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Valuable components in the innovation process: Can there be too much of a good thing?

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Abstract
Previous research shows that the characteristics of components, which are used to create new innovations, have strong influence on innovation outcomes. However, the influence of component ?value? as a very important characteristic has hardly been examined. This is despite the fact, that the value criterion allows investigations into the trajectories of successful innovations and their evolutionary nature - a central concern of research in innovation, science and social progress. This paper provides an empirical analysis of the relationship between component value and innovation performance. It uses evolutionary theory to argue, that component value is curvilinear related to innovation value and that this is particularly true for breakthrough. The analysis of more than 170,000 patented innovations across various industries supports these claims. It shows that the value of components have a positive impact on innovation performance, but only up to a certain point. High levels of component value reduce the innovation value and this is particularly true for old components and breakthrough innovations. The findings illustrate that an increase in valuable inputs not always lead to more valuable outputs and even can be harmful.

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Work in progress

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Abstract

Multiple studies show that the recombination of the characteristics of components in the innovation process influences the value of an innovation. Following this stream of research, this study explores the effect of ‘component value’ on ‘innovation performance’. Building on evolutionary theory and the notion that a component’s value is dependent on technological trajectories, it hypothesises that a component’s value has an inverted U-shaped relationship with its innovation value. Additionally, it proposes that this curvilinear relationship holds for breakthroughs in innovation and is particularly strong for older and explorative components. The analysis of a large-scale patent dataset in the biotechnology and software sector largely supports these claims. It shows that the excess use of valuable components has a negative effect on both innovation value and the generation of breakthroughs in innovation. This effect is particularly strong for innovations based on old components. Thus, results indicate that there “can be too much of a good thing” as an increase in valuable inputs does not always lead to more valuable outputs.

Introduction

A well-established idea within innovation research is that most innovations are a combination of existing technology and knowledge components, and the characteristics of these components influences innovation outcomes (Fleming 2001; Henderson and Clark 1990; Kogut and Zander 1992; Nelson and Winter 1982). This view on innovation led to a stream of research investigating component characteristics and their influence on innovation results, such as component age (Ahuja and Lampert 2001; Katila 2002; Miller et al. 2007), scope (Katila and Ahuja 2002), organisational origin (Katila 2002; Miller et al. 2007), geographic origin (Phene et al. 2006; Rosenkopf and Almeida 2003), technological diversity and distance (Phene et al. 2006; Rosenkopf and Nerkar 2001), and (Fleming 2001).

However, despite this array of studies combined with the fact our economy increasingly relies on the production, refinement and accumulation of ideas (Powell and Snellman 2004), we still only have a limited understanding of how innovation build on previous ideas (Murray and O'Mahony 2007). One factor that has hardly been investigated is the value of the component in the innovation process. We do not know how component value influences innovation value and the generation of breakthrough innovation. This is surprising because 'component value', defined as the economic performance and impact of an innovation, enables detailed investigations into the development of ideas along trajectories and paradigms by linking the success of current innovation to the success of an earlier 'ancestor' innovation. Thus, component value is an important construct for evolutionary theories and their application on innovation, organisational change, success and survival (Dosi 1982; Nelson and Winter 1982).

Additionally, component value can advance research on the resource-based view (RBV), in which the 'value' criteria has a prominent position (Barney 1991, 2001). Despite being one of the most influential theories in strategic management and innovation settings (Armstrong and Shimizu 2007; Galunic and Rodan 1998), 'value' is still relatively under researched in the resource-based view. Newbert (2007) argues that only very few studies directly measure the resource value and relate it to performance indicators (known as the 'conceptual-level approach'). Instead, most studies correlate specific resources, which are assumed to be valuable, with a performance measure (the 'resource heterogeneity approach'). Yet, to truly understand how resources contribute to a specific outcome, their value must be examined directly (Newbert 2007).

Therefore, this study provides one of the first empirical investigations into the question: How do different levels of component value influence the value of innovation and the generation of breakthrough innovation? First, it applies evolutionary theory to argue that component value is positive but curve-linear related (inverted U-shape) to innovation value. Second, it examines the interaction of component value with knowledge age and exploration. Both concepts, central in recent innovation research (Gupta et al. 2006; Rosenkopf and McGrath 2011) and are theoretically linked to component value. 'Component age' directly relates to the time component in evolutionary studies, while 'exploration' captures the familiarity with components (Ahuja and Lampert 2001; Fleming 2001; Li et al. 2008). Finally, the study examines the application of its prediction to the special case of breakthrough innovation. This type of innovation is not only of special interest because it is strongly related to social progress and organisational performance and survival (Ahuja and Lampert 2001; Anderson and Tushman 1990; Christensen 1997; Tripsas 1997), but because it is also assumed to be created differently and relies on different types of components (Ahuja and Lampert 2001; Singh and Fleming 2010).

By analysing the importance of component value in the innovation process, this study contributes to research on innovation and strategy alike. First, it adds to previous innovation research and provides a more complete picture on how component combinations influence innovation outcomes. This is of crucial importance to managers and innovators who try to gain a better understanding of how to combine innovation inputs in order to increase the efficiency of the innovation process while simultaneously reducing its uncertainty. This is particularly true for breakthrough innovations, which appear to have strong influence on social and economic progress, firm survival and business growth (Ahuja and Lampert 2001; Anderson and Tushman 1990; Christensen 1997; Tripsas 1997), but still suffer from a limited understanding among practitioners and scholars (Conti et al. 2010).

Second, this paper contributes to the evolutionary theories on innovation and technological progress (Dosi 1982; Dosi and Nelson 2010; Nelson and Winter 1982) It provides one of the few empirical studies on the cumulativeness of standard innovation along technological trajectories while simultaneously examining rare cases of breakthrough innovation. It makes a strong case for the cumulativeness of innovation, but also highlights the fact the overtime and between paradigms the cumulativeness is limited.

Finally, through the conceptual similarity between resources and components (Galunic and Rodan 1998), this study provides one of the few empirical investigations to link resource value to performance criteria. Review articles on the resource-based view have highlighted the missing empirical research on value criteria and context specific value (Armstrong and Shimizu 2007; Kraaijenbrink et al. 2010; Newbert 2007). Thereby, this study looks beyond value as an absolute concept and highlights the fact that value is context-dependent, a point raised by the critics of the resource-based view (Priem and Butler 2001). Furthermore, while most resource-based research has focused on the positive effects of resources on firm competitiveness and performance, this study shows the possible negative effects of valuable resource. The contextualised understanding of resource value is of central importance to the resource-based view and can enhance its managerial implication (Armstrong and Shimizu 2007).

Innovation and knowledge components

Scholars have long recognised that most developments in science and technology are based on cumulative and local extensions of previous ideas within a given trajectory (Cimoli and Dosi 1995; Dosi 1982; Kuhn 1962; Merton 1973; Murray and O'Mahony 2007; Nelson and Winter 1982). The most known expression of this idea of progress is probably the concept of paradigms introduced by Thomas Kuhn (1958, 1962) and his work on the evolution of scientific fields. With regard to cumulativeness of scientific developments Kuhn argues that, "Most successful scientific research results in change of the first sort [normal science], and its nature is well captured by a standard image: normal science is what produces the bricks that scientific research is forever adding to the growing stockpile of scientific knowledge," (Kuhn 1958). Kuhn's work had a significant influence on innovation and technological progress research (Dosi and Nelson 2010; Teece 2008). In a seminal work on technological trajectories, Dosi (1982) writes: "As 'normal science' is the 'actualization of a promise' contained in a scientific paradigm, so is 'technical progress' defined by a certain 'technological paradigm'. We will define a technological trajectory as the pattern of 'normal' problem solving activity (i.e. of 'progress') on the ground of a technological paradigm (p.152). More recently, Furman and Stern (2006) argue that, "A distinctive feature of modern capitalism is that, across a wide range of industries and technologies, the process whereby researchers stand on the shoulders of giants seems to be self-perpetuating: from information technology to transportation to pharmaceuticals, technological and scientific productivity is maintained by researchers by drawing upon an ever-expanding set of knowledge applicable to their field."

The emphasis on the cumulativeness of innovation within trajectories might seem to clash with ideas on the disruptive nature of innovation (Christensen 1997). However, the cumulative nature of innovation refers to "normal" innovation activity, which forms the majority, where 'success breeds success', or in a change of the classical phrase, the extent "to which innovative advances are made by dwarfs standing on the shoulders of past giants" (Dosi and Nelson 2010). In this cumulative view of progress, new innovations build upon successful ideas from the past, which lead to inherent serial correlations in successes and failures (Dosi and Grazzi 2006).

There a various explanations for the cumulative nature of innovation activities. Firstly, the sociology of science and innovation stresses the significance of institutions, practices and communities in science and technology (Latour 1987; Merton 1973; Murray 2002). Social norms and conventions build frames of reference and normative pressures to stay within those frames of reference. These 'frames' capture how inventors make sense of technologies. They shape how inventors perceive a technology relative to other technologies and which performance criteria they use to evaluate the technology. Thus, technological frames guide inventors in deciding which technology is useful (Kaplan and Tripsas 2008). Furthermore, innovating within an existing frame of reference by using established components makes an innovation more likely to be accepted within the community who built the initial component in the first place.

Secondly, the uncertainty and complexity of the discovery process combined with the cognitive and mental limitations of humans provides another explanation for the cumulative nature of innovation activities (Fleming 2001). The number of potential combinations of constantly increasing components overwhelm the imagination and mental power of human beings (Fleming 2001). Additionally, most of the potential combinations do not yield valuable outcomes and it is difficult to predict the success of an idea. Building on successful combinations, thus, reduces the search possibilities in a positive sense because it indicates a successful path of ideas, which increase the likelihood of success in the future. On the other hand, when disregarding unsuccessful past ideas, inventors can reduce the size of the combinatorial search possibilities and eliminate fruitless avenues (Fleming 2001).

> Hypothesis: 1a: The use of valuable components in the innovation process has a positive relationship to innovation value.

However, even though the reliance on valuable components is most likely beneficial, the excessive use of valuable components should result in a diminishing and even negative marginal contribution to the innovation value. Innovations that heavily rely on previously successful innovations might trade the security of exploitation of established and proven ideas against the necessary risk of exploration. March (1991) argues that in evolutionary models of organisational and technological development, exploitation and exploration have to be balanced; an excess of one type of activity at the cost of the other will most likely leads to a negative outcome. Exploitation ensures continuity and security, whereas exploration provides the variation necessary to develop new and different ideas for successful innovation (March, 1991). The arguments for taking a balanced approach to the nature of components is also supported by previous research on components (Ahuja and Lampert 2001; Katila and Ahuja 2002; Nerkar 2003) and can be extended to the component’s value as it represents the reliance on established and successful innovations (exploitation) and excessive use of valuable components, similar to exploitation, leads to a decrease in innovation outcomes. Additionally, at a given point, the logic of a diminishing rate of returns applies to the additive logic on innovation components as well. Adding further components to a set of components should not provide any benefits because the likelihood of redundancy increases with each additional component. Thus;

Hypothesis 1b: The use of valuable components in the innovation process has a curvilinear (inverted U-shape) relationship to innovation value.

Breakthrough innovation

Breakthrough innovations constitute a special kind of innovation. Not only are they particularly crucial for technological and social progress, organisational profitability and survival, but their creation differs from standard innovations (Ahuja and Lampert 2001; Anderson and Tushman 1990; Christensen 1997; Singh and Fleming 2010; Tripsas 1997). Of particular relevance is that breakthrough innovations differ from the cumulative nature of innovations. Their creation is based on the combination of new and unfamiliar components, which increases the probability of generating distinct, radically different innovation outcomes (Ahuja and Lampert 2001; Phene et al. 2006). While standard innovations consists of cumulative progress along a trajectory within a given paradigm, breakthrough innovations cross these trajectories and create new ones (Anderson and Tushman 1990). Thereby, they not only create technological uncertainty as innovators struggle to master the untested and incompletely understood new ideas (Anderson and Tushman 1990), they often require a more radical and broader change of "technological frames" (Kaplan and Tripsas 2008) or "world view" (Kuhn, 1962). This is similar to Kuhn's (1962) views on paradigm changes. He argues that: "Revolutionary changes … involve discoveries that cannot be accommodated within the concepts in use before they were made. In order to make or to assimilate such a discovery one must alter the way one thinks about and describes some range of natural phenomena. When referential changes of this sort accompany change of law or theory, scientific development cannot be quite cumulative. One cannot get from the old to the new simply by an addition to what was already known," (p. 6-7). As a result, meaning and language are specific to each paradigm and cannot be fully or partially transferred to another paradigm.

In the case of breakthrough innovation, this means that references and value judgements of the existing innovation cannot be used to make inferences with respect to a new innovation. The old heuristic and underlying basic technological frames do not match innovation, establishing a new paradigm, and old criteria for assessing performance, value and quality do not fit the new paradigm.

Thus, past value appraisals of components do not relate positive to breakthrough innovation as the valuation of the components refers to a different valuation paradigm.

The history of science and technology is full of examples of paradigmatic changes, which lead to reassessments of what constitutes valuable technologies, knowledge or methodologies (Anderson and Tushman 1990; Hopkins et al. 2007; Kuhn 1962; Malerba and Orsenigo 2002). For example Hopkins et al., (2007) and Malerba et al., (2002) illustrate how the pharmaceutical industry relied on a series of paradigms over the past two centuries (e.g. botanic expeditions, synthetic organic chemistry, recombinant protein or monoclonal antibody-based drugs). Each paradigm represents a socio-technical environment based on heuristics and technological frames that guided drug development. Each period relied on specific development logics with specific methods, techniques and components, which only partly transferred to subsequent phases.

Furthermore, the value of components does not only positively translate into the successful development of future breakthrough innovations; these components might even have a negative influence on the development of breakthrough innovation. Ahuja and Lampert (1991) describe technological progress as a series of continuous improvements in fitness along a technology trajectory. Thereby the fitness of a technology is understood to be a function based on a composite function of all relevant performance attributes of a technology and its mapping on a technological trajectory, which is the mapping of elements of the technology space onto several distinct, continuous functions. Within a trajectory there is continuity as fitness values of a given technology are closely related to fitness values of proximate technologies. In such a situation, solutions that build on existing solutions are likely to map onto the same technological trajectory and consequently yield very similar fitness values to the ones already obtained by other solutions. The high value of components indicates a particularly strong fit with an existing or past technological paradigm. The high specialisation makes a positive fit with a new paradigm less likely. The more rooted an idea is in an existing paradigm, the less likely it is it will lead or contribute to a new one. Hence, while component value might still be positive relative to breakthrough innovation, very high levels of component value are less likely to be related to breakthrough innovation.

Hypothesis 2: The creation of breakthrough innovation has a curvilinear (inverted U-shape) relationship to the use of valuable components in the innovation process.

Component age and innovation quality

Previous research highlights that component age is an important predictor of innovation value and impact (Ahuja and Lampert 2001; Katila and Ahuja 2002; Miller et al. 2007; Nerkar 2003). The reasons for this are manifold. Mature technologies are considered to be less risky and are more legitimate as they are usually better understood and offer greater reliability relative to more recent and less tested ideas (Ahuja and Lampert 2001; Katila and Ahuja 2002; March 1991). They are also more likely to be embedded in value networks which have co-specialised technologies and processes (Christensen 1997), which makes cumulative innovations easier. However, this may hamper the exploration of new ideas, which relies on different or not yet developed co-ideas and innovation (Ahuja and Lampert 2001). On the other hand, emerging components provide the potential for new and unexplored combinations (Ahuja and Lampert 2001).

These arguments have to be considered when examining component value because the previous value of components does not transfer easily into current innovation value given that technology frames change over time. Technological progress is a series of continuous improvements in fitness along technology trajectories (Ahuja and Lampert 2001). Over time the composition and set of relevant performance attributes of a technology changes, which makes old components less likely to achieve a high fit with the current environment (Ahuja and Lampert 2001). Thus, emerging components have a higher fit with the current environment (Sorensen and Stuart 2000) whereas older components often become obsolete over time (Bosworth 1978; Schott 1978). Furthermore, to be highly valuable in a given period requires a component to have a high fit with the technological environment of this period, but this makes it less likely to fit in a more current environment. Thus, despite the positive effects of established and valuable components on innovation value, the fact that a component is very old should reduce the positive effects of component value and this effect is greater the more valuable components become. This logic is similar to arguments on core rigidities, where formerly valuable resources might become a source of disadvantage when the environment changes and a firm needs to reformulate its strategy (Gilbert 2005; Leonard-Barton 1992). Not adopting or changing the resource base over time most likely leads to competitive disadvantage and negative performance outcomes.

Furthermore, the moderation effect between component value and component age should also hold for breakthrough innovation. First, the use of emerging components is particularly crucial for the generation of breakthrough innovation (Ahuja and Lampert 2001). New components provide exposure to novel modes of reasoning and variation in cause–effect understandings that increase the chance of breakthrough, whereas in the absence of novelty, inventors follow existing innovation patterns (Ahuja and Lampert 2001). Additionally, even though the combinative potential of a component is theoretically infinite, the number of valuable combinations is most likely finite (Fleming 2001). This implies that as a component matures, the likelihood that a high utility combination of a component has not yet been exploited declines over time. Relatively new components offer a higher potential for breakthrough combinations because they not only increase the pool of further combinations, but also because they offer a set of unexplored combinations, which can lead to radical new innovations (Ahuja and Lampert 2001). Secondly as argued in Hypothesis 2, the specialisation and technological fit of valuable components is difficult to transfer across time and paradigms. Thus for standard innovation as much as for breakthrough innovations, the high component value of old components should reduce the likelihood of generating valuable innovations.

Hypothesis 3a: The curvilinear (inverted U-shape) relationship between innovation value and component value is negatively moderated by component age.

Hypothesis 3b: The curvilinear (inverted U-shape) relationship between breakthrough innovation and component value is negatively moderated by component age.

Exploration and innovation quality

The concepts of exploitation and exploration are central to research on components in the innovation process (Fleming 2001; Phene et al. 2006; Rosenkopf and Almeida 2003) and their link to evolutionary theories can be seen in an early definition by March (1991), who argues that: "The essence of exploitation is the refinement and extension of existing competencies, technologies, and paradigms… The essence of exploration is experimentation with new alternatives," (p. 85). Following this definition in the context of this study, exploration is defined as experimentation with components which are technologically distant to the main focus of the innovation, while exploitation refers to the use of components that are technologically similar to the main focus of the innovation.

The exploitation of familiar components provides a starting ground from which innovators can move forward and the experience with these components makes the application more likely to be successful. However, the exploitation of familiar components causes knowledge architectures to reify (Henderson and Clark 1990). Existing approaches to problems in innovation can become dominant and even paradigmatic as cognitive maps become increasingly rigid (Leonard-Barton 1992). A decrease in experimentation also reduces the probability that distinct and different approaches and ideas will emerge (Lei et al. 1996). On the other hand, exploring new and unfamiliar components results in new cause–effect relationships within innovation problems (Lei et al. 1996) and extends the heterogeneity in the problem-solving repertoire (Amabile 1988). Thus, although a firm uses familiar, well-understood technologies with great competence, an absence of novelty and experimentation, the drivers which are likely to help the firm craft innovation and particularly breakthroughs, makes it more reliant on radical differences to existing innovation problems(Ahuja and Lampert 2001). However, an excess of new and unfamiliar components can be a source of confusion, information overload and frenzies of 'experimentation' (Levinthal and March 1993). Furthermore, simultaneously sourcing components from multiple areas will eventually result in diseconomies of scale (Phene et al. 2006). Thus, excess use of explorative components can harm innovation performance.

Furthermore, in evaluating the interaction between value and exploration, it is important to look at the fitness of a technology in its technological space. Using valuable components from a different area (exploration) embodies the risks that inventors do not understand the components completely and that their value is less transferable to new applications. The risk increases with the level of exploration. The greater the components' fit into one technological frame, the smaller the likelihood that the value of the components is transferable into another area characterised by different cause–effect relationships embedded in a different technological ‘frame'. This argument is similar to the logic demonstrated in breakthrough innovation with the distinction that breakthrough innovation refers to innovation grounded in different sequential paradigms within the same technological domain (e.g. organic chemistry and monoclonal antibody design in drug development), whereas exploration refers to innovation that draws components form different paradigms and technological domains that are closely related to existing parallel domains (e.g. monoclonal antibody design and informatics in drug development).

> Hypothesis 4a: The curvilinear (inverted U-shape) relationship between innovation value and component value is negatively moderated by explorative components.

> Hypothesis 4b: The curvilinear (inverted U-shape) relationship between breakthrough innovation and component value is negatively moderated by explorative components.

Method

This study draws on a large-scale US patent data set in two industries: Biotechnology and Software. These two industries are chosen for three reasons. First, innovation and technological recombination is central for organisational performance and survival in these industries. Second, in both industries, patents capture relatively large volumes of innovation activity and the propensity to patent is high, increasing the validity of patent-based measures (Hall and MacGarvie 2010; Phene et al. 2006). Finally, testing the hypothesis in two high technology industries with different institutional norms, technological requirement and industry dynamics increases the validity and generalisability of the results (Sorensen and Stuart 2000). The nature of the underlying technologies are fundamentally different. Software innovation is influenced by information sciences, while biotechnology lies at the intersection of molecular biology, immunology, genetics, and chemistry. Since biotechnology firms have a strong reliance on basic scientific research, they collaborate more actively with universities and research institutes. Biotechnology firms also rely heavily on collaborating with pharmaceutical firms, which provide funding and the competences required in the later stages of drug development (e.g.

clinical trial and marketing distribution). In contrast, the software industry is shaped by a collaboration of producers, who band together to promote technology standards and the use of particular software languages, which makes standards and network externalities more important than in the biotechnology industry. Finally, the software sector is characterised by a lower level of tangible assets because the requirements for laboratories and equipment are generally lower.

The data for this study was collected in five steps. First, the firms in the sample were identified via COMPUSTAT industry classifications and H*oovers, Who Owns Whom*. COMPUSTAT was also used to extract firm financial data. Second, all USPTO patents from 1995 to 1999 were collected for the sample firms. The five-year time frame allows sufficient variances to control yearly fluctuation in short-term patent trends and provides enough potential citation time to calculate relevant forward citation measures. By concentrating on USPTO patents, the study focuses on the biggest coherent patent system, which increases its validity given national patenting systems differ in their application of standards and processes. Third, the cited patents (references) were collected for each of the focal patents. Each patent is required to list all previous patents (prior art) relevant to the underlying patent. The accurateness of the reference list is controlled by the patent officers, which increases its validity. Thus, the citation records are seen to be a credible proxy for built-upon components (Fleming 2001; Katila and Ahuja 2002; Phene et al. 2006). In the fourth step, the forward citations for focal patents and cited patents (references) were collected to calculate innovation and component value. Finally, all additional information from the patent documents (focal and reference patents) was collected to construct various control variables. This procedure yields a focal sample of 634 firms with more than 68,000 patents built on more than eight million components.

Dependent variables

Innovation value: As in previous patent-based studies on innovation, the value of an innovation is approximated by the number of forward citations of patents (Ahuja and Lampert 2001; Phene et al. 2006; Rothaermel and Hess 2007; Singh and Fleming 2010). Forward citations are a well-established proxy for innovation value in patent and technology-based studies because they correlate positively with the market value of the firm, patent renewals, patent quality, intellectual property value and technological importance (Deng et al. 1999; Hall et al. 2005; Harhoff et al. 2003; Jaffe et al. 2000; Lanjouw et al. 1998; Trajtenberg 1990). However, since older patents have more time to receive citation, independent from their content and value, it is important to correct the number of citations for the possible time-to-cite. Therefore, the number of citations is multiplied by an exponential decay factor (Fleming, 2001): $e^{-\left(\frac{\text{application date of citing patent}-\text{publication date of focal patent}}{\text{time constatn of knowledge loss}}\right)}$. The exponential factor represents the loss and decay of knowledge over time. Following Fleming (2001), this factor is set at five years, which implies that approximately one-third of the knowledge remains after five years, equivalent to a yearly loss rate of 18%.

Breakthrough innovation: The definition of breakthrough innovation is based on the technological importance of an idea (Ahuja and Lampert 2001; Conti et al. 2010; Phene et al. 2006; Rosenkopf and Nerkar 2001; Singh and Fleming 2010). The technological importance of innovations vary significantly and very few innovations build a base for technological trajectories or paradigms whereas most inventions yield only limited value and are technological dead ends (Singh and Fleming 2010). The few innovations that serve as the source of many subsequent inventions can be regarded as breakthroughs because they have demonstrated their utility on the path of technological progress and have considerable technological and economic value (Fleming 2001; Phene et al. 2006; Singh and Fleming 2010). Accordingly, breakthrough inventions are defined as a fraction of the most cited patent in a given period. Following previous studies using citation measures, the top two percent of cited patents are defined as breakthroughs (Ahuja and Lampert 2001; Phene et al. 2006). However, all regressions are also performed with the top one and five percent with similar results.

Independent variables

Component value: Following the innovation value logic, component value is measured as the average number of time-to-cite corrections to forward citations for a given cited patent (references). The time-to-cite correction is also based on the multiplication of the number of citations by an exponential decay factor: $e^{-\left(\frac{\text{application date of citing patent}-\text{publication date of focal patent}}{\text{time constatn of knowledge loss}}\right)}$. The time-to-cite correction is particularly important for the value of components as it has a longer possible time-to-cite (1 and 99 years) and alternative correction (e.g. year dummies) are impractical.

Component age: This variable is based on the citation lag of patent references for the focal patent (Ahuja and Lampert 2001; Miller et al. 2007; Phene et al. 2005). This measure assumes that an innovation based on old technologies is more likely to cite older patents while innovation that cites recently developed patents is more likely to work on current issues. The average age of the patent references is measured as the time span between the application date of the priority patent and the average publication date of all cited patents.

Exploration: In the context of this study, exploration refers to experimentation with components which are technologically different to the focal patent, while exploitation is the use of components which are technologically similar to those used to build the focal patent. This conceptualisation of exploration and exploitation is strongly based on to the initial work of March (1991), which defines exploration as experimentation with new alternatives and exploitation as the use of existing competencies, technologies, and paradigms. It is measured using IPC classes to capture the technological distance between a focal patent and its patent references (components) and accounts for the fact that patents have multiple IPC classes. The technological distance (D) between a focal patent and its components is calculated: $D = \sqrt{\sum (p_i - c_i)2}$ where: (p) represents the proportion of IPC subclasses (i) of the focal patent, and (c) represents the proportion of IPC subclasses (i) of all references. This distance measure ranges from a low of zero (very high in technological similarity) to a theoretical maximum slightly above 1.414 (the square root of two) for technological dissimilarity. This measure has the advantage of weighting the different IPC classes based on their usage across all components, taking their relative importance into account.

Control variables

Patents are constructed in a complex institutional environment and built by strategizing actors (Gittelman 2008). Therefore, it is important to include a broad set of innovation and patent-related control variables.

Industry and technology differences can have a strong influence on patenting behaviour (Cohen et al. 2000; Sorensen and Stuart 2000). Thus technological dummies based on international patent classification codes (IPC) are used to control technological differences between patents (sections level). Additionally, since patents can cover several main IPC sections, classes and subclasses, the numbers of IPC subclasses are counted (six digit level) to control for the technological scope of an innovation. The number of inventors is an indicator of the project's size and innovation efforts underlying an innovation (Gittelman and Kogut 2003) and has shown to influence the generation of average and breakthrough innovations (Singh and Fleming 2010), thus the number of inventors is included in all models. The number of patent references of a focal patent is used to approximate the number of components in an innovation. As patents not only list references to other patents but also to scientific publication, a good indicator for the scientific inputs going into a patent (Gittelman and Kogut 2003; Tijssen 2001), the number of scientific components of a focal patent is used to capture the amount of scientific inputs into an innovation. Furthermore, the ratio between technological components and scientific components is used as an indicator for the overall 'science orientation' of a patent. Even though the focal patents are exclusively US based, the components can be international and the geographic origin of components has a direct effect on innovation outputs (Phene et al. 2006). Thus, a Blau’s index is used to control the international component diversity,for the International Component Diversity: $\left[1 - \sum p_i^2\right]$ where: (p) is the percentage of patents from a patent authority in a given region (i). High scores suggest the patent is based on more geographically diverse components. Similarly, the technological diversity of the components can influence the performance and value of innovations (Almeida and Kogut 1997). Therefore, a second Blau-index was calculated based on the technological diversity of components. In this case, (p) represents the percentage of IPC classes (i) across all references of a focal patent. A second control on the component level is the 'technological scope' of the components. It is measured as the number of IPC classes across all components (references) of a focal patent. This is important because the technological scope might be related to component value. Further measures on the level of the components are the variance of the component value and the variance of component age.

The number of patents is used to control the patenting activity and the size of a firm's research activity. The return on assets (ROA) is used to control a firm's profitability. A firm's capabilities in combining components depends on its R&D intensity, thus, the ratio of R&D expenditure to net sales is used as a control. Based on the established discussion on firm size and innovation, firm size is controlled via the number of employees. Finally, the number of R&D alliances is used to account for the external research of a firm and year fixed-effects are applied to account for any systematic differences in the sample period of the application of the focal patents.

Estimation

In this study, innovation performance is measured as a positive ratio variable (time-to-cite corrected forward citations of a focal patent) and is therefore estimated with a classical OLS regression. Based on the skewed distribution, the dependent variable is log transformed and all estimations are done with robust standard errors (White 1980) to correct for potential heteroskedasticity. Additionally, all models are also run with a negative binomial regression (NBR) using the raw citation count as a dependent variable. The negative binomial regression is an extension of the poison regression, which relaxes the assumption of over dispersion, accounts for omitted variable bias, estimates unobserved heterogeneity (Long and Freese 2003) and is frequently used to model citation counts (Corredoira and Rosenkopf 2010; Fleming 2001; Miller et al. 2007; Rothaermel and Hess 2007). When modelling breakthrough innovation, the objective is to estimate the likelihood that a patent falls in the category that has an extreme high citation count. Thus, following previous research, a logistic regression was used to regress on the binomial variable: 0 = average innovation, 1 breakthrough = innovation (Conti et al. 2010; Phene et al. 2006; Singh and Fleming 2010)

Results

Table 1 presents the descriptive statistics and correlation matrix. The data reveals differences between the industries and patent within each industry. For example, a patent cite between 0 and 156 patents with an average number of 13.38 components. Biotechnology patents have, on average, a greater number of components (average 16.33) than software patents (average 11.62). The industry differences are larger for scientific inputs. Biotechnology patents have on average 15.93 scientific components and software patents only 2.84. Biotechnology patents comprise on average also nearly double the amount of IPC classes (Biotechnology = 4.13, Software = 2.21) and this is reflected in the scope of the IPC classes of the components (Biotechnology = 23.31, Software = 9.98). Software patents have on average shorter citation lags (Biotechnology = 7.29, Software = 5.06).

With the exception of firm control variables, firm size and number of patents, all correlations are at a moderate level. The mean VIFs of the full models (based on pooled data) are below three and the VIF of each variable is below four. In order to avoid any possible bias, all models are also performed with one of the two variables (firm size and number of patents) and the results are in line with the present findings.

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Insert Table 1 & 2

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Model 1 in Table 2 presents the results for the control variables. Even though not shown in detail, the technology dummies differ significantly in citation propensity between sectors. Most control variables are very consistent across all models. For example, the Number of Inventors and the Number of Components are consistently positive significant ($p<0.01$). Similarly, Component Age and International Diversity are both with one exception negative significant ($p<0.01$). The firm level controls show only limited influence on the models, but it has to be noted that the sample time frame is relatively short so that time-variant differences are less likely. Additionally, firm fixed effects account for the time-invariant firm differences.

Model 2 adds component value to the regression to test the first hypothesis. The positive and significant coefficient ($p<0.05$) supports hypothesis 1a. Model 3 includes the quadratic term to test the hypothesised curve linearity. In this model, the main regressor for component value remains positive significant ($p<0.01$), while the quadratic term becomes negative significant ($p<0.01$). The overall fit of the model increases using r-square and adjusted r-square statistics.

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Insert Table 1

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Model 4-9 tests the interaction effect of component age and exploration with component value to test hypothesis 3a model 4a. Each interaction is tested individually, with the interaction between the main effect of component value followed by adding the non-linear term of component value (model 4-7) before both interactions a test a nested approach (Model 8 and 9). Throughout all models, the interaction between the main effect of component value is positive ($p<0.01$) and the interaction with the non-linear term of component value is negative ($p<0.01$). Contrary, with the exception of the interaction of the main effect for component value in model 7, the interactions with exploration are not significant.

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Insert Table 2

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Extended analysis: To ease the interpretation and check the validity of the findings multiple additional models were performed. First the sample is split between the two industries. This was necessary because the previous models were firm fixed effects where it is not possible to include an industry dummy and observe the differences between both industries. Model 10 and 11 show the results for the initial test of hypotheses 1a and 2b and model 12 and 13 show the nested interaction models. Even though the strength of the effects changes, the general pattern is consistent with the previous results. Second, the descriptive statistics show a wide distribution in several key variables including component value. To examine the influence of the extreme end, the distribution of the models 14 and 15 are performed without outliers.[1] The results for the reduced sample are in line with earlier findings. Third, based on the discussion in the method section, all models are also performed with a firm-fixed effect negative binomial estimation. Model 16 and 17 show that the different estimation method does not change the interpretation of the findings.

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[1] Multiple methods combined with a sensitivity analysis are used. Model 14 and 15 show outliers defined as the top percentile, which also roughly coincides with the definition of outliers as mean+4* standard deviation.

Insert Figure 1, 2a & 2b

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Finally, to ease the interpretation of non-linear effects, the main results are presented graphically. Figure 1 depicts the relationship between component value and innovation value based on the quadratic estimation for both industries up to the 99th percentile of component value. The graph shows not only the differences between both industries but also that the turning point of the quadratic curve lies well within the observed range of data. Figure 2a and 2b illustrate the interaction between component age and component value for both industries. Based on the positive skewed distribution of component age, the lower values are based on mean -1 1*standard deviation and the upper bound on means + 3* standard deviation. The component value is plotted on the X-axis to better show the curve linearity of the relationship. Both graphs illustrate that at low levels of component value the component age matters only marginally. At medium levels of component value, older components are correlated with a higher innovation value than younger components; however, at high levels of component value older components have a lower correlation to innovation value than younger components.

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Insert Table 3

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Table 3 presents the results for the logistic regression of breakthrough innovation. It is important to notice that breakthrough innovations are relatively rare events and not all firms within the sample create breakthroughs. Thus the Logit models include random firm-fixed effects instead of fixed-firm effects and an industry dummy is included into all models to account for the differences between the two industry sub-samples. Overall, the results are very much in line with the previous findings. Component value has a positive significant ($p<0.01$) relationship with the generation of breakthrough innovation (Model 2) but a high level of component value is less likely to generate breakthrough innovation than a medium level of component value, Model 3. This relationship becomes apparent in the graphical representation in Figure 3. In Model 4 and 6, the interactions of component age and exploration with component value are tested individually before they are tested together in Model 7.

Similar to earlier models, only the interactions for component age are significant ($p<0.01$) and this is also true for the split sample regressions in Model 8 and 9.

The interpretation of interactions in Logit estimation is highly non-intuitive and differs considerable from the classical OLS models (Hoetker 2007; Wiersema and Bowen 2009). The marginal effect of a change in both interacted variables is not equal to the marginal effect of changing the interaction term, rather its value depends on the values taken by all model variables and the sign may be different for different levels of the interacted variables. To assess the direction and statistical significance of the interaction variables, marginal effect on the dependent variables are examined directly in figure 4. The graphs show the curvilinear effect of component age with increasing component value; however, the effect is not significant at higher levels of component value.

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Insert Figure 3

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Discussion

Building on evolutionary theories and the values of components within technological trajectories (Dosi and Grazzi 2006; Fleming 2001; Nelson and Winter 1982), this research explored the effect of component value on innovation value. It assumed that component value has an inverted U-shaped relationship with innovation value. Additionally, it hypothesised that this curvilinear relationship holds for breakthrough innovations and is particularly strong for older and explorative components. The analysis of a large-scale patent dataset supports these claims with the exception of the interaction between exploration and component value. It showed that valuable components contribute positively to innovation performance, but only up to certain level. High levels of component values have a negative effect on innovation value.

These results contribute to existing innovation research that examines the relationship between component characteristics and innovation value and impact (Ahuja and Lampert 2001; Fleming 2001; Katila and Ahuja 2002; Miller et al. 2007; Phene et al. 2006; Rosenkopf and Nerkar 2001; Singh and Fleming 2010). The analysis of a previously unexamined component characteristic supports the idea that different combinations of components lead to distinct innovation outcomes. It also stresses the importance of a nuanced discussion beyond simplified linear relationships of mean outcomes as it examines non-linear relationships along the whole possible distribution of innovation outcomes (Singh and Fleming 2010).

Theoretically, it supports evolutionary claims arguing on the cumulativeness and localness of innovation during periods of ‘normal’ innovation while considering the rare cases of paradigm changes and breakthroughs. As predicted by evolutionary logic, value considerations are context specific; world views and frames are embodied into paradigms and technological trajectories (Dosi 1982; Dosi and Nelson 2010; Kaplan and Tripsas 2008; Kuhn 1962).

Even though the dependent variable of this study is innovation performance and not sustained competitive advantage, its results can inform and enrich discussions on resource-based views of the firm (Armstrong and Shimizu 2007; Barney 1991; Newbert 2007; Priem and Butler 2001). First, it represents one of the few rare large-scale empirical studies to apply a ‘conceptual-level’ approach to resources value. It directly measures the value characteristic and thereby provides a more detailed picture of resources. This is particularly important to derive managerial recommendations from resource configurations (Armstrong and Shimizu 2007; Kraaijenbrink et al. 2010; Newbert 2007; Priem and Butler 2001). Second, recent critiques of the RBV discuss the limited way in which the RBV deals with dynamic issues of resource value, such as contextual boundaries and timing of resources (Kraaijenbrink et al. 2010; Priem and Butler 2001). By analysing resource values within different technological paradigms and periods, this study shows that value is context-dependent and might change, a point raised by the critics of the resource based view (Kraaijenbrink et al. 2010; Priem and Butler 2001).

As one of the first studies to examine component value, it opens the field for other studies to use the construct to answer central questions in organisational theory and strategy. A large stream of research investigates how organisations combine components and resources to innovate and achieve competitive advantage (Cohen and Levinthal 1990; Rothaermel and Hess 2007). For example, Kogut and Zander (1991) make combinative capabilities to the cornerstone of the knowledge-based view of the firm, and (Cohen and Levinthal 1990) discus an organisation's capacity in absorbing external knowledge. However, in order to access and investigate concepts like combinative capabilities and absorptive capacity, it is important to account for the value and quality of the components. For instance, anecdotal evidence suggest that some firms can use less valuables components and combine them into highly valuable outcomes whereby other organisations possess valuable resources but are not able to achieve valuable outputs. To examine the difference between these firms one needs to capture the value of the inputs.

Similarly, recent contributions in entrepreneurship have shifted the discussion of resource value from its neo-classical economic roots into a constructivist world in which value creation starts from imagination and creativity (Denrell et al. 2003; Foss et al. 2008; Kor et al. 2007; Kraaijenbrink et al. 2010). These contributions argue that the practical assessment and evaluation of resources involves subjectivism, knowledge creation, and entrepreneurial judgment. The primary value of resources is not an objective market prices rather it lies within the imaginative and creative capabilities of the people involved in it (Denrell et al. 2003; Kraaijenbrink et al. 2010). Even in this subjective-constructed world view one would have to capture component value, but from the perspective of the actor. The underlying research provides an initial step into this direction by positioning the actor in a certain paradigm or period. However, future research might develop more fine grained schemata to capture value differences between organisations and individuals, and discuss in greater detail the influence of creativity in judgement.

Like all empirical research, this research has a number of limitations that have to be considered in its interpretation. First of all, although the patent data enables the modelling of component value in a valid way, it imposes a number of limitations. For example, not all innovations are patentable and not all patentable innovations are patented. Patent data is also faced by an inherent selection issues. Every patent represents, even though at a minimal level, a successful innovation as firms are unlikely to apply for a patent if they believe that the innovation does not bear a minimum value. Similarly, the patent office will only grant patents for novel, useful and non-obvious developments. Patent data is also criticised to measures only of explicit knowledge components and significant knowledge inputs are often of a tacit nature. However, this limitation is somewhat attenuated by the fact that codified knowledge flows and tacit knowledge are closely linked and complementary (Mowery et al. 1996). Finally, patent references are not able to capture all types of knowledge and ideas going into the innovation process, nor are the reference a direct instance of knowledge transfer or all of them done by the inventors themselves (Alcacer et al. 2009). Nevertheless, studies on the applicability of reference measures in innovation studies support their overall validity and reliability as proxy and indirect measure for inputs in the patenting process (Jaffe et al. 2000). Second, all models are performed with fixed (or random effects in the case of breakthroughs) to account for the time-invariant characteristics of inventing firms. Additionally, a range of control variables employed to capture time variant effects at the level of the firm, the innovation and components. Nevertheless, the measures cannot rule out that unobserved individual characteristics change over time. However, in the context of this study, natural experiments, particularly for breakthrough innovations, are very impractical (Singh and Fleming 2010) and instrumental variables were not found.

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Table 1: descriptive statistics & Correlation Matrix

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	Innovation value (ln)	1																			
2	Component value	0.3779	1																		
3	Industry dummy	-0.2918	-0.211	1																	
4	Number of patents	0.1553	0.1204	-0.662	1																
5	Number of allainces	0.1375	0.0744	-0.4611	0.5073	1															
6	Firm Size	0.1349	0.0875	-0.6656	0.9582	0.4705	1														
7	ROA	0.0204	0.0182	-0.1083	0.16	0.1831	0.1753	1													
8	R&D intensity	-0.0351	-0.0165	0.2193	-0.1941	-0.1391	-0.2307	-0.5116	1												
9	Exploration	-0.0062	0.0755	-0.0637	0.0288	0.0494	0.018	0.0381	-0.019	1											
10	Variance component value	0.1984	0.659	-0.1088	0.0533	0.037	0.0388	-0.0066	-0.0049	0.046	1										
11	Number of components	0.1356	0.0013	0.1496	-0.1168	-0.0847	-0.123	-0.0803	0.0672	-0.0669	0.0084	1									
12	Numberof scientific componer	-0.0174	-0.0075	0.372	-0.2943	-0.1956	-0.3314	-0.2316	0.2485	-0.0597	-0.004	0.3753	1								
13	Science orientation	-0.0945	0.02	0.4472	-0.3611	-0.2155	-0.3888	-0.1632	0.2197	-0.0027	0.0042	-0.0451	0.6361	1							
14	Number of Inventors	0.0314	0.0039	0.2028	-0.0817	-0.0543	-0.0489	0.0139	0.0303	-0.0368	0.0014	0.1131	0.1291	0.1279	1						
15	Intern. component diversity	-0.1973	-0.2459	0.3758	-0.2723	-0.212	-0.2648	-0.0911	0.0975	-0.1873	-0.0893	0.1379	0.2597	0.1863	0.0791	1					
16	Tech. scope (focal patent)	-0.0927	-0.0553	0.3213	-0.2328	-0.1755	-0.2242	-0.0675	0.0961	-0.44	-0.0249	0.0834	0.2066	0.2199	0.1646	0.2237	1				
17	Tech. scope (components)	-0.0161	-0.0428	0.4008	-0.2876	-0.2023	-0.2984	-0.1162	0.1351	-0.0411	-0.0067	0.6728	0.4323	0.1419	0.2012	0.3214	0.3448	1			
18	Component Age	-0.1788	-0.3494	0.2333	-0.1438	-0.1135	-0.1258	0.0025	0.0046	0.014	-0.13	0.184	0.0382	-0.0666	0.0324	0.1344	0.0372	0.1791	1		
19	Citation Lag Variance	-0.0797	-0.1615	0.1276	-0.0751	-0.0627	-0.0642	0.0205	-0.0102	0.0063	-0.0552	0.1061	-0.021	-0.0824	0.0153	0.0553	0.0151	0.1026	0.6502	1	
20	Technological Diversity	-0.0577	-0.0054	0.2997	-0.2136	-0.1511	-0.2034	-0.0728	0.0909	0.1202	0.0413	0.23	0.2189	0.1293	0.1222	0.269	0.2658	0.5098	0.1102	0.0801	1
Overall	Mean	4.00	3.29	0.37	1356.56	5.73	129.04	0.02	0.33	0.53	23.57	13.38	7.73	0.23	2.84	0.23	2.93	14.96	5.90	28.71	0.78
	Std. Dev.	6.46	4.26	0.48	1392.46	7.32	100.77	0.23	1.35	0.24	98.50	15.23	17.02	0.28	2.04	0.24	2.90	16.09	4.62	68.71	0.19
	Min	0.00	0.00	0.00	1.00	0.00	0.00	-5.23	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	1.00	1.00	0.00	0.00	0.00
	Max	254.57	99.43	1.00	4343.00	35.00	307.40	0.28	30.82	1.41	4790.70	156.00	198.00	0.99	38.00	0.78	43.00	205.00	78.00	2178.00	0.99
Bio-tech-nolgoy	Mean	2.30	2.13	1.00	163.02	1.37	35.51	-0.02	0.74	0.51	9.69	16.33	15.93	0.39	3.37	0.34	4.13	23.31	7.29	40.06	0.85
	Std. Dev.	3.59	3.13	0.00	141.11	2.22	29.92	0.35	2.18	0.23	44.62	19.54	23.63	0.32	2.29	0.24	4.04	21.35	5.29	81.85	0.16
	Min	0.00	0.00	1.00	1.00	0.00	0.00	-5.23	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	1.00	1.00	0.00	0.00	0.00
	Max	70.26	50.34	1.00	444.00	11.00	116.18	0.28	30.82	1.41	1294.28	136.00	198.00	0.99	32.00	0.78	43.00	205.00	78.00	1777.33	0.99
Software	Mean	5.02	3.99	0.00	2068.57	8.34	177.13	0.04	0.11	0.54	31.85	11.62	2.84	0.13	2.52	0.16	2.21	9.98	5.06	21.94	0.74
	Std. Dev.	7.49	4.67	0.00	1314.15	8.02	90.03	0.13	0.44	0.24	118.82	11.59	8.10	0.20	1.80	0.21	1.51	8.65	3.94	58.46	0.19
	Min	0.00	0.00	0.00	1.00	0.00	0.01	-5.11	0.00	0.00	0.00	1.00	0.00	0.00	1.00	0.00	1.00	1.00	0.00	0.00	0.00
	Max	254.57	99.43	0.00	4343.00	35.00	307.40	0.27	28.80	1.41	4790.70	156.00	133.00	0.98	38.00	0.77	27.00	137.00	71.00	2178.00	0.99

Table 2: Innovation Value

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	NBR	NBR
	B. / St.Er.	B. / St.Er.	B. / St.Er.	B. / St.Er.	B. / St.Er.	B. / St.Er.	B. / St.Er.	B. / St.Er.	B. / St.Er.	B. / St.Er.	B. / St.Er.	B. / St.Er.	B. / St.Er.	B. / St.Er.	B. / St.Er.	B. / St.Er.	B. / St.Er.
Number of patents	0.000 *	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.001 ***	0.000 **	0.000 **	-0.001 ***	0.000	0.000	0.000	0.000
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Number of allainces	0.003	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.003	0.003	0.002	0.002	0.002	0.002	0.002
	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
Firm Size	0.003 ***	0.002 **	0.002	0.002	0.001	0.002	0.002	0.002	0.001	0.002 *	0.002 *	0.002 *	0.002	0.001	0.001	0.002	0.001
	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
ROA	0.084 *	0.073	0.063	0.061	0.061	0.063	0.062	0.061	0.061	0.054	-0.041	-0.060	0.058	0.053	0.052	0.063	0.061
	-0.048	-0.046	-0.043	-0.042	-0.042	-0.043	-0.042	-0.042	-0.042	-0.045	-0.132	-0.133	-0.044	-0.041	-0.041	-0.043	-0.042
R&D intensity	0.007	0.006	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.002	0.000	-0.013	0.002	0.005	0.005	0.005	0.005
	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005	-0.080	-0.080	-0.004	-0.005	-0.005	-0.005	-0.005
Exploration	-0.264 ***	-0.265 ***	-0.252 ***	-0.246 ***	-0.240 ***	-0.259 ***	-0.218 ***	-0.253 ***	-0.227 ***	-0.214 ***	-0.236 ***	-0.173 ***	-0.166 ***	-0.242 ***	-0.187 ***	-0.252 ***	-0.227 ***
	-0.028	-0.030	-0.029	-0.028	-0.028	-0.034	-0.031	-0.032	-0.030	-0.049	-0.029	-0.015	-0.047	-0.027	-0.026	-0.029	-0.030
Variance componentvalue	0.001 ***	0.000 **	0.000 ***	-0.001 ***	0.000 **	0.000 ***	0.000 ***	-0.001 ***	0.000 ***	-0.002 ***	-0.001 ***	-0.001 ***	-0.001 ***	-0.001 **	-0.001 ***	0.000 ***	0.000 ***
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Number of components	0.008 ***	0.007 ***	0.007 ***	0.007 ***	0.007 ***	0.007 ***	0.007 ***	0.007 ***	0.007 ***	0.005 ***	0.007 ***	0.006 ***	0.005 ***	0.007 ***	0.007 ***	0.007 ***	0.007 ***
	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
Number of Scientific components	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002 ***	0.002 *	0.001	0.001 ***	0.000	0.000	0.000	0.000
	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
Science orientation	0.136	0.083	0.085	0.083	0.087	0.085	0.086	0.084	0.087	-0.195 ***	0.336 ***	0.333 ***	-0.187 ***	0.108	0.107	0.085	0.087
	-0.102	-0.093	-0.089	-0.087	-0.086	-0.087	-0.088	-0.086	-0.085	-0.032	-0.035	-0.031	-0.034	-0.081	-0.080	-0.089	-0.085
Number of Inventors	0.027 ***	0.026 ***	0.026 ***	0.026 ***	0.026 ***	0.026 ***	0.026 ***	0.026 ***	0.026 ***	0.020 ***	0.034 ***	0.033 ***	0.021 ***	0.027 ***	0.027 ***	0.026 ***	0.026 ***
	-0.004	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.004	-0.006	-0.006	-0.004	-0.003	-0.003	-0.003	-0.003
International component diversity	-0.008	0.100 ***	0.132 ***	0.130 ***	0.129 ***	0.131 ***	0.132 ***	0.130 ***	0.130 ***	0.096 ***	0.194 ***	0.208 ***	0.082 ***	0.146 ***	0.143 ***	0.132 ***	0.130 ***
	-0.021	-0.015	-0.017	-0.018	-0.019	-0.018	-0.018	-0.019	-0.020	-0.028	-0.012	-0.012	-0.028	-0.023	-0.024	-0.017	-0.020
Technological scope (focal patent)	0.002	0.001	0.001	0.001	0.002	0.001	0.001	0.001	0.002	0.000	0.018 ***	0.017 **	0.000	0.002	0.003	0.001	0.002
	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.007	-0.007	-0.004	-0.004	-0.004	-0.004	-0.004
Technological scope (components)	-0.001	-0.001	-0.001	-0.001	-0.001 *	-0.001	-0.001	-0.001	-0.002 *	-0.001	-0.002	-0.002	-0.001	-0.002 **	-0.002 **	-0.001	-0.002 *
	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.002	-0.002	-0.001	-0.001	-0.001	-0.001	-0.001
Component Age	-0.024 ***	-0.011 ***	-0.004 ***	-0.009 ***	-0.011 ***	-0.004 ***	-0.004 ***	-0.009 ***	-0.011 ***	0.001	-0.007 ***	-0.018 ***	-0.006 ***	0.003	-0.004 **	-0.004 ***	-0.011 ***
	-0.003	-0.001	-0.002	-0.002	-0.002	-0.002	-0.001	-0.002	-0.002	-0.002	-0.002	-0.001	-0.002	-0.002	-0.002	-0.002	-0.002
Citation Lag Variance	0.000 ***	0.000 *	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Technological Diversity	0.092	0.059	0.015	0.001	-0.017	0.015	0.019	0.000	-0.016	-0.259 ***	0.114 *	0.087	-0.282 ***	0.016	0.001	0.015	-0.016
	-0.070	-0.063	-0.058	-0.057	-0.058	-0.060	-0.058	-0.058	-0.057	-0.070	-0.061	-0.056	-0.070	-0.055	-0.054	-0.058	-0.057
Component value		0.055 ***	0.093 ***	0.081 ***	0.075 ***	0.092 ***	0.102 ***	0.080 ***	0.078 ***	0.125 ***	0.095 ***	0.084 ***	0.091 ***	0.157 ***	0.141 ***	0.093 ***	0.078 ***
		-0.009	-0.006	-0.007	-0.007	-0.010	-0.009	-0.011	-0.010	-0.017	-0.004	-0.006	-0.027	-0.005	-0.008	-0.006	-0.010
Component value (sq)			-0.001 ***	-0.001 ***	-0.001 ***	-0.001 ***	-0.002 ***	-0.001 ***	-0.001 ***	-0.003 ***	-0.001 ***	-0.001 ***	-0.002 **	-0.005 ***	-0.004 ***	-0.001 ***	-0.001 ***
			0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.001	0.000	0.000	-0.001	0.000	0.000	0.000	0.000
Component value x Component Age				0.004 ***	0.009 ***			0.004 ***	0.009 ***			0.008 ***	0.012 ***		0.007 ***		0.009 ***
				-0.001	-0.001			-0.001	-0.001			-0.001	-0.002		-0.001		-0.001
Component value (sq) x Component Age					-0.001 ***				0.000 ***			-0.001 ***	-0.001 ***		0.000 ***		0.000 ***
					0.000				0.000			0.000	0.000		0.000		0.000
Component value x exploration						0.002	-0.015 **	0.002	-0.005			-0.012 *	-0.022		-0.023 **		-0.005
						-0.010	-0.007	-0.009	-0.007			-0.006	-0.019		-0.009		-0.007
Component value (sq) x exploration							0.001		0.000			0.000	0.001		0.001		0.000
							0.000		0.000			0.000	-0.001		-0.001		0.000
Year dummies (1996-1999)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	-0.148	-0.138
IPC dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	All	All	All	All	All	All	All	All	Biotech.	Softw.	Biotech.	Softw.	Reduced	Reduced	All	All
Firm level effect	Fix E.	Fix E.	Fix E.	Fix E.	Fix E.	Fix E.	Fix E.	Fix E.	Fix E.	Fix E.	Fix E.	Fix E.	Fix E.	Fix E.	Fix E.	Fix E.	Fix E.
Constant	0.833 ***	0.701 ***	0.643 ***	0.666 ***	0.670 ***	0.647 ***	0.618 ***	0.671 ***	0.661 ***	0.908 ***	0.543 **	0.568 ***	0.915 ***	0.505 ***	0.517 ***	0.643 ***	0.661 ***
	-0.123	-0.147	-0.148	-0.142	-0.139	-0.158	-0.147	-0.151	-0.138	-0.130	-0.230	-0.214	-0.132	-0.147	-0.144	-0.148	-0.138
R-square	0.089	0.129	0.147	0.151	0.155	0.148	0.148	0.151	0.155	0.142	0.180	0.186	0.151	0.161	0.163	0.147	0.155
R-square Adjusted	0.089	0.129	0.147	0.151	0.154	0.147	0.148	0.151	0.154	0.141	0.179	0.186	0.150	0.160	0.162	0.147	0.154
n	69251	69251	69251	69251	69251	69251	69251	69251	69251	23315	45936	45936	23315	68442	68442	69251	69251

*** p<0.01, ** p<0.05, * p<0.1

Table 3 : Breakthrough Innovation

	1	2	3	4	5	6	7	8	9
	B. / St.Er.	B. / St.Er.	B. / St.Er.	B. / St.Er.	B. / St.Er.	B. / St.Er.	B. / St.Er.	B. / St.Er.	B. / St.Er.
Industry dummy	-3.004 ***	-2.799 ***	-2.363 ***	-2.381 ***	-2.368 ***	-2.392 ***	na	na	-1.259 ***
	-0.284	-0.279	-0.272	-0.277	-0.272	-0.277	na	na	-0.163
Number of patents	0.001 ***	0.001 ***	0.001 ***	0.001 ***	0.001 ***	0.001 ***	0.002	0.001 ***	0.001 ***
	0.000	0.000	0.000	0.000	0.000	0.000	-0.001	0.000	0.000
Number of allainces	0.006	0.006	0.005	0.005	0.005	0.004	0.022	0.002	0.002
	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006	-0.047	-0.006	-0.004
Firm Size	-0.006	-0.007 *	-0.007 *	-0.007 *	-0.007 *	-0.007 *	-0.005	-0.009 **	-0.009 ***
	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.006	-0.004	-0.001
ROA	-0.002	0.109	0.160	0.166	0.162	0.166	-0.422	0.218	0.266
	-0.256	-0.261	-0.253	-0.255	-0.253	-0.256	-0.531	-0.282	-0.199
R&D intensity	0.049	0.059	0.063	0.068 *	0.064	0.068 *	-0.006	0.233 ***	0.088 ***
	-0.042	-0.042	-0.040	-0.039	-0.040	-0.039	-0.072	-0.087	-0.028
Exploration	-0.647 ***	-0.724 ***	-0.587 ***	-0.589 ***	-0.276	-0.352	0.856	-0.308	-0.579 ***
	-0.158	-0.162	-0.161	-0.160	-0.315	-0.262	-1.081	-0.288	-0.161
Variance component value	0.002 ***	-0.001 ***	-0.001 **	-0.001 ***	-0.001 **	-0.001 ***	0.000	-0.001 ***	0.000
	0.000	0.000	0.000	0.000	0.000	0.000	-0.003	0.000	0.000
Number of components	0.013 ***	0.013 ***	0.011 ***	0.011 ***	0.011 ***	0.011 ***	0.008	0.009 ***	0.011 ***
	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.005	-0.004	-0.003
Number of Scientific components	-0.001	0.000	-0.001	-0.001	-0.001	-0.001	0.020 ***	-0.005	-0.002
	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003	-0.006	-0.004	-0.003
Science orientation	1.233 ***	1.074 ***	1.051 ***	0.988 ***	1.048 ***	0.986 ***	-0.837	1.218 ***	1.132 ***
	-0.166	-0.170	-0.170	-0.170	-0.170	-0.170	-0.661	-0.182	-0.169
Number of Inventors	0.099 ***	0.098 ***	0.105 ***	0.105 ***	0.106 ***	0.106 ***	0.089 **	0.116 ***	0.112 ***
	-0.014	-0.014	-0.014	-0.014	-0.014	-0.014	-0.038	-0.016	-0.014
International component diversity	-0.337 *	0.157	0.441 **	0.414 **	0.442 **	0.419 **	-0.295	0.507 **	-0.102
	-0.195	-0.199	-0.204	-0.205	-0.204	-0.205	-0.582	-0.219	-0.192
Technological scope (focal patent)	0.091 ***	0.083 ***	0.082 ***	0.080 ***	0.083 ***	0.081 ***	0.061 **	0.121 ***	0.071 ***
	-0.016	-0.017	-0.016	-0.016	-0.016	-0.016	-0.025	-0.026	-0.016
Technological scope (components)	0.014 ***	0.013 ***	0.012 ***	0.014 ***	0.012 ***	0.014 ***	0.014 **	0.014 ***	0.011 ***
	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.007	-0.005	-0.004
Component Age	-0.125 ***	-0.029 **	0.027 **	-0.073 ***	0.027 **	-0.071 ***	-0.101 **	-0.078 ***	0.014
	-0.014	-0.014	-0.012	-0.018	-0.012	-0.018	-0.050	-0.021	-0.019
Citation Lag Variance	0.002 ***	0.000	0.000	0.000	0.000	0.000	-0.001	0.000	0.000
	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.002	-0.001	-0.001
Technological Diversity	0.925 ***	0.739 ***	0.245	0.191	0.250	0.182	-2.118 ***	0.339	0.284
	-0.219	-0.224	-0.219	-0.218	-0.219	-0.218	-0.652	-0.248	-0.220
Component value		0.125 ***	0.355 ***	0.208 ***	0.396 ***	0.232 ***	0.572 ***	0.217 ***	0.468 ***
		-0.007	-0.015	-0.014	-0.035	-0.025	-0.199	-0.027	-0.029
Component value (sq)			-0.008 ***	-0.002 ***	-0.009 ***	-0.003 ***	-0.014	-0.002 ***	-0.013 ***
			-0.001	0.000	-0.001	-0.001	-0.011	-0.001	-0.001
Component value x Component Age				0.028 ***		0.027 ***	0.085 ***	0.025 ***	0.015 ***
				-0.003		-0.004	-0.020	-0.004	-0.005
Component value (sq) x Component Age				-0.001 ***		-0.001 ***	-0.007 ***	-0.001 ***	-0.001 ***
				0.000		0.000	-0.002	0.000	0.000
Component value x exploration					-0.074	-0.039	-0.268	-0.024	
					-0.055	-0.033	-0.376	-0.037	
Component value (sq) x exploration					0.003	0.001	0.004	0.000	
					-0.002	-0.001	-0.028	-0.001	
Constant	-4.474 ***	-5.528 ***	-6.633 ***	-5.916 ***	-6.811 ***	-6.050 ***	-7.339 ***	-6.285 ***	-7.165 ***
	-0.246	-0.252	-0.251	-0.252	-0.293	-0.280	-0.938	-0.297	-0.239
Year dummies (1996-1999)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IPC dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	All	All	All	All	All	Biotech.	Softw.	Reduced
Firm level effect	Fix E.	Fix E.	Fix E.	Fix E.	Fix E.	Fix E.	Fix E.	Fix E.	Non
n	69251	69251	69216	69251	69216	69251	23315	45936	68508

*** p<0.01, ** p<0.05, * p<0.1

Figure 1

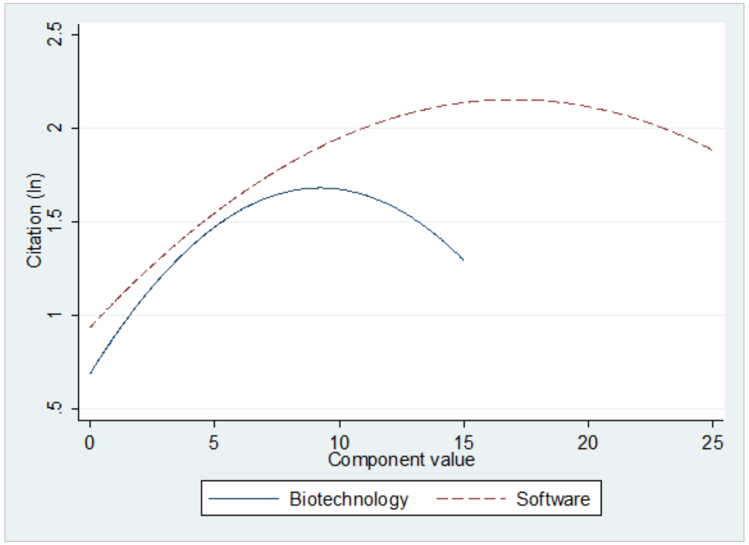

Figure 2a

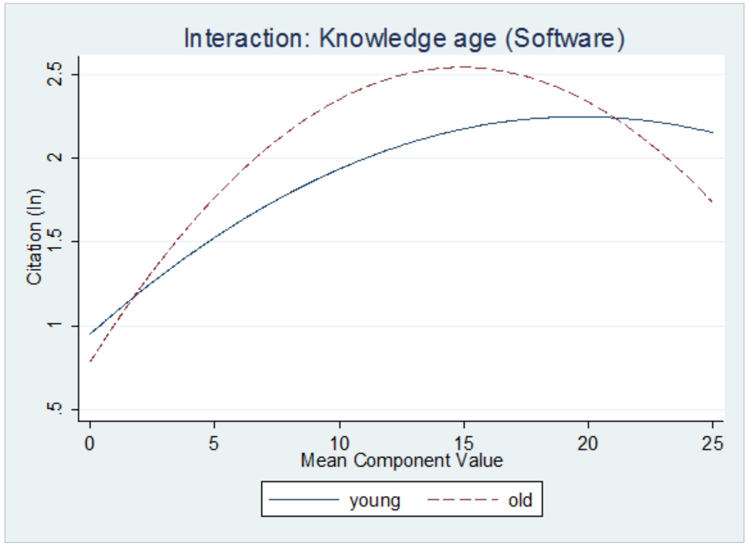

Figure 2b

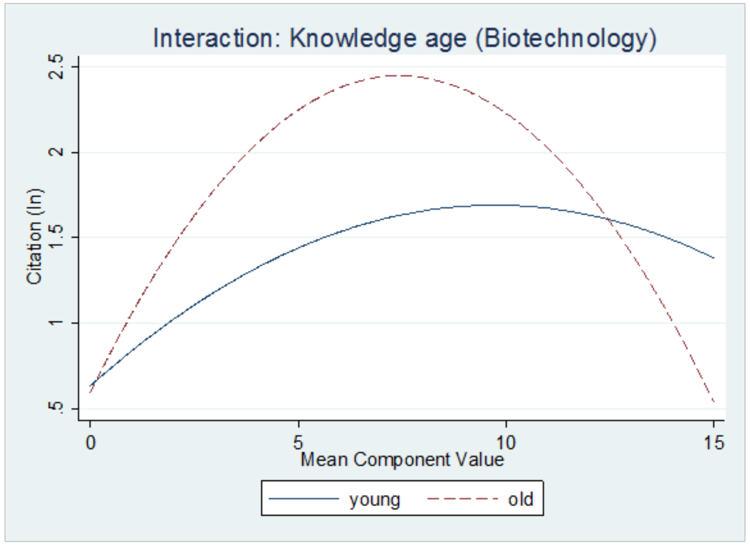

Figure 3