Innovation through exaptation and its determinants : the role of technological complexity, analogy making & patent scope

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Technology as a Complex Exaptive System

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Abstract

The concept of *exaptation* was originally introduced in evolutionary biology. In innovation studies, an exaptation refers to a technology co-opted for its current function thanks to technological features selected for old functions, or that had no function at all. Previous empirical studies have focused on the organizational-level conditions of exaptation. This paper focuses on invention-level conditions such as *technological complexity*, *inventors' analogical ability*, and *patent scope*. To test our hypotheses, we analyse a large sample of U.S. patents obtained from the USPTO and NBER databases.

Key-words: exaptation, complexity, analogy making, patents

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1. Introduction

Recently, the concept of *exaptation* has made its appearance in innovation studies (Andriani and Cohen 2013; Andriani and Carignani 2014; Cattani 2005, 2006; Dew et al. 2004; Furnari 2011; Lane et. Al 2007). Gould and Vrba (1982: 6) originally introduced the concept of exaptation in evolutionary biology to contrast it with that of adaptation and ~~to~~ refer to 'biological characters evolved for other usages (or for no function at all) and later "coopted" for their current role'.[i] In innovation studies, an exaptation refers to a technology that is fit for its current function thanks to technological features that were selected for old functions—or that had none at all—and were later 'co-opted' for their current function. Gutenberg's invention of the printing press, for example, was based on technological components of the wine press co-opted for the new function of printing (Johnson 2010).

An exaptation always implies the 'functional shift' of technological features. To some extent it also implies 'non-anticipation', as very often the emergence of a novel function is the result of a serendipitous process that was not anticipated ex ante. Exaptation has a central importance for innovation for two reasons. First, it is a pervasive phenomenon in many industries and the examples abound. For instance, the birth of the modern pharmaceutical and chemical industries was triggered by multiple exaptations of coal tar (see Andriani and Carignani 2014 for an extensive list of examples).[ii] ~~.~~ As noticed by Dew et al. (2004), exaptations '… are an important part of what entrepreneurs do'. Second, it constitutes an important and little-studied mechanism that underlies the emergence of new technologies and 'the genesis of new markets' (Dew et al. 2004: 70). As noticed by Stuart Kauffman, 'one of the most striking facts about current economic theory' [iii] is the lack of an account of the persistent explosion of technologies, goods, and markets into their 'adjacent possible' through exaptation (Kauffman 2000: 212). In this paper, we frame exaptation as a technological diversity-generating mechanism and explore conditions that foster it.

Despite the increasing interest, the literature on exaptation is still limited in size and it has focused on the theoretical aspect or it has been conducted through case studies and simulations. The few existing ~~Previous~~ empirical studies have focused on the organizational-level conditions for exaptation. For instance, Cattani (2005) has analysed the role played by firm 'pre-adapted-capabilities—that is those capabilities —accumulated in the past that turned out to be useful for co-opting an existing technology for a new function ~~(defined as 'pre-adapted' capabilities)~~. In particular, he has analysed how the accumulation of capabilities in the production of glass allowed big glass manufacturers (such as Corning) to co-opt glass fibers for long-distance communication and thus enter the fiber optics industry. He found that both the stock of pre-adapted capabilities and the extent to which firms build on them increase firms' technological performance. This paper digs deeper into exaptation, adopting a more micro approach and focusing on *invention-level* rather than organizational-level conditions. This focus on invention-level conditions is consistent with a recent call for research on exaptation: Cattani argued that inventors play a 'key role in facilitating the diffusion and recombination of skills and knowledge accumulated in otherwise distinct technological domains [and] future research should explore this issue more deeply' (Cattani 2005: 577). Our focus on invention-level conditions is also consistent with a very recent ~~theoretical~~ contribution by Andriani and Carignani (2014) that analysed the relationship between technological modularity—an invention-level condition—and exaptation, and argued that modularity plays a positive role for exaptation. However, their contribution is mostly theoretical and no empirical test exists on the impact of these conditions on exaptation. Our paper is a first attempt in that direction. Based on the empirics of Fleming and Sorenson (2001)' *Technology as a Complex Adaptive System*, we explore those conditions that foster *Exaptive* (rather than Adaptive) innovations and offer—in this way—a complementary framework.

Our objective is to arrive at a more comprehensive understanding of the invention-level conditions that foster exaptation. We examine: 1) those conditions related to the underlying technology itself such as technological complexity and 'institutional' conditions related to patent scope, which also affects technological development in a significant way; and 2) those conditions related to the inventors 'acting' on the technology and to their ability to draw inventive analogies between different technological domains. This ability, in turn, is a function of their stock of knowledge that spans these domains. This comprehensive treatment of these conditions allows us to focus both on the technology and the agents, and to avoid focusing solely on one while reducing the other to a secondary role (Lane et al. 2007). ~~A quote that best summarises the need for a comprehensive treatment can be attributed to Vincenti (1995: 557), who has repeatedly stressed that technology is 'influenced by many factors besides the technical', and they 'must figure in any complete treatment of the shaping of technology' (see also Vincenti 1991).[iv]~~

We examine the following conditions:

1) *Technological complexity*, which is the necessary[v] condition that makes exaptation 'possible'. Technological complexity is defined in terms of the level of interdependence among the physical components of a technology (Fleming and Sorenson 2001; Kauffman 1993; Ulrich 1995). We focus on technological complexity because, as pointed out by Dew et al. (2004), exaptation follows from the possibility to decompose a technology into its components and therefore directly depends on a not-excessive level of interdependence among them.[vi] A similar point has been raised by Andriani and Carignani (2014: 1609) who note that the possibility to decompose a technology multiplies the design options of the technology and 'the overall effect is a combinatorial explosion of innovative possibilities'.

2) *Inventors' analogical ability*, which is the 'ability to realise' the possibility opened up by technological complexity. New creative syntheses often result from linking different knowledge

domains. This is the ability of inventors to draw inventive analogies between different technological domains. This ability, in turn, is a function of their stock of knowledge that spans these domains.

3) Patent scope, which is, in a certain way, the 'institutional room' that shapes the two previous conditions. Patent scope is the set of hypothetical developments of the technology that, together with the main configuration, are also subject to patent protection. We focus on patent scope because, as recently emphasized by Andriani and Carignani (2014: 1616), 'exaptation-based processes face multiple obstacles that are rooted in the way innovation is conceptualised […] and property rights are regulated'. Similarly, Merges and Nelson (1990) have argued that the possibility to explore novel technological configurations can be seriously limited by the extension of patent scope.

To address these aspects, we proceed in three stages, analysing 1) the relationship between technological complexity and exaptation, then 2) the direct role of inventors' analogical ability and patent scope for exaptation, and then 3) the moderating role of inventors' analogical ability and patent scope in the relationship between technological complexity and exaptation. In order to test our hypotheses, we analyse a large sample of patents obtained from the U.S. Patent and Trademark Office (USPTO) and the National Bureau of Economic Research (NBER) databases. As our objective is to examine the conditions of exaptation at the invention level, we assume that a generic invention is identified by a patent. The main challenge is how to deal empirically with exaptation. As mentioned, exaptation always implies some degree of non-anticipation, which arises when the emergence of a new function of an existing technology has not been originally envisioned (often because it is the result of a serendipitous process). Exaptation also involves, by definition, a functional shift. In order to address both, we introduce a novel proxy based on the proportion of cross-class forward citations. We also introduce a proxy for inventors' analogical ability, while we rely on Fleming and Sorenson (2001) for the measure of technological complexity.

This paper offers several contributions. The first contribution is that it expands the ~~to the~~ innovation literature that has adopted evolutionary analogies (Nelson and Winter 1982) and ~~;~~ builds~~ing~~ on the idea that '...invention…much resembles a biological process' (Gilfillan 1935: 275; Fleming and Sorenson 2001). Several studies have started to shed light on the black box of invention in order to go beyond the simple analysis of the economic and organisational impact of 'given' technological innovations (Fleming and Sorenson 2001; Rogers 1983; Rosenberg 1982; Tushman and Anderson 1986). Some of these studies have described the evolutionary mechanism that lies behind the process of invention and that leads to the emergence of new technological innovations (Fleming and Sorenson 2001). These studies have mainly adopted a 'recombinant' perspective: technological innovations are the result of a recombination of existing technologies, followed by adaptive market selection (Arthur 2009).[vii] However, as noticed by Andriani and Carignani (2014: 1614), recombinant innovation 'may also exhibit an exaptive aspect'. In other words, recombinations are often triggered by the serendipitous discovery of new functions of existing technologies.~~: as the Gutenberg example illustrates, the recombination of movable type and a wine press that led to the printing press was triggered by the discovery of a novel function of the wine press.~~ The adoption of a novel concept—exaptation—and the introduction of a novel measure will therefore allow us to shed light on two important yet neglected issues: 1) a functional shift issue, which arises when recombination is triggered by the emergence of a new functionality of an existing technology;[viii] and 2) a non-anticipation issue, which arises when the emergence of a new functionality has not been originally envisioned (because it is the result of a serendipitous process).[ix]

The second contribution of this paper is the focus on a comprehensive set of invention-level conditions that make exaptation more likely; previous empirical studies have mainly focused on organizational-level conditions. Our focus responds to a call for deeper exploration of the role played by invention (Cattani 2005). The third contribution of our paper is methodological. As mentioned above, the main challenge is to deal empirically with exaptation. To our knowledge, ours is the first attempt to study exaptation at the invention-level using a combination of novel measures and empirical strategies based on state-of-the-art patent literature.

The paper is organised as follows. In Section 2 we formulate testable hypotheses, in Section 3 we describe the data and the empirical setting, and in Section 4 we present the results. Section 5 presents our discussion and conclusions; Section 6 contains a technical appendix.

2. Theory

2.1 Technological Complexity and Design Options

We first define a technology as a system composed of a hierarchy of subparts (Vincenti 1994; Whitney 2005). We then define *technological complexity* in terms of the level of interdependence between the subparts (Fleming and Sorenson 2001; Kauffman 1993; Ulrich 1995).[x] When technological complexity is high, the inventive process of 'decomposition and modification' is constrained by complex interdependencies between the subparts. The idea that such constraints matter for invention is well established in engineering studies. According to Phillips (2007: 4), 'there is a struggle between the creative ideas of machine designers and their recalcitrant, real machinery'—that is between the ideas of inventors and the physical constraints imposed by technologies~~.~~ Similarly, according to Vincenti (1991), inventors ~~they~~ can have more degrees of freedom and arrive more easily at novel solutions when these constraints are low. The importance of constraints is also evidenced by the ~~daily~~ current use of scientific and visual approaches for their representation, such as 'kinematic' principles and the use of 'design structure matrices’ in current engineering practice.[xi] [xii] The different ways to decompose and modify a technology have been classified by the modularity literature, which has defined a set of six different ‘operators’ such that any technological decomposition and modification can be represented by a combination of them (Baldwin and Clark 2000).[xiii]. ‘Substituting’ and ‘augmenting’ operators are of pivotal importance. ‘Substituting operators’ (Baldwin and Clark 2000)—substituting a technological subpart for a better one after the technology has been decomposed—have been studied in the innovation literature that has explicitly focused on the processes of technological ‘adaptation’. ~~For example,~~ In particular, Fleming and Sorenson (2001) have found that technological improvements or adaptations—realised through substituting operators, although they are not explicitly mentioned—are enhanced by intermediate levels of technological complexity. ~~However,~~ ‘A~~a~~ugmenting operators’—which consist in adding a new technological subpart that gives the technology a new functionality and are the implicit focus of our paper (Baldwin and Clark 2000)— ~~have~~ give rise to novel functionalities or exaptations but they have received much less attention in the literature despite their breakthrough-generating nature.

As noted by Dew et al. (2004), exaptation follows from the ‘possibility’ of decomposing a technology into its subparts. Andriani and Carignani (2014) theoretically argue a similar point. We will argue that intermediate levels of complexity positively increase the degrees of freedom to *add* new subparts to a technology and the likelihood of realising configurations with novel functionalities, and therefore of exaptation. This suggests that intermediate levels of complexity increase the ‘design options’ of a technology (Baldwin and Clark 2000) and expand the set of novel functionalities. In fact, as argued by Kauffmann (2000), ‘a system in which combination is easy to happen will rapidly explore the adjacent possible’ (Farmer et al. 2012: 7). Similarly, as argued by Andriani and Carignani (2014: 1609), the possibility to decompose a technology multiplies the design options of the technology and ‘the overall effect is a combinatorial explosion of innovative possibilities’.[xiv] The history of computers illustrates the point very well: modular designs of the 1990s started to include new components with no counterpart in older designs, many of which were ‘never-before-imagined’ software applications (Baldwin and Clark 2000; Langlois and Robertson 1992).

The fact that the ~~potential or~~ likelihood of exaptation increases for intermediate levels of technological complexity means that the relationship between technological complexity and exaptation is sensitive to two opposing effects. First, below a certain threshold, technological complexity has a positive effect on ~~the potential of~~ exaptation. Second, above a certain threshold, technological complexity has a negative effect on ~~the~~ exaptation ~~potential~~ because it significantly limits the possibility of decomposing and modifying a technology through the addition of a new

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subpart that gives the technology 'some new type of functionality' (Baldwin and Clark 2000: 136).[xv] This suggests an inverted U-shaped relationship between ~~the~~ exaptation ~~potential~~ and technological complexity: exaptation is more likely for intermediate levels of technological complexity and is less likely for both very high and very low levels of technological complexity.

High levels of technological complexity expose inventors and designers to a 'complexity catastrophe' (Kauffmann 1993): they will have to devote their efforts to the processing of complex interdependencies and interactions among subparts (Fleming and Sorenson 2001). This will reduce their ability to explore 'augmenting configurations', and therefore ~~the~~ exaptation ~~potential~~. Low levels of technological complexity, on the other hand, allow inventors and designers to eliminate cycling traps and loops in the design process and to explore augmenting configurations more easily (Baldwin and Clark 2000; Fleming and Sorenson 2001). However, low values of technological complexity are achieved through the imposition of 'design rules' that remove certain variables from the set of choices, and this reduces the ability of inventors and designers to explore certain areas of the 'space' of possible designs (Baldwin and Clark 2000; Fleming and Sorenson 2001). As argued by Baldwin and Clark (2000: 69): 'Converting an ordinary design parameter into a design rule entails both benefits and costs. […] Designers will lose the ability to explore some parts of the space of designs—in effect, the architects will restrict the search, declaring some parts of the design space to be out of bounds'. This means that both high levels and low levels of technological complexity reduce the ability of inventors to explore augmenting configurations, and therefore ~~thus the~~ exaptation ~~potential~~. This is consistent with the conclusions of Ethiraj and Levinthal (2004), who analysed the trade-offs between the poor recombinant performance that results from excessively high or low levels of interdependence. Hence, we expect ~~the~~ exaptation ~~potential~~ to be highest for intermediate levels of technological complexity. This leads to our first hypothesis:

H1. Technological complexity exhibits an inverted U-shaped relationship with exaptation ~~the exaptive potential~~.

2.2 Analogy Making

Exaptation also follows from the 'ability' of inventors to draw new creative syntheses that often result from linking different knowledge domains. This is the ability of inventors to draw inventive analogies between different technological domains. This ability, in turn, is a function of their stock of knowledge that spans these domains.[xvi] *Analogy making* plays a central role during the process of invention (Hargadon and Sutton 1997). In a more fundamental way, it 'stands at the very basis of thought and makes human reasoning possible' (see Chalmers at al. 1995).[xvii] Indeed analogy making is gaining ground in management and innovation studies (Gavetti et al. 2005) as well as in the exaptation literature (Furnari 2011). Analogy making is the transfer of a solution from a known field to a new one (Gentner 1983; Gick and Holyoak 1980): 1) inventors identify a synthetic representation of the 'target domain' that contains the problem to be solved (e.g. the printing press); 2) they then recall a synthetic representation from a 'base domain' they had previous experience with and whose problems displayed a similar structure to that of the target problem (e.g. the wine press); 3) this base domain provides solutions to the target problem; and 4) one of the solutions may eventually be applied. Therefore, successful analogy making depends on the inventors' ability to create a map between a base domain and the target problem (Gentner 1983). This ability, in turn, is a function of the inventors' prior knowledge stock in these domains. As argued by Salomon (1994: 372), 'knowledge acquired prior to the analogy task may also affect positive analogical transfer' (see also Gentner and Landers 1985; Gick and Holyoak 1983). This knowledge can be more or less domain specific or generic (Gavetti et al. 2005; Rumelhart 1980; Widerman and Owston 1991).

We hypothesise that inventors' analogical ability allows them to envision a novel function for an existing technology (e.g. for a wine press). Moreover, inventors' analogical ability allows them to arrive at a richer representation of the 'architecture' of the inventive problem (e.g. how to exapt the wine press into a printing press) and to process interdependencies during the inventive process more successfully. This is consistent with recent findings that analogy making is powerful in high-complexity settings (see Gavetti et al. 2005). This has two implications: inventors' analogical abilities have a direct, positive effect on ~~the~~ exaptation ~~potential~~, and they also positively moderate the inverted U-shaped relationship between technological complexity and ~~the~~ exaptation ~~potential~~. This means that for an inventor with greater analogical ability there is a sharper advantage (more exaptive innovations) in moving from low to medium levels of technological complexity: the left-side of the curvilinear relationship will increase more rapidly. Similarly, for an inventor with greater analogical ability there is a sharper advantage in moving from medium to high levels of technological complexity: the right-side of the curvilinear relationship will decrease more slowly.

H2. Inventors' analogical ability positively affects ~~the~~ exaptation ~~potential~~.

H3. Inventors' analogical ability positively moderates the inverted U-shaped relationship between technological complexity and ~~the~~ exaptation ~~potential~~.

2.3 Patent Scope

Exaptation also follows from the possibility to build on a technology whose successive developments are not overly protected by patent scope.[xviii] We define patent scope as the size of the set of hypothetical developments of the technology that, together with the main configuration, are also subject to patent protection. Patent scope is the set of hypothetical 'embodiments' of the technology that were originally envisioned by the inventors, and can be likened to the fence around a real property: it distinguishes inventors' intellectual property from the surrounding 'terrain' of technological possibilities (Merges and Nelson 1990).[xix] Despite its 'institutional' dimension, patent scope acts as an important invention-level condition that shapes successive technological developments (Kitch 1977; Merges and Nelson 1990).[xx] In particular, it plays an important role for those technologies whose developments can proceed on alternative trajectories (Merges and Nelson 1990). As argued by Bonaccorsi (2011), the greater the patent scope, the stronger the monopoly power granted to the technology owner and the fewer the incentives for other firms to develop a new technology that may infringe on the old one. Indeed Klemperer (1990) and Gilbert and Shapiro (1990) have argued that patent scope is a positive input of an innovator's profit function. Reitzig (2003) has argued that patent scope is a 'value driver', and Lerner (1994) has found that patent scope increases the value of biotech firms. Other economists, on the other hand, have stressed the negative aspects of patent scope, such as social losses from monopoly and from the power to block future technological developments (Gallini 1992; Machlup 1958; Scherer 1980; Turner 1969).[xxi]

We hypothesise that the extension of patent scope limits the incentive of inventors~~'~~ ~~incentive~~ to modify a decomposable technology ~~'capitalise on' decomposability in order to~~ and explore new ~~a technology's~~ exaptive options. This is consistent with the idea that patent scope blocks successive technological developments (Kitch 1977; Merges and Nelson 1990). This has two implications: patent scope has a direct negative effect on ~~the~~ exaptation ~~potential~~, and it negatively moderates the inverted U-shaped relationship between technological complexity and ~~the~~ exaptation ~~potential~~. This means that those technologies with greater patent scope are characterised by a sharper disadvantage (less exaptive innovations) moving from low to medium levels of technological complexity: the left-side of the curvilinear relationship will increase more slowly. Similarly, those technologies with greater patent scope are characterised by a sharper disadvantage moving from medium to high levels of technological complexity: the right-side of the curvilinear relationship will decrease more rapidly.

H4. Patent scope negatively affects ~~the~~ exaptation ~~potential~~.

H5. Patent scope negatively moderates the inverted U-shaped relationship between technological complexity and ~~the~~ exaptation ~~potential~~.

3. Methods

3.1 Data

Figure 1 illustrates the expected effects for the main hypothesis and the interactions (H1, H3, and H5 respectively). In order to test our hypotheses, we studied exaptation at the invention level; we identified an invention with a patent and considered a cross-section of U.S. patents. Raw patent data were obtained from the USPTO and NBER databases (Hall et al. 2001), and the main measures were built after merging these databases to the Patent Network Dataverse (Lai et al.

2011). Patent data allowed us to exploit the information contained in forward citations and in the classification system, which proved particularly useful. Forward citations not only reflect the replication around the 'prior art' of an invention, they also reflect the extension of the prior art in novel technological domains (Sorenson et al. 2006). This is demonstrated by the fact that, quite often, forward citations come from different technological classes (Ghiglino and Kuschy 2010).[xxii] This allowed us to introduce a novel proxy of exaptation based on the proportion of cross-class forward citations.[xxiii] ~~The fact that a patent receives cross-class forward citations does not necessarily imply that the underlying invention (or parts of it) has been truly exapted for new functions. We would have had to embark on a detailed case study for each invention -well beyond the scope of our study- in order to assess this. Rather, our measure captures the 'potential' of an invention to be exapted and constitutes, to our knowledge, a first attempt to measure exaptation-like phenomena at the patent-level.[xxiv] We refer to our measure as 'exaptive potential'.~~

Overall, our empirical framework builds strongly on the work of Fleming and Sorenson (2001) (see also: Fleming 2001; Singh and Fleming 2010; Sorenson et al. 2006). That empirical treatment is the first attempt in the innovation literature to deal with issues such as technological complexity (beyond the use of simulations, such as NK simulations). Our empirical framework consisted of the following steps: 1) we considered a random cross-section of U.S. patents granted between January and June 1991 (both the January-June interval and the year 1991 were chosen randomly); 2) for each patent we used a 1991-1999 window of forward citations to calculate ~~its~~ exaptation~~exaptive potential~~; 3) for each patent we then considered a 1975-1990 pre-sample window in order to calculate technological complexity, inventor's analogical ability, and other controls. The estimation sample for the main hypothesis consists of 19,076 patents. Figure 2 illustrates our empirical setting.

3.2 Measures

3.2.1 Exaptation~~ive Potential~~

Exaptation always implies two aspects: the 'functional shift' of an existing invention, and a certain degree of 'non-anticipation', as the functional shift cannot always be envisioned ex-ante and is often the result of a serendipitous process. Our novel measure of exaptation ~~exaptive potential tries to~~ captures both aspects. In order to capture the functional shift, we built on the fact that forward citations often come from different technological classes (Ghiglino and Kuschy 2010). This means that forward citations often reflect the extension of an invention in novel technological domains (Sorenson et al. 2006). We assumed that cross-class forward citations reflect the co-option of ~~potential that~~ an invention ~~is co-opted~~ for novel functions. We therefore assumed that different technological classes identify different functions, and this is consistent with the classification system developed by the USPTO. Indeed the USPTO uses the 'fundamental, direct, or necessary function as the principal basis of classification', where the 'function' is the result achieved by 'similar processes or structures […] by the application of similar natural laws to similar substances' (USPTO 2012b: 3).

In order to capture non-anticipation, we built on the fact that the USPTO assigns a patent to several classes: an OR class, which is mandatory and reflects the most comprehensive claim or main function of the invention, and XR classes, which may reflect alternative applications envisioned when the patent was granted.[xxv] If both the OR and XR classes of the focal patent differed from the OR class of the citing patent (at the three-digit level), we assumed that the functional shift was not originally envisioned when the focal patent was granted. This can be an indirect indication of the fact that the functional shift was conceived later on, maybe as the result of unplanned serendipity. Overall, our measure of exaptation ~~exaptive potential~~ is based on the proportion of cross-class forward citations. In our setting, a forward citation is cross-class if both the OR and XR classes of the focal patent differ from the OR class of the citing patent. Therefore, ~~the~~ exaptation for~~exaptive potential of~~ patent *i* is given by:

$$y_i = \sum_{j=1}^{N} \frac{d_j}{N}$$

where N is the number of forward citations received until the end of 1999,[xxvi] and d_j is a dummy equal to 1 if the both the OR and XR classes of patent i differ from the OR class of the citing patent j (0 otherwise). Therefore, our measure differs from patent generality indexes (Trajtenberg et al. 1997) used in a variety of studies in order to identify general-purpose technologies. These indexes, also based on the range of technology fields that cite the focal patent, are only based on OR classes. Figure 3 contains a graphical illustration of the measure.

According to the fourth and fifth hypothesis, patent scope blocks technological developments of ~~other inventors and~~pursued by different firms and therefore also plays a negative moderating role in the relationship between technological complexity and exaptation. In order to test this hypothesis, we had to modif~~yied~~ our measure of exaptation ~~exaptive potential~~ as follows:

$$y_{i,ext.} = \sum_{j=1}^{N_{ext.}} \frac{d_j}{N_{ext.}}$$

where $N_{ext.}$ is the number of forward citations received from patents that belong~~ing~~ to these different firms, and d_j is defined as above. In order to identify different firms, we used a PDPCO identifier (see *NBER PDP Project User Documentation: Matching Patent Data to Compustat Firms*). The PDPCO identifier is the result of several algorithmic procedures that were designed to match patent data to Compustat Data. Patent ownership may change over time, and therefore dynamic matches are recorded in the PDP database. However, for this study, we considered only the match that corresponds to the first owner.[xxvii]

Example

An illustrative example is the invention of the microwave oven, which resulted from the discovery of a new function—exaptation—of a radar component called 'magnetron'. The discovery happened serendipitously when Mr. Spencer—an engineer working for a U.S military contractor—discovered that the magnetron was responsible for the melting of a candy bar in his pocket. Now the magnetron is a key component of the microwave (Andriani and Carignani 2014).

Mr. Spencer obtained a patent for the first microwave oven in history: U.S. patent No. 2,495,429, *Method of treating foodstuffs*, grant date: Jan. 24 1950. The magnetron, however, was invented several years before by Mr. Hollmann—a German electronic specialist—, who obtained a patent for it: U.S. patent No. 2,123,728, *Magnetron*, grant date: July 12 1938.[xxviii] The microwave patent falls in the OR class No. 426 (*Food or edible material: processes, compositions, and products*) while the magnetron patent falls in the OR class No. 315 (*Electric lamp and discharge devices: systems*), which differs from the microwave OR class as it clearly refers to an entirely different functional domain. The magnetron patent also falls in the XR class No. 313. This class also differs from the microwave OR class, as it refers to other application domains that did not yet include possible uses of the magnetron for cooking. This is evidenced by the corresponding absence of any reference to cooking uses in the claims of the magnetron patent[xxix].

3.2.2 Technological Complexity

We measured technological complexity as in Fleming and Sorenson (2001) (see also Sorenson et al. 2006). The measure is based on the historical difficulty of recombining the subclasses the patent is composed of. The underlying assumption is that patent subclasses are proxies of underlying components, which can be physical components or pieces of knowledge only indirectly connected to physical configurations (Sorenson et al. 2006). The idea behind the measure is that if the patent is composed of subclasses that, in the past, could not be easily re-combined with many other subclasses, this is an indication of the fact that components are characterised by sensitive interdependencies and their actual configuration belongs to a small set of possible alternative configurations. This kind of patent receives a high value of technological complexity. Conversely, if the patent is composed of subclasses that, in the past, could be re-combined easily with many other subclasses, this is an indication of the fact that components are not characterised by sensitive interdependencies and they can be mixed and matched independently. In other words, their actual configuration belongs to a large set of possible alternative configurations. This kind of patent receives a low value of technological complexity. Therefore, we measured the technological complexity of patent i as follows:

$$x_i = \frac{cs_i}{\sum_{j=1}^{cs_i} er_j}$$

where cs_i is the number of subclasses of patent *i*, and er_j is the 'ease of recombination score' of each subclass *j*. In other words, we measured the technological complexity of patent *i* as the inverse of the average ease of subclass recombination. The ease of recombination of a generic subclass *j* is given by:

$$er_j = \frac{N_{sc,j}}{N_{pat,j}}$$

where $N_{sc,j}$ is the number of subclasses that appeared with subclass *j* in $N_{pat,j}$ previous patents.[xxx] The ease of recombination scores were calculated on a 15-year pre-sample window of all the patents granted in the period from 1975-1990. Sorenson et al. (2006) contains an illustration of the measure for a digital technology patent.[xxxi]

3.2.3 Inventors' Analogical Ability

The ability of inventors to draw inventive analogies and exapt existing technologies across different domains is a function of their stock of knowledge spanning these domains. We introduced a novel measure of inventors' analogical abilities that quantifies their multi-domain skills. In order to build the measure, we considered the inventor[xxxii] belonging to the first citing patent. We then extracted, from the Patent Network Dataverse (Lai et al. 2011), the inventor's previous patents that belong to the 1975-1990 pre-sample window. We then counted the number of previous patents whose OR class was equal to the OR class of either the focal patent or the citing patent. Moreover, we controlled for those cases in which previous patents were all concentrated in only one OR class and not equally distributed across the two. Our measure is more specific than the measures of knowledge diversity in the sense that it only captures the accumulation of knowledge in the target and base domains (see 2.2), which is a necessary condition for the emergence of cognitive mappings or analogies between these domains. Moreover, in order to exclude other equally plausible mechanisms at the individual level, we introduce several controls such as knowledge diversity, past experience in several areas, inventive myopia (see 3.2.5).

Inventors' data have several limitations. First, the lack of a consistent and unique identification of inventors at the USPTO often results in name ambiguity on patent records. Several disambiguation algorithms have been developed recently in order to clean inventors' data and make them available to the public. We used the first release of those data (Lai et al. 2011). Second, there is the eventual presence of mismatches and missing data due to algorithmic randomness. To account for these limitations, we dropped those cases in which the citing patent had no inventor identification. Moreover, we controlled for those cases in which the citing patent had one or more inventors with no previous patents.

3.2.4 Patent Scope

We introduced the number of patent claims as a proxy of patent scope. As argued by Lanjouw and Shankerman (2000), patent claims define the scope of legal protection of a technology. Similarly, as argued by Merges and Nelson (1990), they form a protective line around the patent that delimits inventors' intellectual property from the surrounding terrain of technological possibilities.

3.2.5 Control Variables

We introduced several controls in order to rule out unobserved factors that may be correlated with technological complexity and, at the same time, with exaptation (see also Fleming and Sorenson 2001; Fleming 2001; Singh and Fleming 2010; Sorenson et al. 2006).

Inventors' Generic Experience. A patent may be less exaptive not because of greater technological complexity, but because the (team of) inventor(s) that builds on the patent has less prior generic experience. We used the number of previous patents of the (team of) inventor(s) belonging to the first patent that cites the focal patent *i* as a proxy of experience (for a similar measure see Singh and Fleming 2010). Previous patents belong to a 15-year pre-sample window, consisting of all the patents granted from 1975-1990.

Inventors' Diversity of Experience. A patent may be less exaptive not because of greater technological complexity, but because the (team of) inventor(s) has less prior experience with different technological areas. We used the number of technological classes in which the (team of) inventor(s) of patent *i* had previous patents as a proxy of experience diversity, as in Singh and Fleming (2010). Previous patents belong to a 15-year pre-sample window, consisting of all the patents granted from 1975-1990.

Inventors' Team Dummy. A patent may be less exaptive not because of greater technological complexity, but because the inventor that builds on the patent is working alone. We controlled for those cases in which the inventors belonging to the first citing patent are a team.

Inventors' Team Size. Adopting a similar logic, we also controlled for the size of the team.

Concentration Dummy. As mentioned, we controlled for those cases in which the (team of) inventor(s) belonging to the first citing patent had previous patents all concentrated in the OR class of either the cited patent or the citing patent.[xxxiii]

Inventors' Control. As mentioned, we controlled for those cases in which the first citing patent had one or more inventors with no previous patents.[xxxiv]

Combination Familiarity. A patent may be less exaptive not because of greater technological complexity, but because the (team of) inventor(s) that builds on the patent has excessive familiarity with its configuration of components and remains trapped in local search (March 1991). In order to measure familiarity with the configuration of components of patent *i*, we measured the average time proximity of patent *i* to previous patents having an identical configuration of patent subclasses. Previous patents belong to a 15-year pre-sample window, consisting of all the patents granted from 1975-1990. We measured combination familiarity as in Fleming (2001):

$$cf_i = \frac{1}{n}\sum_{j=1}^{n} e^{-\frac{ad.\ i - ad.\ j}{k}},$$

where $\text{ad.}\ i - \text{ad.}\ j$ is the time distance between the application date of patent *i* and the application date of a patent *j* with an identical configuration of subclasses, *n* is the number of previous patents with an identical configuration of patent subclasses, and *k* is a knowledge loss parameter.[xxxv]

Number of Subclasses. A patent may be less exaptive not because of greater technological complexity, but because the (team of) inventor(s) that builds on the patent has to deal with its excessive number of components, and this may represent a cognitive bound. We used the number of patent subclasses as a proxy for the number of components, as in Fleming (2001).

Single Subclass Dummy. Several patents in our sample have only one subclass.[xxxvi] The technological complexity measure is not able to capture interdependencies for those patents. We controlled for them, as in Fleming and Sorenson (2001).

Number of Prior Art Citations. A patent may be less exaptive not because of greater technological complexity, but because it is characterised by higher technological maturity that limits the exploration of exaptive reconfigurations. We used the number of backward citations as a proxy of technological maturity, as in Lanjouw and Shankerman (2001) and Ziedonis (2007).

Scientific References. A patent may be less exaptive not because of greater technological complexity, but because it is characterised by lower levels of generality. We used the number of non-patent references (e.g. references to scientific journals) as a proxy of generality. Moreover, non-patent references are also an indirect proxy of technological maturity, since patents with more scientific references tend to protect early-stage inventions (Hegde 2011; Narin et el. 1997).

Technology Control. We controlled for the average number of citations received by patents in the same technological class of patent *i*, in order to remove systematic sources of variation in the citation process that may affect our dependent variable (see Fleming and Sorenson 2001). If patent *i* falls into different technological classes, we also included those classes in the calculation. For example, suppose that patent *i* falls into one Class 2 and three Classes 16. Let's also suppose that, on average, previous patents belonging to Class 2 and Class 16 receive 2 and 4 citations respectively. Then the average number of citations is given by $[(1/4)\times 2.0]+[(3/4)\times 4.0]=3.5$ (Fleming and Sorenson 2001). In order to calculate the measure, we considered those patents granted in 1985 and the citations received until December 1990 (end of pre-sample window).

Number of Classes. We included this variable because a patent that falls into a broad range of technological classes is more likely to be cited by future patents, and this may affect the denominator of our dependent variable (Fleming and Sorenson 2001). Similarly, a patent that falls into a broad range of technological classes is more likely to be cited by patents that also fall into different technological classes. This may affect the numerator of our dependent variable.

Diversity of Patent Portfolio. In order to test the fifth hypothesis, we looked at how 'cross-firm' forward citations spread across different technological classes. We wanted to rule out those factors that may depend on the propensity of firms' patent portfolios to cite patents belonging to different technological classes. We therefore used pre-sample information to measure firm characteristics. According to Blundell et al. (1995), this means including variables that approximate the accumulation of a firm's technological knowledge and it may constitute an approximation of unobservable factors. For each forward citation received by the focal patent *i*, we calculated the technological diversity of the patent portfolio belonging to the citing patent's firm. We then calculated average technological diversity across all forward citations and introduced it as a control. In order to calculate technological diversity, we computed a Herfindahl index of dispersion across technological classes of the firm's previous patents. We also controlled for the technological diversity of the patent portfolio belonging to the firm of the focal patent *i*. We considered a 10-year pre-sample window in order to calculate these measures.[xxxvii]

Size of Patent Portfolio. Adopting a similar logic, we controlled for the average size of the patent portfolio belonging to the citing patents' firms, and for the size of the patent portfolio belonging to the firm of the focal patent *i*.

Technological Class Fixed Effects. We introduced technological class fixed effects to remove systematic sources of variation in the citation process that may take place across technological classes and be missed by the technology.

Application Year and Citing Year Fixed Effects. We controlled for the application year of the focal patent and for the application years of the first and last citing patents to remove systematic sources of variation in the citing process that may take place over time.

Grant Month Fixed Effects. We introduced grant month fixed effects to rule out eventual truncation issues due to the fact that a patent granted in January 1991 will systematically receive more citations than a patent granted in June 1991.

4. Results

As our dependent variable is a proportion, we adopted the fractional logit estimation procedure proposed by Papke and Wooldridge (1996) (see Appendix 6.1). Table 1 presents descriptive statistics. Mean values and standard deviations are consistent with previous studies (Fleming and Sorenson 2001; Fleming 2001; Singh and Fleming 2010). Table 2 presents bivariate correlations.

Correlation values are generally low, except for inventors' team size and inventors' team dummy and for the number of subclasses and the number of classes.

Table 3 presents the results of our estimation for the first hypothesis. Model 1 reports the baseline model with control variables. Model 2 adds technological complexity and Model 3 adds the squared term of technological complexity. Model 4 shows the full model. Model 5 demonstrates that the main results are insensitive to the inclusion of controls. The coefficient of technological complexity is positive and significant (Model 4). Moreover, the squared term of technological complexity is negative and significant. The result confirms our first hypothesis (H1) that the relationship between technological complexity and exaptive innovation can be described by an inverted U-shaped function.

Table 4 presents the results of our estimation for the second (H2) and third (H3) hypotheses. Model 1 reports the baseline model with control variables. Model 2 adds technological complexity and its squared term, and Model 3 adds the inventors' analogical ability. Model 4 adds the interaction terms of the inventors' analogical ability with technological complexity and its squared term. Model 5 shows the full model. Inventors' analogical ability is positive and significant (Model 5), supporting H2 that analogical ability positively affects exaptive innovation. However, the interaction terms are not significant; this finding does not support H3.

Table 5 presents the results of our estimation for the fourth (H4) and fifth (H5) hypotheses that patent scope blocks the exaptive technological developments of inventors at other firms. ~~In order to test~~ For these hypotheses ~~we had to consider a subset of the initial sample, consisting of 4,685 patents. T~~the sample size decreased smaller—4,685 patents—because of the following reason: the assignees of ~~many~~ several patents of the original sample ~~were~~ are not firms~~,~~ and therefore a unique PDPCO identifier ~~did~~ does not exist for them. In other words, several patents of the original sample did not belong to firms and they had to be excluded in order to build the measure for hypotheses H4 and H5. Model 1 reports the baseline model with control variables. Model 2 adds technological complexity and its squared term and Model 3 adds patent scope. Model 4 adds the interaction terms of patent scope with technological complexity and its squared term. Model 5 shows the full model. Patent scope is positive and significant (Model 5), in contrast with H4 that asserted that it negatively affects exaptive innovation. Moreover, the interaction terms are not significant, which does not support H5. Overall, these results suggest that patent scope (number of patent claims), which is positively correlated with cross-class forward citations, signals patent quality instead of blocking successive technological developments. This is an interesting and unexpected finding; we will come back to it in Section 5. In Table 6 we check the robustness of the main results under alternative specifications (see Appendix 6.2).

5. Discussion and Conclusions

Previous empirical studies have mainly focused on the organizational-level conditions of exaptation. For instance, Cattani (2005) has analysed the role played by those firm capabilities accumulated in the past that turned out to be useful for co-opting an existing technology for a new function (defined as 'pre-adapted' capabilities). This paper explores the invention-level conditions of exaptation, in particular, technological complexity, inventors' analogical ability, and patent scope—a focus consistent with Cattani's call to extend the research on exaptation (2005), and with more recent contributions by Andriani and Carignani (2014).

We situated our analysis in the context of patent data. We analysed a large sample of U.S. patents obtained from the USPTO and NBER databases, assuming that a patent identifies an invention. We introduced a measure of exaptation ~~exaptive potential~~ using cross-class forward citation patterns in a novel way, in order to capture the functional shift of a technology as well as the possibility that this functional shift had not been originally anticipated (being the result of some underlying serendipitous process). Our results showed that our prediction of the curvilinear relationship between technological complexity and exaptation ~~exaptive potential~~ is confirmed. Moreover, inventors' analogical ability plays a direct positive role in exaptive innovation. However, we could not find statistical support for our hypothesis that inventors' analogical ability positively moderates the relationship between technological complexity and exaptive innovation. This result is puzzling, because it suggests that the prior knowledge owned by inventors positively affects exaptive innovation but not because it helps them to arrive at a richer representation of the architecture of the inventive problem and to better process complex interdependencies (Gavetti et al. 2005). As argued by Gavetti et al. (2005), we believe that this linkage between inventors' analogical ability and the architecture of the inventive problem is a crucial aspect that future studies should explore more carefully.

Also, we could not find statistical support for our hypotheses that patent scope is a direct moderator of exaptive innovation. This result is surprising but not puzzling, and may be explained as follows. If patent scope is larger, inventors may experience a stronger incentive to look for new application domains that fall beyond the claims specified in the patent. While larger patent scope may indeed block innovations that fall within the scope claimed by the focal patent, at the same time it may stimulate innovations that fall beyond this scope. This seems to suggest that patent scope blocks more incremental innovations but might stimulate exaptive innovations that may form precursors or more radical innovation. This is consistent with some recent studies that contradict the widespread argument that patent scope blocks *all* downstream technological developments. For example, Katznelson and Howells (2012) have analysed the activity directed at 'designing-around' Edison's patent of the incandescent lamp. They have shown that the legal enforcement of Edison's patent stimulated several downstream developments of major technological importance, some of which were directed to design around Claim 2 of Edison's patent (the hardest claim to circumvent at the time). We suggest this as an issue for future research.

Our paper has several limitations. First, our empirical setting was based on a cross-sectional sample of patents. In order to rule out eventual unobserved heterogeneity, the identification strategy proposed by Mehta et al. (2010)—which is based on the exploitation of the patent grant lag as a source of exogenous variation—may represent a starting point for future studies that will adopt a similar empirical setting. Second, our novel measure may be coarse in the sense that—besides exaptations—it may capture a subset of functional shifts that are due to different technological characteristics such as 'generality'. Although our measure differs from generality (see 3.2.1) and we control for that (see 3.2.5), there is room for improvement: we leave this to future research. Overall, cross-class forward citations are systematic (Ghiglino and Kuschy 2010) and they may reflect the pervasivity of technological exaptation (Dew et al. 2004; Kauffman 2000). Ours is the first attempt to exploit cross-class forward citations in order model exaptation phenomena. ~~our measure of exaptive potential is a coarse measure since it captures the 'potential' of an invention to be exapted for new functions rather a realised exaptation.[xxxviii] In order to understand if each invention/patent in our database has actually been exapted, we would have to embark on a detailed case study of each, well beyond the scope of our study.~~ Third, our empirical setting was based on patent data, characterised by several shortcomings. As mentioned, inventors and firms often apply for patents only to protect their best inventions, so that many inventions have no corresponding patents; this has consequences for generalisability. Moreover, the accuracy of the other patent measures can vary significantly across technologies. For instance, patent subclasses may not always correspond to underlying technological components (Fleming and Sorenson 2001). Future research should explore these measurement issues more deeply.

Despite these limitations, our paper offers several contributions. First, our findings contribute to the general debate on the emergence of radical innovations by further illuminating underlying exaptive mechanisms. We examined those exaptive mechanisms and the invention-level conditions that foster them. Second, our empirical results shed light on a number of specific theoretical arguments that have been made recently in the exaptation literature, particularly that literature that has analysed the role of exaptation, recombination, and modularization (Andriani and Carignani 2014). Third, our findings contribute to the debate on how innovation is shaped by exaptive and adaptive mechanisms. The concept of 'exaptation', which implies a sudden functional shift of a technology, has been introduced to make a distinction from the concept of 'adaptation', which implies a gradual process driven by selective pressures. The conditions that lead to adaptation have been analysed in a comprehensive manner; see Fleming and Sorenson's

Technology as a Complex Adaptive System (2001). Our paper adopts a similar empirical framework in order to fill a gap and explore the conditions of exaptive mechanisms. Although we emphasise exaptation, we do not want to downplay adaptation. As noted by Dew et al. (2004), both exaptation and adaptation play a central role; Andriani and Carignani (2014) note that the two mechanisms are 'intertwined'. Similarly, as argued by Henderson and Clark (1990), innovation is always characterized by periods of novel (exaptive) experimentation, followed by periods of adaptation and design stability. Future research should explore exaptive and adaptive mechanisms, in order to model the exaptation-adaptation cycle (Andriani and Carignani 2014) and explore how it varies depending on invention-level conditions; the 'dynamic' of cross-class/within-class forward citation patterns could be informative.

Appendix

Econometric Specification

Fractional logit estimation (Papke and Wooldridge 1996) is designed to take into consideration the possibility of observing values that pile at the boundaries as well as within the unit interval. We have:

$E(y_i|x_i, Z_i) = G(\alpha\, x_i + \beta\, Z_i)$

where $0 \leq y_i \leq 1$ is the exaptation ~~exaptive potential~~ of patent *i*, x_i is the technological complexity of patent *i*, Z_i is a vector of controls, and G is a known function, which is a logistic in our case:

$$E(y_i|x_i, Z_i) = \frac{exp(\alpha\, x_i + \beta\, Z_i)}{1 + exp(\alpha\, x_i + \beta\, Z_i)}$$

The estimation procedure is a quasi-maximum-likelihood method, as in Gourieroux et al. (1984) and McCullagh and Nelder (1989), where y_i are allowed to be continuous on the unit interval. Parameter estimates are consistent and $\sqrt{N}$ asymptotically normal regardless of the distribution of y_i conditional on x_i: y_i can be a discrete variable, a continuous variable, or it can have both discrete and continuous characteristics (Papke and Wooldridge 1996). The main drawback of the approach is that it assumes that:

$$Var(y_i|x_i, Z_i) = \sigma^2 \frac{exp(\alpha\, x_i + \beta\, Z_i)}{1 + exp(\alpha\, x_i + \beta\, Z_i)} (1 - \frac{exp(\alpha\, x_i + \beta\, Z_i)}{1 + exp(\alpha\, x_i + \beta\, Z_i)})$$

but in fact mechanisms by which this variance assumption may fail can be common. As noticed by Papke and Wooldridge (1996), if we assume that each y_i is the average of n_i independent binary variables y_{ij}, then it can be shown that:

$$Var(y_i|x_i, Z_i) = E(n_i^{-1}|x_i, Z_i) \frac{exp(\alpha\, x_i + \beta\, Z_i)}{1 + exp(\alpha\, x_i + \beta\, Z_i)} (1 - \frac{exp(\alpha\, x_i + \beta\, Z_i)}{1 + exp(\alpha\, x_i + \beta\, Z_i)})$$

and, unless n_i and x_i, Z_i are independent, the variance assumption fails. In our case, y_{ij} is a binary indicator of whether a citation *j* to patent *i* comes from a different technological class, n_i is the number of citations received by patent *i*, and x_i and Z_i are patent characteristics. Therefore, it is unlikely that n_i and x_i, Z_i are independent. McCullagh and Nelder (1989) suggested rejecting the logit quasi-likelihood approach, and relying on a more complicated quasi-likelihood when the variance assumption fails. However, since we were interested in the conditional mean, we followed the approach of Papke and Wooldridge (1996), who propose asymptotically robust inference for the parameters of the conditional mean, rather than abandoning the Bernoulli quasi-likelihood approach because the variance assumption may fail. We thus used robust standard errors, as in Papke and Wooldridge (1996).[xxxix]

Robustness checks

Technological classes may overlap: for example, despite having a different 3-digit code, Class 514 is the same as Class 424.[xl] This may cast doubt on our measure of exaptation ~~exaptive potential~~, which is based on the assumption that a citation that goes from Class 514 to Class 424 reflects a technological shift, taking place between those classes. Table 6 reports some robustness checks. In particular, in the first two columns we checked the robustness of our main results when we used two alternative measures of exaptation ~~exaptive potential~~. Making use of the NBER aggregation of technological classes in broader industrial sub-categories/categories (Hall et al. 2001), we considered a forward citation to be different when it was cross-class and, at the same time, came from a different industrial sub-category/category, noting that technological complexity and its squared term remain significant and with the expected sign. This also means that for exaptive innovation taking place in remote technological areas, the relationship between technological complexity and exaptive innovation can be described as an inverted U-shaped function. In the third and fourth column, we checked the robustness of our main results when we used OLS and TOBIT specifications for our fractional dependent variable. Despite the inappropriateness of these specifications in our setting (see Ramalho et al. 2011),[xli] [xlii] the main results for technological complexity remained significant and with the expected sign. In the fifth column, we manipulated technological complexity and subtracted its sample mean to force the estimated coefficients to reflect parameters that are of theoretical interest (Jaccard 2001). Again, the main results did not change substantially. We also calculated conditional partial effects at means and average partial effects for technological complexity (not reported here). We did not find substantial differences in terms of statistical significance. Finally, as in Fleming and Sorenson (2001), we split technological complexity into 20 percentiles and assigned a dummy variable to each percentile plus a dummy variable for extreme values. We then plotted the exponentiated coefficients of the significant dummies. The plot conformed to a non-linear relationship, as in Fleming and Sorenson (2001).[xliii]

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Figure 1

Theoretical Framework: H1, H3, H5

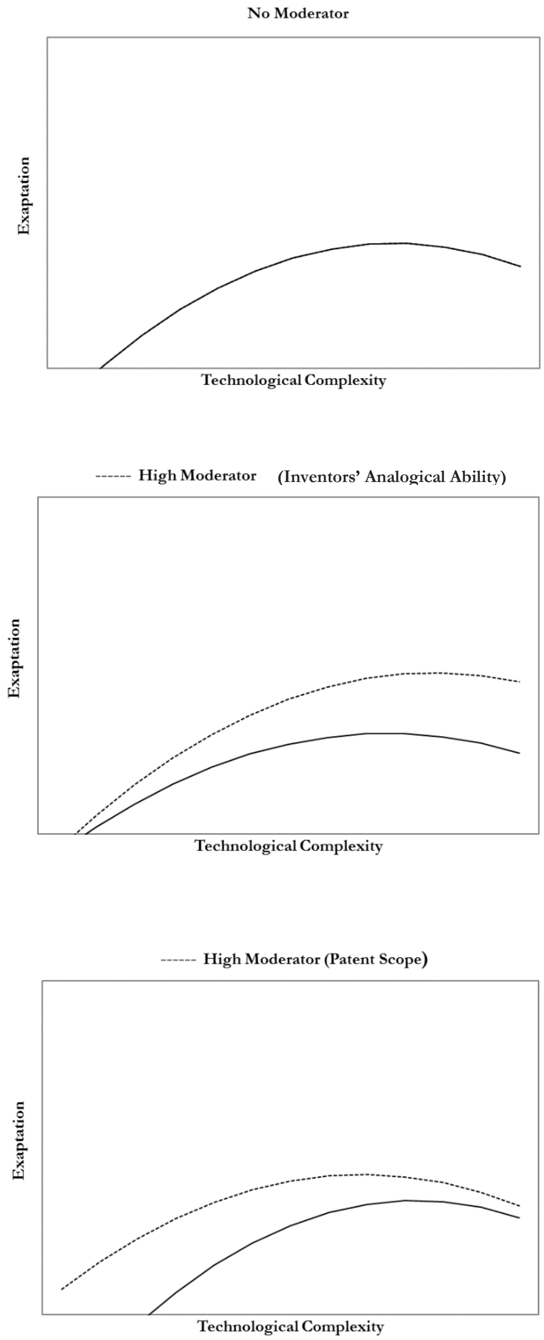

Figure 2

Empirical Framework: Research Design

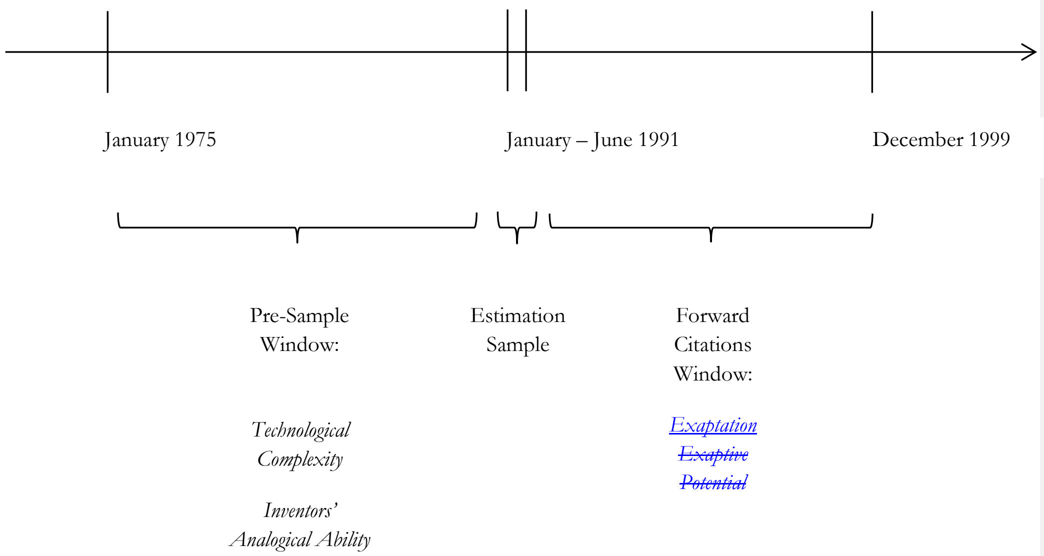

Figure 3

Empirical Framework: Exaptation ~~Exaptive Potential~~

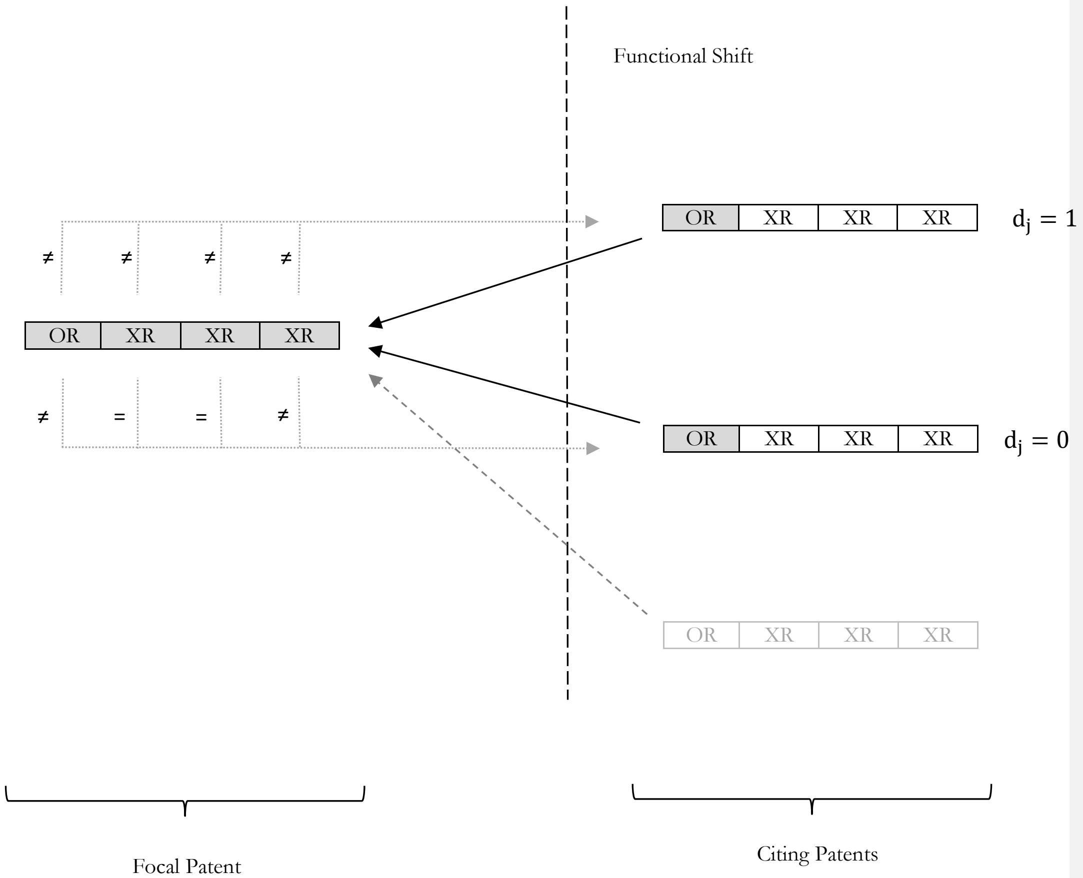

Table 1. Descriptive Statistics

Variable		Mean	Std. Dev.	Min	Max
Exaptation~~Exaptive Potential~~		0.29	0.31	0	1
Technological Complexity		0.67	0.76	0.07	40
Inventors' Analogical Ability		0.93	5.05	0	178
Patent Scope		12.97	10.85	1	292
Inventors' Generic Experience		7.55	19.26	0	472
Inventors' Experience Diversity		2.82	5.29	0	152
Inventors' Team Dummy		0.55	0.49	0	1
Inventors' Team Size		2.13	1.46	1	22
Concentration Dummy		0.10	0.31	0	1
Inventors Control		0.67	0.46	0	1
Combination Familiarity		0.45	0.13	0.01	2.44
Number of Subclasses		4.28	3.43	1	164
Single Subclass Dummy		0.07	0.26	0	1
Number of Prior Art Citations		7.77	7.33	0	173
Scientific References		1.10	3.49	0	110
Technology Control		3.63	1.05	1	11.64
Number of Classes		1.82	0.98	1	9
Diversity of Patent Portfolio	(focal)	0.07	0.11	0.01	1
Size of Patent Portfolio	(citing)	0.10	0.13	0.01	1
Diversity of Patent Portfolio	(focal)	2970.5	2453.1	1	8746
Size of Patent Portfolio	(citing)	2424.6	1905.8	1	8746

Table 2. Correlations

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1.Technological Complexity	1.00															
2. Inventors' Analogical Ability	-0.03	1.00														
3.Patent Scope	-0.00	0.00	1.00													
4.Inventors' Generic Experience	-0.03	0.39	0.01	1.00												
5.Inventors' Experience Diversity	-0.04	0.06	0.01	0.15	1.00											
6.Inventors' Team Dummy	-0.07	0.09	0.03	0.19	0.08	1.00										
7.Inventors' Team Size	-0.07	0.14	0.02	0.27	0.08	0.69	1.00									
8.Concentration Dummy	-0.01	0.20	0.01	0.06	0.04	0.11	0.10	1.00								
9.Inventors Control	-0.00	-0.09	-0.02	-0.18	-0.05	0.26	0.25	-0.13	1.00							
10.Combination Familiarity	-0.05	0.00	0.01	0.01	0.00	0.01	0.00	0.01	0.00	1.00						
11.Number of Subclasses	-0.20	0.05	0.08	0.05	0.06	0.06	0.08	0.05	-0.00	0.06	1.00					
12.Single Subclass Dummy	0.24	-0.01	-0.02	-0.00	-0.00	-0.01	-0.01	-0.01	-0.00	-0.09	-0.27	1.00				
13.Number of Prior Art Citations	0.01	-0.01	0.18	-0.01	-0.02	-0.03	-0.04	-0.00	-0.01	0.01	0.05	-0.05	1.00			
14.Scientific References	-0.05	0.01	0.12	0.00	0.00	0.08	0.08	0.02	0.02	0.01	0.11	-0.01	0.11	1.00		
15.Technology Control	0.04	-0.00	0.04	0.02	0.04	0.08	0.08	0.01	-0.02	0.05	-0.03	0.04	0.00	0.03	1.00	
16. Number of Classes	-0.04	0.05	0.04	0.01	0.05	0.01	0.03	0.11	0.00	0.06	0.50	-0.23	0.05	0.08	-0.00	1.00

Table 3. Hypothesis 1

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Technological Complexity		0.0419**	0.1044***	0.1042***	0.1384***
		(0.0180)	(0.0260)	(0.0260)	(0.0257)
Technological Complexity^2			-0.0031***	-0.0030***	-0.0039***
			(0.0010)	(0.0009)	(0.0011)
Inventors' Analogical Ability				0.0227***	
				(0.0031)	
Patent Scope				0.0016*	
				(0.0009)	
Inventors' Generic Experience	-0.0015**	-0.0015**	-0.0015**	-0.0048***	
	(0.0007)	(0.0007)	(0.0007)	(0.0010)	
Inventors' Experience Diversity	0.0047**	0.0047**	0.0047**	0.0052**	
	(0.0022)	(0.0022)	(0.0022)	(0.0022)	
Inventors' Team Dummy	-0.0365	-0.0363	-0.0357	-0.0307	
	(0.0312)	(0.0311)	(0.0311)	(0.0311)	
Inventors' Team Size	-0.0058	-0.0057	-0.0057	-0.0059	
	(0.0108)	(0.0108)	(0.0108)	(0.0109)	
Concentration Dummy	0.8810***	0.8806***	0.8808***	0.8234***	
	(0.0337)	(0.0337)	(0.0337)	(0.0346)	
Inventors Control	0.1434***	0.1444***	0.1449***	0.1410***	
	(0.0259)	(0.0259)	(0.0259)	(0.0266)	
Combination Familiarity	-0.1190	-0.1148	-0.1235	-0.1226	
	(0.1488)	(0.1488)	(0.1487)	(0.1488)	
Number of Subclasses	-0.0159***	-0.0150***	-0.0137***	-0.0144***	
	(0.0047)	(0.0047)	(0.0046)	(0.0047)	
Single Subclass Dummy	0.1771***	0.1568***	0.1398***	0.1407***	
	(0.0465)	(0.0472)	(0.0475)	(0.0473)	
Number of Prior Art Citations	0.0029**	0.0029**	0.0029**	0.0023	
	(0.0014)	(0.0014)	(0.0014)	(0.0014)	
Scientific References	0.0049	0.0048	0.0048	0.0046	
	(0.0030)	(0.0030)	(0.0030)	(0.0030)	
Technology Control	-0.0304	-0.0302	-0.0292	-0.0307	
	(0.0282)	(0.0282)	(0.0282)	(0.0281)	
Number of Classes	-0.0965***	-0.0987***	-0.1018***	-0.1056***	
	(0.0142)	(0.0142)	(0.0142)	(0.0142)	
Constant	-1.2035*	-1.2180*	-1.2360*	-1.2425*	-1.2503***
	(0.7006)	(0.7036)	(0.7073)	(0.7112)	(0.4508)
Tech Class Fixed Effects	yes	yes	yes	yes	yes
Application Year Fixed Effects	yes	yes	yes	yes	yes
Citing Year Fixed Effects	yes	yes	yes	yes	yes
Grant Month Fixed Effects	yes	yes	yes	yes	yes
Observations	19,076	19,076	19,076	19,076	19,076

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Fractional logit estimation.

Table 4. Hypotheses 2 and 3

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Technological Complexity		0.1044***	0.1047***	0.1055***	0.1049***
		(0.0260)	(0.0261)	(0.0265)	(0.0264)
Technological Complexity^2		-0.0031***	-0.0031***	-0.0031***	-0.0031***
		(0.0010)	(0.0009)	(0.0010)	(0.0009)
Inventors' Analogical Ability			0.0227***	0.0239***	0.0238***
			(0.0032)	(0.0041)	(0.0041)
Tech Compl. * Inv. Analog. Ab.				-0.0027	-0.0026
				(0.0062)	(0.0062)
Tech Compl.^2 * Inv. Analog. Ab.				0.0003	0.0002
				(0.0011)	(0.0011)
Patent Scope					0.0016*
					(0.0009)
Inventors' Generic Experience	-0.0015**	-0.0015**	-0.0048***	-0.0048***	-0.0048***
	(0.0007)	(0.0007)	(0.0011)	(0.0011)	(0.0010)
Inventors' Experience Diversity	0.0047**	0.0047**	0.0052**	0.0052**	0.0052**
	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)
Inventors' Team Dummy	-0.0365	-0.0357	-0.0299	-0.0299	-0.0308
	(0.0312)	(0.0311)	(0.0311)	(0.0311)	(0.0311)
Inventors' Team Size	-0.0058	-0.0057	-0.0060	-0.0059	-0.0058
	(0.0108)	(0.0108)	(0.0110)	(0.0110)	(0.0109)
Concentration Dummy	0.8810***	0.8808***	0.8234***	0.8245***	0.8244***
	(0.0337)	(0.0337)	(0.0347)	(0.0348)	(0.0347)
Inventors Control	0.1434***	0.1449***	0.1405***	0.1404***	0.1409***
	(0.0259)	(0.0259)	(0.0266)	(0.0266)	(0.0266)
Combination Familiarity	-0.1190	-0.1235	-0.1223	-0.1220	-0.1222
	(0.1488)	(0.1487)	(0.1488)	(0.1489)	(0.1488)
Number of Subclasses	-0.0159***	-0.0137***	-0.0140***	-0.0141***	-0.0145***
	(0.0047)	(0.0046)	(0.0047)	(0.0047)	(0.0047)
Single Subclass Dummy	0.1771***	0.1398***	0.1407***	0.1409***	0.1409***
	(0.0465)	(0.0475)	(0.0473)	(0.0473)	(0.0473)
Number of Prior Art Citations	0.0029**	0.0029**	0.0027*	0.0027*	0.0023
	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
Scientific References	0.0049	0.0048	0.0051*	0.0051*	0.0046
	(0.0030)	(0.0030)	(0.0030)	(0.0030)	(0.0030)
Technology Control	-0.0304	-0.0292	-0.0313	-0.0313	-0.0307
	(0.0282)	(0.0282)	(0.0282)	(0.0282)	(0.0281)
Number of Classes	-0.0965***	-0.1018***	-0.1059***	-0.1059***	-0.1056***
	(0.0142)	(0.0142)	(0.0142)	(0.0142)	(0.0142)
Constant	-1.2035*	-1.2360*	-1.2166*	-1.2156*	-1.2416*
	(0.7006)	(0.7073)	(0.7106)	(0.7095)	(0.7102)
Tech Class Fixed Effects	yes	yes	yes	yes	yes
Application Year Fixed Effects	yes	yes	yes	yes	yes
Citing Year Fixed Effects	yes	yes	yes	yes	yes
Grant Month Fixed Effects	yes	yes	yes	yes	yes
Observations	19,076	19,076	19,076	19,076	19,076

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Fractional logit estimation.

Table 5. Hypotheses 4 and 5

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Technological Complexity		0.3454** (0.1370)	0.3344** (0.1377)	0.4598** (0.1839)	0.4549** (0.1826)
Technological Complexity^2		-0.0403* (0.0228)	-0.0392* (0.0231)	-0.0669* (0.0389)	-0.0661* (0.0385)
Patent Scope			0.0077*** (0.0022)	0.0130** (0.0055)	0.0126** (0.0053)
Tech Compl. * Patent Scope				-0.0107 (0.0094)	-0.0101 (0.0092)
Tech Compl.^2 * Patent Scope				0.0023 (0.0026)	0.0022 (0.0026)
Inventors' Analogical Ability					0.0162*** (0.0059)
Inventors' Generic Experience	-0.0016 (0.0018)	-0.0016 (0.0018)	-0.0016 (0.0018)	-0.0016 (0.0018)	-0.0046** (0.0023)
Inventors' Experience Diversity	0.0141** (0.0069)	0.0142** (0.0069)	0.0128* (0.0069)	0.0131* (0.0069)	0.0146** (0.0068)
Inventors' Team Dummy	-0.0588 (0.0742)	-0.0508 (0.0744)	-0.0548 (0.0746)	-0.0564 (0.0746)	-0.0472 (0.0743)
Inventors' Team Size	0.0105 (0.0225)	0.0094 (0.0225)	0.0095 (0.0226)	0.0102 (0.0226)	0.0104 (0.0223)
Concentration Dummy	0.8611*** (0.0796)	0.8617*** (0.0796)	0.8614*** (0.0795)	0.8605*** (0.0796)	0.8188*** (0.0808)
Inventors Control	0.1006 (0.0654)	0.0973 (0.0656)	0.0993 (0.0656)	0.0975 (0.0656)	0.0889 (0.0657)
Combination Familiarity	0.7342** (0.3731)	0.7071* (0.3701)	0.6907* (0.3705)	0.6859* (0.3697)	0.6786* (0.3702)
Number of Subclasses	0.0066 (0.0113)	0.0119 (0.0114)	0.0098 (0.0113)	0.0088 (0.0113)	0.0102 (0.0113)
Single Subclass Dummy	0.4686*** (0.1147)	0.3942*** (0.1180)	0.3966*** (0.1179)	0.3946*** (0.1179)	0.3993*** (0.1180)
Number of Prior Art Citations	-0.0012 (0.0042)	-0.0012 (0.0042)	-0.0038 (0.0043)	-0.0039 (0.0043)	-0.0039 (0.0042)
Scientific References	0.0131 (0.0098)	0.0131 (0.0097)	0.0096 (0.0098)	0.0094 (0.0098)	0.0094 (0.0097)
Technology Control	-0.0643 (0.0636)	-0.0661 (0.0633)	-0.0698 (0.0636)	-0.0713 (0.0636)	-0.0744 (0.0637)
Number of Classes	-0.1932*** (0.0374)	-0.2069*** (0.0380)	-0.2064*** (0.0381)	-0.2046*** (0.0381)	-0.2084*** (0.0380)
Diversity of patent portfolio (focal)	0.0519 (0.2657)	0.0594 (0.2654)	0.0294 (0.2674)	0.0351 (0.2665)	0.0169 (0.2670)
Diversity of patent portfolio (citing)	0.0670 (0.2451)	0.0674 (0.2442)	0.0653 (0.2453)	0.0702 (0.2449)	0.0668 (0.2446)
Size of patent portfolio (focal)	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)
Size of patent portfolio (citing)	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)
Constant	-0.4937 (0.6465)	-0.5829 (0.6472)	-0.5961 (0.6500)	-0.6576 (0.6534)	-0.6937 (0.6514)
Tech Class Fixed Effects	yes	yes	yes	yes	yes
Application Year Fixed Effects	yes	yes	yes	yes	yes
Citing Year Fixed Effects	yes	yes	yes	yes	yes
Grant Month Fixed Effects	yes	yes	yes	yes	yes
Observations	4,685	4,685	4,685	4,685	4,685

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Fractional logit estimation.

Table 6. Robustness Checks

Variables	1) Exap. Sub-category	2) Exap. Category	3) Ols	4) Tobit	5) Compl. De-Mean
Tech. Complexity	0.1102***	0.1274***	0.0210***	0.0319***	
	(0.0306)	(0.0384)	(0.0053)	(0.0091)	
Tech. Complexity^2	-0.0037**	-0.0064**	-0.0006***	-0.0009**	
	(0.0015)	(0.0028)	(0.0002)	(0.0004)	
Tech. Complexity (de-mean)					0.1001***
					(0.0250)
Tech. Complexity^2 (de-mean)					-0.0031***
					(0.0009)
Inventors' Analogical Ability	0.0300***	0.0239***	0.0042***	0.0068***	0.0227***
	(0.0039)	(0.0031)	(0.0005)	(0.0008)	(0.0032)
Patent Scope	0.0006	0.0001	0.0003	0.0008**	0.0016*
	(0.0010)	(0.0011)	(0.0002)	(0.0003)	(0.0010)
Inventors' Generic Experience	-0.0053***	-0.0058***	-0.0007***	-0.0011***	-0.0048***
	(0.0010)	(0.0011)	(0.0001)	(0.0002)	(0.0011)
Inventors' Experience Diversity	0.0077***	0.0053*	0.0009**	0.0018**	0.0052**
	(0.0027)	(0.0028)	(0.0004)	(0.0007)	(0.0022)
Inventors' Team Dummy	-0.0442	-0.0110	-0.0060	-0.0082	-0.0308
	(0.0320)	(0.0364)	(0.0060)	(0.0102)	(0.0311)
Inventors' Team Size	-0.0067	0.0089	-0.0016	-0.0030	-0.0060
	(0.0113)	(0.0127)	(0.0021)	(0.0035)	(0.0110)
Concentration Dummy	0.9545***	0.7496***	0.1804***	0.2886***	0.8234***
	(0.0374)	(0.0398)	(0.0072)	(0.0119)	(0.0347)
Inventors Control	0.1252***	0.0768**	0.0284***	0.0453***	0.1411***
	(0.0271)	(0.0307)	(0.0051)	(0.0086)	(0.0266)
Combination Familiarity	-0.1429	-0.1579	-0.0250	-0.0436	-0.1226
	(0.1588)	(0.1740)	(0.0289)	(0.0493)	(0.1489)
Number of Subclasses	-0.0321***	-0.0223***	-0.0022***	-0.0027**	-0.0144***
	(0.0052)	(0.0054)	(0.0008)	(0.0013)	(0.0047)
Single Subclass Dummy	-0.1375***	-0.1196*	0.0284***	0.0401***	0.1407***
	(0.0526)	(0.0613)	(0.0091)	(0.0155)	(0.0473)
Number of Prior Art Citations	0.0024	0.0055***	0.0005	0.0011**	0.0023
	(0.0015)	(0.0017)	(0.0003)	(0.0005)	(0.0015)
Scientific References	0.0012	-0.0008	0.0009	0.0014	0.0046
	(0.0032)	(0.0036)	(0.0007)	(0.0011)	(0.0030)
Technology Control	0.1469***	0.1232***	-0.0063	-0.0026	-0.0308
	(0.0288)	(0.0323)	(0.0056)	(0.0094)	(0.0282)
Number of Classes	0.4688***	0.3582***	-0.0212***	-0.0296***	-0.1057***
	(0.0147)	(0.0157)	(0.0027)	(0.0045)	(0.0143)
Constant	-4.3419***	-4.3967***	0.2202	0.1227	-1.1737*
	(0.7258)	(0.7248)	(0.2180)	(0.3481)	(0.7112)
Tech Class Fixed Effects	yes	yes	yes	yes	yes
Application Year Fixed Effects	yes	yes	yes	yes	yes
Citing Year Fixed Effects	yes	yes	yes	yes	yes
Grant Month Fixed Effects	yes	yes	yes	yes	yes
Observations	19,076	19,076	19,076	19,076	19,076

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Fractional logit estimation.

Endnotes

[i] Such as birds' wings, that originally served to climb the trees or capture preys and later on they were co-opted for flight (Gatesy and Baier 2005).

[ii] Other examples such as the common microwave oven, which resulted from the discovery of a new function of the radar magnetron (Andriani and Carignani 2014).

[iii] Which is considered the science of allocation under conditions of scarcity (Kauffman 2000).

~~[iv] We should also mention the debate on the 'social construction' of technology, according to which the role played by social aspects cannot be ignored (see Pinch and Bijker 1984).~~

[v] … but not sufficient.

[vi] For example, the exaptation that led to the printing press was most likely triggered by the possibility to decompose the wine press and to add new components (such as the movable type and the printing table) around the co-opted components (the pressing components).

[vii] The concepts of recombination and market selection respectively correspond to the biological concepts of 'variation' and 'selective retention'.

[viii] Functional shifts are fundamental in innovation. A technology brings with itself an infinite potential for novel functions. In other words, the physical structure of a technology has many potential novel functions although we only observe a very limited set of them (Bonaccorsi 2011). This usually happens because of 'functional fixedness', a cognitive bias that limits people to using a technology only in the way it is used traditionally (Margolis and Laurence 2007; McCaffrey 2012; Solomon 1994).

[ix] Non-anticipation is also fundamental. Novel functions cannot always be known or specified ex-ante, since their activation is the outcome of a complex and idiosyncratic interaction between the technology and the contexts of use (Bonaccorsi 2011).

[x] The definition of modularity is similar, although the literature has provided several definitions (Fleming and Sorenson 2000). Modularity refers to the degree to which a technology is composed of modules that are relatively weakly connected to each other (Baldwin and Clark 2000).

[xi] Kinematics principles, which are adopted in several sectors, are based on mathematical representations (Eckhardt 1998; Phillips 2007). For example, the level of constraint of a technology is often expressed in terms of the Kutzbach's criterion given by $F=\alpha n(\beta-6)+6(n-1)$. F is the number of degrees of freedom of the technology and $\alpha=e/n$ is the ratio of the number of links among subparts and the number of subparts; it expresses interdependence. Unless $\beta>6$, increasing levels of α make F negative and generate over-constraints (Whitney 2005).

[xii] Design structure matrices are based on the visual representations of internal constraints (Eppinger 1991, 1997; Steward 1981a, 1981b). They can be defined as $n \; x \; n$ matrices $\mathbf{M}$ in which $\mathrm{M}_{ij} \neq 0$ if subparts i and j interact with each other (Casals et al. 2012).

[xiii] The modularity literature has defined the following operators: substituting, augmenting, splitting, inverting, porting, and excluding.

[xiv] Andriani and Carignani (2013) have started to develop a framework for exaptation and modularity, taking into account the level at which exaptation takes place within a modular architecture. They distinguish between 'radical', 'internal', and 'external' exaptation. The most interesting case is when an exaptation is radical, and this happens when a module is exapted and an entirely new technological architecture, with a new function, arises around the exapted module. An exaptation is internal when a module is exapted inside an existing technological architecture, whose function does not change. An exaptation is external when the entire architecture is exapted for a new function. In a certain way, our paper provides an empirical framework to test the relationship between technological complexity and radical exaptation.

[xv] From now on we will refer to the 'likelihood of exaptation' in a very generic way. In other words, we will not assume any underlying ability to overcome Knightian uncertainty and to pre-state all the possible exaptations (and therefore to assign probabilities) (Dew et al. 2004).

[xvi] For example, it is likely that the exaptation that led to the printing press was made possible by Gutenberg's ability to make an inventive analogy between different knowledge domains, wine making and paper pressing.

[xvii] According to some researchers (De Beaune 2009), analogical transfer is one of the most plausible explanations for the invention of stone knapping by Homo erectus, which is probably the first example of human inventive activity.

[xviii] For instance, it is likely that the exaptation that led to the printing press was facilitated by the possibility to use the wine press in a novel way, unless that use was already protected.

[xix] This interpretation is only valid in patent-law systems known as 'peripheral' (US, UK, and Japan): in those systems the entire set of embodiments exactly defines the 'fence' of protection (Fromer 1999). In patent-law systems known as 'central' (Germany and continental Europe) only few embodiments define protection, and those are used to determine whether potentially infringing items are 'similar enough' to them.

[xx] The issue of scope is central in the technological evolution debate. Indeed, as noticed by Merges and Nelson (1990), scope plays a very important role in the case of complex technologies, whose developments can proceed on different technological trajectories at the same time.

[xxi] The 'blocking' perspective has been recently criticised by Katznelson and Howells (2012).

[xxii] From now on, we will refer to them as 'cross-class' forward citations.

[xxiii] The way we use citations does not raise issues such as those pointed out by Alcacer and Gittelman (2006). They found that almost 40% of citations are added by examiners rather than inventors: this begs the question of whether it is reasonable to assume that citations reflect an exchange of knowledge among inventors of different patents. However, we use citations as maps of 'technical links' between inventions (Martinelli 2010) rather than maps of 'knowledge flows' between inventors.

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[xxv] Usually XR classes are not mandatory unless the controlling claim is too generic and spans different classifications. This situation is common when the controlling claim is Markush Type, which usually occurs in the case of chemical compounds (USPTO 2012b).

[xxvi] We therefore make maximal use of our NBER database, which ends in December 1999. Moreover, all the patents of our estimation sample were granted in 1991. This allows us to capture the bulk of forward citations, which tend to peak 3-5 years after the grant date.

[xxvii] Instead of PDPCO identifiers, we could have directly used identifiers for assignees. However, quite often, assignees are not 'consolidated' since the same firm may appear in different patents with different assignee identifiers (Hall et al. 2001).

[xxviii] Both patents are easily accessible on Google Patents.

[xxix] This is a purely illustrative example of the technological classifications, as the two patents do not cite each other. This is probably due to the old age of the patents—pre 1950—and to the lack of well-established examination and citation procedures at those times.

[xxx] Fleming and Sorenson (2001) measured complexity as the ratio of x_i and the number of patent subclasses. This is because complexity matters when interdependence among technological components is high relative to their number. Instead of dividing by the number of patent subclasses, we introduced it as a separate control, which is the same. Indeed w~~W~~e also tried to divide by the number of subclasses as in Fleming and Sorenson (2001), and we did not find substantial differences in the main results.

[xxxi] Fleming and Sorenson (2004) validated the measure through a survey. They asked inventors how coupled the components of their patent were. They then compared the results of the survey to their measure, and found a strong correlation.

[xxxii] Or, eventually, the single inventor.

[xxxiii] See the measure of the Inventors' Analogical Ability.

[xxxiv] See the measure of the Inventors' Analogical Ability.

[xxxv] We set *k* to 18%, as in Fleming (2001). However, Argote et al. (1990) have estimated a higher value for this parameter.

[xxxvi] Around 7%, as in Fleming and Sorenson (2001).

[xxxvii] We considered the 1980-1990 window.

~~[xxxviii] Despite this, we can expect that actual exaptations are a subset of cross-class forward citations.~~

[xxxix] Stata's *glm* command could not handle Papke and Wooldridge (1996)'s model when their seminal article was published. A few years ago, the command had been enhanced to do so. In addition, Ramalho has developed new Stata code for fractional response models (see http://evunix.uevora.pt/~jsr/FRM.htm).

Gewijzigde veldcode

[xl] In other words, classes 514 and 424 refer to the same kind of technology.

[xli] A TOBIT specification is appropriate when the dependent variable is fractional because of censoring: that is when values below and above the [0 1] interval cannot be observed (Ramalho et al. 2011). In our case, however, the dependent variable is fractional 'by definition' and not because of censoring. Moreover, a TOBIT specification is very strict in terms of distributional assumptions of normality and homoscedasticity of the dependent variable, much like in an OLS regression (Ramalho et al. 2011). In our case, these assumptions are not satisfied since a large percentage of values pile at the boundaries of the [0 1] interval.

[xlii] We also run a two-part BETA fractional regression model, which assumes that boundary values come from a different data-generating process (Ramalho et al. 2011). In our case, however, assuming that 0s and 1s come from a different process would mean assuming that the process that generates forward citations changes depending on the forward citations' levels, which is not a reasonable assumption.

[xliii] See Figure 5 in their paper.