The two faces of inventions : the relationship between recombination and impact in pharmaceutical biotechnology

THE TWO FACES OF INVENTIONS: THE RELATIONSHIP BETWEEN RECOMBINATION AND IMPACT IN PHARMACEUTICAL BIOTECHNOLOGY

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ABSTRACT

´Recombination´ and ´impact´ have become well established constructs to understand the origins of inventions and their importance for the development of future inventions. Despite forming these two familiar ´faces of inventions´, their specific relationship has only marginally been subject to inquiry. To address this, this paper studies the relationship between the level of recombination of inventions and their technological impact, along two steps. First, in contrast to the common idea of a linear relationship between recombination and impact we argue that the relationship is in fact a non-linear one. Second, we distinguish between different levels of recombination (low, intermediate, high) and determine their differential impact, thereby establishing which type of recombination leads to the highest level of technological impact. We test our hypotheses on an extensive dataset, comprised of all USPTO granted patents in the biopharmaceutical industry between 1976 and 2006. Our empirical findings indicate strong evidence for a curvilinear relationship between recombination and impact. In addition, we find that an intermediate level of recombination - formed by a combination of components from local, adjacent and distant knowledge domains - carries the highest level of technological impact of all types of inventions. Finally, we discuss implications for the academic literature and for firms' innovation strategies.

Keywords: Inventions, recombination, technological impact, pharmaceutical biotechnology, breakthroughs

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1. INTRODUCTION

Much of the academic literature on innovation and technological inventions builds on the pioneering work of Schumpeter. In his work, Schumpeter (1934) emphasized the role of recombination as the key process that yields new inventions, and mentioned the phenomenon of creative destruction that can be linked to the impact that inventions may have on an industry and the wider economy (Schumpeter, 1947).[1] These 'two faces' of invention have become well-known concepts to describe and understand both the origins of inventions and their importance for the development of future inventions (Schoenmakers and Duysters, 2010; Nemet and Johnson, 2012). Because of their importance and wide-spread use of both concepts in the innovation literature, the specific relationship between these two faces of invention has been subject to inquiry. In fact, Fleming (2001) paved the way for this study, in which the investigation of the relationship between recombination and impact has been deepened. Notwithstanding the contribution by Fleming (2001), there seems to be a theoretical consensus that inventions with low levels of recombination have (far) less impact than inventions with high levels of recombination. Underlying this idea is the inherent assumption that there is a positive linear relationship between recombination and impact of inventions. In line with this assumption is the commonly made distinction between incremental and radical invention (e.g. Dewar & Dutton, 1986), where incremental invention is generally associated with limited recombination and low impact and radical invention is associated with strong recombination and high impact (Abernathy and Clark, 1985; Dewar and Dutton, 1986;

[1]The idea of 'creative destruction' is not equated with 'technological impact' in this paper. Specifically, 'creative destruction' refers to the economic impact of inventions and innovations on industries, economies and societies, whereas this paper explicitly focuses on the technological impact of inventions.We would like to thank an anonymous reviewer for helping us to clarify this distinction.

Tushman and Anderson, 1986; Tushman and Smith, 2002). Overall, this suggests that the level of recombination and impact are seen to be closely correlated and tend to be portrayed as either both low or both high. However, from business practice we know that there are many inventions that fall somewhere in-between incremental and radical inventions. Inventions with an intermediate level of recombination are sometimes called 'adjacent inventions' (Nagji and Tuff, 2012), such as Apple's iTunes, Lego's Mindstorm and Philip's Senseo.

This phenomenon of adjacent inventions does not fit with the straightforward distinction between incremental and radical inventions, and raises the question what level of impact these inventions with intermediate levels of recombination have? Taking the common idea of a positive linear relationship, the impact of inventions with an intermediate level of recombination would be somewhere between low and high, at an intermediate level. However, if one leaves this idea of a linear relationship between recombination and impact and considers the possibility of a non-linear relationship instead, different possibilities arise. In case of a U-shaped relationship, inventions of an intermediate level of recombination would have a very low impact, whereas in case of an inverted U-shaped relationship, inventions of an intermediate level of recombination would have the highest impact.

This paper addresses these issues as follows. First, we argue and show that the relationship between recombination and impact is in fact highly non-linear. Second, we determine the differential impact of different types of recombination, thereby establishing which types of recombination are optimal for generating impactful inventions.[2] Following the common idea of recombination as the combination of knowledge components within or across technological knowledge domains (Stuart and Podolny, 1996), different studies have taken different approaches. Whereas Nemet & Johnson (2012) emphasized the role of distance

[2]The impact of an invention can be determined either from a market perspective or a technological perspective. However, we will concentrate on the recombination of a technological invention in other subsequently developed new technological inventions, because most technological inventions are not immediately created for (end-user) usage.

between domains, Schoenmakers & Duysters (2010) considered the number of domains as a proxy for recombination. We build on these ideas by conceptualizing and measuring recombination in a more fine-grained way that combines both the number of domains and the distance between them. This approach enables us to develop a more detailed understanding of which specific combinations of number of domains and their distances maybe associated with low, intermediate and high levels of recombination respectively. In this way, we also contribute to the literature by developing a more detailed understanding of the important concept of recombination that still remains underspecified in comparison with the notion of technological impact.

Empirically, we rely on the biopharmaceutical industry, which is characterized by a large number of technological inventions of different levels of recombination and different levels of technological impact. Moreover, in this industry patents are heavily used for intellectual property protection (Gambardella, 1995). During the 1980s and 1990s the biopharmaceutical industry exhibited increasing numbers of patent applications, signaling the widespread activity of invention creation. For our study, we selected all biopharmaceutical patents granted between 1976 and 2006 from a dataset from the United States Patent and Trademark Office (USPTO) combined with patent data from the National Bureau of Economic Research (Hall et al., 2001). Patents are used in this study, because they form an acknowledged proxy for inventions (Griliches, 1990; Hagedoorn and Cloodt, 2003; Lanjouw and Schankerman, 2004) and they contain detailed information on the technological components of this underlying invention.

This paper proceeds as follows. First, the level of recombination and impact of inventions are discussed in more detail. Next, the relationship between the two constructs is theoretically explored based on which two hypotheses are specified. Subsequently, we present

our empirical study and estimation model. Finally, we will show our results and discuss the various implications of our findings for both theory and practice.

2. THEORETICAL FRAMEWORK AND HYPOTHESES

In this section, we develop a theoretical framework by describing our key concepts, namely recombination and impact of inventions. Subsequently, we explore the nature of the relationship between these two concepts, based on which we specify two hypotheses.

2.1 Recombination

Recombination is considered as the creation process that leads to new inventions (Schumpeter, 1934; Nelson and Winter, 1982; Hargadon and Sutton, 1997). As the world consists of a nearly countless number of components there are basically no limitations to the process of recombination, although some (sets of) components are more likely to be combined relative to other sets of components (Stuart and Podolny, 1996; Fleming, 2001). This seemingly infinite potential for recombination notwithstanding, the dominant approach taken in most of the literature until now is to distinguish between incremental inventions and radical inventions (Abernathy and Clark, 1985; Dewar and Dutton, 1986; Tushman and Anderson, 1986; Tushman and Smith, 2002). Incremental inventions are associated with recombination that consists of combining improved components that are already connected within a technological domain or from technologically proximate domains, whereas radical inventions are associated with recombination that combines new components that were previously unconnected and typically originate from distant technological domains. Here, Henderson and Clark´s (1990) framework further distinguishes between two intermediate categories, formed by modular and architectural innovation, which they categorize as either overturned components with unchanged linkages or reinforced components with changed linkages.

Whereas the inclusion of these two intermediate categories refines to some extent the coarse-grained distinction between incremental and radical innovation, it still reflects a rather discrete understanding of types of recombination. To be able to establish the true nature of the relationship between recombination and impact, we go beyond these dichotomous distinctions of recombination and will conceptualize it in a more fine-grained way.

We define recombination as the degree in which the technologies that are combined within an invention are distributed over different technological domains. This definition is in line with two recent studies that have considered recombination in terms of either the distance between technological domains (Nemet and Johnson, 2012) or the number of technological domains from which technologies have been recombined (Schoenmakers and Duysters, 2010). We build on these approaches but also argue that a more accurate understanding of recombination requires the consideration of both the distance and number of technological domains. In line with Hargadon and Sutton (1997), we see new inventions as created from combinations of existing knowledge from disparate domains. This implies that recombination is in particular the distribution of technological components over different technological domains, suggesting that it is a combination of both the number of technological domains and distance among them. Seen in this way, the level of recombination of an invention increases when components are distributed over more technological domains at larger technological distances. Inventions consisting of components from only the local technological domain or from the local and adjacent domains may be associated with a low to moderate level of recombination. Inventions consisting of components from technological domains at larger distances and an increasing number of domains may be associated with a high(er) level of recombination.

2.2 Technological impact of inventions

A number of studies have focused on the technological impact of inventions as a way to assess their importance for technological development (Ahuja and Lampert, 2001; Rosenkopf and Nerkar, 2001; Phene et al., 2006). In addition, several alternative concepts are used for impact such as usefulness (Fleming, 2001), technological importance (Ahuja and Lampert, 2001), and invention quality (Lanjouw and Schankerman, 2004; Lahiri, 2010). These different concepts notwithstanding, each refers to the same underlying notion of technological impact that entails the extent in which a new combination is used for the development of future inventions. The common measure for technological impact in the studies mentioned above is based on a count of the number of received forward citations of a patent. In this way, technological impact refers to the number of times that a new combination is used in future technological inventions (Fleming, 2001; Nemet and Johnson, 2012).[3] The extent to which inventions are used in future inventions provides an indication of their importance and usefulness for future technological development, either within or beyond a technological domain.

2.3 The relationship between recombination and impact

Below we discuss two different mechanisms that under lie the relationship between the level of recombination and technological impact of inventions, namely the degree of novelty and inventor familiarity. We will discuss both mechanisms and argue why a non-linear relationship follows from their combination.

2.3.1 Degree of novelty

Following our idea of recombination as the *distribution* over different domains, i.e. the combination of both the number of domains and the distance among them, we argue that

[3] For instance, the impact of the discovery of recombinant DNA becomes apparent in the following invention, such as the invention of recombinant human insulins by Genentech in 1978 (Walsh, 2005).

different levels of recombination will carry different degrees of novelty. When only components from within the local technological domain are recombined, the resulting inventions will carry a relatively low degree of novelty. Both the components used and the linkages between them will be close to what is considered as common knowledge within the technological domain, implying that these new combinations possess a rather limited degree of novelty relative to previously combinations in the field. By combining technological components from more distant technological domains, the level of recombination increases. To the extent that unconnected components from more distant technological fields are included, the degree of novelty goes up. As a consequence, these new combinations possess a higher degree of novelty relative to previous combinations in the field and hence carry a higher likelihood of impacting subsequent technological development, both within and beyond focal technological domains (Rosenkopf and Nerkar, 2001; Hargadon, 2003). So, new combinations of technologies that build on distant technological origins will have a higher degree of novelty and a higher likelihood of being the source of future technological development, as compared to inventions that are based on components from a single technological origin (Rosenkopf and Nerkar, 2001; Schoenmakers and Duysters, 2010). Thus, the degree of novelty rises with increasing levels of recombination, which suggests a positive relationship between the level of recombination and its subsequent technological impact.

One example from the biopharmaceutical industry is formed by the combination of bio- and nanotechnology, which provides numerous opportunities for recombination on the nanometer level. From the perspective of biotechnology as the focal technological domain, the domain of nanotechnology can be seen as distant, because nanotechnology comes from the cluster of electronical and mechanical technologies that are at a high technological distance from the cluster made up of technologies such as drugs and chemicals, and from which also biotechnology originates (Marsili, 2001). An example of a combination of

technologies from both domains is formed by cancer treatment. Here, near-infrared light responsive gold nanorods (e.g. material with a size between 1 and up to 100 nanometer, where one nanometer is one-millionth of a millimeter) are combined with a chemotherapeutic drug – i.e. doxorubicin – and infused into the patient's body. By means of directing near-infrared light external of the body on the place where the tumor is located, the nanoparticles generate heat and release the chemotherapy drugs targeted directly at the cancer cells (Xiao et al., 2012). This example is just one of many possible combinations of bio- and nanotechnology, which are currently investigated. It illustrates that nanotechnology offers novelty for drug discovery, when recombining it with technologies from the local biopharmaceutical domain.

The line of reasoning presented above would support the idea of a linear and positive relation between recombination and impact. However, a high degree of novelty in and by itself may not be sufficient to generate high impact as we will explore in the next paragraph.

2.3.2 Familiarity and recognizability

Generally, when components are combined from within the same technological domain, they will build on existing knowledge from within this domain and therefore carry a high of degree of familiarity relative to previous combinations in the field. In this way, inventions that are the result of recombination of components from within the same technological domain will typically enjoy a high level of recognizability and will also carry a high degree of ´cognitive legitimacy´, i.e. the degree in which the invention is understood and considered as ´appropriate and right´ (Aldrich and Fiol, 1994). This is also in line with studies in psychology demonstrating that a deep understanding of a particular domain forms an important prerequisite for developing high-impact ideas (Simontin, 1999a, 1999b). This suggests that to the extent in which an invention is made up of components that are combined

from within the same local technological domain, its degree of familiarity and recognizability relative to previous combinations in the field, will be generally stronger.

On the other hand, when components of a new combination originate from more distant technological domains, the level of recombination of an invention typically increases but the familiarity of the new invention will be (much) lower. These new combinations lack recognizability and carry low(er) cognitive legitimacy (Aldrich and Fiol, 1994), So, higher levels of recombination of an invention will thus result in lower degrees of familiarity, recognizability and cognitive legitimacy relative to previous combinations in the different technological domains, which decreases the likelihood that such inventions will be used for the creation of future inventions. Overall, this suggests that familiarity and recognizability decrease with increasing levels of recombination, which implies in general a negative relationship between the level of recombination and its subsequent technological impact.

2.3.3 Combined effects: the relationship between recombination and impact

The discussion above suggests that there are two sides to recombination. On the one hand, inventions characterized by low levels of recombination will generally carry low uncertainty regarding usefulness and high familiarity due to stronger cognitive legitimacy, but may fall short of novelty. On the other hand, inventions with a high level of recombination typically carry a high degree of novelty but may lack familiarity. This suggests that with increasing levels of recombination, the degree of novelty increases as the invention carries more potential value for impacting upon existing and/or initiating new technological trajectories. To the extent that these inventions' components are (still) recognizable and carry familiarity from the perspective of one or more of the combined technological domains, the likelihood of their use as a component for future recombination increases (Audia and Goncalo, 2007; Nooteboom et al., 2007).

However, with a further increase in novelty through inclusion of components from more distant technological domains, the familiarity and recognizability of the invention will commonly decrease (Shane, 2000). For example, the study by Shane (2000) shows that both the degree of novelty of 3D printing and familiarity with drugs delivery play a central role in the application of 3D printing technologies in the pharmaceutical industry. On the one side, the novelty of 3D printing is illustrated in the following quote: "*I certainly never would have thought that someone would make pills with the 3DP^{TM} process"* (Shane, 2000, p.456). On the other side, entrepreneurs declared that "*to make use of the 3DP^{TM} process for drug delivery, you had to know something about what drugs and drug delivery systems are made from and how drug manufacture operates*". The latter shows that a basic understanding of drugs and the drugs system is necessary to create valuable new combinations with 3D printing technologies within the biopharmaceutical industry. Without including information on drugs and the drugs systems, 3D printing technologies may not have found their application in pharmaceuticals. This indicates that components of new combinations from the local technological domain may form important 'feedstock' for the creation of potentially useful new combinations. Hence beyond a certain level of recombination, the downward effect from insufficient familiarity may exceed the upward effect from an invention's degree of novelty, as the low degree of familiarity and recognizability of the invention generally decreases the likelihood that it will be used as the basis for new inventions.

Overall, this suggests that inventions *in-between* low and high levels of recombination may benefit from familiarity and recognizability as well as from their degree of novelty, and therefore exhibit a high degree of impact. In comparison, low recombination inventions will generate only limited impact because of an insufficient degree of novelty, whereas high recombination inventions will also generate limited impact due to an insufficient degree of familiarity and recognizability. In general, this points toward a non-linear relationship

between recombination and impact. Therefore, we argue that when the level of recombination increases, its impact will augment first until a point beyond which it will decrease. This suggests our first hypothesis:

H1. There is an inverted-U shaped relationship between the level of recombination and impact of technological inventions.

The hypothesis above states that inventions containing an intermediate level of recombination will carry higher levels of technological impact, as it strikes a careful balance between familiarity and recognizability on the one hand and the degree of novelty on the other hand. This raises the question which specific types of new combinations make up for an intermediate level of recombination that address this balancing act, materializing in higher levels of impact? In order to illustrate how recombination evolves from the use of components over different technological domains, the following figure (1) illustrates a classification of "*near*", "*adjacent*", and "*distant*" technologies within the biopharmaceutical industry.

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Insert Figure 1 about here "Near, adjacent, and distant technological domains"

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The biopharmaceutical industry is concerned with the development of drugs and therapies based on molecular biological processes, chemical processes dealing with peptides or proteins, and multicellular living organisms and unmodified parts thereof and related processes. The classification of the United States Patent Office indicates the biopharmaceutical industry, in which the codes '*424*', '*435*', '*436*', '*514*', '*530*', and '*800*'

correspond with patents that are related to the biopharmaceutical industry (Phene et al., 2006; Van de Vrande, 2013). These classes are displayed in table 1 in this paper. In the pursuit of findings specific cures for specific diseases, inventors investigate and compare the DNA structures of sick and healthy cells (Gambardella, 1995), and combine these with numerous drug compounds in order to test how and which drugs can target the disease (Dougherty and Dunne, 2011). Then, within the biopharmaceutical industry, the local or so-called "near" technologies have been developed that are concerned with the development of new drugs and therapies that are for example based on genetics and rDNA technologies (e.g. represented by the black technological domain in figure 1). The recombination of these "near" technologies adds to the familiarity and recognizability of subsequent inventions in the biopharmaceutical industry. In addition, the biopharmaceutical industry has evolved from the wider technological fields "chemicals" and "drugs" (Marsili, 2001). Within these technological domains, broad technologies may exist that are "adjacently" related to the specific technologies of the biopharmaceutical industry. That is, biopharmaceuticals is a specific subdomain in the wider fields of "chemicals" and "drugs" (e.g. visualized by the grey technological areas in figure 1). It can be asserted that biopharmaceutical engineers have a similar formal background in terms of training as chemical engineers and/or drug developers. They will be familiar with similar technologies and are more likely to use the same language and terminology due to their common background. Moreover, biopharmaceutical engineers will recognize elements of technologies from the wider chemicals and drugs fields that are concerned with molecules and chemical formulas. In this way, drugs have been developed that consist of a chemical shell around a genetic treatment, which would resemble a combination of near and adjacent technologies (e.g. a combination of technologies from the black and grey domains of figure 1). Therefore, broad technologies from "chemicals" and "drugs", which are not directly biopharmaceutical, can be considered as "adjacent" to the

biopharmaceutical industry, so that these technologies from the wider chemical and drugs industries are still likely to be recognized by biopharmaceutical engineers. Then, recombining "adjacent" technologies will add novelty to the local domain but also be close enough to carry sufficient familiarity. In addition, there are "distant" technologies that do neither reside in the biopharmaceutical subdomain, nor in the wider fields of "chemicals" and "drugs". The earlier mentioned examples of nanotechnology and 3D-printing are two illustrations of such "distant" technologies that add to the "degree of novelty" of inventions (e.g. the two white technological domains on the right and left side of the domains "chemicals" and "drugs". Then from these three "classes" of technologies – i.e. "near", "adjacent", and "distant" – intermediary levels of recombination can be achieved along three different routes.

First, building on technological components from both local and distant domains, results in inventions that strike a balance between familiarity and novelty. Within such inventions, the local components bring familiarity whereas distant components carry novelty. Building on local and distant domains implies maximizing familiarity in some building blocks and novelty in others. For example, the 3D-printing of human cells – such as skin tissues – illustrates the maximization of familiarity by incorporating "near" technologies, as the investigation and dissection of skin cells and skin DNA strands. The maximization of the degree of novelty is shown by the application of 3D-printing as a technology for producing skin tissues. This is shown in figure 1 as a combination of technologies from the black (biopharmaceutical) and white (3D printing) technological domains.

A second approach constitutes a middle-way by building on technological components from both local domains, adjacent and distant domains (i.e. technologies from the black, grey and white areas of figure 1). Components from local domains – i.e. technologies from the biopharmaceutical industry – carry the familiarity, whereas components from distant domains, such as 3D-printing or nanotechnology, carry the novelty. Subsequently, components from the

adjacent domains "chemicals" and "drugs" may form the 'bridge' between the near and distant technologies.

A third and final approach that would also yield inventions with an intermediate level of recombination is to build on technological components from adjacent domains that are neither completely local nor distant, but in-between these two (e.g. building only on technologies from the grey area of figure 1). As these adjacent components are not directly from the local technological domain, they carry a lower degree of familiarity. In a similar vein, as they do not include knowledge from distant domains, they also carry less novelty to have meaningful impact. That is, recombining only adjacent technologies will not result in balancing between familiarity and novelty, as it does not fully entail both of these characteristics. In this way, combining components from only adjacent domains implies both limited familiarity and an insufficient degree of novelty in such invention's building blocks.

In sum, each of these three types represents an intermediate level of recombination. However, only inventions that consist of both components from near and distant domains, or from near, adjacent and distant domains strike a balance between familiarity and novelty by maximizing both dimensions. Overall, this suggests our second hypothesis:

H2. Inventions that are based on combinations of components from near and distant or near, adjacent and distant domains are more impactful than inventions that are based on components from only adjacent domains.

3. METHODS

The following section describes the data, sample and measures for the concepts recombination, types of new combinations and technological impact.

3.1 Data

In order to explore the relationship between recombination and technological impact we required data on technological inventions, for which both the technological origins and their technological impact are well documented. Moreover, to ensure that large numbers of technological inventions with different levels of recombination and technological impact are created we wanted to focus on a high-tech industry in which technological development is fast paced. The biopharmaceutical industry is such an industry (Gambardella, 1995). During the 1980s and 1990s, the biopharmaceutical industry demonstrated increasing numbers of patent applications in the United States, signaling a growing number of technological inventions that are created. Furthermore, the biopharmaceutical industry characterizes itself as one in which most inventions are actually patented for intellectual property protection (Hall et al., 2001). All biopharmaceutical US patents granted since 1976 were selected for this study. The benefits of using patent and patent citation data are numerous. Most important is that these data provide information on many characteristics of inventions, which have been consistently reported over time (Hall et al., 2001). Moreover, patent data have often been used in previous studies as a proxy for technological inventions.[4]

The approach of equalizing patents with inventions is especially valid for high tech industries such as the biopharmaceutical industry, in which patenting is common practice. In order to be patentable, invention needs to be 'novel' and 'non-obvious' (USPTO, 2007). In addition, a patent's level of recombination can be approximated, because each patent's backward citations reveal whether and which components from previous inventions are recombined. Moreover, from patent citation data we can also observe differences in terms of technological impact because each patent can be cited by subsequent patents. Accordingly,

[4] See among others the following sample of studies that used patent data as a proxy for invention or innovation: Trajtenberg, 1990; Trajtenberg et al., 1997; Harhoff et al., 1999; Ahuja and Lampert, 2001; Watanabe et al., 2001; Fleming, 2001; Hagedoorn and Cloodt, 2003; Lanjouw and Schankerman, 2004; Dahlin and Behrens, 2005; Phene et al., 2006; Gilsing et al., 2008.

the level of recombination and the technological impact of inventions can be captured by investigating patents and their citations, because a patent document consists of detailed and ordered information on the origins of the invention (Hall et al., 2001; Schoenmakers and Duysters, 2010).

In particular, data on patent citations provide a large amount of information, which can be related to both concepts. Legally, every inventor is assigned with the task to cite earlier patents on which the technological claims of his invention are built. This process of citing other patents is controlled by patent examiners, who are supposed to be knowledgeable in the field and therefore able to add or take out citations to prior patents that the patent applicant has missed or added erroneously. However, this is hardly the case in the biopharmaceutical industry as most citations are already added by the patent applicants (Alcácer et al., 2009). Accordingly, we suggest that patent citations are a valid proxy for the technological components that the invention consists of (Trajtenberg et al., 1997). On the basis of patent citations, two sets of measures are constructed, i.e. one set based on backward citations, which are specified in the focal patent and one set based on forward citations, which are specified in patents citing the focal patent. First, this paper uses backward citations as proxies for the inventions' level of recombination, because citations to other patents refer to the technological origins of these inventions (Trajtenberg et al., 1997; Ahuja and Lampert, 2001; Schoenmakers and Duysters, 2010). Second, forward citations are used as a proxy for the invention's technological impact on future technological development, because these have been related to concepts as innovative performance (Hagedoorn and Cloodt, 2003), breakthrough inventions (Ahuja and Lampert, 2001; Phene et al., 2006), economic value of inventions (Trajtenberg, 1990; Hegde and Sampat, 2009), patent importance (Carpenter et al., 1981; Albert et al., 1991; Trajtenberg et al., 1997; Fleming, 2001; Hall et al., 2005), patent value (Reitzig, 2003), and technological impact (Rosenkopf and Nerkar, 2001). The measure

for technological impact in this study is also based on the number forward citations. Next, our sample will be discussed followed by a description of the variables in this study.

3.2 Sample

The initial sample in this study consists of all patents classified in the biotechnological industry that were granted between 1976 and 2006 by the USPTO. The technological classification scheme of 2006 from the USPTO was used by the patent examiner to assign each patent with a primary technology class, which data was drawn from the NBER patent database (Hall et al., 2001). In this technological classification scheme, the three-digit USPTO classification was used, in which the codes '*424*', '*435*', '*436*', '*514*', '*530*', and '*800*' correspond with patents that are related to the biopharmaceutical industry (Phene et al., 2006; Van de Vrande, 2013).[5] The descriptions of each of these codes can be found in table 1.

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Insert Table 1 about here "Patent classes and their descriptions"

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Initially, our sample consisted of 202.697 biopharmaceutical patents that were granted between 1976 and 2006. These patents had 1.399.356 backward and 1.252.401 forward citations in total. For 1.335.837 backward citation patents we were able to identify the technological class, because our data on the technology classification went back to patents which were granted from 1963 onwards. The other patents that were cited by any of our sampled patents, but either granted before 1963 or withdrawn at any point in time, were discarded. Next, we narrowed the time frame for the impact dimension to ten years after the

[5] In fact, we also checked the number of patents in our sample per assignee and looked at the names of the assignees. This list demonstrates a sample of biopharmaceutical firms.

grant year of our sampled patents. This means that the dependent variable is based on 876.687 forward citations to our focal patents from all other patents applied for within ten years after the grant year of the sampled patent. Finally, our biotechnology sample consisted of 22.937 patents without any backward citations to patents.[6] Next, we will describe the measures that we constructed for our analyses.

3.3 Dependent variable

Technological impact. A commonly used indicator for a patent's technological impact is the number of forward citations, i.e. the number of times other patents cite a focal patent. The main argument throughout the literature is that the more a patent is cited by future patents the higher the technological impact of a patent (Trajtenberg, 1990; Fleming, 2001; Hagedoorn and Cloodt, 2003; Nemet and Johnson, 2012).

In order to further validate this measure, we control for the truncation effect by considering the number of forward citations within a ten year time frame. This means that the 'number of forward citations' concerns all citing patents that are applied for within ten years after the grant year of the focal patent (Hall et al., 2001). This time span of ten years for measuring the number of forward citations is more than in line with earlier research using this measure. For example, Fleming (2001) uses a time interval of six years and five months and Gilsing et al. (2008, p. 1723) state that "*different scholars have argued that a moving window of five years is an appropriate timeframe for assessing the technological impact of prior inventions*". Still, there can be inventions, of which the technological impact may not evolve in the first couple of years after the patent was granted. As we want to be conservative about

[6] A crosscheck with the NBER patent data convinced us that this number is correct. These patents are sometimes a continuation of co-pending or a division of a series of US patent applications. In other cases, the patents cite foreign patent documents or non-patent literature. Only a small number (57) of patents consisted of no backward citations to any other document, although these patents were in most cases also part of patent application series. These patent application series can be regarded as a group of patent applications that refer to one another.

this and sure that we capture most of the forward citations, we computed the 'number of forward citations' per patent within the ten years after the patent was granted. As a robustness check we also ran regression models with the number of forward citations per patent within five years after the patent was granted.

Moreover, using either time frame puts limits on the size of the sample for analysis, for two reasons. First, there is a lag between the application year and grant year of a patent (see figure 2). Our data from the NBER and USPTO only consisted of the patents granted until 2006. The average time between the application year and grant year of the patents in our sample is 2,4037 years with a standard deviation of 1,2765. This means that most of the patents applied for in the years before 2006, will not already be granted in 2006. Figure 2 shows the cumulative line chart for patents by the number of years that are between their year of application and their grant year. It can be seen that around 80 percent of all patents is granted within three years after application. Secondly, there is also a time lag between the grant year of the sampled patent and the application year of the patent that is citing the sampled patent (see figure 2 – the dotted line). On average, it takes 1,3829 years before a patent is first cited. In figure 2 the distribution is shown on how many of its forward citations a patent receives in the number of years after it is granted. The figure shows that all patents have received around 53 percent of their forward citations within five years after their grant date. After ten years, all patents have received around 80 percent of their total number of forward citations.

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Insert Figure 2 about here "Time lag between application and grant year of a patent - Time lag between grant year cited patent and application year citing patent"

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To be sure that we have most of the forward citations and our measure for technological impact is valid, the analysis with the forward citations received within ten years contains all biopharmaceutical patents granted between 1976 and 1993. The analysis with the forward citations received within five years contains all biopharmaceutical patents granted between 1976 and 1997.

3.4 Independent variables

Level of recombination. In recent work on the level of recombination of patents Nemet & Johnson (2012) emphasized the role of distance between domains whereas Schoenmakers & Duysters (2010) considered the number of domains as a proxy for recombination. In developing a more fine-grained measure for recombination, we build on these ideas by combining both the number of domains and the distance between them. This measure enables us to develop a more detailed and refined understanding of which specific combinations of number of domains and their distances maybe associated with low, intermediate and high levels of recombination respectively. Whereas Nemet and Johnson (2012) consider the role of distance, we argue that it differs whether a patent only cites one distant domain through one citation or through, for example. 10 or more citations. In both cases, the distance is the same but the ´borrowing´ from distant domains is 10 times stronger than in case of only one citation. So, by including the number, we are able to measure not only from how far away new knowledge originates but also the amount of novel knowledge that is included.

We argued that the level of recombination of an invention is determined by the spread of technological components of which a patent is comprised over technological domains. Essentially, technological inventions with high levels of recombination are inventions that consist of technological components from distant technological domains. It follows that the

higher the average distance between the patent classes of the backward cited patents and the patent class of the sampled patent, the higher the recombinant nature of the invention under protection of the specific patent is.

Specifically, the technological distance between patents was determined as follows. When the sampled patent and the backward cited patent are assigned to one of the three-digit biotechnology classes, i.e. classes '*424*', '*435*', '*436*', '*514*', '*530*', and '*800*', this citation is a technologically 'near' citation. Second, every patent is assigned to a one-digit patent category by Hall et al. (2001). The biopharmaceutical industry has been evolved on the border between "chemicals" and "drugs", which are represented by category '1' and '3'. When the backward cited patent is not assigned to a three-digit biotechnology classes, i.e. classes '*424*', '*435*', '*436*', '*514*', '*530*', and '*800*' , but assigned to another class within "chemicals" or "drugs" this citation is technologically 'adjacent' to the sampled patent and therefore categorized as an 'adjacent' citation. Finally, when the backward cited patent is not assigned to the "chemicals" or "drugs" category, this citation is technologically 'distant' from the sampled patent. Next, the level of recombination was determined by attaching different weights to the 'near', 'adjacent', and 'distant' backward citations. That is, a near citation is weighted with '1', an adjacent citation is weighted with '2', and a distant citation is weighted with '3'. Accordingly, the measure for the level of recombination is computed as follows.

$$Recombination\ of\ patent\ i = \sum_{k=1}^{N_i} \left(\frac{N_{ik} * v}{N_i} \right)$$

N_i denotes the number of backward citations for each patent i across k patent classes, whereas *v* denotes the value corresponding to the technological distance between the sampled patent and the backward cited patent. The sum of these weighted backward citations is then divided by the number of backward citations. Table 2 shows six examples of the level of recombination for an invention with three backward citations.

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Insert Table 2 about here "Example measure level of recombination"

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For example, patent 'A1' cites three other patents from a biopharmaceutical class. All three citations are near citations with a value of '1' so that all three alternative recombination scores will be '1'. When each of the three backward citations come from patents in a different category – i.e. 'near', 'adjacent ', and 'distant' - as is the case for example patent 'A5', the recombination measures changes accordingly. The recombination measure is then (1+2+3) / 3 = 2. Because our study proposes an inverted-U shaped relationship, we first entered the linear recombination variable in the analysis. Next, we also modeled the relationship by entering a squared term for recombination. Robustness checks are carried out with different weights attached to the different categories, see paragraph 4.2.

Recombination dummies. For testing the second hypothesis, seven dummy variables were created in order to test which recombinations were most likely to generate the highest impact levels. The variable 'near' is '1' in case a patent cites only near backward citations and '0' if otherwise. The variable 'near-distant is '1' in case a combination consists of both near and distant backward citations and '0' if otherwise. The variable 'near-adjacent-distant' is '1'in case an invention is a recombination of both near, adjacent, and distant technological components and '0' if otherwise. The other four dummies were coded similarly. The reference category consists of patents without any backward citations to US patents.

3.5 Control variables

Several control variables were added in the regression models, which could be of influence on the relationship between recombination and impact. A detailed description of the econometric estimations is given in following section.

Number of backward citations. (BW patent cites) The recombination measure is based on the diversification of the technological domains of the patents that were cited by the focal patent. However, this measure could be influenced by the sheer number of backward citations of a patent. Therefore, we entered the number of backward citations of each patent as a control variable in our models. The argument is that many backward citations will more likely be diversified across technological domains as opposed to a few backward citations.

Age of backward citations. (Age) Another control variable is the mean age of the backward citations. Scholars have indicated that more impactful patents are based on younger components as compared to less impactful patents (Schoenmakers and Duysters, 2010; Nemet and Johnson, 2012). The variable 'age' is calculated by taking the grant year of the sampled patent minus the grant year of the backward citations. Then the average is taken over all backward citations in the sampled patents. Higher values on this variable correspond to the recombination of relatively older components.

Number of other citations. (Other cites) Besides references to patent documents, patents can also cite documents such as articles in scientific journals, books, magazines from trade organizations etc. The citations to these non-patent literature is said to possibly indicate the use of scientific knowledge during the creation of the invention, which in turns is associated with the level of recombination of the invention by some scholars (Carpenter et al., 1981; Trajtenberg et al., 1997; Dahlin and Behrens, 2005; Schoenmakers and Duysters, 2010). In order to control for the influence of non-patented components on impact, we constructed the variable 'number of other citations'.

Number of foreign citations. (Foreign cites) Patent documents can also contain citations to foreign patent documents. We controlled for these foreign components, because these may influence both the level of recombination as well as the technological impact. When more foreign patents are cited by a patent, the degree of novelty of the patent based on these foreign patents may be higher. This will have a positive influence on impact, which we need to control for.

Number of inventors. (Inventors) Many inventions are the result of multiple inventors recombining ideas and technologies (Hargadon, 2003). The number of inventors may affect the level of recombination of an invention, because more inventors will have a larger pool of knowledge about components from earlier inventions to tap from. Therefore, the recombinant potential of a pool of inventors will be larger as compared to a single inventor. Moreover, the number of inventors on a patent may also increase the impact of an invention, because the more inventors are knowledgeable about the invention, the more likely this knowledge will be used for future inventions. Accordingly, the 'number of inventors' is used as a control variable.

Number of assignees. (Assignees) Besides the names of inventors, also the names of the patent assignees are printed on the patent. The assignee has the exclusive intellectual property right to exploit the knowledge about the invention, which is protected by the patent. For most patents, the assignee corresponds to a firm, although sometimes independent inventors have applied for patents. Furthermore, most patents are only assigned to one firm, but sometimes patents are assigned to multiple firms. When there are multiple assignees printed on a patent, these assignees are all likely to be familiar with the invention. The more assignees are familiar with an invention, the more likely it is that they will recombine any of the components in a new combination in the future, thereby affecting the impact dimension. The number of assignees is thus added as a control variable.

Number of claims. (Claims) An invention that is patented may cover multiple technological claims of discovery, which can be seen as the scope of the patent. We propose that more claims on a patent document may require more technological components, so that there might be a positive relationship between the level of recombination and the number of claims. Furthermore, it is also to be expected that patents with more claims of discovery have a higher propensity to be cited by future patents. In view of that, the 'number of claims' in our sampled patents is taken into account as a control variable.

Number of patent classes. (Number of classes) Patents may be assigned to multiple patent classes. Although the primary patent class has been used for the sampling strategy, we do control for other cross reference classes to which patents have been assigned as this may be another indication of the scope of a patent. Hence, patents with a broader scope (e.g. assigned to multiple patent classes) may be more likely to be cited by subsequent patents from a wider variety of patent classes.

Number of patents granted to an assignee. (Assignee size) The earlier mentioned controls differ across patents. However, also assignee characteristics may affect the technological impact of inventions. Therefore, we include two extra control variables regarding characteristics of the assignee. First, we control for the number of biopharmaceutical patents that have been granted to an assignee in the particular year besides the focal patent. The reason for including this control variable is because it may be that independent inventors and small firms are more likely to have their patents infringed and, presumably, not cited despite similar technologies.

Average number of claims per patent of the assignee. (Average claims) Second, we control for another assignee characteristics, namely the average number of claims per patent granted to the assignee. Basically, this variable captures the patenting strategy of a firm by determining whether firms choose to apply for one or a few patents with multiple claims or

for multiple patents with a lower number of claims. This variable was constructed by summing the claims of all biopharmaceutical patents granted to the assignee in a particular year and dividing this by the total number of biopharmaceutical patents granted to this assignee.

Grant years and technological classes. (Year dummies and class dummies) Finally, we included multiple dummy variables for the years, in which the sampled patents have been granted to their assignees in order to control for so-called cohort effects. These dummies capture whether patents granted in particular years have higher impact levels than patents granted in other years. For example, there have been years in which more patents have been granted as well years in which there have been more assignees active. Then, in a crowded industry with many actors applying for patents, patents may be more likely to become cited. Therefore, the 'year dummies' have also been replaced by the 'number of assignees active in the industry in a particular year', which resulted in a small and statistically significant positive effect on the impact of inventions. Hence, we controlled for whether patents receive more citations due to a higher number of active patent assignees in specific years, which resembles a more crowded industry (Klepper and Simons, 2005). Additionally, five dummies have been created corresponding to the biopharmaceutical 3-digit patent classes that were used to obtain the sample. In this way we controlled for the extent in which patents across these biopharmaceutical patent classes have different levels of technological impact.

3.6 Analyses

In order to explore the relationship between recombination and impact, we ran several analyses of different regression models with the number of forward citations within ten years as measure for the dependent variable. Given that our dependent variable is a count variable with overdispersion (see table 4), we use negative binomial regression models. In total, two

sets of three models are shown for both dependent variables. First, only the control variables are entered (model 1 and 4). Next, the linear term for the level of recombination was entered in the second and fifth model. The third and sixth model consisted of the linear and the squared term for level of recombination. The analysis with the forward citations received within five years (model 1-3) contains all patents granted between 1976 and 1997, so that sample size for these analyses is 81.838 patents. The models with the number of forward citations received within ten years after the grant date of the sampled patents (model 4-6) take into account all patents granted between 1976 and 1993, so that the ultimate sample size for these analyses is 56.709 patents.

4. RESULTS

4.1 Results

In table 4 the descriptive statistics and correlations between the variables are shown. The values of the bivariate correlations are rather small indicating that our analyses do not suffer from multicollinearity problems.

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Insert Table 3 about here "Descriptive statistics and correlations"

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Insert Table 4 about here "Level of recombination and impact - negative binomial regressions"

- - -

First, the baseline models (model 1 and 4) show statistically positive effects from the number of claims on a patent, number of classes, citations to other documents, citations to foreign

patents, and the number of citations to previous patents as well as a negative effect of the age of the backward citations. These effects are consistent across all models that we estimated. In contrast to what we expected, there is a statistically significant negative effect from the number of inventors listed on a patent on the technological impact. Interestingly, the variable that captures the number of granted patents to an assignee shows a small statistically significant positive effect on short term forward citations (i.e. citations received within five years after the grant year of the patent (b = 0.001 in model 1-3)) and a small statistically significant negative effect on the long term forward citations (b = -0.001 in model 4-6). In addition, assignees with a patenting strategy that correspond to applying for less patents, but with multiple claims seems to result in higher technological impact levels, which can be derived from the positive effect of the average number of claims per patent by the assignee of the focal patent.

When we enter the linear term of the recombination measure (model 2 and 5), we find a small statistically significant positive effect on the number of forward citations (b = 0,108 and b=0,065). Log-likelihood ratio tests (Long and Freese, 2006) reveal that the inclusion of the linear recombination term implies a significant improvement of the model fit. However, the same tests reveal that the model fit is further improved by including the squared term of recombination in the regression analysis (model 3 and 6). In these models the linear coefficient is still positively significant whereas the squared term shows a statistically significant negative coefficient (b = -0,138 in model 3 and b = -0,124 in model 6). These coefficients combined suggest the existence of an inverted-U shaped relationship between the degree recombination and technological impact of inventions. To assess whether an inverted-U-shaped relationship is really present in the observed range of the variables, the results from the third and sixth model are plotted in figure 3. The graph in the figure demonstrates the effect of recombination on impact when considering all possible combinations of values on

the other variables (Hoetker, 2007). This is needed, because a negative binomial regression model is multiplicative so that the effect depends on the values of all other covariates in the model. Figure 3 clearly reveals two inverted-U-shaped relationships thereby providing strong support for hypothesis 1.

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Insert Figure 3 about here "The effect from recombination on impact"

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The next step was to see which new combinations were most likely to result in the highest impact. Here, our second hypothesis specifies that inventions that are based on combinations of components from near and distant or near, adjacent and distant domains are more impactful than inventions that are based on components from only adjacent domains. Table 6 shows the results from the negative binomial regression model with seven dummies that correspond to all possible different types of recombination. Model 1 and 2 use the number of forward cites within a five year time window as the dependent variable whereas model 3 and 4 use a ten year time window. The results, however, are extremely similar for both dependent variables. For both dependent variables, the model with the variables capturing the type of recombination shows significantly better model fit compared to the model with only the control variables.

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Insert Table 5 about here "Different combinations and impact - negative binomial regressions"

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The results presented in model 2 and 4 clearly show that all types of recombination have a positive effect on an invention's impact compared to the reference category (i.e. models without backward cites). Moreover, interesting differences in the impact effects of different types of recombination are revealed. As is it difficult to derive such differences directly from the results presented in Table 6, we used marginal effect analyses to estimate the average number of forward cites a patent would receive within a five year time window if it only differed on the type of recombination. From these estimations we subtracted the average number of cites to clarify the differentials between categories. The results of these estimations are presented in figure 4 which provides a clear insight on the magnitude of the differences in an invention's impact based on its type of recombination. In figure 4, the three types of recombination result in intermediary levels of recombination are depicted in black, whereas the other types of recombination are in grey.

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Insert Figure 4 about here "Different types of recombination and their effects on impact"

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A number of important observations can be derived from figure 4. First, we find that both ´near´ and the combination of ´near-adjacent´ yield an about average degree of impact, suggesting that recombination based on core expertise does generate a ´respectable´ pay-off in terms of impact. Moreover, the impact of building on 'near' or 'near-adjacent' technologies is twice that of building only on ´distant´ domains. These findings are in line with Nemet and Johnson´s study (2012) as far as the positive effect of building on ´near technologies´ that

they reported. However, for some industries Nemet and Johnson (2012) found a negative effect of ´far technologies´ that differs from our findings on a albeit smaller, but still positive effect of distant recombination. This difference could be attributable to their empirical setting, formed by computers & communications, electronics and medical & drugs. About 78% of their observations pertain to the first two technological fields, computers & communications and electronics, which form so-called ´systemic´ technologies that make up and form part of a larger technological system (Breschi and Malerba, 1997, Marsili, 2001). Typically for such a systemic technological field is that those new inventions, which are technologically too far different from the prevailing technological system, will not fit in and are therefore likely to have a low(er) impact or may even have an adverse effect on impact in these two industries as reported in their study. Our empirical setting of pharmaceutical biotechnology forms almost an ideal-type of a so-called ´standalone´ technological field that allows for (much) more degrees of freedom as also inventions based on distant technologies can have a meaningful impact, because they are unlikely to conflict with an existing technological system (Breschi and Malerba, 1997, Marsili, 2001).

In addition to the findings of Nemet and Johnson (2012), our findings show that different ways to accomplish an intermediary level of recombination will result in very different levels of impact. Building only on adjacent technological domains actually results in a much lower than average impact. Instead, a much higher degree of impact can be achieved by building on near and distant technological domains. This clearly shows that the way in which an intermediary level of recombination is achieved is highly important for an invention's impact. Clearly, maximizing familiarity with some of an invention's building blocks and maximizing the degree of novelty with others results in higher impact as compared to average degrees of familiarity and novelty in each building block of an invention. Second, combinations of components from near, adjacent and distant technological domains are most

likely to result in the highest level of subsequent impact. We will get back to the implications of these findings in the discussion section.

4.2 Robustness checks

Several complementary analyses were run in order to test the robustness of our findings. One robustness check was to transform all control variables to their natural logarithm, because the skew of the controls might influence the outcomes of the analyses. In these models we still found statistically strongly significant support for an inverted-U shaped relationship between recombination and both number of forward cites a patent receives both within a five and a ten year time window.

A second robustness check was carried out by attaching different weight to the 'near', 'adjacent', and 'distant' backward citations. The results are shown with recombination weights '1', '2', and '3' in the sequence of categories above. Alternative weights were '1', '3', and '5' as well as '1', '4', and '9', in order to increase the range of the variables. These alternative weighting schemes also demonstrated a clear inverted-U shaped relationship between recombination and impact.

Furthermore, we checked whether the same results would appear if instead of using a continuous measure for the impact of a patent we created a dummy variable that captures whether the invention belongs to the top of the most impactful inventions. This alternative dependent variable was created by selecting the top 1 percent, top 2 percent, and top 5 percent of patents with the most forward citations and giving these a value of '1' (Ahuja and Lampert, 2001; Phene et al., 2006; Srivastava and Gnyawali, 2011; Conti et al., 2013). Using a logit regression model, we again found statistical significant results for an inverted U-shaped relationship between recombination and technological impact. Finally, similar logit regression analyses were conducted with the dummies for the different combinations of components and

also here the inventions that combined ‘near’, ‘adjacent’ and ‘distant’ components had the highest likelihood for belonging to the most impactful inventions[7]. All in all, these analyses show that our findings considering the relation between recombination and impact of inventions are highly robust.

5. CONCLUSION & DISCUSSION

Within this study, we sustained the work of Schumpeter (1934; 1947) through an investigation of the relationship between recombination and technological impact. Despite forming these two well-known ´faces of inventions´, their specific relationship has only marginally been subject to inquiry. The (implicit) assumption in the literature is that there is a positive linear relationship between recombination and impact of inventions, implying that inventions with low levels of recombination have (far) less impact than inventions with high levels of recombination (Schoenmakers and Duysters, 2010; Nemet and Johnson, 2012). To address the validity of this assumption, the purpose of this paper has been to establish in how far the relationship between recombination and impact is a linear one or exhibits non-linearity instead. In addition, we have determined the differential impact of different levels of recombination, and which level of recombination -low, intermediate or high - will be most impactful. With regard to the former, we found strong support for an inverted-U shaped relationship between recombination and technological impact. With regard to the latter, we found that the highest impact comes from the intermediate recombination that is made up of near - adjacent - distant domains. These findings have a number of important implications.

First, from our analyses of all biopharmaceutical patents, the found inverted U-shaped relationship between recombination and impact implies that both low and high levels of recombination carry a limited impact, whereas an intermediate level of recombination

[7]Results from these robustness checks are available upon request from the authors.

generates the highest impact. Low level recombination is within one technological domain, yielding inventions with many familiar components but lacking enough degree of novelty. The other less impactful inventions are formed by highly recombinant inventions that are created through the recombination of only technologically distant components. Although they come with a high degree of novelty, the lack of familiarity, recognizability and cognitive legitimacy surrounding these inventions hampers their impact. The implication is that the common idea in the literature of incremental inventions having low impact and radical inventions having high impact (Abernathy and Clark, 1985; Dewar and Dutton, 1986; Tushman and Anderson, 1986; Tushman and Smith, 2002) is no longer tenable. In fact, we even find that new combinations of components from *only local* technological domains generate more impact than components from *only adjacent or only distant* domains (see figure 4). This reconfirms the idea that a deep understanding of a particular domain forms an important prerequisite for developing impactful ideas (Simontin, 1999a, 1999b; Shane, 2000). In contrast, components from only distant domains may be too disparate to lead to impactful inventions.

Second, an intermediate level of recombination has the highest impact, although we have to discriminate carefully between three different types of inventions that make up for this category. As predicted, combining only adjacent domains yields the lowest impact of all inventions. For such an intermediate type of recombination, the familiarity and degree of novelty are traded-off against each other, leading to inventions that may be seen as 'worst-of-both-worlds'. In contrast, the combination of local and distant domains yields the near-highest impact as it combines both novelty and familiarity. The highest impact is found for what may form the 'perfect' type of intermediate recombination, namely a combination of near - adjacent – distant technologies. This combination implies a careful balance between familiarity and novelty by building not only on local and distant domains but also by

including a ‘bridge’ between the two through the inclusion of technologies from adjacent domains. In this way, familiarity and novelty are not traded-off against each other. Instead, synergy is created between the two that leads to coherence *and* renewal, leading to the highest pay-off in terms of impact. In other words, the combination of near -adjacent - distant technologies may represent the ‘best of three worlds’, making that such adjacent inventions carry the highest level of impact.

Third, these findings also carry implications for a more detailed understanding of the concept of recombination that has remained somewhat underspecified compared to the notion of impact. Schumpeter’s original idea of recombination is based on his classical distinction between recombination made up of novel combinations of unlinked components, and recombination made up of the reconfiguration of already linked components (Schumpeter, 1934; Henderson and Clark, 1990). Whereas this distinction suggests that these two categories arise from different approaches, our findings suggest that an overlooked possibility is formed by combining these two ‘routes’, i.e. combining unconnected components through inclusion of distant domains and reconfiguring already connected components through local domains. If on top of that, both approaches are not only combined but also explicitly *linked* through the inclusion of components from adjacent domains, the rewards will be high in terms of impact.

Of course, our study is not without limitations. First, the usual limitations of patent data apply, such as that our data represents only industry settings in which patents serve as proxies for inventions. Furthermore, due to data limitations we did not distinguish citations made by the patent applicant from citations made by the patent examiner (Alcácer and Gittelman, 2006; Alcácer et al., 2009), and we mainly focused on the primary patent class of each patent (Benner and Waldfogel, 2008). Another limitation of our study is that we only analyzed the effect of recombination on technological impact. Even though technological impact is an

important dimension of invention impact, it is not the only relevant dimension of impact. Logical extensions of our work would therefore be to assess whether inventions with high technological impact are also more likely to become breakthrough inventions and whether technological impact is related to economic or financial impact. The latter extension brings us to a third limitation of our study, namely its level of analysis. Economic and financial impact is generated by new products, processes or services which are seldom comprised of a single patent. Instead, they often make use of insights and technologies from many different patents. Therefore, we call for future research that bridges firm level studies on innovation and invention and studies on the invention level such as this one. Studies on packages of patents or studies on new product development are two alternatives for such a bridge. Specifically on the level of the firm, future research could consider the organizational implications for developing a capability that enables firms to bridge three different technological domains, namely one near, one adjacent and one distant. Future studies could also reflect on what firm-internal capabilities and organizational adaptations are required for recombination as well for impact. Moreover, future research could address in how far these capabilities can be developed in collaboration with external partners. Finally, the effect of developing impactful inventions on a firm's financial performance is the next step to consider.

Overall, our study carries an important message for the dominant approach in the literature to dichotomize types of inventions. A common denominator underlying the different types of dichotomies is that they remain silent on whether they refer to the recombination side of inventions or to their impact side. Distinctions such as between incremental and radical inventions, modular and architectural innovation or continuous and discontinuous inventions (Tushman and Anderson, 1986; Henderson and Clark, 1990) seem to point more to the recombination side of inventions. Whereas the distinction between sustaining and disruptive inventions (Christensen, 1997), between evolutionary and revolutionary inventions (Nelson

and Winter, 1982) or between non-breakthrough and breakthrough inventions (Ahuja and Lampert, 2001; Phene et al., 2006) seem to point more to the impact side. Conflation of recombination and impact leads to lack of analytical clarity and may possibly have led to the development of these different types of dichotomies in an attempt to improve transparency. In addition, the reliance on these dichotomous distinctions has led scholars to overlook the phenomenon of adjacent inventions. By making the explicit distinction between recombination and impact, we have been able to identify this important in-between category and have found that it yields the highest impact. Accordingly, researchers should well reconsider the definitions of different types of inventions by identifying the distinctive dimension - recombination or impact - underlying their definition.

In terms of managerial implications we find that R&D managers need to be aware of the need to develop strategies for creating combinations of local, adjacent and distant knowledge components in order to attain technologically impactful inventions. This is in contrast to the common idea that the most impactful inventions are highly recombinant ones that combine components from multiple distant technological domains. In addition, our findings are also highly informative to the claim by Henderson and Clark (1990) why the intermediate category of inventions presents a formidable yet subtle challenge for firms. To create high-impact inventions they need to balance what of their existing knowledge base remains useful and what becomes useless and thus requires the inclusion of novel knowledge. Striking this balance requires firms to recognize what is useful and what is not, which may be quite difficult for established firms (Henderson and Clark, 1990). We show that a trap here is formed by forgetting about the usefulness of a firms´ existing knowledge base through only focusing on adjacent and/or distant domains. Instead, our findings indicate that accomplishing this balancing act effectively requires that managers should specifically focus on the creation of inventions based on both proximate and distant technologies, and preferably *in*

combination with a ‘technological bridge’ between the two through inclusion of components from adjacent domains. So, to the extent that a firm’s R&D strategy aims at high impact inventions, managers should place more emphasis on carefully nurturing a hybrid capability of thinking within *and* across three boxes at the same time - one nearby, one adjacent and one distant.

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--- Table 1: Patent classes and their descriptions---

Classification	Description
424	Drug, bio-affecting and body treating compositions.
435	Chemistry: Molecular biology and microbiology.
436	Chemistry: Analytical and immunological testing.
514	Drug, bio-affecting and body treating compositions.
530	Chemistry: Natural resins or derivatives; peptides or proteins; lignins or reaction products thereof.
800	Multicellular living organisms and unmodified parts thereof and related processes.

Source: http://www.uspto.gov/web/patents/classification/

--- Table 2: Example measure level of recombination ---

Sampled Patent	Domain of backward cited patent	Number of backward citations per domain	Recombination Value	Level of Recombination
A1	Near	3	1	*Low*
A2	Near	2	1.33	*Low - Medium*
A2	Adjacent	1		
A3	Near	2	1.67	*Low - Medium*
A3	Distant	1		
A4	Adjacent	3	2	*Medium*
A5	Near	1	2	*Medium*
A5	Adjacent	1		
A5	Distant	1		
A6	Near	1	2.33	*Medium - High*
A6	Distant	2		
A7	Adjacent	1	2.67	*Medium - High*
A7	Distant	2		
A8	Distant	3	3	*High*

--- Table 3: Descriptive statistics and correlations ---

	Variable	Mean	STD	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13
1	BW patent cites	4.37	6.07	0	329	1.00												
2	Age	6.38	4.85	0	33	0.30	1.00											
3	Other	5.24	11.22	0	490	0.17	0.03	1.00										
4	Foreign	1.61	3.31	0	181	0.37	0.13	0.22	1.00									
5	Inventors	2.74	1.83	1	32	-0.03	0.00	-0.01	0.12	1.00								
6	Assignees	1.03	0.18	1	6	0.00	-0.01	0.06	0.02	0.10	1.00							
7	Claims	12.83	11.64	0	258	0.13	0.04	0.08	0.07	-0.02	0.00	1.00						
8	Classes	6.08	6.38	1	260	0.07	0.03	0.01	0.09	0.08	0.00	0.15	1.00					
9	Assignee size	18.71	25.35	1	193	-0.01	-0.02	-0.02	0.08	0.09	-0.03	-0.01	0.06	1.00				
10	Average claims	12.84	7.56	1	194	0.13	0.05	0.09	0.05	-0.07	-0.01	0.65	0.09	-0.02	1.00			
11	Recombination	1.17	0.64	0	3	0.27	0.55	-0.08	0.06	-0.01	-0.03	0.07	0.06	0.01	0.06	1.00		
12	FW cites 5 yrs.	3.80	6.59	0	200	0.21	0.02	0.19	0.16	0.00	0.02	0.16	0.10	-0.01	0.13	0.02	1.00	
13	FW cites 10 yrs.	6.44	11.95	0	672	0.20	0.03	0.17	0.11	-0.02	0.01	0.16	0.10	-0.05	0.13	0.01	0.85	1.00

Note: Descriptives are based on 81838 observations (all patents between 1976 and 1997)

The descriptives and correlations with FW cites 10 yrs. are based on all patents between 1976 and 1993 (N=56709), because of the truncation effect

--- Table 4: Level of recombination and impact - negative binomial regressions [a] ---

	Forward cites within 5 years			Forward cites within 10 years		
	Model_1	Model_2	Model_3	Model_4	Model_5	Model_6
BW patent cites	0.028***	0.026***	0.024***	0.038***	0.037***	0.033***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Age	-0.019***	-0.026***	-0.030***	-0.018***	-0.023***	-0.027***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Other cites	0.013***	0.013***	0.013***	0.017***	0.017***	0.017***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Foreign cites	0.010***	0.011***	0.010***	0.008**	0.008**	0.008**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Inventors	-0.007*	-0.008*	-0.007*	-0.014**	-0.014***	-0.014**
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Assignees	0.057*	0.058*	0.053	0.074	0.074	0.069
	(0.027)	(0.027)	(0.027)	(0.039)	(0.039)	(0.038)
Claims	0.014***	0.014***	0.014***	0.015***	0.015***	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Classes	0.022***	0.022***	0.022***	0.024***	0.024***	0.024***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Assignee size	0.001***	0.001***	0.001***	-0.001**	-0.001**	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Average claims	0.004***	0.003***	0.003***	0.003**	0.003**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Recombination		0.108***	0.433***		0.065***	0.365***
		(0.011)	(0.027)		(0.013)	(0.034)
Recombination^2			-0.138***			-0.124***
			(0.010)			(0.012)
Constant	0.728***	0.668***	0.583***	1.235***	1.203***	1.124***
	(0.039)	(0.039)	(0.040)	(0.051)	(0.052)	(0.053)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Technology dummies	Yes	Yes	Yes	Yes	Yes	Yes
Alpha	0.216***	0.213***	0.208***	0.177***	0.176***	0.172***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.010)
Likelihood ratio test		140.81***	282.99***		42.51***	184.61***
Chi2	10627.42	10791.62	10963.33	9546.65	9639.57	9762.43
N	81838	81838	81838	56709	56709	56709

[a] Robust standard errors in parentheses.

--- Table 5: Different combinations and impact - negative binomial regressions [a] ---

	Forward cites within 5 years		Forward cites within 10 years	
	Model_1	Model_2	Model_3	Model_4
BW patent cites	0.028***	0.019***	0.038***	0.027***
	(0.001)	(0.001)	(0.002)	(0.002)
Age	-0.019***	-0.030***	-0.018***	-0.027***
	(0.001)	(0.002)	(0.002)	(0.002)
Other cites	0.013***	0.013***	0.017***	0.018***
	(0.001)	(0.001)	(0.001)	(0.001)
Foreign cites	0.010***	0.010***	0.008**	0.008**
	(0.002)	(0.002)	(0.003)	(0.003)
Inventors	-0.007*	-0.007*	-0.014**	-0.013**
	(0.003)	(0.003)	(0.004)	(0.004)
Assignees	0.057*	0.050	0.074	0.065
	(0.027)	(0.027)	(0.039)	(0.038)
Claims	0.014***	0.014***	0.015***	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)
Classes	0.022***	0.022***	0.024***	0.024***
	(0.001)	(0.001)	(0.001)	(0.001)
Assignee size	0.001***	0.001***	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Average claims	0.004***	0.003***	0.003**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Near		0.309***		0.302***
		(0.021)		(0.027)
Adjacent		0.229***		0.157***
		(0.029)		(0.033)
Distant		0.210***		0.228***
		(0.051)		(0.064)
Near-Adjacent		0.380***		0.306***
		(0.023)		(0.029)
Near-Distant		0.409***		0.383***
		(0.034)		(0.04)
Adjacent-Distant		0.351***		0.328***
		(0.054)		(0.063)
Near-Adjacent-Distant		0.482***		0.464***
		(0.031)		(0.038)
Constant	0.728***	0.579***	1.235***	1.106***
	(0.039)	(0.040)	(0.051)	(0.053)
Year dummies	Yes	Yes	Yes	Yes
Technology dummies	Yes	Yes	Yes	Yes
Alpha	0.216***	0.206***	0.177***	0.169***
	(0.008)	(0.008)	(0.009)	(0.010)
Likelihood ratio test		537.60***		376.91***
Chi2	10627.42	11134.02	9546.65	9997.84
N	81838	81838	56709	56709

[a] Robust standard errors in parentheses.

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Figure 1: Near, adjacent, and distant technological domains

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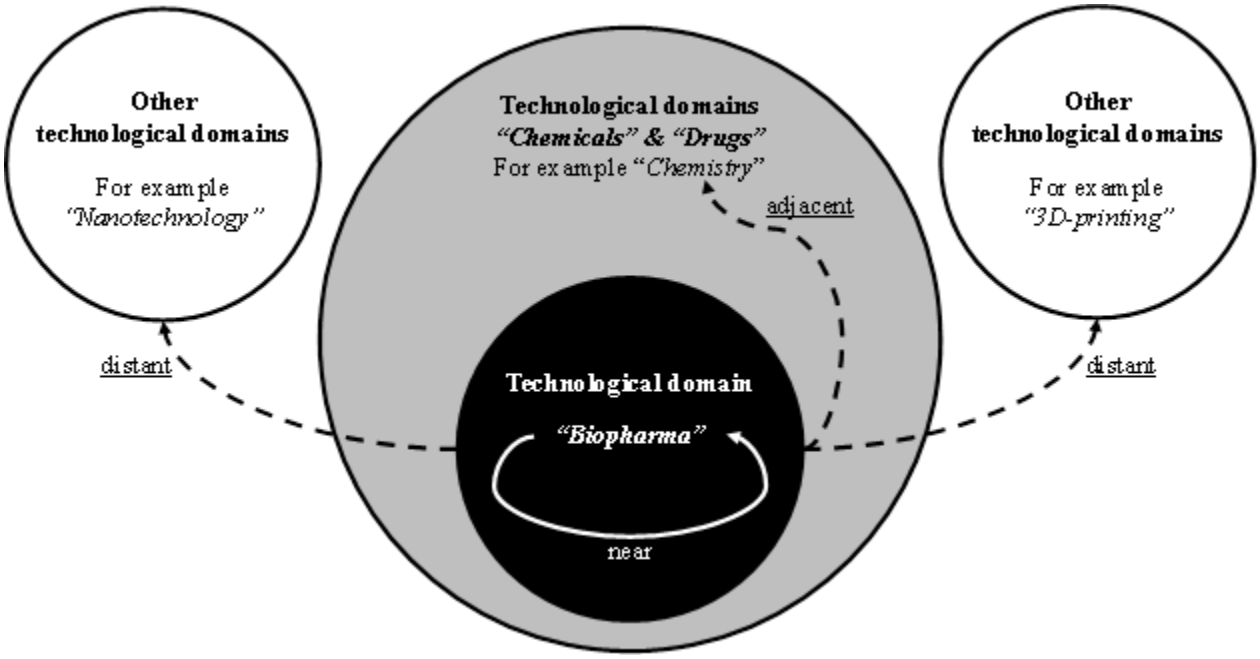

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Figure 2: Time lag between application and grant year of a patent–

Time lag between grant year of the cited patent and application year of the citing patent

- - -

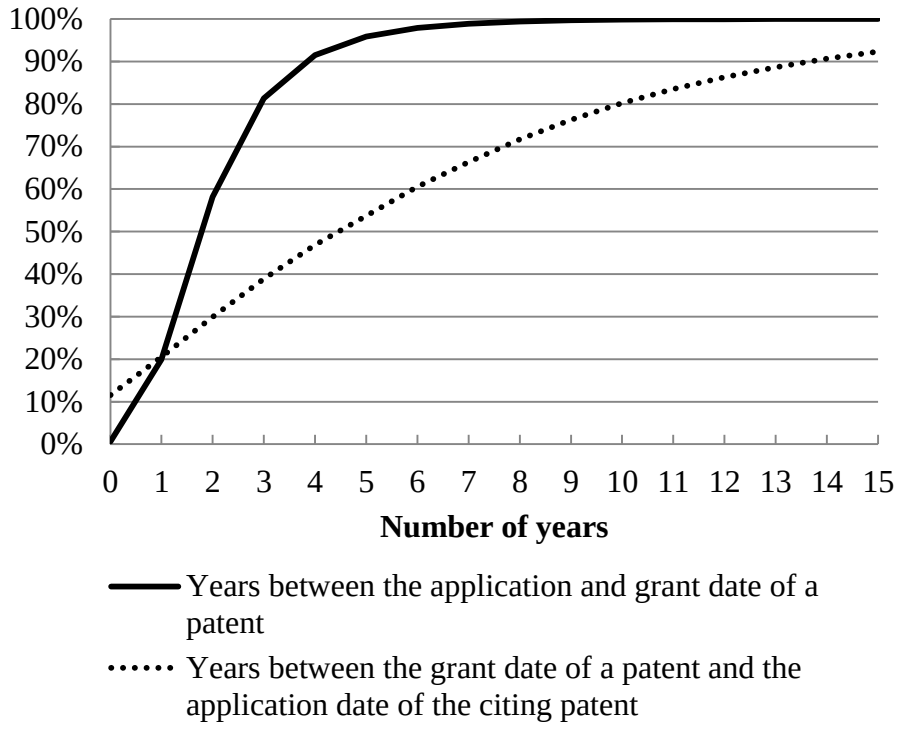

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Figure 3: The effect from recombination on impact

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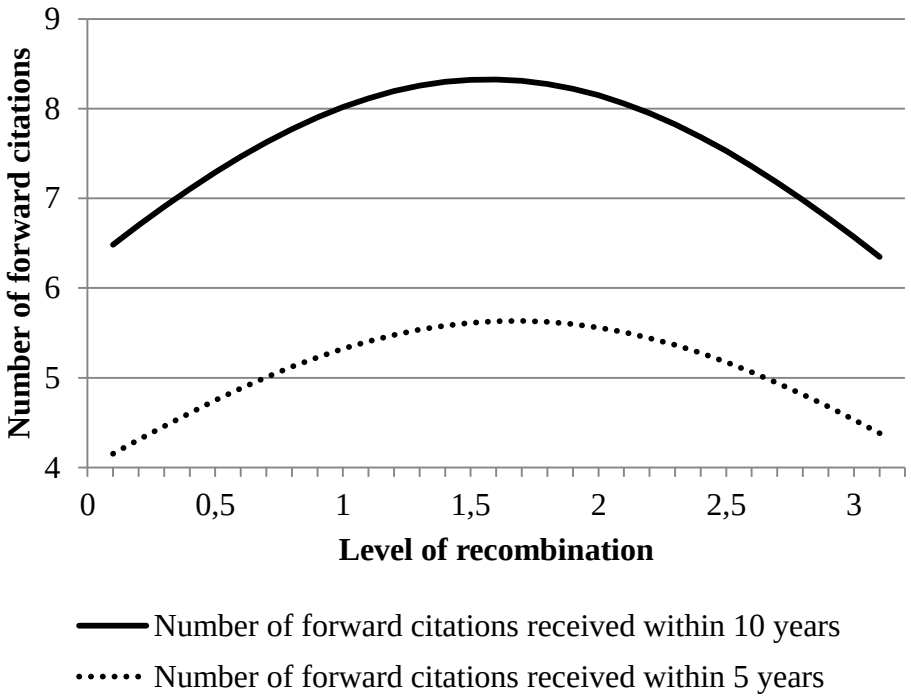

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Figure 4: Different combinations and their effects on impact

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