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Identification of "Valuable" Technologies via Patent Statistics in India: An Analysis Based on Renewal Information

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Abstract

This study assesses the degree to which the patent attributes can capture the value of patents across discrete and complex innovations. We use the patents applied between 1995 to 2002 and granted on or before December 2018 from the Indian Patent Office. Here the patent renewal information is utilized as a proxy for the patent value. We have used generalized logistic regression model for the impact assessment analysis. The results reveal that the technology classification (i.e., discrete versus complex innovations) play an important role in patent value assessment, and some technologies are significantly different than the others even within the two broader classifications. Moreover, the non-resident patents in India are more likely to have a higher value than the resident patents. The significance pattern among the technological fields suggests that the patenting laws need to be revisited to enhance the efficiency.

Keywords: Patent value, Discrete innovation, Complex innovation, Patent reform, Renewal information

JEL Classification: O31, O32, 034

Patent value, Discrete innovation, Complex innovation, Patent reform, Renewal information

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1. Introduction

Considering different roles in the innovative process, the patents are used differently across the industrial and technology fields. To begin with, Levin et al. (1987) and Cohen et al. (2000) pointed out that (a) the efficiency of patents as an instrument for appropriating the return from R&D fluctuates across firms and industries, and (b) the patents are more powerful for product innovation as compared to process innovation. Generally, patents are more likely to be filed in a sector where R&D cost is high, and imitation is cheap (e.g., chemicals, pharmaceuticals, and machinery). The nature of R&D also plays a vital role in determining the importance of a patent. For example, patents tend to be of high value when R&D is highly capital intensive and highly uncertain (pharmaceuticals). On the other hand, when technological change is exceptionally fast and the effective innovation life is short, a patent may not adequately reward innovators (Orsenigo and Sterzi, 2010). Patenting behaviors have kept on evolving throughout the evolution of the industry. In India, patenting activities started gaining interest in the late 1990s; however, still, not many studies are dedicated to the value and quality aspects of innovation. The purpose of this study is to understand the quality differences between cumulative/complex and discrete technology innovations.

For a discrete technology (also referred to as the single product innovation), a single patent secures distinct products that can be brought to the market independently. At the same time, complex technology innovations are described by a bundle of complementary patents building a so-called patent thicket or a thick web of overlapping patents (Shapiro, 2001). For some economists, patent thickets problems weaken innovation incentives by diminishing profit from innovation through patent inflation and prosecution while permitting litigious firms to earn much on patents of dubious technological significance (Shapiro, 2001; Bessen, 2004). This leads to an inconclusive link between social and private value of patents. Many scholars have argued that the distinction between complex and discrete technologies affects indicators' performance in the theoretical literature (Roycroft and Kash, 1999; Kingston, 2001). A challenging question is whether or not we can differentiate the patents' value across the technological fields and develop a conceptual framework for clarifying this diversity? Second, how patent system should deal with these differences? This study is an attempt to answer the question and capture the value differences among different technological fields.

However, an in-depth analysis of the patent quality indicators is required to conclude the patent systems' relevance for different technology fields separately. We use an extensive database of complex and discrete technology patents to assess how well patent characteristics perform in explaining the probability that a patent will be renewed. Our analysis includes three most commonly used indicators. First, the *inventions' complexity* is measured by patent technology scope (4-digit IPC class), inventor size, and the grant lag.

Second, the *filing strategy* includes the structure and quality of the drafted document (number of claims) and protecting the same patent in a different jurisdiction (family size). Third, the *ownership group* that is patent owned by India (resident) or foreigners (non-resident). In this study, the technology is disaggregated into 33 categories (as per Schmoch 2008).

This study systematically identifies valuable patents from different technology and ownership groups by ranking them according to the renewal fee scale. In India, the renewal fee changes every 7th, 11th, and 15th year during the patent life. We argue that the change in the fee scale is likely to influence the patentee's renewal decision. Thus, the observable patent value is coded as 1 if a patent does not survive the first renewal fee hike (at the 7th year), 2 if it expires between 7th and 11th year, 3 if the life of a patent is between 11th and 15th year, and 4 if it survives more than 15 years. We treat this coded patent value as our response variable in this study.

Since the outcome variable is ordinal, we follow William (2006) and use the ordered logit model to identify the valuable technologies for disaggregated complex and discrete technology fields. We started with the most popular proportional odds model but realized that not all explanatory variables meet the proportionality assumption; subsequently we apply an alternative model, called the ‘generalized ordered logit model’. Both models are run separately for the two samples (discrete and complex technology fields) and together as combined samples. The patents belonging to the discrete technology fields are supposed to have a higher value (Cohen et al., 2000) We witness a similar behaviour for our patents as well (see results in Section 5). Among the patent characteristics, ownership category: the non-resident patents in India have a higher value than the resident patents.

The rest of the paper is organized as follows: Section 2 presents an overview of patent valuation literature and formulates working hypotheses. Data collection and the statistical models are discussed in Section 3. Section 4 presents the models, Section 5 summarizes the results by technologies and ownership category, and Section 6 concludes the chapter by discussing the implications of these findings for evaluating the need for IPRs in India.

2. Literature Review and Hypothesis Development

The literature review is categorized into two different segments: an overview of patent valuation and the development of different hypotheses.

2.1. Overview of literature on patent value

Incessant technology advancement and evolution have pushed the need to recognize promising technological opportunities for organizations. Since patents contain information about innovation, they are viewed as fundamental data sources for technological capabilities (Lai et al., 2021). Technological capabilities are defined as a firm's need to support innovation acquisition utilizing skills and knowledge (Tsai, Chang, & Hung, 2018). Innovation's monetary value can be estimated in terms of its influence based on patent value estimation (Jee, Kwon, Ha, & Sohn, 2019). Patents feature the useful application of innovation just as its business potential or market value (Chang et al., 2017). The evaluation of patent data is crucial for companies' decision-making process, future technological advancement, and strategic plans (Kumar et al., 2020; Lai et al., 2020). Kabore and Park (2019) noticed that firms that put resources into patent assessment could shape their investment incentives for the technological innovation process. Besides, patents have been linked to the successful acquisition of venture capital by start-ups (Mann and Sager, 2007), increased sales (Balasubramanian and Sivadasan, 2011), increased exports (Chalioti, Drivas, Kalyvitis, and Katsimi, 2020) and possibly fortify future merger and acquisition (Breitzman, Thomas, and Cheney, 2002). In this context, academia and research evaluated the value of patents across the technological field using various techniques and methods.

The accurate valuation explains the technological originality, progressiveness, and commercial potential (Kuznets, 1962). However, the concept of patent value is not found in absolute and abstract terms, and it varies with the perspective of the valuing agency. The importance of IP on firms' competitive advantage has encouraged scholars to study IPs' effective value and management (Klaila and Hall, 2000). There are three common ways to estimate patent value from different perspectives. The first set of studies measure the patent value primarily based on a company's market value and other performance indicators. The second category of studies adopt innovation survey methods where inventors are asked to gauge the value of their patents;

and the third type of literature considers qualitative variables along with other patent level information as the determinants of patent value (Reitzig, 2004; Zeebroeck, 2011). The nature of patent value is divided into two components: the intrinsic and the extrinsic dimensions. The intrinsic value theory argues that a patent's value is derived from its technological significance (Thoma, 2014). Under this framework, it is assumed that a valuable patent will be in-forced after they are granted and complete 20 years of the legal term. On the other hand, a patent's extrinsic value is captured through market value, product development, novelty, inventive steps, and geographical scope (Grimaldi and Cricelli, 2019).

In this study, we focus on the intrinsic value of the patents. Under the intrinsic value theory, various patent value indicators are suggested, including backward citations, forward citations (Harhoff et al., 1999) claims (Bessen, 2008; Danish et al., 2019) patent family size, and litigations (Lanjouw and Schankerman 1999). The patent data's legal status gives essential information about the legal events, including expiration of a patent, renewal information, claims, change of legal identity, and other related information. Patent value indices constructed based on legal status are grant index (Zeebroeck, 2011), litigation index (Lanjouw and Schankerman, 2001; Hsieh, 2013), inventor index (Caviggioli et al., 2013), claim index (Trappey et al., 2012) and renewal index (Hikkerova et al., 2014). Since all these indices are based on literature, their applicability and validity can be verified. Hikkerova et al. (2014) study the patent life cycle in the European context. They argue that patent and their renewals are critical because they protect inventions and reinforce information about the utility and quality of invention. Similarly, utilizing a litigation index, Lanjouw and Schankerman (2001) find that cost of participating in litigation over IP assets lessens their value as an incentive to put resources into research. Also, they show that there is a substantial variation across patents in their exposure to litigation risk.

Besides, there are several other patent value indices available in the literature, such as the technology index (Thoma, 2014), market conditions index (Grimaldi et al., 2015), and finance index (Ernst et al., 2010). Since the information on the return from a patent (in monetary terms), citation information, and litigation information are not available in India, this study uses legal information, i.e., the patent renewal information, to construct the value index. Econometric studies on patent valuation have found that patent renewal fees are related to patent rents' value, and most valuable patents are kept in-forced for a longer time (Hikkerova et al., 2014).

The patent's value is connected to the particular attributes of technology and the R&D process, and the nature of the market, and the competition pattern. It is possible to identify important attributes of valuable technologies that build taxonomies and generalizations. The patent's role is higher when imitation is accessible, i.e., when the ratio between imitation costs and innovation costs is lower (e.g., chemicals, pharmaceuticals, machinery). Additionally, patents generally are more significant in the technologies where R&D is exceptionally capital concentrated and highly uncertain (pharmaceutical). When technical change is quick and the effective life of innovation is short, patents may not adequately reward innovators (semiconductors and software are good examples).

Moore (2005) formulates an ordered logit model to identify the worthless patents filed at USPTO. Even though there is a uniform patent term for all patents (20 years from the date of application), renewal expenses charged at regular intervals (once in three years after grant) by USPTO make a true differentiation. Despite having a uniform patent life term across the technologies, Moore’s study finds that patent expires in the early stage due to non-payment of renewal fee share identifiable characteristics. Also, she finds that 53.71 percent of patents lapsed due to non-payment of renewal fees at some point in the renewal cycle. It shows that patentees have an idea of sunk cost, and therefore they do not want to further increase their loss by renewing not so valuable patents.

In the Indian context, no study has considered patents' characteristics to measure patents' innovative output. The data-based patent valuation has two unique advantages. First, it can be performed for any patent without the requirement for exclusive or classified information since data is public and accessible in the electronic data set. Second, patent information-based valuation is objective, quick, and economical.

As per Section 53, Rule 80 of the Indian patent act 1970, if a patent must be kept enforced, the patentee has to pay an annual patent maintenance fee (3rd year onwards from the date of application) after the patent has been granted. The present study follows the Patents (Amendment) Act, 2002, which became effective from 20th May 2003. The renewal fee schedule is shown in Table 1 (also converted in dollar value at 2020 price).

Table 1: Annual renewal fee schedule in India

Renewal Years	3 to 6	7 to 10	11 to 15	16 to 20
India	\$56.09 (INR 4000)	\$168.30 (INR 12000)	\$336.60 (INR 24000)	\$561.00 (INR 40000)
Renewal level	1	2	3	4

Source: Indian Patent Office (IPO)

Recall that we use these three cutoff points to distribute the patents into four regions: patents with a value less than the first cutoff points expire within the first six years. Patents with values in between the first and second cutoff points survive at least six years but expire before the 11th year, whereas the patents with values between the second and third cutoff points expire between the 11th and 15th year, and the patents with values greater than the third cutoff value live at least 16 years and may mature to the full legal term.

We structure our analysis around the crucial distinction between complex and discrete technologies. The distinction between complex and discrete technology was first introduced by Levin et al. (1987) and has by now been studied by an extensive body of research (Merges and Nelson,1990; Cohen, Nelson, and Walsh, 2000; Harhoff and von Graevenitz, 2009). The research indicates that a "complex" innovation field comprises of multiple complementary patents, often held by various inventors within one product. For example, a BluRay player incorporates several thousand patents held by various major players of the business. Contrary to that, only a few patents complete the product in discrete technologies that can be brought to the market independently. Generally, the IP for one product is held by one single owner.

The patent indicators vary with the complexity of the technology. For example, a patent web's density in a complex industry (cumulative innovation) generally affects the average number of claims and citations. Blind and Thumm (2010) find that patents identified as essential to the technological standard have more claims. The presence of overlapping patents could give incentives to raise the number of claims, as expanding the number of claims builds the odds of the patent being relevant to future innovation in similar technological areas (Baron and Delcamp, 2012). Important divergences between complex and discrete technologies have been revealed in a couple of empirical analyses of indicator performance. Hall et al. (2005) find that when innovation is cumulative, the quality of patent, in general, is less likely to correlate with its value. In a different approach, Lanjouw and Schankerman (2004) argue that patent quality is the only underlying factor that could jointly affect the number of claims, forward and backward citation, and size of the families. Here, the patent quality refers to the number of claims, family size, technology scope, and grant lag. The value indicator could be anything that captures the patent's return from the inventor's perspective, such as renewal life and litigation.

2.2. Hypothesis development

It has been found in the earlier study that the cumulativeness of a technological field (complex technology patents) and discrete technology patents have an impact on the patent value. For instance, complex technology patents mechanically affect the average number of forward citations (Nagaoka 2005). The identification of discrete and complex technology is based on Graevenitz et al. (2011) and Baron and Delcamp (2012).

To begin with, we first conduct a test of hypothesis to verify whether the categorization of technologies in discrete versus complex innovations has any impact on the patent value.

> *$H1_0$: Discrete innovation has lower patent value than complex/cumulative innovation.*

> *$H1_a$: Discrete innovation has higher patent value than complex/cumulative innovation.*

The function and the mechanism of patents can differ as indicated by external factors, like the type of assignee, the grant year, and the technology field. Patents are extremely heterogeneous, and only a few patents are important, while a large number are rarely utilized. Thus, in order to use patents objectively in innovation studies, we need to analyze the value/quality of patents based on identifiable characteristics.

> *$H2_0$: Patent characteristics have no impact on the value of patents in the discrete and complex technologies*

> *$H2_a$: At least some patent characteristics have significant influence (positively or negatively) on the value of patents in the discrete and complex technologies*

To understand the valuable technology by ownership category, the patents are divided into two categories: the patents filed by Indians at IPO (resident patents) and the patents filed by foreigners at IPO (this is referred to as the non-resident patents). We include the resident and non-resident dummy in the formal model specification and based on which we conduct the following hypothesis test.

> *$H3_0$: non-resident patents have a lower value than resident patents in India*

> *$H3_a$: non-resident patents have a higher value than resident patents in India*

The hypothesis test results are discussed in Section 5.

3. Data Description and Variable Selection

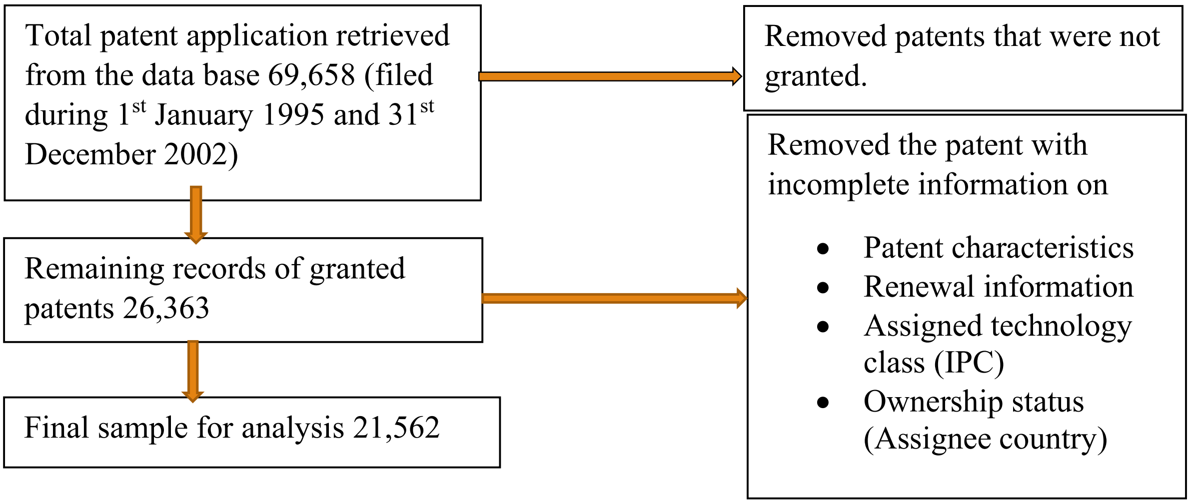
This section focuses on the sources of data, processing, and model specification.

3.1. Data

One of our objectives is to analyze how various patent characteristics are linked with the private value of the patent. We collected patent-wise information from IPO for all granted patents filed/applied between 1st January 1995 and 31st December 2002. The total number of patents applied at IPO by resident and non-residents during the sampling period was 69,658, out of which only 26,362 patents were granted. Furthermore, only 21,562 patents contained complete information on the renewal time and patent characteristics used in this study (Figure 1).

All patents are partitioned into subsets corresponding to technology areas using the Schmoch's (2008) classification (as updated in 2010 and 2011), which relies on the International Patent Classification (IPC) codes contained in the patent documents. The five major sectors: electrical, instruments, chemistry, mechanical, and "otherfield" are further subdivided into 33 sub-technology groups[1]. To avoid double-counting of patents, this study uses the first classification codes of each patent to determine the technology class.

Figure 1: Different stages of data collection from Indian Patent Office (IPO)



We bisect these 33 technology areas according to the definition of complex and discrete technologies suggested by Cohen et al. (2000) and Graevenitz et al. (2011) to assign 1 if it falls in the complex category and 0 if discrete (see Table 2).

[1] The detailed list of the IPC classes contained in each technology field can be found at www.wipo.int/ipstats/en/statistics/patents/pdf/wipo_ipc_technology.pdf

Table 2: Classification of technologies into discrete and complex innovations

Classification	Technology Area
Discrete (12)	Organic fine chemistry, Biotechnology, Pharmaceuticals, Macromolecular chemistry polymers, Food chemistry, Basic materials chemistry, Materials metallurgy, Surface technology and coating, Chemical engineering, Handling, Textile and paper machines, Furniture and games
Complex (21)	Electrical machinery apparatus and energy, Audio-visual technology, Telecommunications, Digital communication, Basic communication processes, Computer technology, Semiconductors, Optics, Measurement, Analysis of biological materials, Control, Medical technology, Environmental technology, Machine tools, Engines pumps turbines, Other special machines, Thermal processes and apparatus, Mechanical elements, Transport, Other consumer goods, Civil engineering

Out of the total sample of 21,562 patents, 49.55% (10,685) patents belong to the complex technology fields, and 50.44% (10,877) of the patents fall under discrete technology categories. As per our results, since there is a significant difference between the discrete and complex technologies with respect to the patent value estimation, we fitted models for both discrete and complex technologies separately. According to the ownership dummy variable, the share of non-resident patents is around 83 percent (18078) (and the number of resident patents is 3484). Next we discuss patent characteristics for which the data were collected from the IPO website.

3.2. Patent characteristics

In order to determine whether there are any observable indicia of a patent value or lack of value, we estimate the likelihood of renewal across a large number of variables. In particular, we examine the role of the following characteristics which may influence the likelihood of a patent owner failing to pay the maintenance fees: (a) number of claims, (b) family size, (c) technology scope, (d) grant lag, (e) the number of inventors listed in the patent (inventor size), and (f) ownership dummy for a foreign or Indian resident patentee. We now briefly describe each of these variables/patent characteristics:

(a) Claims: A patent has a bunch of claims that portray what is ensured by the patent. The principal claim explains the fundamental novel highlights of the innovation in their broadest structure, and the subordinate claims describe a feature of the innovation. In this article, we take the total number of claims to determine the renewal decision factor. The patentee intends to increase the claims as much as possible to get a maximum incentive from the innovation.

(b) Family size: A group of patents protecting the same innovation constitutes a 'family' (also called parallel patents). Filing and maintaining a patent in different countries is associated with high costs, and only a fraction of patents seek protection outside their home market. Therefore, the family size (the number of jurisdictions (patent offices) in which a patent is filed) indicates the importance of a patent.

(c) Technology scope: The examiner assigns each patent a 9-digit code based on the IPC classification system. We use the 4-digit subclass count in a patent to describe the technology scope—the broader the technology, the higher the count of the 4-digit subclass of a patent.

(d) Grant-lag: The grant lag is defined as the time elapsed between the filing and grant date of a patent. Harhoff and Wagner (2009) and Régibeau and Rockett (2010) find evidence of an inverse relationship between patent value and the grant lag. We investigate the impact of grant-lag on patent value in the Indian context.

(e) Inventor size: We use the inventor count given in the patent data to indicate the project's size and complexity (Gambardella et al., 2006).

(f) Ownership: A patent filed at IPO and assigned to India is called a resident patent (coded as 0), but if it is assigned to another country, then it is called a non-resident patent (coded as 1).

Table 3 outlines the usage of these patent characteristics in the existing literature. Descriptive statistics on the patent characteristics are presented in Section 5.1.

Table 3: Summary of the response variable (renewal level) and independent variables (patent characteristics) used in the regression models.

Variable	Description	References
Renewal level (RL)	Each patent is classified in one of the four categories (1, 2, 3, and 4) based on the number of years a patent has been renewed (see Table 1).	Reitzig (2004); Moore (2005); Bessen (2008)
Family Size (FS)	The number of jurisdictions a patent is filed in.	Kabore and Park (2019); Harhoff et al. (2003)
Number of Claims (NC)	Number of innovations claimed in a patent.	Reitzig (2004); Caviggioli et al. (2013)
Grant Lag (GL)	Time elapsed between filing and grant date.	Harhoff and Wagner, (2009)
Technology Scope (TS)	Number of technological domains a patent belongs to. Four-digit IPC-code captures the information.	Squicciarini et al. (2013); Lerner (1994)
Inventor Size (NI)	The number of inventors involved in a patent. It also measures the R&D size and scale of a patent.	Kiehne and Krill (2017)

4. Empirical Models

The response variable in our models is defined by the four-level ordered categorical variable that characterize the patent renewal life guided by India's renewal fee structure (referred to as "renewal level" in Table 1). Given that the dependent variable is divided into more than two categories with a meaningful sequential order, the most intuitive and popular choice of the model is an ordinal logit regression model which efficiently analyses the patent valuation with respect to different patent characteristics and technological domains.

4.1. Proportional odds model

A common approach for modeling such an ordinal response is to use the proportional odds model (POM) developed by McCullagh (1980), also known as the cumulative logit regression model. If the response variable Y (here, the renewal level) has J ordered categories ($J = 4$, as per Table 1), then the model is given by (Long and Cheng 2004)

$$\log\left(\frac{\Pr(Y \leq j|x)}{\Pr(Y > j|x)}\right) = \tau_j - x'\boldsymbol{\beta}, \quad j = 1,2,\ldots,J-1, \tag{1}$$

where j represents the renewal level (i.e., $j = 1,2,3$), $\boldsymbol{\beta}$ is the vector of regression coefficients corresponding to the input vector (i.e., the patent characteristics), and τ_j is the cutoff effect between response category boundaries. The negative and positive signs of $\boldsymbol{\beta}$ coefficients are interpreted similarly as in the OLS and binomial logistic regression. The proportional odds model assumes regression coefficient $\boldsymbol{\beta}$ to be the same across the three logit equations.

On several occasions, the proportionality assumption is violated, and thus, the results obtained are biased. One of the most popular method to test the proportionality assumption is proposed by Brant (1990), which uses an omnibus chi-square test. A significant test statistic would indicate that the parallel regression assumption has been violated, which happens to be the case here for a few patent characteristics. Results are presented in Section 5.2. Consequently, we adopted an alternative model, the Generalized ordered logit model (GOLM), suggested by Williams (2006; 2016).

4.2. The generalized ordered logit model

The main idea here is that both the intercept and the regression coefficient vector $\boldsymbol{\beta}$ (corresponding to the patent characteristics) can vary across the J categories of response (i.e., renewal level). The model statement is given by

$$\log\left(\frac{\Pr\,(Y \leq j|x)}{\Pr\,(Y > j|x)}\right) = \alpha_j - x_j'\boldsymbol{\beta_j}, \qquad j = 1,2, \dots, J-1, \tag{2}$$

where J is the number of outcome categories of the ordinal dependent variable, α_j if the relative cutoff effect for category j and $\boldsymbol{\beta_j} = (\beta_{j1}, \beta_{j2}, \ldots \beta_{jk})$ correspond to the regression coefficients with respect to the k independent variables (patent characteristics and technological indicators). Note that the proportional odds model (POM) is a special case of GOLM, where the regression parameter vector $\boldsymbol{\beta_j}$ are the same for each categorical level $j = 1, \dots, J-1$. The econometric model applied in this study simplifies the real-world process and contains the salient feature of patent valuation phenomena.

5. Empirical Results

We start by summarizing the data from various standpoints and then discuss the two logit models (POM and GOLM). We particularly focus on assessing technological domains in influencing the patent value measured via the "renewal level". The hypotheses listed in Section 2.2 are also tested and discussed here.

5.1. Descriptive statistics

The most basic summary (mean and standard deviations) of the patent characteristics for the samples in discrete and complex technologies are presented in Tables 4 and 5, respectively.

Table 4: Summary statistics and correlation matrix of patent characteristics for discrete technology patents

	Claims	Inventor size	Family size	Technology Scope	Grant lag
Claims	1				
Inventor size	0.02	1			
Family size	0.22	0.01	1		
Technology Scope	0.23	0.09	0.82	1	
Grant lag	-0.01	0.07	-0.08	-0.10	1
Mean	12.68	2.93	18.82	8.17	8.05
Std Deviation	12.21	2.06	20.48	11.35	2.58
Observations	10,685	10,685	10,685	10,685	10,685

Source: Authors' calculation.

Table 5: Summary statistics and correlation matrix of patent characteristics for complex technology patents

	Claims	Inventor size	Family size	Technology Scope	Grant lag
Claims	1				
Inventor size	0.07	1			
Family size	0.25	0.02	1		
Technology Scope	0.23	0.08	0.77	1	
Grant lag	-0.06	0.07	-0.14	-0.11	1
Mean	13.63	2.32	15.81	5.57	8.31
Std Deviation	13.62	1.72	19.18	6.13	2.44
Observations	10,877	10,877	10,877	10,877	10,877

Source: Authors' calculation.

A few notable findings are as follows. The average grant lag for discrete technology patents filed during 1st January 1995 and 31st December 2002 at IPO is 8.05 years, whereas, in the complex technology category, the grant lag is slightly higher (8.33 years). In recent times, India's average grant lag has reduced to 64 months (5 years), which is still higher than 22 months in China and European patent offices and 24 months in the US (WIPO, 2019).

The patenting strategies are not quite the same for discrete and complex innovation. For example, in complex/cumulative innovation, not all complementary parts of innovation should be patented in every office to exclude possible imitation. Along these lines, the average family size is bigger in discrete (18.82) than in complex (15.81) innovations. Moreover, the presence of overlapping patents in cumulative innovation could give motivations to raise the number of claims, as expanding the number of claims builds the odds of the patent to be applicable to future improvements of a jointly held innovation (Berger et al., 2012). The descriptive statistics also validates Berger et al., (2012) argument on the average number of claims in the complex innovations (13.63) being higher than the discrete innovations (12.68). In contrast, patents filed at the Japanese Patent Office (JPO) and European Patent Office (EPO) have average claims of 10.4 and 14.7, respectively. In China, the average number of claims is 8.1 (IP5 Statistics Report, 2017). Broad claims suggest that the patent could successfully block the access to incremental innovation based on original technology, and thus, it is one of the important determinants of patent value.

The pairwise correlation matrices in Tables 4 and 5 show that no two patent characteristics are highly linearly related. We also computed the VIF (variance inflation factor) values (see Table 6) which are very small (close to 1) and hence reject multicollinearity among the predictors.

Table 6: Variance inflation factor (VIF) values of the patent characteristics for all 21,562 patents

Variable	VIF	Tolerance (1/VIF)
Technology Scope	1.69	0.59
Family Size	1.65	0.6
Claims	1.04	0.96
Inventor Size	1.03	0.97
Grant Lag	1.01	0.99
Mean VIF	1.29	-

Source: Authors' calculation.

We now look at the distribution of patents and the renewal behavior. Table 7 presents the empirical distribution of patents according to the renewal level for discrete, complex, and combined categories. The table reveals a somewhat increasing trend, which is expected because if someone has filed a patent, then the patent is likely to be worthy enough to be renewed for at least a few years. Some studies have found that the expected renewal life of a patent is shorter in developing countries than developed countries (e.g., Gupeng and Xiangdong, 2012). This may be attributed to the fact that a bulk of innovations are of incremental value.

Table 7: Distribution of patents in different response categories

Patent life	Renewal level	Discrete (%)	Complex (%)	Combined (%)
0 to 6th year	1	16.98	16.87	17.14
7th year to 10th year	2	12.37	12.09	12.66
11th year to 15th year	3	27.28	26.91	26.75
16th year to 20th year	4	43.37	44.13	43.46
	Total patents	100 (10,685)	100 (10,877)	100 (21,562)

Source: Authors' calculation.

Further analysis of patents with respect to the major technological fields reveals that electrical patents are more likely to be maintained by their owners. In contrast, mechanical patents expire more often at an early age (see Table 8). Moreover, a high percentage of patents belonging to instruments and "otherfield" have never been renewed by their owners'. Around 17.14% of the total patents across different technologies have never been renewed, and 56.5% of patents expire before the 16th year. This implies most of the learning from the patent happens in the early stage of the patent application. Thus, a significant number of patents expire without completing 20 years of the lifetime.

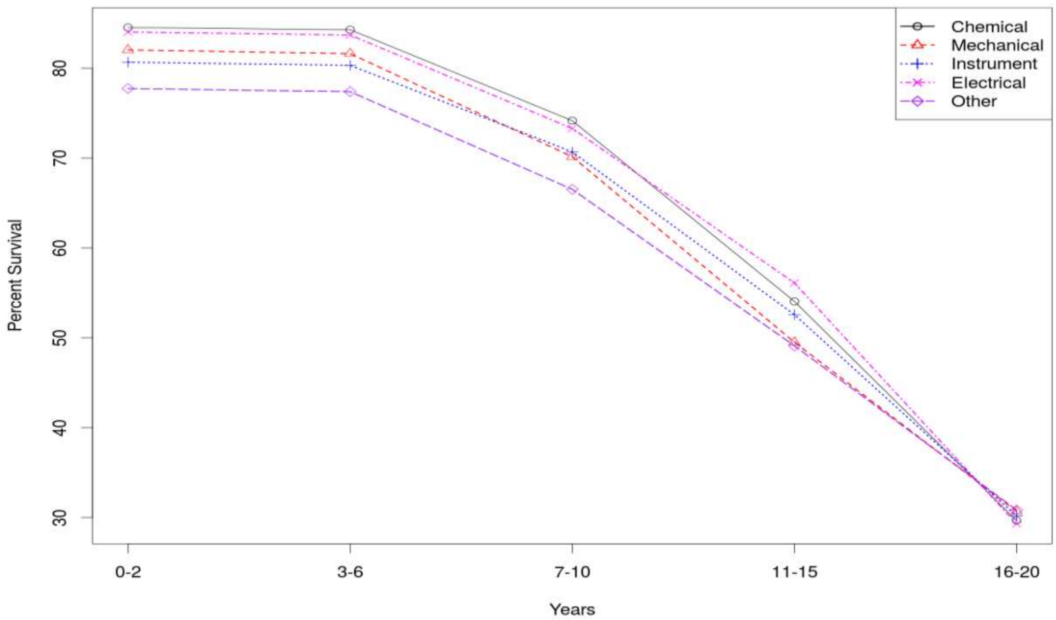
Table 8: Patent survival rate in different technology fields

	Never Renewed	3rd to 6th	7th to 10th	11th to 15th	16th to 20th
Electrical	15.96	0.39	12.44	23.45	47.76
Instruments	19.32	0.43	11.99	25.63	42.64
Chemistry	15.46	0.29	12.01	27.12	45.12
Mechanical	17.95	0.51	14.05	29.43	38.06
Others	22.25	0.45	14.04	26.18	37.19
Total	18.18	0.38	12.66	26.75	43.46

Note: All values are in the percentage of total patents for each category.

Figure 2 depicts the patent survival rate for different technology categories. It is clear from Figure 2 that the number of patents that expire between 0-2 years of patent life is highest in "otherfield" category and lowest in chemistry. As expected, the differences in patent survival rates decline across the technology as it approaches the 16th year of their life.

Figure 2: Patent Survival Curve for Different Technology Group



5.2. Ordered logit regression model results

Here, we fit the proportional odds model (POM) for the combined sample to quickly check hypothesis H1 (difference between the impact of discrete and complex technological innovations on patent values).

Table 9: Regression coefficients of proportional odds model for the combined sample

Explanatory variables	Coefficient
Claims	0.00 (0.02)
Inventor size	0.33*** (0.03)
Family size	0.21*** (0.02)
Technology scope	-0.08*** (0.03)
Grant lag	0.78*** (0.05)
Ownership	0.17*** (0.17)
Complex	-0.06** (0.03)
Cut1	0.95 (0.12)
Cut2	1.69 (0.12)
Cut3	2.84 (0.12)
Observations	21,562

Notes: Here, ***, **, and * denote $p < 0.01$, $p < 0.05$ and $p < 0.10$, respectively.

It is clear from Table 9 that the "complex" dummy has a significant negative coefficient, that is, discrete and complex technology innovations are significantly different, and discrete innovations have a higher patent value than the complex technologies (reject $H1_0$). As a result, we study the technology innovations separately for the two classes (see Table 10). We also conducted a Brant test (1990) for validating the parallel regression assumption in POM.

Table 10: Regression coefficients of proportional odds model and Brant test results of discrete and complex technology

	Discrete Technology		Complex Technology	
Explanatory variables	Coefficient	Brant test	Coefficient	Brant test
Claims	-0.04** (0.03)	2.57	0.03 (0.02)	23.89***
Inventor size	0.37*** (0.04)	5.63*	0.29*** (0.04)	6.74**
Family size	0.18*** (0.03)	11.87***	0.23*** (0.03)	3.39
Technology scope	-0.08** (0.03)	2.41	-0.05 (0.04)	18.99***
Grant lag	0.85*** (0.06)	220.91***	0.71*** (0.07)	342.87***
Ownership	0.23*** (0.05)	39.16***	0.09 (0.06)	3.67
Cut1	1.03 (0.16)		0.91 (0.18)	
Cut2	1.74 (0.16)		1.67 (0.18)	
Cut3	2.91 (0.16)		2.80 (0.18)	
Observations	10,685		10,877	

Notes: Here, ***, **, and * denote $p < 0.01$, $p < 0.05$ and $p < 0.10$, respectively.

A significant test statistic provides evidence that the parallel regression assumption has been violated (more specifically, inventor size, family size, and ownership dummy for discrete technology; and claims, inventor size, technology scope, and grant lag for complex technologies). The large values of chi-square test statistics (shown in Table 10) suggest that several explanatory variables violate the proportionality (or parallel) assumption. Thus, we investigate the alternative model: generalized ordered logit model (GOLM).

5.3. Generalized ordered logit regression model results

GOLM assumes that the regression coefficient vector $\boldsymbol{\beta}_{\boldsymbol{j}}$ may vary across different logit equations with respect to different "renewal levels" $j = 1,2,3$. The results are presented in three panels corresponding to $P(Y \leq 1)$, $P(Y \leq 2)$, and $P(Y \leq 3)$[2]. That is, the first panel analyzes the model for "renewal level" category 1 vs. 2, 3, and 4; the second panel presents the regression coefficients for "renewal level" category 1, 2 vs. 3, 4; and so on. For a quick check, we fitted this model for the complete data set using complex vs. discrete technology dummy and found consistent result (as in Table 9) that the two innovation categories are significantly different, and the complex innovations in India are less valuable as compared to discrete innovations. Subsequently, we analyze the two technologies separately. Tables 11 and 12 present the model results for complex and discrete technologies respectively.

Table 11: Analysis of Generalized ordered logit regression model (GOLM) for complex innovation (Reference category: computer technology)

	1 vs 2 3 4	1 2 vs 3 4	1 2 3 vs 4
Explanatory variables	Coefficient	Coefficient	Coefficient
Claims	-0.05 (0.04)	-0.02 (0.03)	0.05* (0.03)
Inventor size	0.38*** (0.06)	0.32*** (0.05)	0.23*** (0.05)
Family size	0.24*** (0.04)	0.29*** (0.04)	0.23*** (0.03)
Technology scope	0.06 (0.06)	0.00 (0.05)	-0.16*** (0.04)
Grant lag	-0.30*** (0.10)	1.23*** (0.09)	0.76*** (0.08)
Ownership	0.01 (0.08)	0.01 (0.07)	0.13* (0.07)
Electrical machinery, apparatus, energy	-0.17 (0.11)	0.03 (0.10)	-0.13*** (0.09)
Audio-visual technology	0.12 (0.14)	0.21** (0.11)	0.30 (0.10)
Telecommunications	0.22* (0.12)	0.38*** (0.11)	0.53*** (0.10)
Digital communication	0.11 (0.19)	0.42*** (0.15)	0.67*** (0.14)
Basic communication processes	-0.08 (0.20)	0.48*** (0.18)	0.39*** (0.15)
Semiconductors	-0.09 (0.24)	0.36* (0.20)	0.20 (0.18)
Optics	-0.14 (0.20)	0.07 (0.17)	0.10 (0.16)
Measurement	0.15 (0.14)	0.34*** (0.12)	0.13 (0.11)
Analysis of biological materials	-0.53** (0.24)	-0.21 (0.20)	-0.21 (0.21)
Control	0.21 (0.23)	0.31* (0.18)	0.38** (0.16)
Medical technology	-0.34*** (0.12)	-0.11 (0.11)	-0.15 (0.10)
Environmental technology	0.22 (0.19)	0.30*** (0.16)	-0.13 (0.15)
Machine tools	0.06 (0.14)	0.31*** (0.12)	0.11 (0.11)
Engines, pumps, turbines	0.17 (0.14)	0.26** (0.11)	-0.12 (0.11)

[2] Precisely jth panel gives cumulative result in which categories 1 through j have been recoded to 0 and categories j+1 through M have been recoded to 1 (Williams 2006).

Other special machines	-0.19 (0.13)	0.07 (0.11)	-0.09 (0.11)
Thermal processes and apparatus	-0.12 (0.16)	0.22 (0.14)	0.12 (0.13)
Mechanical elements	-0.02 (0.14)	-0.05 (0.12)	-0.21* (0.11)
Transport	0.15 (0.14)	0.01 (0.11)	-0.44*** (0.11)
Other consumer goods	-0.13 (0.16)	-0.03 (0.14)	-0.16 (0.13)
Civil engineering	-0.27* (0.15)	-0.02 (0.13)	-0.11 (0.13)
_cons	1.28*** (0.26)	-3.02*** (0.23)	-2.78*** (0.22)

Notes: Here, ***, **, and * denote $p < 0.01$, $p < 0.05$ and $p < 0.10$, respectively. Numbers in parentheses are standard errors.

Table 12: Analysis of Generalized ordered logit regression model (GOLM) for discrete innovation (Reference category: pharmaceutical)

	1 vs 2 3 4	1 2 vs 3 4	1 2 3 vs 4
Explanatory variables	Coefficient	Coefficient	Coefficient
Claims	-0.04* (0.03)	-0.04* (0.03)	-0.04* (0.03)
Inventor size	0.33*** (0.04)	0.33*** (0.04)	0.33*** (0.04)
Family size	0.20*** (0.03)	0.20*** (0.03)	0.20*** (0.03)
Technology scope	-0.04 (0.04)	-0.10*** (0.04)	-0.14*** (0.04)
Grant lag	-0.05 (0.09)	1.31*** (0.08)	0.97*** (0.07)
Ownership	0.10 (0.07)	0.13** (0.06)	0.47*** (0.06)
Organic fine chemistry	0.00 (0.08)	-0.05 (0.07)	-0.21*** (0.07)
Biotechnology	0.19** (0.10)	0.19** (0.10)	0.19** (0.10)
Furniture, games	-0.65*** (0.15)	-0.65*** (0.15)	-0.65*** (0.15)
Macromolecular chemistry, polymers	-0.17** (0.08)	-0.17** (0.08)	-0.17** (0.08)
Food chemistry	-0.13 (0.15)	-0.05 (0.13)	0.21* (0.13)
Basic materials chemistry	0.03 (0.07)	0.03 (0.07)	0.03 (0.07)
Materials, metallurgy	0.14* (0.08)	0.14* (0.08)	0.14* (0.08)
Surface technology, coating	-0.05 (0.11)	-0.05 (0.11)	-0.05 (0.11)
Chemical engineering	-0.02 (0.07)	-0.02 (0.07)	-0.02 (0.07)
Handling	-0.21** (0.09)	-0.21** (0.09)	-0.21** (0.09)
Textile and paper machines	-0.26*** (0.10)	-0.37*** (0.09)	-0.46*** (0.09)
_cons	0.96*** (0.23)	-2.57*** (0.20)	-3.20*** (0.19)

Notes: Here, ***, **, and * denote $p < 0.01$, $p < 0.05$ and $p < 0.10$, respectively. Numbers in parentheses are standard errors.

The second hypothesis of the paper is to find the impact of readable patent characteristics on the value indicator of the patent. Some of this study concerning the second hypothesis suggests a significant impact of patent level characteristics on the value of the patent. A few observations from Tables 11 and 12 are as follows. (i) The coefficients of inventor size are positive across the three panels (corresponding to the renewal level cutoff), suggesting that a patent with many inventors and large family size is more likely to be maintained to a full term in both discrete and complex innovations. Since patents are territorial in nature, the invention is only protected in countries where patentees see the potential benefits. The existence of a patent in one country has no meaning in the legal system of other countries. The theoretical argument has been well established in the literature (Basberg, 1987; Putnam, 1996; Lanjouw et al., 1998). Reitzig (2004) conducted interviews with patent attorneys that confirmed that a patent's value is associated with the patent family size. Our study in the Indian context finds the positive impact of family size on the patent's renewal life. This implies that patents in other countries of the same invention are effective for identifying valuable patents.

(ii) The impact of the number of claims on the patent value is negative and significant in the discrete technology category, whereas it is found positive in a complex technology category. The result obtained reveals different patenting strategies in the discrete and complex technology category. For instance, overlapping patents in the cumulative/complex innovation provides an incentive to raise the number of claims, as increasing the number of claims raises the chance of the patent to be relevant to future developments of a jointly held technology (Berger et al. 2012).

(iii) Technology scope coefficients in both discrete and complex technology samples have a negative sign. This implies that patents having broader technology scope are less likely to fall in the higher value category. It also suggests that patent breadth, an indicator of technology broadness in India, is not as important as it is found in the developed countries context (Putnam 1996). The patent with higher grant lag is more likely to fall in the high-value category in both samples.

(iv) We further test the third hypothesis that says any differences in the value of resident patents in both discrete and complex technology categories. Foreign-owned patents (non-resident) in discrete and complex technology categories have a higher value than domestic patents. The greater difference being that non-resident patents are more likely to have a higher value in the discrete category than complex patents. The overall model for ownership of the patent also finds similar results.

(v) Returning to the study’s main focus, we now discuss the effect of technological domains on the value of patents measured via its renewal length. In the discrete technology group, we used pharmaceutical as the technology baseline for the regression (randomly chosen). Biotechnology, food chemistry, and material metallurgy patents are more valuable than the baseline category. On the other side, organic fine chemistry; macromolecular chemistry polymers; handling; textile, and paper machines are less valuable than the baseline category. We also find that many technology fields -furniture, games; basic materials chemistry, chemical engineering; and surface technology coating are insignificant and have similar impact on patent value as compared to the baseline category.

Among the complex technology category, we selected computer technology as the base category. It shows that Audio-visual technology; telecommunications; digital communication; basic communication processes, semiconductors, measurement; Environmental technology; Machine tools; Engines, pumps, turbines; control; are more valuable compared to the baseline category. The greatest difference is that semiconductors, measurement; Environmental technology; Machine tools; Engines, pumps, turbines are more likely to fall in panel 2; and audio-visual technology; telecommunications; digital communication; basic communication processes; control; panel 3 (higher value category).

We also find that electrical machinery, apparatus, energy; analysis of biological materials; medical technology; mechanical elements; transport is less likely to fall in the higher value category. The greatest difference is that analysis of biological materials and medical technology patents is more likely to fall in the lower value category than the baseline category. Table 13 summarized the results of both discrete and complex technology field.

Table 13: Summary of combined results

Discrete (Base category: Pharmaceutical)	Sign of significance	Complex (Base category: Computer technology)	Sign of significance
Biotechnology	(+) significance	Audio-visual technology	(+) significance
Food chemistry	(+) significance	Telecommunications	(+) significance
Materials, metallurgy	(+) significance	Digital communication	(+) significance
Handling	(-) significance	Basic communication processes	(+) significance
Organic fine chemistry	(-) significance	Semiconductors	(+) significance
Textile and paper	(-) significance	Measurement	(+) significance
Furniture, games	(-) significance	Environmental technology	(+) significance
Macromolecular chemistry, polymers	(-) significance	Machine tools	(+) significance
		Engines, pumps, turbines	(+) significance
		Analysis of biological materials	(-) significance
		Medical technology	(-) significance
		Mechanical elements	(-) significance
		Transport	(-) significance
		Civil engineering	(-) significance

Source: Authors' own calculation

For a benchmark comparison, we also fitted the GOLM model to the full data containing 21,562 patents and 33-technological categories (with pharmaceutical as the reference category[3]). The

[3] Our generalized ordered regression model automatically selects the reference category to the last technology group in the model. However, choosing any other technological field in the place of pharmaceutical will not alter the basic outcomes of the regression (Williams, 2016).

results are summarized in Table 14. The general observation here is that electrical and communication patents are more likely to be maintained than pharmaceutical patents. Pharmaceutical patents are more likely to be maintained than medical technology and less likely to Biotech patents. Moore (2005) found that biotech patents are more valuable than drug, agricultural, and organic compounds patents in the US. The present study reveals that biotech patents are more likely to be maintained than patents belonging to simple devices in India. This can be less expensive in terms of R&D.

Table 14: GOLM analysis by technology sub-categories (reference category: pharmaceutical)

	Renewal level 1		Renewal level 2		Renewal level 3	
Variables	Coefficient	Std.Err.	Coefficient	Std.Err.	Coefficient	Std.Err.
Electrical machinery apparatus	-0.02	0.08	-0.136*	0.08	-0.162**	0.08
Audio-visual tech	0.233**	0.12	0.061	0.1	0.248***	0.09
Telecommunications	0.388***	0.09	0.253***	0.09	0.490***	0.08
Digital communication	0.225	0.17	0.263*	0.14	0.635***	0.13
Basic communication	0.007	0.19	0.334**	0.17	0.360***	0.14
Computer technology	0.088	0.1	-0.178**	0.09	-0.051	0.09
Semiconductors	0.166	0.16	0.166	0.16	0.166	0.16
Optics	0.008	0.14	0.008	0.14	0.008	0.14
Measurement	0.272**	0.11	0.147	0.11	0.065	0.1
Analysis of biological materials	-0.323*	0.17	-0.323*	0.17	-0.323*	0.17
Control	0.277*	0.15	0.277*	0.15	0.277*	0.15
Medical technology	-0.197***	0.09	-0.305***	0.09	-0.211**	0.09
Organic fine chemistry	0.049	0.08	-0.01	0.07	-0.122*	0.07
Biotechnology	0.253***	0.09	0.253***	0.09	0.253***	0.09
Macro-molecular polymer	-0.053	0.08	-0.053	0.08	-0.053	0.08
Food chemistry	-0.156	0.15	-0.005	0.13	0.227*	0.12
Basic material chemistry	0.125*	0.07	0.125*	0.07	0.125*	0.07
Materials, metallurgy	0.237***	0.07	0.237***	0.07	0.237***	0.07
Surface technology	0.059	0.11	0.059	0.11	0.059	0.11
Chemical engineering	0.106	0.07	0.106	0.07	0.106	0.07
Environmental tech.	0.298*	0.18	0.104	0.15	-0.212	0.14
Handling	-0.101	0.09	-0.101	0.09	-0.101	0.09
Machine tools	0.08	0.09	0.08	0.09	0.08	0.09
Engines pumps turbines	0.292**	0.12	0.125	0.1	-0.168	0.09
Textile and paper	-0.122	0.09	-0.230***	0.09	-0.303	0.09
Other special machines	-0.136	0.09	-0.136	0.09	-0.136	0.09
Thermal processes	0.041	0.11	0.041	0.11	0.041	0.11
Mechanical elements	0.072	0.12	-0.198**	0.1	-0.246	0.1
Transport	0.245**	0.11	-0.139	0.09	-0.488	0.1
Furniture, games	-0.565***	0.15	-0.565***	0.15	-0.565	0.15
Other consumer goods	-0.181*	0.11	-0.181*	0.11	-0.181	0.11
Civil engineering	-0.206**	0.11	-0.206**	0.11	-0.206	0.11
Constant	1.368***	0.09	-0.575***	0.08	-1.398	0.08
LR chi square	2162.24***					
Number of observations	21,562	21,562	21,562	21,562	21,562	21,562

Note: Here, ***, **, and * denote $p < 0.01$, $p < 0.05$ and $p < 0.10$, respectively. Reference category is pharmaceutical

6. Conclusion

Our objective in the chapter was to approach the problem from a developing country perspective that remained understudied in the literature. Hence, our methodological approach and results reinforce that patent's characteristics can be analysed to capture if it is "valuable". Given the challenges and importance of securing the grant and clearing uncertainty of property rights, it is important to examine whether inventor composition plays a role (Drivas and Kaplanis, 2020). Singh and Fleming (2010) and Schettino, Sterlacchini, and Venturini (2013)) find that bigger inventors size deliver more significant and higher quality innovation than single innovators; further, innovation developments are bound to come from cooperation. Agiakloglou et al. (2016) have shown that inventions by a team of inventors are also more likely to be commercialized. We in this study find that number of inventors is positively associated with the higher category patent value across the discrete and complex technology. This implies that R&D size irrespective of technology field influences the patent value.

The patent family that refers to the subsequent inventions of the same technological inventions and the patent collections of related patents applied in different countries are also positive and significant in both discrete and complex technology filed. This study used the patent family, where all documents have exactly the same priority numbers. The previous study on the economic valuation of patents finds patent family size a major influencing factor on the economic value of the patent portfolio at the firm level. Albeit patent application in another nation would bring about extra expenses, it is expected that the patentee will acknowledge this to get the market position for the development (Neuhäusler & Frietsch, 2013).

In contrast, a technological scope is negatively associated with high-value patents in both discrete and complex technology samples. The theoretical literature says that the correlation between technological scope and value could be hypothesized to be negative, positive, or zero depending on the two effects' relative strength (Omland, 2011). The grant lag on the patent value is positive and significant; this can be interpreted by saying that patents having higher value are more likely to face delays in the grant.

Sectors characterized by discrete product technologies are typically drugs, chemicals, steel, and metal products. In contrast, examples of complex product technologies are electronics, software, and semiconductors values estimated separately in this study. We find that patenting strategy and the value differ significantly between discrete and complex technology in India. As argued in the literature, complex technology is inherently difficult to replicate, and therefore the value of a patent is 'in this respect' is lower. However, this study using a more disaggregated technology field reveals that not all complex technologies patents are less valuable. Similarly, not all discreet patents are valuable. For a better understanding of the discrete and complex technology value, we subdivided our technology class. In the discrete category, biotechnology, material metallurgy, and food chemistry are more valuable.

The combined regression result suggests that the consumer electronic industry, audio-visual tech, telecommunications, digital communication, and basic communication have a higher value in the complex technology categories. The results also reveal that only a few technologies have significant value while a large number of technologies are either having a lesser value or no value at all. In the combined repression result, we find that the foreign patents (non-resident patents) are more likely to have a higher value than domestic patents. This result hold for both the sample of discrete and complex technology patents. Given the lower R&D followed by non-robust innovation capability across the technology class in India could be the major reason for having lower quality patents. Thus, to achieve the technological progress emerging economy like India needs to improve the quality of the innovation across the technology field.

Our findings have implications for the R&D managers and policymakers. The recognizable indicia of value, importance, or probability of renewal give the knowledge to help the patent law reforms. For example, the value of patents concentrated in few technological fields suggests that the law needs to be tailored to address these specificities. Further, to weed out low-quality patents from the system, the patent office needs to make certain changes. For example, the Indian patent office should strategically increase the renewal fee for commercially utilized patents. One of the important observations of this article is that India's average patent life is around 12 years. Since most of the patentee's learning and commercial benefits occur during the initial years, the maintenance fee schedule needs to be revised while accounting for such aspects. The higher support fee toward the initial stage over the long run may encourage more rapid transfer of the technologies to the public domain. Further, strategic revision of the fee schedule will also help in weeding-out the low-quality patents from the system.

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