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## **Only Time Will Tell? Recombinant Lag and the Technological Value of Inventions**

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### **Abstract**

Focusing on the temporal dimension of knowledge recombination, studies examine the extent to which the age of components influences the value of inventions. However, this research neglects that components vary substantially in terms of when they were last used. To address this gap, we introduce the concept of recombinant lag, i.e. the time that components in knowledge recombination have remained unused, and test its impact on the technological value of inventions. We predict that components that remain unused for longer periods become less technologically relevant and more difficult to retrieve. However, we also expect that, beyond a certain point, the uniqueness and untapped recombinant potential of components that remain unused for longer periods outweigh these two disadvantages. Analyzing 20,906 fuel cell patent families, we find that the recombinant lag of components used in knowledge recombination has a U-shaped relationship with the technological value of resulting inventions. Our findings contribute to a richer understanding of the temporal dimension of knowledge recombination and help to uncover the technological potential of shelved components.

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**ABSTRACT**

Focusing on the temporal dimension of knowledge recombination, studies examine the extent to which the age of components influences the value of inventions. However, this research neglects that components vary substantially in terms of when they were last used. To address this gap, we introduce the concept of recombinant lag, i.e. the time that components in knowledge recombination have remained unused, and test its impact on the technological value of inventions. We predict that components that remain unused for longer periods become less technologically relevant and more difficult to retrieve. However, we also expect that, beyond a certain point, the uniqueness and untapped recombinant potential of components that remain unused for longer periods outweigh these two disadvantages. Analyzing 20,906 fuel cell patent families, we find that the recombinant lag of components used in knowledge recombination has a U-shaped relationship with the technological value of resulting inventions. Our findings contribute to a richer understanding of the temporal dimension of knowledge recombination and help to uncover the technological potential of shelved components.

**Keywords:**

Knowledge recombination; temporal dimension; component reuse; invention

## INTRODUCTION

Knowledge recombination is recognized as a core process in the creation of inventions (Gruber, Harhoff, & Hoisl, 2013; Savino, Petruzzelli, & Albino, in press). This process entails that inventions originate from the recombination of existing components or the reconfiguration of existing combinations of components (Fleming, 2001; Galunic & Rodan, 1998; Yayavaram & Ahuja, 2008)<sup>1</sup>. Along with the technological and geographical diversity of recombined components (Phene, Fladmoe-Lindquist, & Marsh, 2006; Rosenkopf & Nerkar, 2001), some studies have identified the age of components as an important dimension that drives the value of inventions that result from knowledge recombination (Katila, 2002; Nerkar, 2003). These studies have consistently argued that older components are less technologically relevant and more difficult to retrieve, decreasing the value of inventions that combine these components (Capaldo, Lavie, & Petruzzelli, in press; Katila, 2002; Nerkar, 2003; Schoenmakers & Duysters, 2010; Sørensen & Stuart, 2000).

Whereas extant research on the temporal dimension of knowledge recombination has examined the impact of component age on the value of inventions, it ignored that components with a similar age can vary in terms of when they were last used. In this way, no distinction is made between (i) a 20-year-old component that was last used 10 years ago and (ii) a 20-year-old component that was last used 1 year ago. We, however, expect that the technological relevance and retrievability of a component does not merely depend on when such a component was created but rather hinges on when the component was used for the last time. Moreover, we expect that components that have remained unused for longer periods might entail advantages in terms of

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<sup>1</sup> 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).

uniqueness and untapped recombinant potential that prior research on the age of components did not identify. In this paper, we therefore shift away attention from the age of components toward recombinant lag, which we define as the time that components in knowledge recombination have remained unused, and test its impact on the technological value of inventions<sup>2</sup>.

We hypothesize a U-shaped relationship between the recombinant lag of components and the technological value of resulting inventions. On the one hand, as components remain unused for longer periods, their technological relevance and retrievability are likely to decrease. On the other hand, components with high levels of recombinant lag are highly unique and embody substantial untapped recombinant potential. Moreover, beyond a certain tipping point, we expect the positive effects of uniqueness and untapped recombinant potential to outweigh the disadvantages of recombinant lag. Relying on a sample of 20906 patent family applications in the fuel cell technology, we find robust evidence for our core hypothesis. These findings contribute to a richer theoretical understanding of the temporal dimension of knowledge recombination and illuminate the potential value of shelved components (Garud & Nayyar, 1994).

## **THEORY**

In this section, we first provide an overview of extant research on knowledge recombination and the value of inventions, giving special attention to the temporal dimension of knowledge recombination. Subsequently, we discuss the core theoretical mechanisms that drive the relationship between the age of components and the value of inventions. Finally, we point to

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<sup>2</sup>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).

the need to explicitly consider component reuse to understand the temporal dimension of knowledge recombination. We therefore introduce the concept of recombinant lag.

### **The temporal dimension of knowledge recombination**

Knowledge recombination scholars extensively study the relation between the technological, geographical and organizational attributes of components and their influence in knowledge recombination (Miller, Fern, & Cardinal, 2007; Phene et al., 2006; Rosenkopf & Nerkar, 2001). These studies argue that inventions that recombine components from diverse technological domains, geographical regions and organizations have a broader scope of applicability and therefore tend to be more valuable (Battke, Schmidt, Stollenwerk, & Hoffmann, 2016; Kaplan & Vakili, 2015; Rosenkopf & Nerkar, 2001). Given their broad scope of applicability, these inventions can subsequently be used as a base for future recombination efforts (Kim & Kogut, 1996).

Besides the abovementioned component-level characteristics, some studies also take in consideration the temporal attributes of components (Katila, 2002). In particular, these studies consider the age of components as an important driver of value in knowledge recombination (e.g. Capaldo et al., in press; Katila, 2002; Nerkar, 2003). Existing studies have mainly discussed the advantages and liabilities of recombining recent versus old components. These studies generally find that inventions that recombine older components are less technologically valuable (Capaldo et al., in press; Fabrizio, 2009; Kelley et al., 2013; Nerkar, 2003; Schoenmakers and Duysters, 2010; Sørensen & Stuart, 2000; Trajtenberg, Henderson, and Jaffe, 1997). In addition, they associate the extensive recombination of older components with slow learning or the inability to keep up with current technological trends (Bierly & Chakrabarti, 1996; Fabrizio, 2009; Sørensen & Stuart, 2000; Wuyts & Dutta, 2014).

The main theoretical arguments for this negative relationship are twofold. The first is that old components are less technologically relevant and therefore less valuable in knowledge recombination<sup>3</sup>. Old components are generally perceived as obsolete and unrepresentative of the best current technological alternatives as they are less likely to incorporate cutting-edge methods and functionalities into their design (Ahuja and Lampert, 2001; Heeley and Jacobs, 2008; Jaffe & Trajtenberg, 1999; Nerkar, 2003). As a result, new inventions that incorporate old components are less aligned with the current and future state of technology (Katila, 2002; Nerkar, 2003; Sørensen & Stuart, 2000). In contrast, recombination of recently-created components allows remaining ahead of others in the technological race and producing inventions that have high technological and commercial value (Hohberger, 2014).

The second argument used to explain the negative relationship between component age and value of inventions is linked to memory decay effects. The understanding of older components is diluted over time, making them more difficult to integrate into new combinations (Argote & Epple, 1990; Capaldo et al., in press; Garud & Nayyar, 1994; Katila, 2002; Nerkar, 2003). Memory decay effects entail the depreciation of knowledge and information over time. For example, when important blueprints and other records pertaining to specific components are lost (Argote & Epple, 1990; Garud & Nayyar, 1994), memory decay is likely to occur.

### **Component reuse and recombinant lag**

Despite the growing interest of scholars in the temporal dimension of knowledge recombination, most studies have solely focused on the age of components, ignoring that components can also vary in terms of when they were last used. We emphasize that two

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<sup>3</sup> In this context, we define technological relevance as the degree to which components fit with current technological standards (Sørensen & Stuart, 2000).

components with the same age may have been last reused at different points in time, which is likely to influence their technological relevance, retrievability, uniqueness and recombinant potential. For instance, in Figure 1, components 1 and 2 have the same age but component 1 was reused more recently than component 2. We argue that these differences in recency of reuse can have important implications. We expect that a recently reused component is more technologically relevant. At the same time, we acknowledge that a component that has remained unused for prolonged periods is more unique. Shifting away from the age of components, the present study therefore studies the relation between recombinant lag, which captures the recency of reuse of components, and their value in knowledge recombination.

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Insert Figure 1 about here  
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Component reuse has already been identified as an important factor that drives the value of knowledge recombination (Fleming, 2001; Katila & Ahuja, 2002; Yang, Steensma, & Phelps, 2010). Focusing on the frequency of reuse of components, scholars have mainly argued that component reuse is positively related to the value of inventions (e.g. Boh, Evaristo, & Ouderkerk, 2014; Dibiaggio, Nasiriyar, & Nesta, 2014; Fleming, 2001; Katila & Ahuja, 2002). Reusing components produces knowledge and information related to the technological specificities of these components which inventors might subsequently use to guide their recombination efforts (Fleming, 2001; Ghosh, Martin, Pennings, & Wezel, 2014; Yang et al., 2010)<sup>4</sup>. Each time a component is reused, it becomes clearer to what extent this component substitutes or

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<sup>4</sup> For example, there is evidence that inventors read domain-specific journals and scan the patents of other inventors to vicariously learn about their recombination efforts and stay up to date with current technological standards (Yang et al., 2010). Moreover, in order to learn how to recombine particular components, inventors may disentangle various inventions in which these components were reused (Hargadon & Sutton, 1997; Sorenson et al., 2006; Zander & Kogut, 1995).

complements other components in knowledge recombination (Dibiaggio et al., 2014; Fleming, 2001; Fleming and Sorenson, 2001; Yayavaram & Ahuja, 2008; Wang, Rodan, Fruin, & Xu, 2014). However, since components can only be reused a finite number of times before their recombinant potential is depleted (Ahuja & Lampert, 2001; Fleming & Sorenson, 2001), some studies acknowledge that relying on components that have been excessively reused reduces the value of resulting inventions (e.g. Katila & Ahuja, 2002)<sup>5</sup>.

Existing studies thus point to component reuse as an important dimension of knowledge recombination. However, these studies mostly focus on the frequency of reuse of components, but do not consider the recency of reuse. As a result, they ignore that components may have identical frequencies of reuse but a different recency of reuse. For example, although components 1 and 2 in Figure 1 have identical frequencies of reuse, component 1 was reused more recently than component 2, which may significantly impact the value of inventions that apply these two different components.

In sum, scholars have examined how the age of components affects the value of inventions, but they have not considered that these components may also vary in terms of when they were last used. Therefore, we examine the concept of recombinant lag, arguing that it can aptly capture the technological relevance, retrievability, uniqueness and recombinant potential of components. In the following section, we further develop these arguments, hypothesizing a U-shaped relationship between the recombinant lag of recombined components and the technological value of resulting inventions.

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<sup>5</sup> Similarly, Capaldo et al (in press) suggest that frequency of reuse may further decrease the value of older components by reducing their recombinant potential and uniqueness.

## **HYPOTHESIS**

### **The negative effects of recombinant lag**

Prior research shows that, in order to create valuable inventions, inventors should recombine components with high technological relevance (Fabrizio, 2009; Nerkar, 2003; Sørensen & Stuart, 2000). We argue that, when recombinant lag decreases, the technological relevance of components increases. First, a recent instance of reuse can be taken as a sign that a component incorporates technological methods and functionalities that are still relevant in the current technological environment. In contrast, components that have not been reused for long periods are less likely to be useful in knowledge recombination in the current technological environment (Guan and Liu, 2016; Wang et al., 2014). Second, components that were recently reused have their recombinant potential rejuvenated, such that their technological specificities will be aligned with current technological demands. In particular, a recently reused component is likely to have been recombined in a manner that matches current technological demands, as opposed to a component that was reused a long time ago. This rejuvenation of recombinant potential will make recently reused components suitable for addressing present-day technological problems and opportunities even when they were originally generated a long time ago.

In order to create technologically valuable inventions, inventors should also have a good understanding of how components function and how they should be integrated into new inventions (Fleming, 2001; Fleming & Sorenson, 2001). We argue that inventors are likely to have a better understanding of the technological specificities of components that were more recently reused. In particular, more recent instances of reuse provide access to more salient sources of knowledge and information that can be utilized to enrich the understanding of components' technological specificities (Sorenson, Rivkin, & Fleming, 2006). In contrast, when

recombinant lag increases and this source of knowledge and information becomes more temporally distant, retrieving an accurate depiction of components and their technological specificities will become more difficult due to memory decay effects (Argote & Epple, 1990; Garud & Nayyar, 1994). Retrieving knowledge and information of temporally distant events also tends to be more difficult because inventors have a cognitive bias towards recent events (Levinthal & March, 1993), implying that they recall better events which happened recently. However, we expect that memory decay effects do not linearly reduce the value of inventions. Instead, the most significant losses of knowledge and information generally occur in the first years after use (Argote, 2012; Katila and Ahuja, 2002). Therefore, we apply these insights and expect that the rate at which knowledge and information depreciate is highest during the first years of inactivity of components, after which this rate decreases.

### **The positive effects of recombinant lag**

Next to the technological relevance and retrievability of components, prior studies have also identified the uniqueness of components as an important driver of value of inventions (e.g. Fleming, 2001; Phene et al., 2006). These studies argue that inventions that recombine unique components will be more technologically valuable since they deviate substantially from conventional technological practices (Ahuja & Lampert, 2001; Arts & Veugelers, 2015; Carnabuci & Bruggeman, 2009; Fleming, 2001; Phene et al., 2006; Kaplan & Vakili, 2015). We argue that components that have remained unused for longer periods are more unique since they are non-obvious and difficult to retrieve for most inventors (Gavetti, 2012; Katila, 2002). Inventors generally have a narrow consideration scope for components (Jones, 2009; Melero & Palomeras, 2015) and they tend to recombine similar components from familiar technological areas (Katila & Chen, 2008; Patel & Pavitt, 1997; Stuart & Podolny, 1996). Since components

that remain unused for longer periods become more unfamiliar and more likely to fall outside the consideration scope of most inventors, their uniqueness and value in knowledge recombination will be higher.

Components that have not been reused for longer periods are also more likely to embody valuable untapped recombinant potential. In particular, certain components, which cannot be further recombined due to missing complementary resources, imperfect technological foresight, or because they were technologically ahead of present technological alternatives, are often shelved so that they can be reused at a future point in time (Cattani, 2005; Garud & Nayyar, 1994; Nerkar, 2003; Wang & Hagedoorn, 2014). Subsequently, when these components can finally be recombined, the resulting inventions will open up valuable unexplored paths of technological development that were neglected, overlooked or unexploitable in the past (Garud & Nayyar, 1994; Nerkar, 2003).

### **Recombinant lag and the technological value of inventions**

To summarize, we argue that components become less technologically relevant and more difficult to retrieve as they remain unused for longer periods. However, consistent with prior research (i.e. Argote, 2012), we expect that the rate at which components become more difficult to retrieve due to memory decay effects diminishes after a certain point. Hence, we expect the effect of the disadvantages of recombinant lag on the technological value of new inventions to become less pronounced beyond a certain point. At the same time, we argue that components that remain unused for longer periods become more unique and more likely to embody important untapped recombinant potential. Beyond a certain tipping point, we expect these two advantages of recombinant lag to outweigh the disadvantages. Accordingly, we predict that:

Hypothesis 1. The recombinant lag of components used in knowledge recombination has a U-shaped relationship with the technological value of resulting inventions.

## **METHODOLOGY**

### **Sample and data collection**

**Empirical context.** To test our hypothesis, we collected data on inventions related to fuel cell technology. Specifically, we studied the patent family applications of the 200 firms with the highest number of patent applications in this technology.

Invented in 1839 by Sir 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 in the Space Program. In subsequent decades, the potential of this technology has been exploited in distributed energy generation, portable electronic devices, and automobiles.

Given the long technological lineage of fuel cell technology, numerous recent inventions rely on components that originated decades earlier, hence making this technology suitable for our study. In addition, the potential for knowledge recombination in fuel cell technology is high (Vasudeva & Anand, 2011), mainly because the constituent components of fuel cells are highly modular (Baldwin & Clark, 2000; Furr & Snow, 2015; Pogutz, Russo, & Migliavacca, 2009). Finally, focusing on one specific technology reduces any unobserved between-technology heterogeneity (Noseleit & de Faria, 2013).

**Patent data.** To study fuel cell inventions, we relied on patent data retrieved from the European Patent Office's (EPO) PATSTAT database<sup>6</sup>. Due to its wide and detailed coverage of patenting activities, numerous studies rely on the PATSTAT database to study inventions (e.g. Belderbos, Cassiman, Faems, Leten, & Van Looy, 2014; Gruber et al., 2013). However, whereas the vast majority of studies use single patent authority applications to study inventions, we are among the first to use patent family applications (Bakker, Verhoeven, Zhang, & Van Looy, 2016; Battke et al., 2016; Hohberger, Almeida, & Parada, 2015). To delineate patent families, we relied on the DOCDB patent family definition as proposed by the EPO. The DOCDB patent family captures all patent applications relating to one invention but filed at different patent authorities (Albrecht, Bosma, van Dinter, Ernst, van Ginkel & Versloot-Spoelstra, 2010). The use of patent families to denote inventive activities has a number of advantages over single patent applications (Bakker et al., 2016; de Rassenfosse, Dernis, Guellec, Picci, & van Pottelsberghe de la Potterie, 2013; Martínez, 2011). First of all, captures a wider array of inventions since it does not limit itself to one patent authority (Bakker et al., 2016). Secondly, it overcomes the home-country bias of single patent authority applications (Criscuolo, 2006; de Rassenfosse et al., 2013). Thirdly, it provides a more complete coverage of prior art citations than single patent authority applications (Albrecht et al., 2010).

A particular advantage of using patents to study inventions is that they are required by law to record their technological antecedents through prior art citations (backward citations hereafter) (Criscuolo & Verspagen, 2008). Backward citations delineate property rights by denoting parts of

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<sup>6</sup> 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 general reliability of this data (Criscuolo & Verspagen, 2008), and the fact that we sampled from an industry in which patenting propensity rates are generally elevated, these concerns are alleviated (Arundel & Kabla, 1998).

the new invention which have already been covered in previous inventions, and upon which the new invention may not lay claim (Gay & Le Bas, 2005). Following earlier research, we studied patents' backward citations to examine the components that are recombined to create new inventions (Battke et al., 2016; Belenzon, 2012; Jaffe & de Rassenfosse, 2016; Miller et al., 2007; Nemet & Johnson, 2012; Nerkar, 2003; Phene et al., 2006; Rosenkopf & Nerkar, 2001). Since we studied patent families, however, we aggregated all backward citations at the patent family-level (Bakker et al., 2016). To illustrate this, consider the example in Figure 2 where the nodes represent single patent authority applications, the squares represent patent family delineations and the arrows represent citations. Taking patent family 4 as our focal observation, we would record backward citations to patent families 1, 2 and 3 and forward citations to patent families 5, 6 and 7. Importantly, even though patent E cites patent C and patent F cites patent D, we only record one backward citation since patents C and D pertain to the same patent family.

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We collected all patent family applications filed in IPC class H01M8 which corresponds to fuel cell technology (Fuel Cell Today, 2011; OECD, 2009). Our data collection procedure allowed us to identify a total of 20,906 patent family 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<sup>7</sup>.

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<sup>7</sup> The latter step was necessary as we relied on fixed four-year window external forward citations to measure the technological value of inventions, and we observed that the number of citations in our database decreased rapidly after 2011. To avoid left censoring of the data, we took the precautionary step to limit our analysis to the years extending to and including 2007. Nevertheless, robustness checks revealed no apparent differences in our findings when including all available data.

**Firm ownership data.** To ensure that the examined patenting activities captured the full extent of firms' technological activities (Sampson, 2007)<sup>8</sup>, 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). Subsequently, 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 in Bureau van Dijk's ORBIS Database<sup>9</sup>. We subsequently matched the names of these subsidiaries to those available in the patent database<sup>10</sup>. 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 sample included 141 firms.

## Variables

**Dependent variable.** To measure the Technological value of inventions, we relied on forward citations (i.e. citations made to the patent family; see Figure 2). Forward citations have often been used to indicate the technological value of inventions (e.g. Ahuja & Lampert, 2001; Battke et al., 2016; Jaffe & de Rassenfosse, 2016; Fleming, 2001; Nemet & Johnson, 2012; Rosenkopf & Nerkar, 2001) and they correlate positively with the economic value of patents

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<sup>8</sup> We also needed to pinpoint which patent citations were internal (i.e. citations between patents from the same applicant) and which were not. In particular, when capturing the technological value of inventions, it is crucial to distinguish between internal and external forward citations since they may reflect different value indications (Almeida & Phene, 2004; Hoetker & Agarwal, 2007; Kim, Song, & Nerkar, 2012). Similarly, recombining internal components may considerably influence the technological value of inventions (e.g. Rosenkopf and Nerkar, 2001).

<sup>9</sup> A particular advantage of this database is that it let us retrieve the complete ownership structure of firms, such that we were able to pinpoint which of the subsidiaries' own subsidiaries were ultimately owned by the parent firm (up to 10 levels deep).

<sup>10</sup> To be sure we captured all relevant subsidiaries, we also checked for potential name changes and other names that companies 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. When ambiguities still persisted, we also inspected the address that was listed on the patent application of the entity (provided that they were available).

(Hall, Jaffe, and Trajtenberg, 2005; Harhoff, Narin, Scherer, and Vopel, 1999; Trajtenberg, 1990). A high citation count indicates that a component is frequently used as an input for new inventions. Moreover, since older patents may receive more citations because they have been in existence for longer (Fleming, 2001; Nemet & Johnson, 2012; Wang, 2016), we applied a fixed four-year window to forward citations (i.e. we only counted forward citations in the 4 years after the creation of an invention, irrespective of the year in which the invention was created). Finally, as is common practice, we excluded internal forward citations (Hoetker & Agarwal, 2007; Miller et al., 2007).

**Independent variable.** To measure Recombinant lag, we collected data on all the forward citations made to the backward citations of the patent families in our sample<sup>11</sup>. We then calculated how many years elapsed between the priority year of the focal patent and the last citation that was made to its respective backward citations. In case there were no prior citations made to the backward citation, recombinant lag was set equal to the age of the backward citation (i.e. the time that elapsed between the priority year of the focal patent and the priority year of the backward citation). For example, if patent A is filed in 1995, and patent A is subsequently cited in the application of patent B in 1997 and the application of patent C in 2002, then patent B receives a value of 2 and patent C a value of 5 for recombinant lag (see Figure 3). For each patent family, we took the median value of recombinant lag of its backward citations (Nerkar, 2003; OECD, 2009). We took the median value of recombinant lag to more aptly capture the typical time that recombined components had remained unused<sup>12</sup>. Relying on the median value of a

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<sup>11</sup> Note that we collected data on all the forward citations made to these backward citations, regardless of the technological field to which they pertained or the type of applicant (i.e. we also included forward citations from Universities, individuals and NGO's). This allowed us to retrieve a total of 1,628,171 citations made to the backward citations of the patent families in our sample.

<sup>12</sup> We also run robustness checks using the mean and maximum value of recombinant lag of backward citations of patent families, and the results remained stable.

variable is also warranted when the distribution of this variable is skewed. In our case, the distribution of recombinant lag was skewed to the right, indicating that most components had remained unused only shortly (i.e. 58% of backward citations had been reused or were created in the preceding year).

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**Patent-level control variables.** Following prior research on the technological value of inventions, we included eight control variables in the models. Below, we describe these eight control variables and their expected influence on the technological value of inventions.

We controlled for several attributes of recombined components. Patents with more backward citations are more likely to be located in the search space of other firms (Podolny & Stuart, 1995), increasing the likelihood that they form a base for future recombination efforts. To control for this fact, we included the variable Backward citations which counts the number of backward citations of the patent family. Moreover, inventions that rely strongly on internal components tend to receive fewer citations (Kim et al., 2012; Rosenkopf & Nerkar, 2001). The variable Internal citations 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. Earlier research also demonstrated that the frequency of reuse of components may increase the amount of information that is available about these components (Fleming, 2001; Katila & Ahuja, 2002). To control for this fact, the variable Prior reuse counts the average number of times that the patent family's backward citations were previously cited by other patent families (Miller et al., 2007). The Technological distance of recombined components may further influence the technological value of resulting inventions (e.g. Nemet & Johnson, 2012; Phene et al., 2006;

Rosenkopf & Nerkar, 2001; Trajtenberg et al., 1997). To control for this fact, we computed the measure of technological distance from Trajtenberg et al. (1997) which calculates technological distance at the IPC class-level, attributing higher values of technological distance to citations made to more distant IPC classes. For example, citations made to a different one-digit IPC class (e.g. a citation from class H, which refers to electricity, to class G, which refers to physics) will contribute to a higher value of technological distance than those made within the same one-digit, but different three-digit, IPC class (e.g. a citation from class H01M, which broadly refers to batteries, to class H01C, which broadly refers to resistors). We also controlled for the fact that inventions that draw from broad technological domains may have a broader scope of applicability and, thus, a higher technological value (Belderbos et al., 2014; Nerkar, 2003). To do this, we computed the measure of Technological breadth which measures technological breadth at the backward citation-level (Gruber et al., 2013). For example, using this measure, a patent that cites 1 patent in technology class H01M and 1 patent in technology class H01C would receive a lower value of technological breadth than an otherwise equal patent that cites 2 patents in both technology classes H01M and H01C (Gruber et al., 2013).

We also controlled for attributes of the patent family. Singh and Fleming (2010) found that single inventors tend to generate inventions with poorer outcomes than teams of inventors. Moreover, Taylor and Greve (2006) found that teams of inventors recombine components differently from single inventors. Hence, to control for these effects, we included the variable Team size which measures the size of the team that contributed to 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 (de Rassenfosse, 2013; Fischer & Leidinger, 2014; Guan & Liu, 2016; Harhoff et al., 2003). Hence, the number of patent authorities in which a

patent was filed may be indicative of the quality of the underlying invention. To control for this effect, we included the variable Patent authorities which counts the number of unique patent authorities in which patents in the patent family were filed. Earlier research also noted that, since granted patents have passed patent examiners' evaluation of patentability, their technological value is generally higher (Belderbos et al., 2014). 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. Finally, we included firm and year dummies in each model to control for unobserved heterogeneity.

### **Analytical method**

As our dependent variable was a count variable that is overdispersed (i.e. the standard deviation of the variable exceeds the mean), we used negative binomial regressions to test our hypothesis (Cameron & Trivedi, 1990; Hausman, Hall, & Griliches, 1984). This method of analysis has also been employed by prior research that uses patent data (e.g. Fleming, 2001; Nemet & Johnson, 2012; Rosenkopf & Nerkar, 2001). To control for heteroskedasticity, we included robust standard errors in all models (White, 1980)<sup>13</sup>.

### **Results**

**Descriptive statistics.** Table 1 shows summary statistics and the correlation coefficients between the dependent, independent and control variables. On average, the patents in our sample receive 2.49 citations in the first four years after creation, which is in line with previous studies (e.g. Fleming, 2001). Moreover, similar to Arts and Veugelers (2015), we find that 38.6% of these patents receive no forward citations in the first four years after creation. With regards to

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<sup>13</sup> We additionally ran the models using robust standard errors clustered at the firm-level. This did not affect the results.

recombinant lag, the patents in our sample typically cite patents that have remained unused for 1.72 years, suggesting that most inventions rely on components that have remained unused relatively shortly.

Since some correlation values exceed 0.30 (e.g. between technological distance and technological breadth) and to check for potential multicollinearity problems, we looked carefully at the variance inflation factors (VIF) and at the condition numbers of our models. The VIF analysis returns a maximum value of 1.45 and an average value of 1.20 for all variables. Even when including the quadratic term of recombinant lag, VIF values remain well below the threshold value of 10 (Mason & Perreault, 1991). Moreover, the condition numbers are 6.17 for the main model and 6.20 for the model including the quadratic term of recombinant lag, both well below the threshold value of 15 (Mason & Perrault, 1991). Consequently, we are confident that multicollinearity is not an issue in our models.

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Insert Table 1 about here  
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**Regression results.** Table 2 provides 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. The number of backward citations has a positive and statistically significant effect on the technological value of inventions (model 1:  $\beta = 0.014$ ,  $p < .001$ ), suggesting that inventions that recombine many different components are more technologically valuable (Podolny & Stuart, 1995). The share of internal citations of the patent family has a negative and statistically significant effect on the technological value of inventions (model 1:  $\beta = -0.256$ ,  $p < .001$ ), 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 frequency of reuse of recombined components has a positive and statistically significant effect on the technological value of

inventions (model 1:  $\beta = 0.01$ ,  $p < .001$ ). Hence, recombining components that were frequently reused positively influences the value of inventions (e.g. Fleming, 2001; Katila and Ahuja, 2002). The technological distance of recombined components decreases the technological value of resulting inventions (model 1:  $\beta = -0.5$ ,  $p < .001$ ), suggesting that fuel cell patents benefit largely from relying on components from proximate technological fields (e.g. Nemet & Johnson, 2012). In contrast, 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:  $\beta = 0.19$ ,  $p < .001$ ). 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:  $\beta = 0.027$ ,  $p < .001$ ), 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:  $\beta = 0.113$ ,  $p < .001$ ), providing evidence that a broader scope of protection may be indicative of the quality of an invention. Finally, the control variable Patent granted has a positive and statistically significant effect on the technological value of inventions (model 1:  $\beta = 0.213$ ,  $p < .001$ ).

In models 2 and 3 we test Hypothesis 1. We find a negative and statistically significant effect of recombinant lag on the technological value of inventions (model 2:  $\beta = -0.067$ ,  $p < .001$ ). In model 3, we include the quadratic term of recombinant lag and find a positive and statistically significant effect (model 3:  $\beta = 0.003$ ,  $p < .001$ ), indicating the existence of a curvilinear relationship between recombinant lag and the technological value of inventions. To detect whether this relationship is the hypothesized one (i.e. a U-shaped relationship), we perform the three step procedure proposed by Lind and Mehlum (2010) and further discussed by Haans, Pieters and He (in press) for testing U-shaped relationships. All criteria of this procedure are met: (i) the linear coefficient is negative and statistically significant and the quadratic coefficient is positive and statistically significant, (ii) the 95 percent confidence interval of the inflection point

is within the range of observable points, and (iii) the left part of the slope is negative and statistically significant ( $p < .001$ ) and the right part of the slope is positive and statistically significant ( $p < .01$ )<sup>14</sup>. Taken together, we find support for your hypothesis that recombinant lag has a U-shaped relationship with the technological value of inventions. Figure 4 plots this relationship and shows that the inflection point occurs at a value of recombinant lag of 18.18.

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Insert Table 2 about here  
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Insert Figure 4 about here  
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### **Robustness checks**

To assess the robustness of our findings, we run several alternate model specifications<sup>15</sup>. First, we look more deeply into the recombinant lag variable. We check whether the U-shaped relationship is driven by extreme values of recombinant lag by excluding the 99<sup>th</sup> percentile of recombinant lag from the model. This does not change the results, as we still find a U-shaped relationship between recombinant lag and the technological value of inventions. We also recalculate recombinant lag by taking the mean value ( $M_{\text{Mean lag}} = 2.45$ ,  $SD = 2.09$ ) and maximum value ( $M_{\text{Maximum lag}} = 6.89$ ,  $SD = 8.07$ ) of recombinant lag of the backward citations of the patent family. The results remain similar to the ones with our original measure of recombinant lag, although model fit worsens overall in both cases. We also include age as a control variable in models 4-6. Age is calculated by the average time that elapsed between the priority year of the focal patent family and the priority years of the backward citations (Katila, 2002; Sørensen &

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<sup>14</sup> We also include the cubic term of recombinant lag into the models to check whether we are dealing with an S-shaped relationship, rather than a U-shaped relationship (Haans et al., in press). Although all terms are statistically significant and in the expected direction, the results are strongly driven by the presence of outliers. Moreover, multicollinearity issues are likely present, as VIF values for the linear, quadratic and cubic terms are well above the threshold value of 10 (Mason & Perreault, 1991).

<sup>15</sup> These results are available upon request.

Stuart, 2000; Trajtenberg et al., 1997). We find that age has a negative and statistically significant effect on the technological value of inventions (model 4:  $\beta = -0.013$ ,  $p < .001$ ). However, we find no evidence of a curvilinear relationship between age and the technological value of inventions (also see Figure 5)<sup>16</sup>. Thus, age appears to have a strictly negative linear relationship with the technological value of inventions. This provides additional evidence that when recombinant lag is not accounted for, the existence and relevance of shelved components in knowledge recombination cannot be detected.

Second, we run alternative model specifications by (i) employing alternative dependent variables (i.e. excluding patents that have not been cited within the first four years of creation, including internal forward citations, excluding external forward citations, excluding non-fuel cell forward citations, excluding citations made within the year of creation of the invention, and increasing the window of forward citations to 5 years, 10 years, and all years), (ii) excluding all patent families filed before 1990, given the fact that fuel cell technological developments only really took off after this year, (iii) excluding patent families with a single backward citation (Fleming, 2001), since these types of patent families may not reflect actual knowledge recombination processes because they merely utilize one component (Ghosh et al., 2014), (iv) including separate control variables for Internal prior reuse and External prior reuse ( $M_{\text{Internal prior reuse}} = 0.62$ ,  $SD = 2.65$ ;  $M_{\text{External prior reuse}} = 6.32$ ,  $SD = 7.11$ ), (v) including the quadratic terms of technological distance and technological breadth as additional control variables (separately, due to high collinearity), and (vi) including dummies in each model for the unique patent authorities in which the invention was filed. The main results do not change markedly with any of these alternate specifications.

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<sup>16</sup> We additionally ran the models with the median age of backward citations, but results remained similar.

Finally, we add two new control variables that count the number of patent families from inside the firm (Internal reuse depth) and outside the firm (External reuse depth) that cite the same patents as the focal patent in the same year ( $M_{\text{Internal reuse depth}} = 0.54$ ,  $SD = 1.03$ ;  $M_{\text{External reuse depth}} = 1.66$ ,  $SD = 1.67$ ). These variables measure how the extent of simultaneous component reuse by the firm and others may influence the value of inventions<sup>17</sup>. We average the value of these variables for all the backward citations of the patent family. We find that internal reuse depth has a negative and statistically significant effect on technological value ( $p < .001$ ), while external reuse depth has a positive and statistically significant effect on technological value ( $p < .001$ ). However, including these two variables into the model does not markedly alter our main results.

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Insert Figure 5 about here  
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## DISCUSSION AND CONCLUSION

This study explores the relation between recombinant lag – the time that components in knowledge recombination have remained unused – and the technological value of inventions. Whereas existing studies have mostly focused on the age of components, this study demonstrates that the technological value of inventions is substantially driven by the time that recombined components have remained unused. Specifically, our results show robust evidence of a U-shaped relationship between recombinant lag and the technological value of inventions. However, we find that an increase in recombinant lag only has a positive effect on the technological value of inventions for high values of recombinant lag. This implies that, for the most part, components

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<sup>17</sup> To clarify how this variable is measured, if patent A cites patent B, but in the same year 2 other patents from the same firm and 3 other patents outside the firm also cite patent B, then internal reuse depth takes a value of 2 and external reuse depth takes a value of 3.

become less valuable in knowledge recombination as they remain unused for longer because they become (i) less technologically relevant and (ii) more difficult to retrieve. At the same time, due to the substantial uniqueness and untapped recombinant potential that components with extreme values of recombinant lag embody, inventions that recombine these components will be more technologically valuable. These findings contribute to knowledge recombination literature in several ways.

First, this study underlines the fact that the temporal dimension of knowledge recombination and component reuse should be jointly considered in research on the value of knowledge recombination. With the exception of a recent study by Capaldo et al. (in press), remarkably little attention has been paid to the interaction between these two aspects of knowledge recombination. Instead, most studies make the assumption, 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). However, we show that components vary substantially in terms of when they were last used, and that this may significantly impact the value of inventions that apply these components. Notably, recent instances of component reuse may offset particular disadvantages associated with the recombination of older components. For example, more recent instances of component reuse may offset potential memory decay effects by keeping components fresh in inventors' memory. Moreover, recent instances of reuse may increase the technological relevance of components by aligning their technological specificities with current technological standards.

Second, we contribute to component reuse literature by addressing the dimension of time in component reuse. Thus far, most studies in this literature have either focused on the frequency (e.g. Fleming, 2001; Katila & Ahuja, 2002) or source (e.g. Belenzon, 2012; Yang et al., 2010) of

component reuse, neglecting the importance of the timing of reuse (Argote & Miron-Spektor, 2011; Katila and Chen, 2008). Crucially, without considering recombinant lag, we cannot capture how the effects of reuse might change over time. Our findings suggest that the knowledge and information that are produced when components are reused might vanish over time due to memory decay effects (Argote, 2012). Moreover, our findings suggest that the recombinant potential of components does not merely depend on their frequency of reuse, but also on the time that they have remained unused.

Third and finally, we provide unique insights into the value of shelved components in knowledge recombination, shedding light on a new source of novelty for knowledge recombination (Rosenkopf & McGrath, 2011). In their seminal study, Garud and Nayyar (1994) emphasized the importance of shelving and maintaining components which emerged ahead of their time. Moreover, they argued that the stock of existing components should be continually re-evaluated in order to identify and reuse shelved components when the time is right (Garud & Nayyar, 1994; Hargadon & Sutton, 1997; Wang & Hagedoorn, 2014). However, existing studies have failed to capture the existence of shelved components and their relevance in knowledge recombination, as they merely studied the age of components. We find evidence that recombining components which have remained shelved for prolonged periods may result in technologically valuable inventions. This can be explained by the fact that shelved components are unknown to most inventors and they tend to be difficult to retrieve, hence increasing their uniqueness in knowledge recombination (Gavetti, 2012; Katila, 2002). Moreover, revisiting shelved components may lead to the recognition of hitherto unexplored paths of technological development (Garud & Nayyar, 1994; Nerkar, 2003).

Interestingly however, we find that only extreme values of recombinant lag have a positive influence on the technological value of inventions. Specifically, we find that inventions become more technologically valuable when they recombine components that have typically remained unused for 18 years or longer. An explanation for this could be that these components pertain to prior technological generation, which only few inventors will be familiar with (Furr & Snow, 2015). As a result, these components will be substantially more unique and valuable in knowledge recombination.

### **Limitations and future research**

The present study has certain limitations which must be kept in mind, and which nonetheless provide important inquiries for future research. First, we focused on the value of shelved components in knowledge recombination, but we did not examine the antecedents of recombining these components. Examining the antecedents of recombining shelved components is important because it would produce insights into how firms can optimize the utilization of the existing stock of components. Moreover, as recently emphasized by Carnabuci and Operti (2013), we generally know too little about the drivers of different types of knowledge recombination. For example, future studies could look into the role of interfirm collaborations in driving the recombination of shelved components. Notably, Tsang (2000) suggests that firms can access important complementary resources through interfirm collaboration which allow them to uncover the potential value of dormant resources.

Second, we used patent data to study shelved components. This data allowed us to examine the value of these components on a large scale, using methods and measures validated by previous studies. However, this data does not lend itself particularly well to fine-grained analysis of particular components in knowledge recombination. Therefore, we urge future

research to conduct in-depth qualitative studies on shelved components, identifying their primary characteristics. These studies would carry important managerial implications, as they would help firms identify which components should be taken off the shelf for knowledge recombination.

Third, we used backward citations to denote the components that new inventions build upon, even though some studies have raised concerns about this approach (e.g. Alcacer & Gittelman, 2006). An alternative would be to rely on technological subclasses (Carnabuci & Operti, 2013). However, it has not yet been proven whether this approach has clear empirical merits over the use of backward citations (Aharonson & Schilling, 2016).

Finally, we acknowledge that our findings may be sensitive to the sample that we chose. In particular, fuel cell technology is quite unique in that it has gone through several waves of technological development, allowing for the emergence of components which remain unused for prolonged periods. However, there is no a priori reason to believe that our findings are technology-specific, as the theoretical underpinnings for why certain components remain unused for prolonged periods and why these components may be valuable in knowledge recombination are not confined to the technology that we sampled from. Nevertheless, future research should attempt to replicate our findings in other settings. In the domain of scientific literature, there is at least some evidence that components which have remained unused for long periods are pervasive (Ke, Ferrara, Radicchi, & Flammini, 2015; Van Raan, 2004).

## **Conclusion**

In this paper, we have contributed to a richer understanding of the temporal dimension of knowledge recombination by introducing the concept of recombinant lag and to test its implications for the value of inventions. We hope that our findings inspire academic scholars to further explore the temporal dimension of knowledge recombination in different technological

and organizational settings and can help practitioners in optimizing the productivity and value of their existing knowledge stock.

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**TABLE 1****Descriptive statistics**

|                          | Mean | SD   | Min | Max    | 1     | 2     | 3     | 4     | 5     | 6     | 7    | 8    | 9    | 10 |
|--------------------------|------|------|-----|--------|-------|-------|-------|-------|-------|-------|------|------|------|----|
| 1 Technological value    | 2.49 | 4.26 | 0   | 85     | 1     |       |       |       |       |       |      |      |      |    |
| 2 Recombinant lag        | 1.72 | 1.76 | 0   | 58     | -0.09 | 1     |       |       |       |       |      |      |      |    |
| 3 Backward citations     | 9.08 | 9.61 | 1   | 179    | 0.30  | -0.13 | 1     |       |       |       |      |      |      |    |
| 4 Internal citations     | 0.16 | 0.22 | 0   | 1      | -0.06 | -0.07 | -0.07 | 1     |       |       |      |      |      |    |
| 5 Prior reuse            | 6.94 | 8.07 | 0   | 327.88 | 0.12  | -0.20 | 0.23  | -0.05 | 1     |       |      |      |      |    |
| 6 Technological distance | 0.11 | 0.12 | 0   | 1      | -0.12 | 0.16  | -0.33 | -0.01 | -0.07 | 1     |      |      |      |    |
| 7 Technological breadth  | 0.65 | 0.36 | 0   | 0.99   | 0.10  | -0.04 | 0.21  | -0.06 | 0.12  | 0.34  | 1    |      |      |    |
| 8 Team size              | 2.99 | 1.96 | 1   | 18     | 0.07  | -0.02 | 0.06  | -0.02 | 0.005 | -0.02 | 0.03 | 1    |      |    |
| 9 Patent authorities     | 2.40 | 2.00 | 1   | 19     | 0.30  | -0.11 | 0.37  | -0.04 | 0.16  | -0.19 | 0.14 | 0.04 | 1    |    |
| 10 Patent granted        | 0.72 | 0.45 | 0   | 1      | 0.19  | -0.06 | 0.22  | 0.02  | 0.09  | -0.13 | 0.09 | 0.03 | 0.26 | 1  |

**TABLE 2**

**Technological value of inventions as function of patent characteristics<sup>a</sup>**

|                         | Dependent variable: Four-year fixed window external forward citations |                      |                       |                      |                      |                        |                      |
|-------------------------|---|----------------------|-----------------------|----------------------|----------------------|------------------------|----------------------|
|                         | Model 1   | Model 2              | Model 3               | Model 4              | Model 5              | Model 6                | Model 7              |
| Recombinant lag         |   | -0.067***<br>[0.008] | -0.107***<br>[0.0132] |                      |                      | -0.064***<br>[0.00860] | -0.105***<br>[0.014] |
| Recombinant lag squared |   |                      | 0.003***<br>[0.001]   |                      |                      |                        | 0.003***<br>[0.001]  |
| Backward citations      | 0.014***<br>[0.001]   | 0.014***<br>[0.001]  | 0.014***<br>[0.001]   | 0.015***<br>[0.001]  | 0.015***<br>[0.001]  | 0.014***<br>[0.001]    | 0.014***<br>[0.001]  |
| Internal citations      | -0.256***<br>[0.046]  | -0.304***<br>[0.046] | -0.312***<br>[0.046]  | -0.305***<br>[0.046] | -0.305***<br>[0.047] | -0.311***<br>[0.046]   | -0.316***<br>[0.046] |
| Prior reuse             | 0.010***<br>[0.002]   | 0.008***<br>[0.002]  | 0.007***<br>[0.002]   | 0.012**<br>[0.002]   | 0.012***<br>[0.002]  | 0.008***<br>[0.002]    | 0.007***<br>[0.002]  |
| Technological distance  | -0.501***<br>[0.112]  | -0.387***<br>[0.112] | -0.383***<br>[0.112]  | -0.502***<br>[0.112] | -0.502***<br>[0.113] | -0.392***<br>[0.112]   | -0.386***<br>[0.112] |
| Technological breadth   | 0.186***<br>[0.032]   | 0.172***<br>[0.032]  | 0.175***<br>[0.032]   | 0.194***<br>[0.032]  | 0.194***<br>[0.032]  | 0.174***<br>[0.032]    | 0.176***<br>[0.032]  |
| Team size               | 0.027***<br>[0.005]   | 0.027***<br>[0.005]  | 0.027***<br>[0.005]   | 0.027***<br>[0.005]  | 0.027***<br>[0.025]  | 0.027***<br>[0.005]    | 0.027***<br>[0.005]  |
| Patent authorities      | 0.113***<br>[0.005]   | 0.110***<br>[0.005]  | 0.109***<br>[0.005]   | 0.112***<br>[0.005]  | 0.112***<br>[0.005]  | 0.110***<br>[0.005]    | 0.109***<br>[0.005]  |
| Patent granted          | 0.213***<br>[0.025]   | 0.210***<br>[0.025]  | 0.210***<br>[0.025]   | 0.215***<br>[0.025]  | 0.215***<br>[0.005]  | 0.211***<br>[0.025]    | 0.210***<br>[0.025]  |
| Age                     |   |                      |                       | -0.013***<br>[0.003] | -0.013**<br>[0.006]  | -0.002<br>[0.003]      | -0.001<br>[0.003]    |
| Age squared             |   |                      |                       |                      | 0.000<br>[0.000]     |                        |                      |
| Observations            | 20906   | 20906                | 20906                 | 20906                | 20906                | 20906                  | 20906                |
| Pseudo R-squared        | 0.118   | 0.119                | 0.12                  | 0.118                | 0.118                | 0.119                  | 0.12                 |
| Log Likelihood          | -37583.6  | -37522.1             | -37505.8              | -37567.9             | -37567.9             | -37521.7               | -37505.7             |

† p < .10

\* p < .05

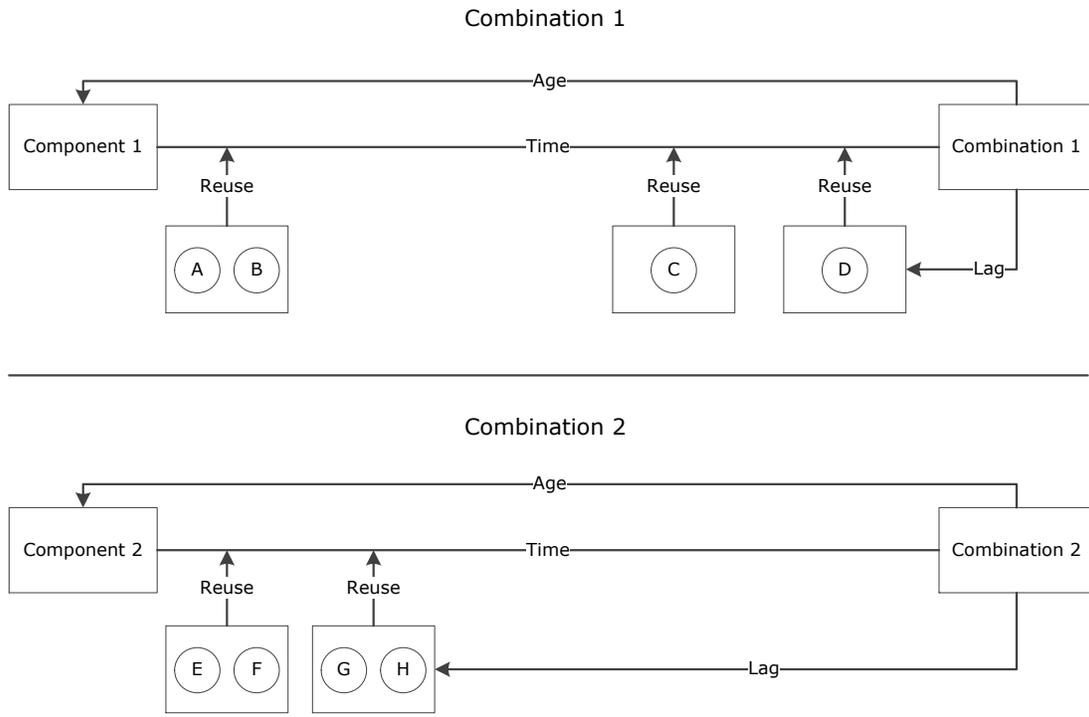
\*\* p < .01

\*\*\* p < .001

<sup>a</sup> Robust standard errors between brackets. Firm and year dummies included in all models

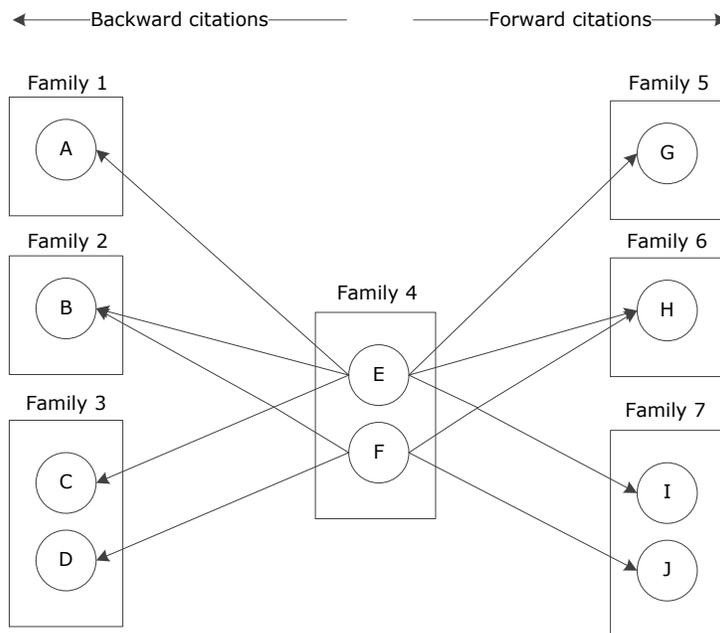
**FIGURE 1**

**Recombinant lag, age and prior frequency of reuse**



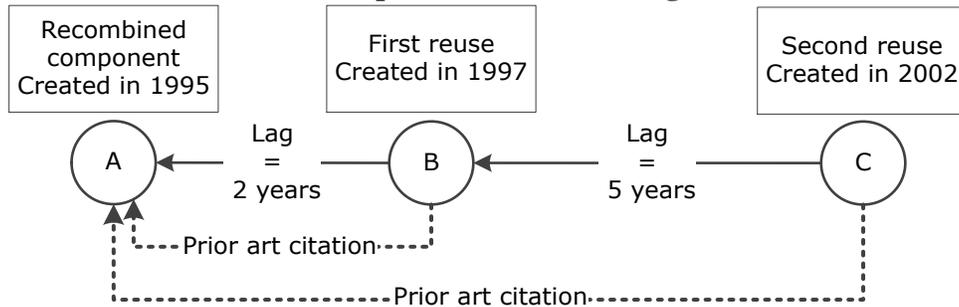
**FIGURE 2**

**Example of patent family citations**



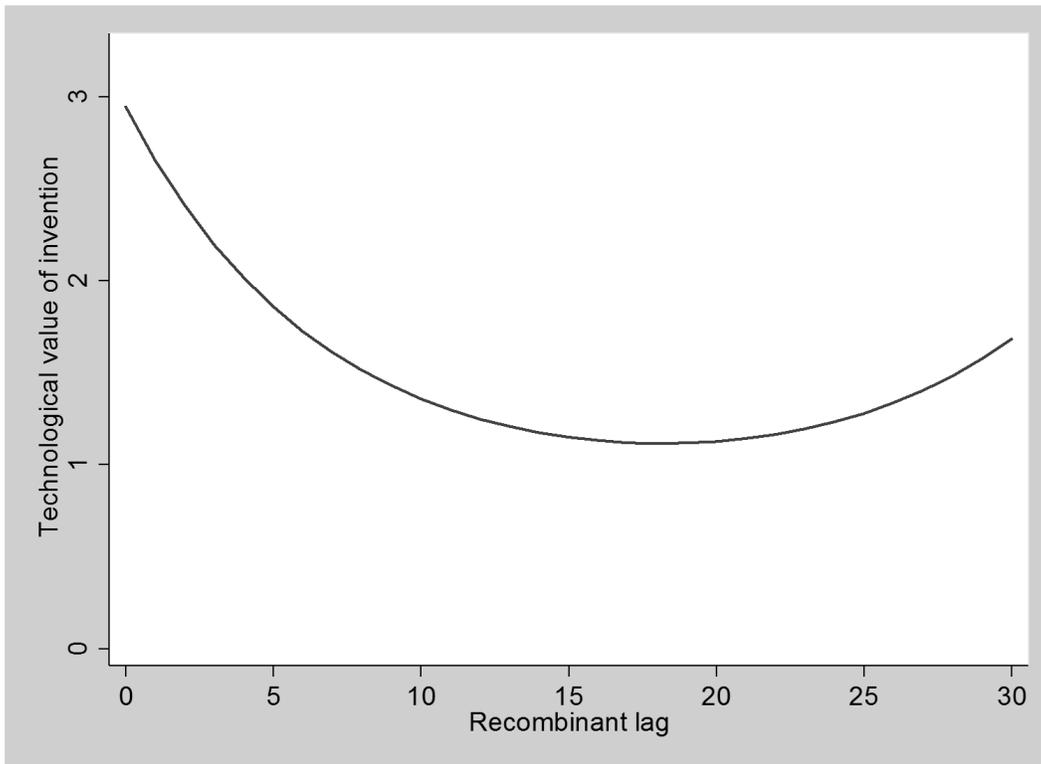
**FIGURE 3**

**Example of recombinant lag**



**FIGURE 4**

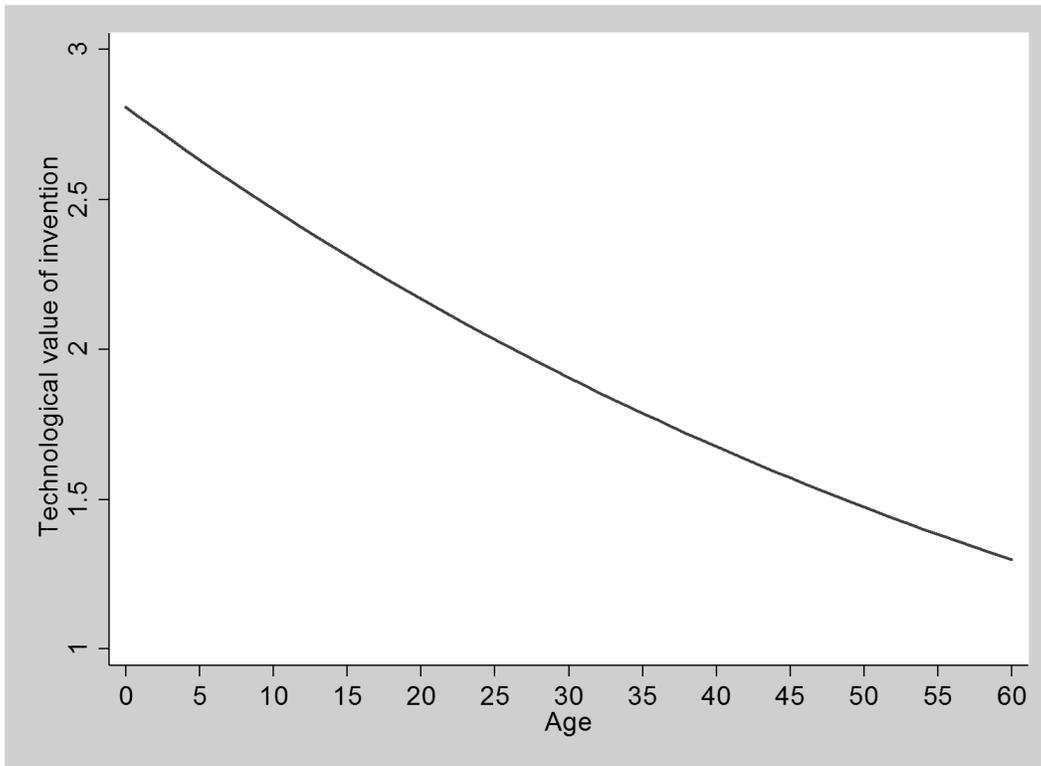
**Influence of recombinant lag on technological value of inventions<sup>a</sup>**



<sup>a</sup> Figure based on model 3 in Table 2

**FIGURE 5**

**Influence of age on technological value of invention<sup>b</sup>**



<sup>a</sup> Figure based on model 5 in Table 2