: A patent analysis in the technological field of nano-energy. ***Research policy***, 45: 97-112.

Haans, R. F., Pieters, C., & He, Z. L. 2016. Thinking about U: Theorizing and testing U-and inverted U-shaped relationships in strategy research. ***Strategic Management Journal***, 37: 1177-1195.

Hagedoorn, J. 2002. Inter-firm R&D partnerships: An overview of major trends and patterns since 1960. ***Research policy***, 31: 477-492.

Hall, B. H., Jaffe, A., & Trajtenberg, M. 2005. Market value and patent citations. ***RAND Journal of Economics,*** 36: 16-38.

Hamel, G. 1991. Competition for competence and interpartner learning within international strategic alliances. ***Strategic Management Journal***, 12: 83-103.

Hardin, J. W., Hilbe, J. M., & Hilbe, J. 2012. ***Generalized linear models and extensions*** (3rd ed.). College Station, TX: Stata press.

Hargadon, A. B. 2002. Brokering knowledge: Linking learning and innovation. ***Research in Organizational Behavior***, 24: 41-85.

Hargadon, A., & Sutton, R. I. 1997. Technology brokering and innovation in a product development firm. ***Administrative Science Quarterly***, 42: 716-749.

Harhoff, D., Scherer, F. M., & Vopel, K. 2003. Citations, family size, opposition and the value of patent rights. ***Research Policy,*** 32: 1343-1363.

Harrison, J. S., Hitt, M. A., Hoskisson, R. E., & Ireland, R. D. 2001. Resource complementarity in business combinations: Extending the logic to organizational alliances. ***Journal of Management***, 27: 679-690.

Hashai, N., Kafouros, M., & Buckley, P. J. 2018. The performance implications of speed, regularity, and duration in alliance portfolio expansion. ***Journal of Management***, 44: 707-731.

Hausman, J., Hall, B. H., & Griliches, Z. 1984. Econometric models for count data with an application to the patents-R&D relationship. ***Econometrica,*** 52: 909-938.

Heeley, M. B., & Jacobson, R. 2008. The recency of technological inputs and financial performance. ***Strategic Management Journal***, 29: 723-744.

Hellman, H. L., & van den Hoed, R. 2007. Characterising fuel cell technology: Challenges of the commercialisation process. ***International Journal of Hydrogen Energy***, 32: 305-315.

Henderson, R. 1995. Of life cycles real and imaginary: The unexpectedly long old age of optical lithography. ***Research Policy***, 24: 631-643.

Henderson, R. M., & Clark, K. B. 1990. Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. ***Administrative Science Quarterly,*** 35: 9-30.

Henderson, R., & Cockburn, I. 1994. Measuring competence? Exploring firm effects in pharmaceutical research. ***Strategic Management Journal***, 15: 63-84.

Henderson, R., & Cockburn, I. 1996. Scale, scope, and spillovers: The determinants of research productivity in drug discovery. ***The Rand Journal of Economics***, 27: 32-59.

Hoetker, G. 2007. The use of logit and probit models in strategic management research: Critical issues. ***Strategic Management Journal***, 28: 331-343.

Hohberger, J. 2014. Searching for emerging knowledge: The influence of collaborative and geographically proximate search. ***European Management Review***, 11: 139-157.

Hohberger, J. 2017. Combining valuable inventions: Exploring the impact of prior invention value on the performance of subsequent inventions. ***Industrial and Corporate Change***, 26: 907-930.

Howard-Grenville, J., Buckle, S. J., Hoskins, B. J., & George, G. 2014. Climate change and management. ***Academy of Management Journal***, 57: 615-623.

Ireland, R. D., Hitt, M. A., & Vaidyanath, D. 2002. Alliance management as a source of competitive advantage. ***Journal of Management***, 28: 413-446.

Jaffe, A. B. 1986. Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. ***The American Economic Review***, 76: 984-1001.

Jaffe, A. B., & de Rassenfosse, G. 2017. Patent citation data in social science research: Overview and best practices. ***Journal of the Association for Information Science and Technology***, 68: 1360-1374.

Jaffe, A. B., Trajtenberg, M., & Fogarty, M. S. 2000. ***The meaning of patent citations: Report on the NBER/Case-Western Reserve survey of patentees***. NBER Working Paper No. 7631. National Bureau of Economic Research, Cambridge, MA.

Jiang, R. J., Tao, Q. T., & Santoro, M. D. 2010. Alliance portfolio diversity and firm performance. ***Strategic Management Journal***, 31: 1136-1144.

Kafouros, M. I., Buckley, P. J., & Clegg, J. 2012. The effects of global knowledge reservoirs on the productivity of multinational enterprises: The role of international depth and breadth. ***Research Policy***, 41: 848-861.

Kaldellis, J. K., & Zafirakis, D. 2011. The wind energy (r) evolution: A short review of a long history. ***Renewable Energy***, 36: 1887-1901.

Kapoor, R., & Adner, R. 2012. What firms make vs. what they know: How firms' production and knowledge boundaries affect competitive advantage in the face of technological change. ***Organization Science***, 23: 1227-1248.

Karim, S. 2009. Business unit reorganization and innovation in new product markets. ***Management Science*,** 55: 1237-1254.

Katila, R. 2002. New product search over time: Past ideas in their prime? ***Academy of Management Journal***, 45: 995-1010.

Katila, R., & Ahuja, G. 2002. Something old, something new: A longitudinal study of search behavior and new product introduction. ***Academy of Management Journal***, 45: 1183-1194.

Katila, R., & Chen, E. L. 2008. Effects of search timing on innovation: The value of not being in sync with rivals. ***Administrative Science Quarterly****,* 53: 593-625.

Katz, R., & Allen, T. J. 1982. Investigating the Not Invented Here (NIH) syndrome: A look at the performance, tenure, and communication patterns of 50 R & D Project Groups. ***R&D Management***, 12: 7-20.

Kelley, D. J., Ali, A., & Zahra, S. A. 2013. Where do breakthroughs come from? Characteristics of high-potential inventions. ***Journal of Product Innovation Management****,* 30: 1212-1226.

Khanna, T., Gulati, R., & Nohria, N. 1998. The dynamics of learning alliances: Competition, cooperation, and relative scope. ***Strategic Management Journal***, 19: 193-210.

Kim, C., Song, J., & Nerkar, A. 2012. Learning and innovation: Exploitation and exploration trade-offs. ***Journal of Business Research***, 65: 1189-1194.

Kogut, B. 1988. Joint ventures: Theoretical and empirical perspectives. ***Strategic Management Journal***, 9: 319-332.

Kogut, B., & Zander, U. 1992. Knowledge of the firm, combinative capabilities, and the replication of technology. ***Organization Science***, 3*:* 383-397.

Kotha, R., Zheng, Y., & George, G. 2011. Entry into new niches: The effects of firm age and the expansion of technological capabilities on innovative output and impact. ***Strategic Management Journal***, 32: 1011-1024.

Lahiri, N., & Narayanan, S. 2013. Vertical integration, innovation, and alliance portfolio size: Implications for firm performance. ***Strategic Management Journal***, 34: 1042-1064.

Lampel, J., Shamsie, J., & Shapira, Z. 2009. Experiencing the improbable: Rare events and organizational learning. ***Organization Science***, 20: 835-845.

Lane, P. J., & Lubatkin, M. 1998. Relative absorptive capacity and interorganizational learning. ***Strategic Management Journal***, 19: 461-477.

Lavie, D. 2007. Alliance portfolios and firm performance: A study of value creation and appropriation in the US software industry. ***Strategic Management Journal***, 28: 1187-1212.

Lavie, D., & Miller, S. R. 2008. Alliance portfolio internationalization and firm performance. ***Organization Science***, 19: 623-646.

Lavie, D., & Rosenkopf, L. 2006. Balancing exploration and exploitation in alliance formation. ***Academy of Management Journal***, 49: 797-818.

Laursen, K. 2012. Keep searching and you'll find: What do we know about variety creation through firms' search activities for innovation? ***Industrial and Corporate Change***, 21: 1181-1220.

Laursen, K., & Salter, A. 2006. Open for innovation: The role of openness in explaining innovation performance among UK manufacturing firms. ***Strategic Management Journal***, 27: 131-150.

Leiponen, A., & Helfat, C. E. 2010. Innovation objectives, knowledge sources, and the benefits of breadth. ***Strategic Management Journal***, 31: 224-236.

Leten, B., Belderbos, R., & Looy, B. V. 2016. Entry and technological performance in new technology domains: Technological opportunities, technology competition and technological relatedness. ***Journal of Management Studies***, 53: 1257-1291.

Levinthal, D. A., & March, J. G. 1993. The myopia of learning. ***Strategic Management Journal***, 14: 95-112.

Levinthal, D. A., & Wu, B. 2010. Opportunity costs and non-scale free capabilities: Profit maximization, corporate scope, and profit margins. ***Strategic Management Journal***, 31: 780-801.

Lewin, A. Y., Massini, S., & Peeters, C. 2011. Microfoundations of internal and external absorptive capacity routines. ***Organization Science***, 22: 81-98.

Li, Y., Vanhaverbeke, W., & Schoenmakers, W. 2008. Exploration and exploitation in innovation: Reframing the interpretation. ***Creativity and Innovation Management***, 17: 107-126.

Lind, J. T., & Mehlum, H. 2010. With or Without U? The appropriate test for a U-Shaped relationship. ***Oxford Bulletin of Economics and Statistics,*** 72: 109-118.

Majchrzak, A., Jarvenpaa, S. L., & Bagherzadeh, M. 2015. A review of interorganizational collaboration dynamics. ***Journal of Management***, 41: 1338-1360.

Makri, M., Hitt, M. A., & Lane, P. J. 2010. Complementary technologies, knowledge relatedness, and invention outcomes in high technology mergers and acquisitions. ***Strategic Management Journal***, 31: 602-628.

Manning, K. 2013. ***Organizational Theory in Higher Education***. New York, NY: Routledge.

Martínez, C. 2011. Patent families: When do different definitions really matter? ***Scientometrics,*** 86: 39-63.

Marsh, S. J., & Stock, G. N. 2006. Creating dynamic capability: The role of intertemporal integration, knowledge retention, and interpretation. ***Journal of Product Innovation Management***, 23: 422-436.

Mason, C. H., & Perreault Jr, W. D. 1991. Collinearity, power, and interpretation of multiple regression analysis. ***Journal of Marketing Research***, 28: 268-280.

Melero, E., & Palomeras, N. 2015. The Renaissance Man is not dead! The role of generalists in teams of inventors. ***Research Policy***, 44: 154-167.

Miller, D. J., Fern, M. J., & Cardinal, L. B. 2007. The use of knowledge for technological innovation within diversified firms. ***Academy of Management Journal,*** 50: 307-325.

Mora-Valentin, E. M., Montoro-Sanchez, A., & Guerras-Martin, L. A. 2004. Determining factors in the success of R&D cooperative agreements between firms and research organizations. ***Research Policy***, 33: 17-40.

Mowery, D. C., Oxley, J. E., & Silverman, B. S. 1996. Strategic alliances and interfirm knowledge transfer. ***Strategic Management Journal***, 17: 77-91.

Murray, F., & O'Mahony, S. 2007. Exploring the foundations of cumulative innovation: Implications for organization science. ***Organization Science,*** 18: 1006-1021.

Nakamura, H., Suzuki, S., Kajikawa, Y., & Osawa, M. 2015. The effect of patent family information in patent citation network analysis: A comparative case study in the drivetrain domain. ***Scientometrics***, 104: 437-452.

Nelson, R. R., S. G. Winter. 1982. **An Evolutionary Theory of Economic Change**. Cambridge, MA: Harvard University Press

Nemet, G. F., & Johnson, E. 2012. Do important inventions benefit from knowledge originating in other technological domains? ***Research Policy***, 41: 190-200.

Nerkar, A. 2003. Old is gold? The value of temporal exploration in the creation of new knowledge. ***Management Science,*** 49: 211-229.

Nooteboom, B., Vanhaverbeke, W., Duysters, G., Gilsing, V., & Van den Oord, A. 2007. Optimal cognitive distance and absorptive capacity. ***Research policy***, 36: 1016-1034.

Ohtsuki, J., Seki, T., Miyazaki, M., & Sasaki, A. 1995. Development of indirect internal reforming molten carbonate fuel cell. ***Electrical Engineering in Japan***, 115: 64-75.

Olsen, A. Ø., Sofka, W., & Grimpe, C. 2016. Coordinated exploration for grand challenges: The role of advocacy groups in search consortia. ***Academy of Management Journal***, 59: 2232-2255.

Olsson, O., & Frey, B. S. 2002. Entrepreneurship as recombinant growth. ***Small Business Economics***, 19: 69-80.

Perry, M. L., & Fuller, T. F. 2002. A historical perspective of fuel cell technology in the 20th century. ***Journal of the Electrochemical Society,*** 149: 59-67.

Petruzzelli, A. M., & Savino, T. 2014. Search, recombination, and innovation: Lessons from haute cuisine. ***Long Range Planning***, 47: 224-238.

Phelps, C. C. 2010. A longitudinal study of the influence of alliance network structure and composition on firm exploratory innovation. ***Academy of Management Journal***, 53: 890-913.

Phene, A., & Tallman, S. 2014. Knowledge spillovers and alliance formation. ***Journal of Management Studies***, 51: 1058-1090.

Phene, A., Fladmoe-Lindquist, K., & Marsh, L. 2006. Breakthrough innovations in the US biotechnology industry: The effects of technological space and geographic origin. ***Strategic Management Journal***, 27: 369-388.

PNNL. 2017. Pathways to Commercial Success. https://energy.gov/sites/prod/files/2017/10/f37/fcto_2016_pathways_commercial_success.pdf [18 November 2017]

Podolny, J. M., & Stuart, T. E. 1995. A role-based ecology of technological change. ***American Journal of Sociology***, 100: 1224-1260.

Popp, D., Hascic, I., & Medhi, N. 2011. Technology and the diffusion of renewable energy. ***Energy Economics***, 33: 648-662.

PR Newswire. 1997. ***Delphi Forms Fuel Cell Research Alliance*** (May 20, Flint Michigan). Accessed November 18, 2017.

PR Newswire. 2003. ***TotalFinaElf Partners with Nuvera to Optimize Hydrocarbon Fuels for Fuel Cells*** (April 9, Milan Italy; Cambridge Massachusetts). Accessed July 20, 2017.

Prater, K. 1990. The renaissance of the solid polymer fuel cell. ***Journal of Power Sources,*** 29: 239-250.

Rosenkopf, L., & Almeida, P. 2003. Overcoming local search through alliances and mobility. ***Management Science***, 49: 751-766.

Rosenkopf, L., & McGrath, P. 2011. Advancing the conceptualization and operationalization of novelty in organizational research. ***Organization Science***, 22: 1297-1311.

Rosenkopf, L., & Nerkar, A. 2001. Beyond local search: Boundary-spanning, exploration, and impact in the optical disk industry. ***Strategic Management Journal***, 22: 287-306.

Sampson, R. C. 2007. R&D alliances and firm performance: The impact of technological diversity and alliance organization on innovation. ***Academy of Management Journal***, 50: 364-386.

Satyapal, S. 2017. 2016 Annual Progress Report: DOE Hydrogen and Fuel Cells Program. https://www.nrel.gov/docs/fy17osti/66806.pdf [18 November 2017]

Savino, T., Messeni Petruzzelli, A., & Albino, V. 2017. Search and recombination process to innovate: A review of the empirical evidence and a research agenda. ***International Journal of Management Reviews,*** 19: 54-75.

Schildt, H., Keil, T., & Maula, M. 2012. The temporal effects of relative and firm-level absorptive capacity on interorganizational learning. ***Strategic Management Journal***, 33: 1154-1173.

Schilling, M. A. 2009. Understanding the alliance data. ***Strategic Management Journal***, 30: 233-260.

Schilling, M. A. 2015. Technology shocks, technological collaboration, and innovation outcomes. ***Organization Science***, 26: 668-686.

Schilling, M. A., & Phelps, C. C. 2007. Interfirm collaboration networks: The impact of large-scale network structure on firm innovation. ***Management Science***, 53: 1113-1126.

Schoenmakers, W., & Duysters, G. 2010. The technological origins of radical inventions. ***Research Policy,*** 39: 1051-1059.

Schumpeter, J., 1934. **The Theory of Economic Development**. Cambridge, MA: Harvard University Press

Sharaf, O. Z., & Orhan, M. F. 2014. An overview of fuel cell technology: Fundamentals and applications. ***Renewable and Sustainable Energy Reviews***, 32: 810-853.

Sidhu, J. S., Commandeur, H. R., & Volberda, H. W. 2007. The multifaceted nature of exploration and exploitation: Value of supply, demand, and spatial search for innovation. ***Organization Science***, 18: 20-38.

Singh, J. 2008. Distributed R&D, cross-regional knowledge integration and quality of innovative output. ***Research Policy***, 37: 77-96.

Singh, J., & Fleming, L. 2010. Lone inventors as sources of breakthroughs: Myth or reality? ***Management Science,*** 56: 41-56.

Sonenshein, S. 2014. How organizations foster the creative use of resources. ***Academy of Management Journal***, 57*:* 814-848.

Sorenson, O., Rivkin, J. W., & Fleming, L. 2006. Complexity networks and knowledge flow. ***Research Policy,*** 35: 994-1017.

Srivastava, M. K., & Gnyawali, D. R. 2011. When do relational resources matter? Leveraging portfolio technological resources for breakthrough innovation. ***Academy of Management Journal***, 54: 797-810.

Steele, B. C., & Heinzel, A. 2001. Materials for fuel-cell technologies. ***Nature***, 414: 345-352.

Strumsky, D., & Lobo, J. 2015. Identifying the sources of technological novelty in the process of invention. ***Research Policy***, 44: 1445-1461.

Stuart, T. E., & Podolny, J. M. 1996. Local search and the evolution of technological capabilities. ***Strategic Management Journal***, 17: 21-38.

Subramanian, A. M., & Soh, P. H. 2017. Linking alliance portfolios to recombinant innovation: The combined effects of diversity and alliance experience. ***Long Range Planning***, 50: 636-652.

Subramanian, A. M., Bo, W., & Kah-Hin, C. 2018. The role of knowledge base homogeneity in learning from strategic alliances. ***Research Policy***, 47: 158-168.

Tanner, A. N. 2014. Regional branching reconsidered: Emergence of the fuel cell industry in European regions. ***Economic Geography***, 90: 403-427.

Taylor, A., & Greve, H. R. 2006. Superman or the fantastic four? Knowledge combination and experience in innovative teams. ***Academy of Management Journal***, 49*:* 723-740.

The Daily Yomiuri (Tokyo). 1999. ***Ghosn vows unwavering commitment to Nissan revival plan*** (November 5, Tokyo). Accessed November 18, 2017.

Thompson, P., & Fox-Kean, M. 2005. Patent citations and the geography of knowledge spillovers: A reassessment. ***American Economic Review***, 95: 450-460.

Trajtenberg, M., Henderson, R., & Jaffe, A. 1997. University versus corporate patents: A window on the basicness of invention. ***Economics of Innovation and New Technology***, 5: 19-50.

Tushman, M.L., & Anderson, P. 1986. Technological discontinuities and organizational environments. ***Administrative Science Quarterly***, 31: 439-465.

Tzabbar, D. 2009. When does scientist recruitment affect technological repositioning? ***Academy of Management Journal***, 52: 873-896.

Valentini, G. 2012. Measuring the effect of M&A on patenting quantity and quality. ***Strategic Management Journal***, 33: 336-346.

Van de Vrande, V. 2013. Balancing your technology-sourcing portfolio: How sourcing mode diversity enhances innovative performance. ***Strategic Management Journal***, 34: 610-621.

Vasudeva, G. 2009. How national institutions influence technology policies and firms' knowledge-building strategies: A study of fuel cell innovation across industrialized countries. ***Research Policy***, 38: 1248-1259.

Vasudeva, G., & Anand, J. 2011. Unpacking absorptive capacity: A study of knowledge utilization from alliance portfolios. ***Academy of Management Journal***, 54: 611-623.

Vasudeva, G., Zaheer, A., & Hernandez, E. 2013. The embeddedness of networks: Institutions, structural holes, and innovativeness in the fuel cell industry. ***Organization Science***, 24: 645-663.

Verbong, G., Geels, F. W., & Raven, R. 2008. Multi-niche analysis of dynamics and policies in Dutch renewable energy innovation journeys (1970–2006): Hype-cycles, closed networks and technology-focused learning. ***Technology Analysis & Strategic Management***, 20: 555-573.

Wadhwa, A., & Kotha, S. 2006. Knowledge creation through external venturing: Evidence from the telecommunications equipment manufacturing industry. ***Academy of Management Journal***, 49: 819-835.

Wadhwa, A., Phelps, C., & Kotha, S. 2016. Corporate venture capital portfolios and firm innovation. ***Journal of Business Venturing***, 31: 95-112.

Wang, C., Rodan, S., Fruin, M., & Xu, X. 2014. Knowledge networks, collaboration networks, and exploratory innovation. ***Academy of Management Journal***, 57: 459-514.

Wang, P., Van De Vrande, V., & Jansen, J. J. 2017. Balancing exploration and exploitation in inventions: Quality of inventions and team composition. ***Research Policy***, 46: 1836-1850.

Wassmer, U. 2010. Alliance portfolios: A review and research agenda. ***Journal of Management***, 36: 141-171.

Weitzman, M. L. 1998. Recombinant growth. ***The Quarterly Journal of Economics***, 113: 331-360.

Wiersema, M. F., & Bowen, H. P. 2009. The use of limited dependent variable techniques in strategy research: Issues and methods. ***Strategic Management Journal***, 30: 679-692.

Williams, R. 2012. Using the margins command to estimate and interpret adjusted predictions and marginal effects. ***Stata Journal***, 12: 308-331.

Williamson, O. E. 1991. Comparative economic organization: The analysis of discrete structural alternatives. ***Administrative Science Quarterly***, 36: 269-296.

Wuyts, S., & Dutta, S. 2014. Benefiting from alliance portfolio diversity: The role of past internal knowledge creation strategy. ***Journal of Management***, 40: 1653-1674.

Yang, H., Phelps, C., & Steensma, H. K. 2010. Learning from what others have learned from you: The effects of knowledge spillovers on originating firms. ***Academy of Management Journal,*** 53: 371-389.

Yayavaram, S., & Ahuja, G. 2008. Decomposability in knowledge structures and its impact on the usefulness of inventions and knowledge-base malleability. ***Administrative Science Quarterly***, 53: 333-362.

Zahra, S. A., & George, G. 2002. Absorptive capacity: A review, reconceptualization, and extension. ***Academy of Management Review***, 27: 185-203.

Zander, U., Kogut, B. 1995. Knowledge and the speed of the transfer and imitation of organizational capabilities: An empirical test. ***Organization Science,*** 6: 76-92.

Chapter 7. English Summary

Knowledge recombination – i.e. the recombination of existing knowledge components in order to generate new inventions – underlies much of technological growth. By studying knowledge recombination, we are able to gain important new insights into when and how valuable new inventions are generated. In extant literature, numerous studies rely on knowledge recombination, principally using it to explain performance heterogeneity across different levels of analysis, such as the individual, team, or organization. Despite the fact that knowledge recombination features so prominently in the conceptual/empirical framework of extant studies, few studies make serious attempts to advance our understanding of this concept beyond what is already known about it. Simultaneously, in the core literature that examines knowledge recombination, it is often recognized that knowledge recombination is still poorly understood in many areas. The core objective of this dissertation is therefore to substantially advance our understanding of knowledge recombination, creating new insights about the origins of new inventions. To address this core research objective, we conduct three empirical projects on knowledge recombination, using novel and extensive data from the fuel cell industry.

7.1. Project 1: Recombinant Lag and the Value of Inventions

In the first project, we study how attributes of recombined components influence the technological value of new inventions. Knowledge recombination research traditionally focuses on original knowledge component attributes, assuming that components' recombinant value is largely pre-determined at creation. In contrast, joining an emerging literature stream on knowledge reuse trajectories, we argue that when components are used in different combinations over time, their recombinant value may change considerably. Contributing to this latter stream of literature, we focus on the temporal dimension of component reuse and introduce the concept of recombinant lag – i.e. the time that recombined components have remained unused.

Making use of insights from organizational learning theory, we first hypothesize that recent reuse creates learning opportunities about a component's contemporary applications in recombination, effectively rejuvenating its recombinant potential. Hence, recent reuse is expected to be associated with inventions with higher technological value. In the second hypothesis, we predict that this main relationship is moderated by the frequency at which recombined components were previously reused. In particular, we posit that when components were reused more frequently, ambiguities associated with the rejuvenation effect of recent reuse are reduced, augmenting its value-enhancing effect.

To test these hypotheses, we analyze 21,117 patent families from the fuel cell industry. Our findings indicate that there is an unexpected U-shaped relationship between recombinant lag and the value of inventions. Moreover, this main relationship is moderated by components' prior frequency of reuse. Subsequently, we conduct post-hoc exploratory data analyses, advancing the concept of dormant component knowledge – i.e. valuable components that have remained unused prolongedly – as a potential explanation for these unexpected patterns. We are also able to produce first indications for the generalizability of these unexpected findings, collecting additional patent data from the wind energy industry.

With these findings, we contribute in two major ways to extant knowledge recombination literature. First, exploring distinct theoretical mechanisms associated with frequency and recency of reuse, we show that not only the magnitude of reuse information flows (i.e. frequency of reuse), but also the timing of creation of these reuse information flows (i.e. recombinant lag) is a crucial determinant of a component's current recombinant value. Second, we contribute to the literature that examines the temporal dimension of knowledge recombination. Specifically, controlling for component age, we find a distinct and robust influence of recombinant lag on the technological value of new inventions, indicating that these two dimensions of time complement each other.

7.2. Project 2: Knowledge Pool Applicability in R&D Alliances

In the second project, we study factors that allow focal firms to more intensively recombine the component knowledge of R&D alliance partners. Using knowledge recombination insights, alliance scholars often argue that, by means of collaborating with external partners that possess larger and more technologically diverse knowledge pools, the focal firm obtains valuable new opportunities to generate component combinations. Inspecting recent knowledge recombination literature, however, we find that studies tend to focus more on the applicability of components, rather than solely their quantity or diversity. Interestingly, however, alliance research largely neglects that there is substantial variance in components' level of applicability. To address this critical research gap, we introduce the concept of knowledge pool applicability – i.e. the extent to which components situated in the knowledge pool can be used in different application domains – and examine its influence on the focal firm's recombination of R&D alliance partners' components.

Relying on emerging knowledge recombination insights, we first hypothesize the existence of an inverted U-shaped relationship between the partner's knowledge pool applicability and the focal firm's intensity of partner-specific recombination. We argue that, initially, partner's knowledge pool applicability provides flexibility to the focal firm in terms of where and how it may apply components accessed from the partner. However, beyond a certain threshold value, it is expected that important learning complexities associated with overly-applicable component knowledge emerge, reducing partner-specific recombination amply. In the second hypothesis, we shift the focus towards the focal firm's own knowledge pool applicability. We hypothesize that, having previously built widely-applicable component knowledge, the focal firm is able to more flexibly and effectively engage in knowledge recombination within the partner's knowledge pool, increasing its partner-specific recombination.

To test these two hypotheses, we analyse 461 R&D alliance dyads of 88 firms in the fuel cell industry. Our findings provide strong support for the first hypothesis, showing that partner's knowledge pool applicability has an inverted U-shaped relationship with the focal firm's partner-specific knowledge recombination. In contrast to our expectations, however, we find that the knowledge pool applicability of the focal firm has a U-shaped relationship with its partner-specific recombination.

These findings contribute in two ways to extant alliance literature. First, we shift the theoretical lens from the aggregate knowledge pool to individual components within the knowledge pool. Rather than to assume broad applicability of components from aggregate knowledge pool characteristics (e.g. diversity or size), we emphasize the importance of examining whether individual components are, in fact, broadly applicable or not. Second, we show the importance of theorizing on capabilities that allow the focal firm to engage more intensively engage in recombination of its R&D alliance partners' component knowledge. In sum, our findings indicate the importance of taking an in-depth knowledge recombination perspective to examining the performance implications of R&D alliances.

7.3. Project 3: Going-Together in Challenge-Based R&D Projects

In the third project, we study the problem-solving performance implications of going-together and going-alone strategies in challenge-based R&D projects. Recent years have seen a rapid increase in the number of large-scale government-funded programs that are aimed at addressing society's greatest challenges, such as climate change and population aging. Within these programs, organizations, ranging from firms to universities, engage in challenge-based R&D projects to attempt to solve extant problems within a specific field. In the literature on grand societal challenges, an implicit assumption is often made that going-together strategies – i.e. projects in which the focal organization formally involves partners – always lead to higher quality technological solutions than going-alone strategies – i.e. projects in which the focal organization operates independently. These performance differences are often explained by pointing to the possibility of recombining heterogeneous component knowledge of partners through collaboration.

In this project, using insights from the knowledge-based view, we deviate from these prior studies and argue that not every organization can actually reap the knowledge recombination benefits of going-together strategies. More specifically, we argue that organizations require abilities to identify, retrieve, and recombine partners' component knowledge in order to reap the knowledge recombination benefits of going-together. Based on this, we develop theoretical arguments to suggest that three distinct characteristics of the focal organization – institutional background, internal knowledge pool size, and challenge-based R&D project portfolio size – influence whether going-together strategies outperform going-alone strategies, in terms of problem-solving performance.

To test our hypotheses, we analyse a highly unique dataset comprising detailed project-level information on 414 challenge-based R&D projects within the U.S. Department of Energy's Hydrogen and Fuel Cells Program over a 14-year time period (2003-2016). Our findings provide evidence that, on average, going-together strategies outperform going-alone strategies. Noteworthily, however, we find that firms perform considerably better when going-together rather than going-alone, but research organizations do not. Moreover, we find that the problem-solving performance gap between going-together and going-alone strategies widens substantially when the focal organization has a larger internal knowledge pool. Finally, contrary to expectations, our findings indicate that the focal organization's R&D project portfolio size initially increases the positive problem-solving performance gap between going-together and going-alone but, beyond a certain point, decreases it.

Jointly, these findings contribute to extant research on grand challenges and open innovation. Specifically, our findings call into question the oft-assumed advantages that prior research associates with going-together strategies, when it comes to addressing extant technological problems within a field. We find that, for many types of organizations, going-alone strategies seem to perform equally well in terms of problem-solving performance than going-together strategies.

7.4. Conclusion

This dissertation develops several important theoretical contributions that help us to better understand the process of knowledge recombination. First, we underline the fact that components do not have a recombinant value that is pre-determined at creation; instead, components' recombinant value may change considerably over time through reuse. In this respect, we make an important contribution by arguing that, next to the frequency of reuse of components, their recombinant lag should also be taken into account. Second, we point out that, when examining the performance implications of R&D alliances, it can be useful to examine the applicability of individual components that comprise the knowledge pool of partners, rather than to solely focus on aggregate knowledge pool characteristics, such as size or diversity. In support of this, controlling for the knowledge pool size, diversity, and distance of R&D alliance partners, we consistently found a strong effect of knowledge pool applicability on the focal firm's recombination of partner's component knowledge. Third, in contrast to prior research which often assumes a somewhat direct relationship between partners' knowledge inputs and the focal organization's own knowledge outputs, we found that organizations require idiosyncratic combinative capabilities in order to considerably benefit from interorganizational collaboration.

This dissertation also carries important practical contributions. First, following the emerging open innovation paradigm, we point out that it is important that information flows that are produced when new inventions emerge diffuse accurately and rapidly to other inventors, facilitating the subsequent generation of valuable inventions. Moreover, our findings indicate that interorganizational collaboration strategies may play a decisive role in helping organizations detect new sources of component knowledge and generate high-quality technological solutions. Second, we argue that it is important to implement strong resource management strategies in order to generate valuable new inventions. In the first project, we found that knowledge components which have remained unused for prolonged periods of time, represent unexpected sources of value for knowledge recombination. Hence, we encourage organizations to regularly reevaluate the existing knowledge stock such that these types of components can be unearthed, leading to considerable technological value realization. Moreover, findings from the second and third project suggest that prior experience with creating new inventions needs to be adequately managed by the focal organization, such that it can be deployed in order to improve subsequent knowledge recombination efforts.

Chapter 8. Nederlandse Samenvatting

Kennisrecombinatie – oftewel, de recombinatie van bestaande kenniscomponenten om nieuwe uitvindingen te genereren – ligt ten grondslag aan technologische groei. Door kennisrecombinatie te bestuderen, kunnen we nieuwe inzichten verkrijgen over wanneer en hoe waardevolle nieuwe uitvindingen worden gegenereerd. Het concept van kennisrecombinatie wordt rijkelijk toegepast in de bestaande literatuur, met als belangrijkste focus het verklaren van prestatieverschillen op verschillende analyseniveaus, zoals het individu, het team of de organisatie. Ondanks dat kennisrecombinatie zo prominent aanwezig is in het conceptuele / empirische kader van bestaande studies, doen maar weinig studies een serieuze poging om ons begrip van dit concept verder te brengen dan wat er al over bekend is. Tegelijkertijd wordt in de kernliteratuur rondom kennisrecombinatie regelmatig erkend dat het begrip van kennisrecombinatie op veel gebieden nog steeds beperkt is. Het hoofddoel van dit proefschrift is daarom om ons begrip van kennisrecombinatie te vergroten, en daarmee nieuwe inzichten te creëren over de oorsprong van nieuwe uitvindingen. Om deze kerndoelstelling te bereiken, voeren we drie empirische projecten uit over kennisrecombinatie, waarin wij gebruikmaken van nieuwe en uitgebreide gegevens uit de brandstofcelindustrie.

8.1. Project 1: Recombinante Vertraging en de Waarde van Uitvindingen

In het eerste project onderzoeken we hoe attributen van gerecombineerde componenten de technologische waarde van nieuwe uitvindingen beïnvloeden. Kennisrecombinatieonderzoek richt zich traditioneel op oorspronkelijke kenniscomponentattributen, ervan uitgaande dat de recombinante waarde van componenten bij creatie grotendeels vooraf bepaald is. In tegenstelling stellen wij dat, wanneer componenten in verschillende combinaties in de tijd worden hergebruikt, hun recombinante waarde aanzienlijk kan veranderen. Hiermee voegen we ons bij de opkomende literatuurstroom met betrekking tot kennishergebruik trajecten. Wij dragen hieraan bij door ons te concentreren op de tijdsdimensie van kennishergebruik en het concept van recombinante vertraging – oftewel, de tijd dat componenten ongebruikt zijn gebleven – te introduceren.

Gebruikmakend van inzichten uit de 'organizational learning theory', stellen we eerst de hypothese dat recent kennishergebruik een verjongingseffect creëert dat het component in de 'state-of-the-art' van technologie integreert. Dit wordt mogelijk gemaakt door de generatie van kennishergebruik informatiestromen over de hedendaagse toepassingen van het component in kennisrecombinatie. Daarom verwachten we dat recent kennishergebruik wordt geassocieerd met uitvindingen met een hogere technologische waarde. De tweede hypothese voorspelt dat deze hoofdrelatie wordt gemodereerd door de frequentie waarmee gerecombineerde componenten eerder werden hergebruikt. In het bijzonder stellen we dat wanneer componenten in het verleden vaker zijn hergebruikt, ambiguïteiten die samenhangen met het verjongingseffect van recent hergebruik worden verminderd, waardoor het waarde bevorderende effect ervan wordt vergroot.

Om deze hypothesen te testen, analyseren we 21.117 octrooifamilies uit de brandstofcelindustrie. Onze bevindingen geven tegen de verwachting in aan dat er een U-vormige relatie bestaat tussen recombinante vertraging en de technologische waarde van uitvindingen. Bovendien wordt deze hoofdrelatie gemodereerd door de frequentie waarmee gerecombineerde componenten eerder werden hergebruikt. Vervolgens voeren we post-hoc verkennende data-analyses uit, waarbij we het concept van slapende kenniscomponenten – oftewel, waardevolle componenten die langdurig ongebruikt zijn gebleven – als mogelijke verklaring voor deze onverwachte patronen naar voren schuiven. Door middel van de verzameling van aanvullende octrooigegevens van de windenergie-industrie, zijn we bovendien in staat om eerste indicaties te produceren voor de generaliseerbaarheid van deze onverwachte bevindingen.

Onze bevindingen dragen op twee belangrijke manieren bij aan de bestaande literatuur over kennisrecombinatie. Ten eerste, door verschillende theoretische mechanismen te onderzoeken die verband houden met de frequentie en recentheid van kennishergebruik, wordt aangetoond dat niet alleen de omvang van kennishergebruik informatiestromen (ofwel, de frequentie van hergebruik), maar ook de timing van creatie van deze kennishergebruik informatiestromen (ofwel, recombinante vertraging) een bepalende factor is van de huidige recombinante waarde van een component. Ten tweede dragen we bij aan de literatuur die de tijdsdimensie van kennisrecombinatie onderzoekt. In concrete bewoordingen, als we componentleeftijd gelijk houden, vinden we een duidelijke en robuuste invloed van recombinante vertraging op de technologische waarde van nieuwe uitvindingen, wat aangeeft dat deze twee tijdsdimensies elkaar sterk aanvullen.

8.2. Project 2: Kennispool Toepasbaarheid en O&O Allianties

In het tweede project bestuderen we factoren die de mate van recombinatie van kenniscomponenten van O&O alliantiepartners door het focale bedrijf beïnvloeden. Gebruikmakend van kennisrecombinatie inzichten beweren alliantie onderzoekers vaak dat het focale bedrijf door middel van samenwerking met externe partners met grotere en meer technologisch diverse kennispools, waardevolle nieuwe kansen creëert om componentcombinaties te genereren. Echter, op basis van de recente literatuur over kennisrecombinatie concluderen wij dat studies zich in toenemende mate richten op de toepasbaarheid van componenten, in tegenstelling tot hun hoeveelheid of diversiteit. Interessant is bovendien dat bestaand alliantieonderzoek grotendeels voorbijgaat aan het feit dat er aanzienlijke variatie is in het toepassingsniveau van componenten. Om deze kritische onderzoekshiaat aan te pakken, introduceren we het concept van kennispool toepasbaarheid – oftewel, de mate waarin componenten die zich in de kennispool bevinden, in verschillende toepassingsdomeinen kunnen worden gebruikt – en onderzoeken we de invloed daarvan op de recombinatie van componenten van O&O alliantiepartners door het focale bedrijf.

Op basis van opkomende kennisrecombinatie inzichten, voorspellen we allereerst een omgekeerde U-vormige relatie tussen de kennispool toepasbaarheid van de partner en de intensiteit van partner-specifieke recombinatie van het focale bedrijf. We stellen dat kennispool toepasbaarheid van partners aanvankelijk flexibiliteit biedt voor het focale bedrijf, in termen van waar en hoe het componenten die worden verkregen van de partner kan toepassen. Voorbij een bepaalde drempelwaarde wordt echter verwacht dat belangrijke leercomplexiteiten geassocieerd met overmatig toepasbare componentkennis naar voren komen, waardoor de partner-specifieke recombinatie van het focale bedrijf ruimschoots wordt verminderd. In de tweede hypothese verplaatsen we de focus naar de eigen kennispool toepasbaarheid van het focale bedrijf. We stellen de hypothese dat het focale bedrijf, door eerder opgebouwde breed toepasbare componentkennis, in staat is om kennisrecombinatie activiteiten flexibeler en effectiever uit te voeren binnen de kennispool van partners, resulterend in een toename van partner-specifieke recombinatie.

Om deze twee hypothesen te testen, analyseren we 461 O&O alliantie-dyades van 88 bedrijven in de brandstofcelindustrie. Onze bevindingen onderschrijven de stelling dat de kennispool toepasbaarheid van de partner een omgekeerde U-vormige relatie heeft met de partner-specifieke kennisrecombinatie van het focale bedrijf. In tegenstelling tot onze verwachtingen, vinden we echter dat de kennispool toepasbaarheid van het focale bedrijf een U-vormige relatie heeft met partner-specifieke recombinatie.

Deze bevindingen dragen op twee manieren bij aan de bestaande literatuur over allianties. Ten eerste wordt de de theoretische lens van geaggregeerde kennispoolkarakteristieken verplaatst naar individuele componenten binnen de kennispool. In plaats van brede component toepasbaarheid aan te nemen op basis van geaggregeerde kennispoolkarakteristieken (zoals diversiteit of grootte), benadrukken we het belang van het onderzoeken van de daadwerkelijke toepasbaarheid van individuele componenten binnen de kennispool. Ten tweede laten we zien hoe belangrijk het is om te theoretiseren over capaciteiten die het focale bedrijf in staat stellen de componentkennis van zijn O&O alliantiepartners intensiever te recombineren. Kortom, onze bevindingen geven aan hoe belangrijk het is om kennisrecombinatie op een hoog detail-niveau te analyseren om de implicaties voor de prestaties van O&O allianties te bepalen.

8.3. Project 3: Samenwerking in Uitdagings-Gebaseerde O&O Projecten

In het derde project bestuderen wij de probleemoplossende prestaties van samenwerkingsstrategieën en zelfstandige strategieën in uitdagings-gebaseerde O&O projecten. In de afgelopen jaren is het aantal grootschalige, door de overheid gefinancierde, programma's die gericht zijn op het aanpakken van grootschalige maatschappelijke uitdagingen zoals klimaatverandering en vergrijzing, snel toegenomen. Binnen deze programma's nemen organisaties, variërend van bedrijven tot universiteiten, deel aan uitdagings-gebaseerde O&O projecten om bestaande technologische problemen binnen een specifiek gebied op te lossen. In de literatuur over deze grootschalige maatschappelijke uitdagingen wordt vaak een impliciete veronderstelling gemaakt dat samenwerkingsstrategieën – oftewel projecten waarbij de focale organisatie formeel partners betrekt – altijd leiden tot een hogere kwaliteit van technologische oplossingen dan zelfstandige strategieën – oftewel projecten waarbij de focale organisatie zelfstandig opereert. Deze prestatieverschillen worden vaak verklaard door te wijzen naar de mogelijkheid om heterogene componentkennis van partners door samenwerking te recombineren.

In dit project, gebruikmakend van inzichten uit de 'knowledge-based view', wordt afgeweken van deze eerdere onderzoeken en beargumenteren wij dat niet elke organisatie de kennisrecombinatie voordelen van samenwerkingsstrategieën kan benutten. Concreet stellen we dat organisaties specifieke vaardigheden nodig hebben om de componentkennis van partners te identificeren, te verkrijgen, en te recombineren, om zodoende de kennisrecombinatie voordelen van samenwerkingsstrategieën te kunnen realiseren. Op basis hiervan ontwikkelen we theoretische argumenten om te onderbouwen dat drie verschillende kenmerken van de focale organisatie – namelijk institutionele achtergrond, interne kennispoolgrootte, en de omvang van de uitdagings-gebaseerde O&O projecten portfolio – van invloed zijn op het probleem-oplossend vermogen van samenwerkingsstrategieën ten opzichte van zelfstandige strategieën.

Om onze hypotheses te testen, analyseren we een zeer unieke dataset met gedetailleerde informatie op projectniveau over 414 uitdagings-gebaseerde O&O projecten binnen het waterstof- en brandstofcellenprogramma van het Amerikaanse Ministerie van Energie gedurende een periode van 14 jaar (2003-2016). Onze bevindingen leveren bewijs dat, gemiddeld genomen, samenwerkingsstrategieën betere probleemoplossende prestaties produceren dan zelfstandige strategieën. Opmerkelijk is echter dat hoewel bedrijven aanzienlijk beter presteren wanneer ze samenwerken in plaats van zelfstandig opereren, dit niet geldt voor onderzoeksorganisaties. Bovendien zien we dat de probleemoplossende prestatiekloof tussen samenwerkingsstrategieën en zelfstandige strategieën aanzienlijk groter wordt wanneer de focale organisatie een grotere interne kennispool heeft. Ten slotte wijzen onze bevindingen er, in tegenstelling tot de verwachtingen, op dat de uitdagings-gebaseerde O&O portfolio-omvang van de focale organisatie de positieve probleemoplossende prestatiekloof tussen samenwerkingsstrategieën en zelfstandige strategieën aanvankelijk vergroot, maar dat het deze voorbij een bepaald punt verkleint.

Gezamenlijk dragen deze bevindingen bij aan het bestaande onderzoek naar grootschalige maatschappelijke uitdagingen en open innovatie. Specifiek stellen onze bevindingen vraagtekens bij de vaak veronderstelde voordelen die bestaande literatuur toebedeelt aan samenwerkingsstrategieën als het gaat om het aanpakken van technologische problemen binnen een veld. We vinden dat voor vele soorten organisaties, zelfstandige strategieën en samenwerkingsstrategieën een vergelijkbaar probleem-oplossend vermogen tentoonspreiden.

8.4. Conclusie

In dit proefschrift ontwikkelen wij verschillende theoretische bijdragen die ons helpen het proces van kennisrecombinatie beter te begrijpen. Ten eerste onderstrepen we het feit dat kenniscomponenten niet per definitie een recombinante waarde hebben die vooraf wordt bepaald bij creatie; in plaats daarvan kan de recombinante waarde van componenten in de loop van de tijd aanzienlijk veranderen via kennishergebruik. In dit opzicht leveren we een belangrijke bijdrage door te stellen dat, naast de frequentie van hergebruik van componenten, ook rekening moet worden gehouden met hun recombinante vertraging. Ten tweede wijzen we erop dat het bij het onderzoeken van de implicaties van O&O allianties voor bedrijfsprestaties nuttig kan zijn om de toepasbaarheid van afzonderlijke componenten binnen de kennispool van partners te onderzoeken, in plaats van een eenzijdige focus op geaggregeerde kennispoolkenmerken, zoals grootte of diversiteit. Ter ondersteuning hiervan vinden we dat er een sterk effect bestaat van kennispool toepasbaarheid op de intensiteit van partner-specifieke recombinatie van het focale bedrijf wanneer we de kennispoolgrootte, -diversiteit en -afstand van O&O alliantiepartners gelijk houden. Ten derde, in tegenstelling tot eerder onderzoek dat vaak een enigszins directe relatie veronderstelt tussen de kennis input van partners en de eigen kennis output van de focale organisatie, hebben we geconstateerd dat organisaties idiosyncratische combinatieve capaciteiten nodig hebben om aanzienlijk profijt te halen uit samenwerking.

Dit proefschrift ontwikkelt ook belangrijke praktische bijdragen. Ten eerste wijzen wij erop dat het, in lijn met het opkomende open innovatieparadigma, belangrijk is dat informatiestromen resulterend uit nieuwe uitvindingen nauwkeurig en snel naar andere uitvinders verspreid worden, om zo vervolgens hun recombinatie processen te vergemakkelijken. Bovendien geven onze bevindingen aan dat inter-organisatorische samenwerkingsstrategieën een beslissende rol kunnen spelen bij het opsporen van nieuwe bronnen van componentkennis en het genereren van hoogwaardige technologische oplossingen binnen organisaties. Ten tweede voeren we aan dat het belangrijk is om adequate strategieën voor resource management te implementeren om waardevolle nieuwe uitvindingen te genereren. In het eerste project ontdekten we dat kenniscomponenten, die gedurende langere perioden ongebruikt zijn gebleven, onverwachte bronnen van waarde vertegenwoordigen voor kennisrecombinatie. Daarom moedigen we organisaties aan om de bestaande kennisvoorraden regelmatig opnieuw te evalueren zodat dit soort componenten kan worden blootgelegd, wat kan leiden tot een aanzienlijke realisatie van technologische waarde. Bovendien suggereren de bevindingen uit het tweede en derde project dat eerdere ervaring met het bouwen van nieuwe uitvindingen adequaat moet worden beheerd door de focale organisatie, zodat het kan worden ingezet om latere kennisrecombinatie inspanningen te verbeteren.

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Holmer Kok

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