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The relation between knowledge accumulation and technical value in interdisciplinary technologies

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ABSTRACT

A challenging task in technology management is the early identification of potentially valuable inventions. The depth, breadth, and age of the body of knowledge underlying an invention are theorized to indicate the technical experience of the sectors relevant to the invention. Prior research assessing this body of knowledge have focused on the content of knowledge through bibliometric and semantic indicators but neglected the structural role of knowledge underlying a patent. Focusing on technical value, we propose a new metric that accounts for the structural maturity of knowledge preceding an invention. Using a composite patent value and multiple generation citation networks, we compare knowledge accumulation in 60 originating patents for inventions in the energy-harvesting sector over a 100-year observation period, resulting in an analysis of 1900 patents. The results indicate that our metric for knowledge accumulation reveals a statistically significant correlation between the structural maturity of the knowledge that contributes to the specific invention and technical value of a patent. The structural view on knowledge accumulation explains at least as much variance in the composite value of patents as current knowledge content-based indicators, and, unlike those indicators, is useful as a leading rather than lagging indicator. This metric can therefore find application in technology forecasting as a forward indicator of the technical value of inventions.

1. Introduction

The need to identify superior inventions has fuelled studies in patent valuation techniques. These techniques value a patent based upon the importance the patent holds for other inventions (Albert et al., 1991; Carpenter et al., 1981; Hall et al., 2005; Harhoff et al., 1999) or the commercial strategy of the company that applies the patent (Baron and Delcamp, 2012; Harhoff et al., 2003; Lerner, 1994). Even though the limitations of using patent indicators for assessing patent value have been raised (Reitzig, 2004; Van Zeebroeck, 2011; van Zeebroeck and van Pottelsberghe de la Potterie, 2011), the increasing number of studies in this domain point to the fact that patents can be valuable sources of information on the *potential* value of inventions.

Patent valuation techniques may broadly be divided into single-level relationship and multiple-level relationship based methods. Single-level relationship methods use surface-level metadata about the patent (such as citations, claims, classifications etc.) while multiple-level relationship methods consider indirect factors that affect patent value (such as knowledge background and technological complexity). While single-level relationship techniques are useful in understanding a broad picture of the sector, they can fail to differentiate the technical feasibility of inventions that perform similar functions. For example, citation counts will reveal that thin-film photovoltaics based on Cd-Te technology have been referenced more often than Ga-As technology; however, within Cd-Te technologies, citation counts alone cannot indicate if physical-vapour deposition based inventions are more feasible than chemical-vapour deposition based inventions. Valuation techniques that utilise single-level metadata about the patent do not account for the differences in the knowledge content between inventions. It is also important to note that a majority of these techniques are post hoc in their predictive ability as they use indicators that are time dependent. For example, citations received by the patent and its family size may increase with time. Patent renewal decisions come into force only after a certain number of years after the grant of the patent. For a valuation technique to be practical and useful, one should be able to apply it at the early stage of the invention. However, the information used by patent-based indicators becomes available about 18 months after the filing date of the patent (Reitzig, 2004). This time frame may vary based on the patent office. Hence, these techniques cannot be used to evaluate an invention when the patent in question is new.

The use of references may be seen as an exception to this approach. References, also known as backward citations, describe the knowledge

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upon which the invention is based. The idea is that the more references a patent has and the more mature those references are, the likelihood of the technical viability of the patent increases. The patent will have a higher probability of being implemented into products (Beierlein et al., 2015; McNamee and Ledley, 2012; McNamee and Ledley, 2013). Nerkar (2003) showed that it is important that both old and new knowledge are applied toward the target patent, though. The author argues that recombining knowledge from broad time periods enables uncovering of valuable knowledge that is forgotten or whose time has not come yet. The age of the knowledge indicates that it has had the time to be tested and perfected. Nonetheless, it is generally true that the age of the knowledge preceding an invention is an essential factor that may have an effect on the technical value of inventions (Karlsson and Åhlström, 1999).

There are at least two significant problems with a reference-based approach to evaluating the technical value of a patent. First, the amount of knowledge in any domain will always increase with time. If the age of knowledge preceding the target patent is referenced to the registration date of the target patent, then newer inventions by definition, will always refer to more mature knowledge. Yet, it may not be true that the newer patent is more technically viable at its date of registration than the older patent at its date of registration. Second, scholars have argued that one needs to consider the relationship with patents that have an indirect effect on the target patent. As such, they have tried to define these indirect relationships and their effect on patent value. Such thinking has given rise to a structural view of inventions.

The knowledge structure of an invention is comprised of interconnected and interdependent knowledge elements. Scholars have argued that the technological background, which makes up the knowledge structure of an invention, is an important indicator of its value (Harhoff et al., 2003; Hu et al., 2012; Lin et al., 2007). In prior studies, authors used patents' immediate references as its knowledge base. Hu et al. (2012) included two generations of references to include the influence of technological complexity on the value of the invention. Bosworth (2004), on the other hand, included many more generations of references in his study to demonstrate that such structures can be used to explore the ancestral roots of a patent. Ellis et al. (1978) drew out a similar patent citation network to study the important milestones in a technological field. It is unclear how many generations of citations were included in their study. A partial structure cannot give a complete view of the influencing factors of patent value. This research considers the complete knowledge structure of an invention by including all the generations of references in evaluating the patent value. In order to account for the maturity of the complete knowledge structure, we propose a new indicator to measure knowledge accumulation (KA) in a patent citation network. We use this new indicator to distinguish between high value and low value patents. We compare our method with some of the other known patent evaluation techniques given in literature.

This article is organized as follows. Section 2.1 describes the literature on existing patent valuation techniques. Section 2.2 explains knowledge accumulation and leads to our hypothesis. Section 3 outlines the methodology employed, with Section 3.1 describing the process of constructing the patent citation network and Section 3.2 describing the derivation of KA based on that knowledge network. Section 3.3 describes the calculation of composite patent value. Section 4 describes our data followed by a discussion of results in Section 5. Finally, Section 6 presents the conclusions and recommendations for future study.

2. Patent valuation

2.1. Existing patent valuation methods

Patent analysis, which probably started in legal firms as a prior-art search, has now found application as a management tool. As a management tool, patent analysis informs managers about the competitive landscape of the technology (Choe et al., 2013), technological trends of a sector (Wu and Leu, 2014), potential collaborators (Lee, 2010), infringement possibilities (Reitzig, 2004), and future product development pathways (Su et al., 2009). The literature contains different techniques to assess patents to meet these purposes. These techniques may be broadly divided into bibliometric approaches and content-based approaches. Content-based analysis uses text-mining techniques such as text segmentation, summary extraction, and co-word analysis to detect technological trends (e.g. see Gerken and Moehrle, 2012; Tseng et al., 2007; Yoon et al., 2011). Bibliometric approaches, on the other hand, analyse patent value indicators such as citation counts (Carpenter et al., 1981; Verspagen, 2007), claims (Baron and Delcamp, 2012; Lerner, 1994), patent life (Bessen, 2008), family size (Harhoff et al., 2003; Sternitzke, 2009), processing time (Lin et al., 2007) and other metrics using statistical and mathematical techniques.

Many companies hold a patent portfolio rather than a single patent. To understand the value of a patent portfolio, the evaluation methods assess the portfolio from bibliometric-technological and economic-strategic perspectives (Grimaldi et al., 2015) in order to manage the portfolio strategically and optimize its full potential. Whether the analyst is considering the value of a particular patent or a patent portfolio, the analyst is typically concerned with two forms of value. They consider the commercial value of market transactions (Hall et al., 2005) with respect to internal business strategies (Harhoff et al., 2003). Commercial value is the perceived value of the invention in the market and depends on various factors such as the ability of the company to market it, market conditions, and the socio-economic environment. The technical value on the other hand is associated with the practical realization of the technology described by the patent at a commercial scale. The technical value is generally revealed through the importance of the patent to the implementation of successive technologies (Carpenter et al., 1981; Harhoff et al., 1999). The technical value results from the maturity of the technology.

This research focuses on assessing the technical value of an invention. We focus on technical value because inventions employing highly mature technologies generally result in successful products (Beierlein et al., 2015; McNamee and Ledley, 2012; McNamee and Ledley, 2013) and find application in future technologies, thus likely demanding a higher net present commercial value. Different techniques have been demonstrated to evaluate the technical value of an invention. These measures have attempted to consider the underlying technical base of a patent rather than its surface-level metadata alone. Hu et al. (2012) used indicators based on a patent citation network, also termed an "ego patent citation network". Hu et al. (2012) defines the *Technical Interest Index* (TII) of a patent as an indicator of the innovative density of the technological knowledge flow. It is measured as the squared root of the total number of citations of its references.

$$\mathrm{TII} = \sqrt{\mathrm{CIT}} \tag{1}$$

where CIT denotes the total number of citations received by the references of patent A. Hu argues that a patent's technical value reflects its technological knowledge base, knowledge flow, and technological complexity.

The technical value of an invention has also been defined through its "basicness" or its closeness to science. Trajtenberg (1997) suggests that "basicness" can be measured through the following equation:

$$\mathrm{IMPORTB} = \mathrm{NCITED} + \lambda \sum_{j=1}^{\mathrm{ncited}} \mathrm{NCITING}_{A-1,j} \tag{2}$$

where NCITED is the number of patents cited (references) by the target patent A, λ is a discount factor ($0 < \lambda < 1$) meant to down weight the second-generation patents, $A - 1$ indicates the cited patents, and NCITING is the number of patents citing the originating patent. In other words, NCITING is the citations received by the references of the target patent. IMPORTB reflects the extent to which a given patent stands on a wide base of previous inventions that are themselves important. Trajtenberg argues that more basic patents would have fewer important predecessors and therefore lower values of IMPORTB. Academic patents are considered more basic in nature. Such patents, while introducing new or radical knowledge, do not result in commercial products immediately (Czarnitzki et al., 2009) as the technology is not mature enough yet. This indicates a nascent level of research/knowledge underlying the invention.

Narin (1993) uses *technology cycle time* (TCT) to determine the length of time it takes a firm to use a new technology. It is measured as median age of the patents cited by a given patent. A shorter TCT indicates a higher patenting activity in the area implying higher technological strength. Bierly and Chakrabarti (1996) showed that a high knowledge base level in a firm will lead to faster technology cycle time by allowing members of the firm to better understand and interpret external advances in the field and allowing the firm to combine new technologies effectively with other complementary technologies.

Trajtenberg (1997) describes the value of a patent through its *Originality and Generality*. Originality is a measure of the technological roots of a patent. A large "Originality" value indicates broader technological roots of the underlying research (Trajtenberg, 1997). The idea behind this measure is that highly original research is an outcome of coming together of divergent ideas. This relationship is expressed as:

$$\mathrm{ORIGINAL} = 1 - \sum_{m=1}^{M} \left(\frac{\mathrm{NCITED}_m}{\mathrm{NCITED}} \right)^2 \tag{3}$$

where m is the index of patent classes, and M the number of different classes to which the cited patents belong. NCITED is the total citations made by patent A and NCITED_m is the citations made in each patent class m. Originality is a measure of the diversity of the knowledge roots of a patent and not necessarily of the quantity of that knowledge. The Generality of a patent is the extent to which the follow up technical advances are spread across different technological fields, rather than being concentrated in just a few of them. This has been represented as:

$$\mathrm{GENERAL} = 1 - \sum_{m=1}^{M} \left(\frac{\mathrm{NCITING}_m}{\mathrm{NCITING}} \right)^2 \tag{4}$$

where m is the index of patent classes, and M the number of different classes to which the citing patents belong. NCITING is the total citations received by patent A and $\mathrm{NCITING}_m$ is the citations received in each patent class m associated with patent A. The value of GENERAL ranges from 0 to 1, with 1 indicating less concentration and 0 indicating high concentration within patent classes. Trajtenberg argues that a highly general patent provides a base for numerous subsequent technological changes. Such patents may receive high social returns. Fischer and Leidinger (2014) observed that a higher generality increased the probability of a patent to be traded, and Mathew et al. (2012) observed that the generality of a patent is positively correlated to its price. While the generality of a patent indicates that more subsequent inventions from different technology classes can be based upon it, generality is not necessarily an indicator of the knowledge base of the patent itself. However, a high GENERAL has been observed in highly cited patents. This indicates that the technical maturity of an invention contributes to its generality at some level.

While all these techniques attempt to value a patent based on its knowledge base, certain shortcomings exist in them. Primarily, these techniques consider only the first-level references of the patent, which represent the direct knowledge influencing the invention. They fail to account for the knowledge that has an indirect effect, that is, the references of references, and so on. Such knowledge is found in the multiple-level references of the patent. Also, techniques such as TII and IMPORTB rely on forward citations of the references in their measurement of the technical value. This would pose a problem in the evaluation of patents that cite latest prior art, as this knowledge wouldn't have had the time to accrue enough citations. Therefore, the value indicated by these techniques would change with time making them unsuitable for forecasting purposes. Other techniques such as those based on technology life cycle have attempted to take into account the entire knowledge accumulation of the sector (Beierlein et al., 2015). However, these techniques have been used to assess the developments of the technological field and not for the assessment of individual inventions. In sum, while these prior techniques have demonstrated the importance of examining the knowledge structure underlying an invention, they have done so only to a partial degree.

2.2. Knowledge accumulation and knowledge structure

Another way to quantify the maturity of the knowledge structure underlying an invention is through its knowledge accumulation. Knowledge accumulation may be defined as the collective body of knowledge, know-how, and experiences gathered in a sector over time. Knowledge accumulates through a process of diffusion and upgrade (Zhuang et al., 2011). Knowledge diffusion happens when knowledge is absorbed from another agent while knowledge upgrade happens when new knowledge is created based on existing knowledge. Accumulation of knowledge is associated with increased firm performance (Forés and Camisón, 2016; Jiménez-Jiménez and Sanz-Valle, 2011), enhanced productivity (Evenson and Kislev, 1973) and business longevity (Chirico, 2008). Knowledge accumulation in inventions is visible in the form of methods, procedures and experiences of success and failure that have led to the creation of the invention (Dosi, 1982). For example, the steam engine as we know today is the outcome of the collective work of many inventors over three hundred years working on various aspects of the engine (Kerker, 1961). The success of Ethernet lay in the coming together of various technologies including coaxial cables, bus topology, packet switching, layering, and network interfaces (Fontana and Nuvolari, 2009).

Knowledge accumulated in inventions becomes apparent by observing the knowledge structure of the invention. The structure of an invention has been described as an intricate network of core and supporting technologies (Arthur, 2007). These supporting technologies in turn are comprised of other core and supporting technologies. In a patent citation network, the knowledge structure becomes visible through multiple-generation references of a patent. Multiple-generation citations are references of references and have also been termed as "indirect citations" (Atallah and Rodriguez, 2006) and "multiple-round citations" (Bosworth, 2004). Studies based on patent analysis have hinted on the existence of a structure behind inventions. This can be seen in the work of Bosworth (2004), Atallah and Rodriguez (2006), Hu et al. (2011, 2012), Rousseau (1987), von Wartburg et al. (2005) and others. These studies explored various features of the knowledge structure of the invention and amongst other things, differed in terms of "how much" of the knowledge structure is included in the study. When one consolidates all the knowledge elements leading to this assembly, both direct and indirect, the accumulation of knowledge behind the invention becomes apparent. Hence, the total direct and indirect knowledge accumulation should be a suitable indicator of the technical value of an invention. This knowledge is present at the conception of the invention, making this a suitable indicator for evaluating new inventions. Hence, we hypothesize that:

The total direct and indirect knowledge accumulation is positively correlated to the technical value of the invention.

3. Methodology

The purpose of this study is to show that knowledge accumulation is an indicator of the technical value of an invention. In order to do so, we first construct the knowledge structure of the invention through its citation network. Using this knowledge structure, we then calculate the knowledge accumulation behind the invention.

3.1. Patent citation network

Patent data for the purpose of building citation networks was collected from Espacenet. This database was ideally suited for our purpose because the intention was to capture the knowledge background of the inventions on a global level. Patents sometimes cite other patents that come from different jurisdictions. In such situations Espacenet provides access to a consolidated database with over 90 million patent publications from 90 countries. We collected US patent data from three sectors: Inductive vibration energy harvesting (IV), piezoelectric energy harvesting (PZ), and carbon nanotubes (CNT). The time period for the search was 1989–1991 for PZ and 2000–2002 for CNT. We chose a later time period for CNT patents since research and patenting in this sector picked up only after mid 1990s. In case of IV energy harvesting, due to scarce patenting activity, we broadened the search to patents published after 1988. The oldest patent in our dataset from this sector was published in 1989. The choice of the time frames ensured that these inventions had had enough time to accumulate citations and at the same time there was an observable period of knowledge accumulation.

We used a combination of keywords and International Patent Classification (IPC) codes to search for patents in each sector. The goal was to find as many patents as possible in the sectors. For example, to search for patents in the PZ sector, the keywords “piezoelectric”, “piezo”, “energy” and “harvest” were used in various combinations and searched in the title and abstract of patents along with a combination of IPC H02N2 and H01L41. Unique combinations were used until no new patent was found in the search. Similarly, we used the keywords “inductive”, “vibration”, “induction”, “energy” and “harvest” in various combinations along with IPC H02K35 for IV sector. For CNT sector, we used IPCs C01B31 and D01F9 in combination with keywords pertaining to this technology such as “Carbon nanotube”, “Nanotube” and “CNT”. The search results in each sector were consolidated and duplicates were removed. Thus, the initial search yielded us 289 PZ publications, 101 CNT publications, and 140 IV publications.

The patents in each sector were then screened to limit the results to patents that have at least one of the above-mentioned IPCs as the main classification and preferably the only classification. We verified that none of the patents in our list had the same priority number. This ensures that the patents belong to different families thus described different inventions. Finally, the resultant patents were manually screened to ensure that they described inventions pertaining to the field chosen. Thus, in the period 1989–1991, we found 52 PZ US granted patents, and from 2000 to 2002 there were 96 CNT US publications that met our criteria. Of the 96 CNT publications, 33 were granted patents while the remaining were patent applications. In the IV sector, there were 38 granted patents and 26 patent applications that met our criteria. To determine a relevant sample size, we used the software G*Power 3.1. G*Power is a stand-alone power analysis program for statistical tests. Details about this program are can be found in Faul et al. (2009). Using the parameters effect size (f^2 = 0.35), type I error rate (α = 0.5), and power ($1 - \beta = 0.8$), we calculated a sample size of 20. Based on this number, we randomly chose 20 granted patents from each sector.

We then created a citation network based on patent co-classification. Studies in the past have demonstrated the use of co-classification for the purpose of tracing prior knowledge (Curran and Leker, 2011). In each of these inventions, the backward citations were identified. Only patents carrying the core IPC of the field were recorded while the remaining were discarded. This formed the first generation of backward citations. The process was repeated with each one of the patents in this level to form the second-generation backward citation network. Such multiple generation citations have also been termed as “indirect citations” (Atallah and Rodriguez, 2006) and “multiple round citations” (Bosworth, 2004) in the literature. The process was continued until no new relevant patent was found in the references. All of the patents across multiple generations formed the knowledge structure of the originating, target invention. This process was carried out for all the patents in the sample set. The year of application of each patent in the knowledge structure was recorded. Knowledge accumulation was then calculated for each sample as described in the following section.

3.2. Indicator for knowledge accumulation

Assuming patent A represents invention **A**, then the knowledge accumulation (KA) for patent A can be given as:

$$\mathrm{KA_A} = \frac{n_A}{\sum_{\mathrm{m=1}}^{\mathrm{M}} N_m}$$

where n_A is the total number of patents in the knowledge structure of the target patent, i.e., the volume of knowledge that has been used in creating this patent. N_m represents the number of patents existing in patent class m up to the year of filing (T_x) of the patent A and M represents the number of patent classes that together describe the technology of the sector. The equation aggregates the efforts that have taken place in the sector before the target patent. A larger n_A indicates that the target patent sources a larger body of knowledge. A larger N_m indicates more knowledge existing in the sector and hence more possible solutions from which to choose.

However, the knowledge for the target patent should be scaffolded by mature technology. Each piece of knowledge associated with the patent is itself scaffolded by other technology, and the maturity of this overall knowledge structure is relevant in calculating knowledge accumulation. We therefore introduce a time factor to take into account the age of the knowledge that precedes the target patent. The time factor permits the measure of knowledge accumulation to account for structural maturity rather than a simple chronological measure of (knowledge) age for the target patent.

Knowledge used in this patent can hence be represented by:

$$n_A = \sum_{\mathrm{i=0}}^{\mathrm{x}} n_i (T_x - T_i)$$

where n_i is the number of patents filed in year T_i in the knowledge structure of patent A. The subscript i takes the values 0, 1, 2, 3, …, x − 2, x − 1, x, where T_0 indicates the year of application of the earliest patent in the knowledge structure and T_x indicates the year of application of the target patent A. We also take into consideration that while both long-term knowledge and recent knowledge are needed in creating inventions, recent knowledge is more influential (Nerkar (2003)). To take into account the influence of recent knowledge we introduce the weighting factor α_i:

$$\alpha_i = 1 - \frac{T_x - T_i}{T_x - \mathrm{T_0} + 1}$$

Making the appropriate algebraic substitutions, the knowledge accumulation of patent A can be represented by:

$$\mathrm{KA}_A = \frac{1}{\sum_{\mathrm{m=1}}^{\mathrm{M}} N_m} \sum_{\mathrm{i=0}}^{\mathrm{x}} \alpha_i n_i (T_x - T_i) \tag{5}$$

Eq. (5) has been used in this study to calculate the knowledge accumulation of the sample patents.

3.3. Composite technical value of patent (PV)

We determine the technical value of our sample patents by combining various patent value indicators. This process yields a composite technical value, the use of which has been demonstrated in various studies (Hall et al., 2007; Lanjouw and Schankerman, 2004; Thoma, 2014; Van Zeebroeck, 2011). Researchers of these studies claim that since all the patent indicators correlate with patent value with some variance, combining the indicators would help localize that value.

Hence, depending on which indicators are combined, one can extract either the technical value or the commercial value of the patent. In this study, to extract the technical value, we combined the following patent variables:

a) *Citations*: A patent receiving citations from subsequent patents is an indication of its technical value. The difficulty with using citation counts is that they take time to accrue and patents continue to receive citations even after their term. This makes comparison between patents filed in different years difficult. One of the solutions adopted in the literature to overcome this difficulty is to limit the citations to the first few years of the patent life (Lanjouw and Schankerman, 2004; Van Zeebroeck, 2011). Our dataset shows two different filing behaviours. Patents from PZ and CNT sectors were filed within three years of each other. Hence, we consider the total citations received by these patents while calculating the composite technical value. On the other hand, patents from IV sector have a longer time period between their filing dates. Thus, for these samples we only consider the citations received in the first five years after their filing to calculate the composite technical value.
b) *Family and survival term*: Size of the patent family, represented by the number of countries in which protection is sought for an invention, and its survival term have been shown to be positively correlated to the patent value (Harhoff et al., 2003). This implies that the invention is technically strong and has commercial importance in a larger geography. Hence the family size and survival term of a patent indicates technical value of invention. We utilise the scope-year index (van Pottelsberghe de la Potterie and van Zeebroeck, 2008) to capture the geographical scope and term survival of the patent. This indicator is expressed as:

$$SY_A = \frac{\sum_{y=1}^{Y}\sum_{r=1}^{R} G_i(ry)}{R*Y} \tag{6}$$

where SY_A stands for the Scope-Year index of a given patent A over R countries and Y years of maintenance. $G_i(r,y)$ is a variable that takes the value 1 if the granted patent i in the patent family of A was active in country r in year y from its filing date, and 0 otherwise. The index is normalised to its maximum value representing Y years of maintenance in R countries. We set Y to 10 years, which takes into account 2 renewal periods of the patent.

c) *References*: References, also known as backward citations, represent the knowledge foundation of the patent. Studies have shown that patents referring to more prior art tend to be more valuable (Harhoff et al., 2003; Lin et al., 2007). Hence, a longer and more diverse reference base indicates a larger technical knowledge base, which should be indicative of the technical value of the patent. This study does not take into account non-patent references such as journal articles.

3.4. Calculation of PV

In patent studies, scholars have used factor analysis (Hall et al., 2007; Lanjouw and Schankerman, 2004; Thoma, 2014; Van Zeebroeck, 2011) to create a composite patent value. However, due to the limitations of sample size, we use a more generic mathematical approach (Song et al., 2013). In this approach, the sum of the z scores for each of the above-mentioned patent variable is transformed to a T score to create the composite technical value of the patent. A z score is a numerical measurement of value's relationship with the mean in a group of values. z score is calculated by subtracting the observation with the mean of all observations and dividing the result by the standard deviation of all observations. The z scores have a mean of 0 and a standard deviation of 1 and range from positive to negative numbers. A z score of 0 implies that the score is identical to the mean value. This normalises the distribution of the values. Converting these values to T score then returns the results from between 0 and 100.The composite technical value of patent, PV, is thus calculated as:

$$PV = \overline{X}' + \frac{\sum_{v=1}^{V} z_i}{V}(SD') \tag{7}$$

where V denotes the number of patent variables, z_i denotes the z scores of these patent variables, $\overline{X}'$ is the new desired mean and SD' is the desired standard deviation. We set $\overline{X}'$ to 50 and SD' to 10 as suggested by Song et al. (2013). For each patent in our sample set, we calculated the composite technical value as per the method described above.

We perform a multiple linear regression analysis to determine the predictive power of KA. We estimate patent value through the following equation:

$$PV = B_0 + B_{KA}KA + B_{IV}DIV + B_{PZ}DPZ + B_{CNT}DCNT + \varepsilon \tag{8}$$

where PV represents the composite technical patent value and DIV, DPZ, and DCNT are the dummy variables representing the sectors studied.

3.5. Other patent value indicators from literature

For each patent in our sample set, we calculated TII, IMPORTB, TCT, GENERAL, and ORIGINAL as per Eqs. (1)–(4) as described in Section 2.1. We then check for correlation between KA and these patent value indicators.

4. Data

To test our hypothesis, we studied three different technological areas that find application in energy harvesting: inductive vibration energy harvesting, piezoelectric energy harvesting, and carbon nanotubes. Energy harvesting is the process by which energy is derived from external sources (e.g. solar power, thermal energy, wind energy, salinity gradients and kinetic energy), captured, and stored for eventual distribution. The ever-growing demand for energy has been pushing technological advancements in this sector for the past few decades. Energy harvesting products cater to a wide market sector such as sensors, consumer electronics, healthcare, and military amongst others. With embedded and remote systems becoming more attractive, the need to supply uninterrupted power to them has now become an engineering challenge. Batteries suffer from a limited life span and hence need to be replaced regularly. This has resulted in a need for advanced energy harvesting devices. According to market studies, the global demand for energy harvesters is expected to reach $3.3 billion by 2020 (CompaniesandMarkets.com, 2015).

IV energy harvesting involves the use of kinetic energy released by vibrations in the environment to harness energy. While knowledge about inductive power generation has existed for a long time, using the knowledge to create a micro energy generating devices has been a recent technical achievement (Beeby et al., 2006). In PZ energy harvesting, mechanical strain energy is transformed into electrical energy through the use of piezoelectric materials. The earliest PZ devices extracted energy from impact (Beeby et al., 2006). There has been an increased interest in this technology since early 2000s. CNTs are allotropes of carbon with a cylindrical structure. These nanomaterials are known to have unique properties valuable for many fields such as electronics, optics, healthcare, etc. Due to their excellent electrical properties, they have been gathering interest in energy storage and energy harvesting applications (Kotipalli et al., 2010; Li et al., 2010; Li et al., 2011; Umeyama and Imahori, 2008). Single walled carbon nanotubes have been shown to increase the efficiency of solar panels (Li et al., 2009; Molinaro, 2007).

The selection of this dataset for analysis has important economic, environmental, and experimental implications. The inventions in these sectors may be seen as eco-innovations since they not only boost the economic growth, but also lead to sustainable low-carbon systems. Eco-innovations may be the key to reducing greenhouse gas emissions, improving energy security and promoting a green economy. Research shows that increased awareness toward environment-oriented lifestyle, favourable government policies and private sector initiatives has stimulated a growth in eco-innovations in many countries (Albino et al., 2014). Such eco-innovations tend to be intrinsically interdisciplinary and based upon both recent technological breakthroughs and long-term durable knowledge. For example, photovoltaic systems and wind power require suitable storage such as a battery bank; thus, advances in those systems require a simultaneous interdisciplinary advance in battery technology. Research in wind energy, batteries, and photovoltaic systems has been ongoing for quite some time and include more recent breakthroughs in structure (wind power) and materials (batteries and photovoltaic). Installed systems have taken slightly different technology choices such as the choice of blade design and electricity storage chemistry. Therefore, the knowledge structures of eco-innovations will be useful to investigate as they will be inter-disciplinary, have a long-term history, and have slightly different knowledge structures due to the technology choices of installed systems.

Interdisciplinary research can be defined as integration of information, data, techniques, tools, perspectives, concepts and/or theories from two or more disciplines or bodies of specialised knowledge. Such mixing of ideas is known to be a great way to stimulate generation of new approaches to problem solving. Much work has been done to understand and measure interdisciplinarity (Huutoniemi et al., 2010; Kodama et al., 2013; Tijssen, 1992). Kodama et al. (2013) adopted the *Herfindahl–Hirschman* Index (HHI) of control as a measure of interdisciplinarity in their study. Using this measure, we find that out of the three technological areas being investigated, CNT (HHI = 0.866) is the most interdisciplinary technology, followed by PZ (HHI = 0.844), and IV (HHI = 0.767).

These technological areas also display different levels of research activity. Patenting behaviour is an indicator of research activities in a sector. Strong patenting activity is a result of active research, indicating a potentially large volume of knowledge accumulation. Fig. 1 shows the patenting activity of the three sectors in the last 100 years. Discovered just a few decades ago, research in CNT picked up in early 1990s. Hence patenting in this sector is a rather recent phenomenon. A study on nanotechnology patenting trends (Dang et al., 2010) found that between 1981 and 2008, IPC C01B (which include carbon nanotubes) ranked in the top 5 of the nanotechnology patent applications worldwide. An analysis of the technology areas showed that in applications filed in People's Republic of China in 2008, which ranked second in worldwide nanotechnology patent applications, “carbon nanotube” was a highly-mentioned topic. PZ sector has the most patents of the three sectors with an average of over 200% growth decade on decade. Compared to other sectors such as organic photovoltaic solar cells (Lizin et al., 2013) and wind energy (Europe) (Kapoor et al., 2016), this sector has experienced a higher patenting rate in the last two decades. Growth in IV sector, on the other hand, has been slower. The research activity seems to have picked up pace in the 2000s with 75% of the total patents in this sector published between 2002 and 2017.

5. Results and discussion

Descriptive statistics of the sample set are given in Table 1. The samples of IV sector have a mean KA of 0.89 (SD = 0.29), and each patent has received an average of 3 citations (SD = 2.82) in the first 5 years of its life. These patents have an average of 10 generations of backward citations with the earliest patent dating back to 1903. This provided an observation period of around 100 years for each invention. Thus, we found that the initial 20 patents of IV sector drew their knowledge from over 1200 patents in their knowledge structure. Inventions in PZ sector have an average of 78 patents in their knowledge structure over 8 generations. These 20 inventions drew their knowledge from over 490 inventions. Patents in this sector displayed a mean KA of 0.28 (SD = 0.23). The earliest patent in this dataset dates back to 1926 for an observation period of 65 years.

In this research, the earliest patent cited in the CNT sector, was published in 1915 giving us an observation period of 100 years. Though the patenting activity started late in this sector, we found an average of 238 patents in the knowledge structure of the inventions in this sector. These inventions displayed a mean KA of 0.11 (SD = 0.07).

Fig. 2 shows the citation distribution over multiple generations of all the three sectors. Similar to what was discovered by Atallah and Rodriguez (2006) with forward citations, we observe an inverted-U shape distribution in backward citations. This result contrasts with the prediction by Bosworth (2004) that tracing citations backwards in time will produce a monotonically increasing number of patents. The reason for this difference could be the time span of the data being observed. Since Bosworth used US patent citations, his data was limited to the mid-1970s. Hence, Bosworth could observe the backward citations up to 24 years (1976–2000) or five generations only. Using patent data from Espacenet, we were able to observe more than 13 generations of backward citations.

5.1. Correlation and linear regression

Similar to other patent valuation studies (Gambardella et al., 2008;

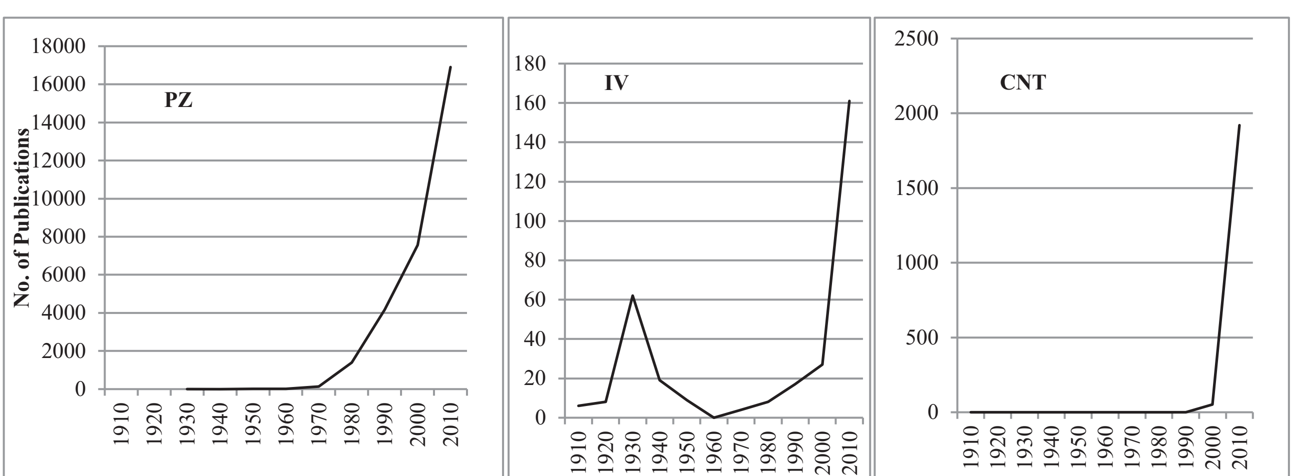

Fig. 1. Patenting activity in the sectors.

Table 1
Descriptive statistics of the sample set.

	IV				PZ				CNT			
	Min	Max	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max	Mean	Std. dev.
KA	0.59	1.66	0.89	0.29	0	1.08	0.28	0.23	0	0.28	0.11	0.08
References	1	48	14	11.37	3	20	10	4.83	1	30	9	7.64
Citations	–	–	–	–	3	86	20	20.62	1	279	93	84.79
5 year citations	0	12	3	2.82	–	–	–	–	–	–	–	–
PV	41.03	58.41	50.00	4.95	42.26	62.67	50.00	6.03	41.20	65.14	50	6.38
Valid N (listwise)	20				20				20			

Harhoff et al., 2003; von Wartburg et al., 2005), we carried out correlation and regression analysis on our samples. Table 2 shows the results of correlation test between KA and PV for the three sectors. The results show that KA has a positive correlation with PV in all the sectors (IV: $r(18) = 0.465$, $p < 0.05$; PZ: $r(18) = 0.714$, $p < 0.01$; CNT: $r(18) = 0.475$, $p < 0.05$). The correlations are statistically significant, with a large effect size seen in PZ sector and a medium effect size seen in IV and CNT sectors. According to Cohen (1992) a correlation coefficient value above 0.5 represents a large effect size. This validates our hypothesis that knowledge accumulation is an indicator of the technical value of a patent.

To test the predictive power of KA, a multiple linear regression was then carried out. We control for the technology sector using dummy variables, as shown in Eq. (8). The results are presented in Table 3. A significant regression equation was found ($F(3,56) = 6.057$, $p < 0.001$), with an R^2 of 0.245. Coefficients of regression for KA ($B_{KA} = 13.407$, $t(54) = 4.263$, $p < 0.001$) and the sectors ($B_{PZ} = 8.197$, $t(54) = 3.266$, $p < 0.002$; $B_{CNT} = 10.564$, $t(54) = 3.573$, $p < 0.001$) are significant, indicating that they are important predictors of patent value. However, a higher standardized coefficient of KA ($B_{KA} = 0.939$) shows that knowledge accumulation has a stronger effect on patent value. Hence, while the sector is a significant factor in influencing the value of a patent, the degree of knowledge accumulation amplifies that value. A one standard deviation increase in KA increases the value of a patent by 7.4% in IV sector as compared to 5.1% and 1.6% in PZ and CNT sectors respectively. This implies that the effect of knowledge accumulation on patent value is less pronounced on highly interdisciplinary technologies.

A comparison with the regression results presented in other studies (Table 4) shows that our model explains at least the same amount of variance as other metrics and a higher R^2 value than some other studies. While it is not possible to compare our results directly with the other studies, because the dependent variables, predictors, and sectors differ, the results show that a satisfactory proportion of the variance in patent value can be predicted by knowledge accumulation. As we will explain later, our measure of knowledge accumulation has the benefit of being a leading indicator.

Table 2
Pearson correlation test for KA and PV.

		PV		
		IV	PZ	CNT
KA	Pearson correlation	0.465*	0.714**	0.475*
	Sig. (2-tailed)	0.039	0.001	0.034
	N	20	20	20

** Correlation is significant at the 0.01 level (1-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

5.2. Comparison of KA with other patent value indicators

In the next step, we test the correlation between KA and other patent value indicators mentioned in the literature. Studies have attempted to define the technical value of an invention in various ways. This has resulted in a number of different value indicators. It is yet unclear whether these indicators together represent the total technical value or if each one represents some aspect of the technical value. In

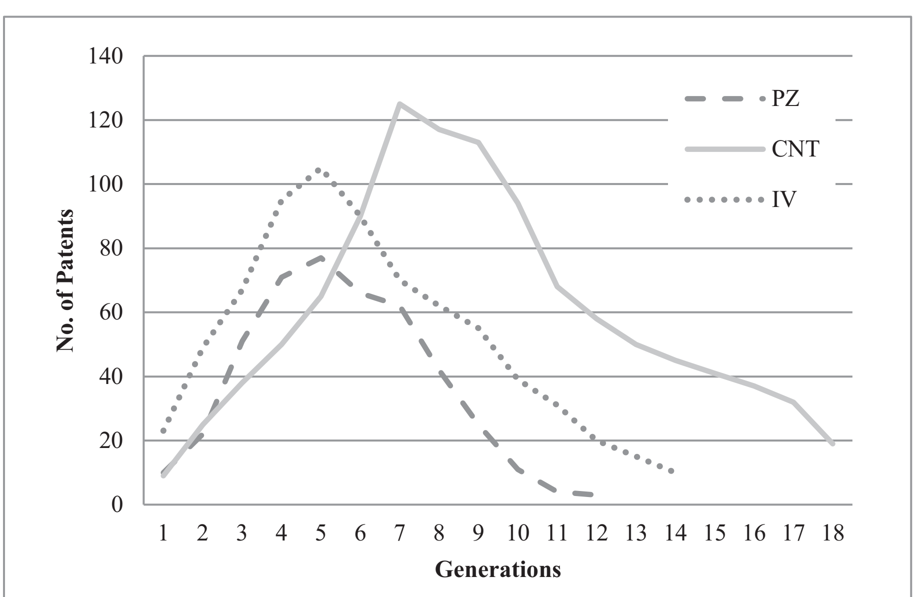

Fig. 2. Backward citation distribution of patents over generations.

Table 3
Regression analysis of patent value with knowledge accumulation.

Model summary

Model	R	R square	Adjusted R square	Std. error of the estimate
1	0.495[a]	0.245	0.205	5.09973

[a] Predictors: (Constant), DCNT, DPZ, KA.

ANOVA

Model		Sum of squares	df	Mean square	F	Sig.
1	Regression	472.556	3	157.519	6.057	.001[b]
	Residual	1456.406	56	26.007		
	Total	1928.962	59			

[a] Dependent variable: PV.
[b] Predictors: (Constant), DCNT, DPZ, KA.

Coefficients

Model		Unstandardized coefficients		Standardized coefficients	t	Sig.
		B	Std. error	β		
1	(Constant)	38.036	3.03		12.554	0.001
	KA	13.407	3.145	0.939	4.263	0.001
	DPZ	8.197	2.51	0.681	3.266	0.002
	DCNT	10.564	2.957	0.878	3.573	0.001

[a] Dependent variable: PV.
Base category: DIV.

case of the second scenario, with the increasing number of these indicators, the probability of multicollinearity between them also increases. Hence, it is important to determine whether KA is a new value indicator or if it is detecting a value that is already measured by an existing indicator. The simplest method to answer this question is through a correlation matrix. We calculated the technical patent value of the sample set based on the metrics mentioned in Section 2.1. We then checked for correlations between KA and these metrics. Table 5 shows the results of this test for the PZ sector dataset since the results lead to the same conclusions for the other sectors. The results show that there is a high correlation between TII and IMPORTB. Hence, these indicators are essentially measuring the same value. We do not find similarly high, statistically significant correlations between KA and any other indicator. We find a significant positive correlation between KA-TII and KA-IMPORTB. Though KA, TII, and IMPORTB all seem to be good indicators of patent value, there exist some differences between them. The measure of KA takes into account the entire knowledge foundation of the invention, while TII and IMPORTB only consider the immediate knowledge (first level references) that has led to the invention thus ignoring the indirect effects of knowledge elements. Unlike TII and IMPORTB, the value of KA does not change with time, as its measurement does not depend on forward citations. This quality makes it an ideal technical value indicator for the newly granted patents. We do not find a statistically significant correlation between KA-GENERAL, KA-TCT, or KA-IMPORTB, which means that these metrics are measuring different dimensions of potential patent value.

6. Conclusion

Patent-valuation analysis is a growing field that is increasingly finding applications in technology planning and management. The techniques have grown from mere patent counts to complex models. We contributed to this field of study by introducing the concept of knowledge accumulation. The concept of knowledge accumulation

Table 4
Comparison with other regression models.

Sector	Study	Dependent variable	Independent variable	R^2	Comments
Biotechnology	(Lin et al., 2007)	Citations	Examination time, claims, references, dummy variables for inventor location	0.14 to 0.36	Citations reflect the value of invention
Manufacturing	(Hall et al., 2000)	Market value of firm	R&D stock, patent stock, citations	0.16 to 0.25	
Biotechnology	(Lerner, 1994)	Firm valuation	Equity index, number of patents, breadth of patent claims	0.11 to 0.12	Ordinary least square regression model used
Multiple sectors	(Harhoff et al., 2003)	Patent value based on inventors' response to questionnaire	Patent scope, citations, family size, references, non-patent references, opposition, annulment	0.12 to 0.17	Ordered probit method used

Table 5
Spearman's rho correlation results for PZ energy harvesting sample set.

		TII	IMPORTB	TCT	KA	Original	General	Citations
TII	Correlation coefficient	1.000	0.997**	− 120	0.551*	0.420	0.487*	0.488*
	Sig. (2-tailed)	.	0.000	0.163	0.012	0.065	0.029	0.029
	N	20	20	20	20	20	20	20
IMPORTB	Correlation coefficient	0.997**	1	0.132	0.541*	0.423	0.487*	0.509*
	Sig. (2-tailed)	0	.	0.578	0.014	0.063	0.03	0.022
	N	20	20	20	20	20	20	20
TCT	Correlation coefficient	0.12	0.132	1	− 0.436	0.631**	0.347	0.116
	Sig. (2-tailed)	0.613	0.578	.	0.055	0.003	0.134	0.627
	N	20	20	20	20	20	20	20
KA	Correlation coefficient	0.551*	0.541*	− 0.436	1	0.1	0.168	0.055
	Sig. (2-tailed)	0.012	0.014	0.055	.	0.675	0.479	0.817
	N	20	20	20	20	20	20	20
ORIGINAL	Correlation coefficient	0.42	0.423	0.631**	0.1	1	0.517*	0.053
	Sig. (2-tailed)	0.065	0.063	0.003	0.675	.	0.02	0.823
	N	20	20	20	20	20	20	20
GENERAL	Correlation coefficient	0.487*	0.487*	0.347	0.168	0.517*	1	0.593**
	Sig. (2-tailed)	0.029	0.03	0.134	0.479	0.02	.	0.006
	N	20	20	20	20	20	20	20
Citations	Correlation coefficient	0.488*	0.509*	0.116	0.055	0.053	0.593**	1
	Sig. (2-tailed)	0.029	0.022	0.627	0.817	0.823	0.006	.
	N	20	20	20	20	20	20	20

** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

takes a knowledge structure view on the value of patents, that is, the structure of the knowledge upon which a patent is based. The vast body of knowledge that shapes a technological sector is partially responsible for the technical viability of an invention. Hence, a higher knowledge accumulation should lead to a higher technical value of the invention. Our structural view attempts to find indicators of the structure inherent in the citation network of a patent so as to disentangle the intrinsic structural effects at work in mediating the transformation of knowledge into practical products, i.e., innovation. In terms of advancing theory on technology forecasting, our research implies that every technology, even very complex ones such as energy harvesting and generation technologies have some sort of underlying structure. The potential for improvement in those technologies due to their structures is relevant to questions of scientific interest in technological forecasting.

Based on the study of 60 inventions in three different technological domains of the energy-harvesting sector, this study identified a positive correlation between knowledge accumulation and the composite technical value of a patent. We created a multiple-generation citation network to assess knowledge accumulation. The composite technical value was calculated using patent indicators citations, references, family size, and patent term. In the PZ sector, which was the most interdisciplinary of the three chosen sectors, knowledge accumulation explained the highest variance in patent value. A low strength of correlation in the CNT and IV sector indicates that there are other dynamics in play that affect the technological patent value in addition to knowledge accumulation. While we observed that the sector is also a significant predictor of the value of invention, a larger study involving more inventions and technology sectors will provide further insight into how knowledge accumulation varies with sector characteristics. We detected a correlation between KA and value indicators TII and IMPORTB. Most significantly, our metric of knowledge accumulation was able to account for a higher proportion of the variance in patent value than some existing metrics. Since the metric does not strongly correlate or does not correlate at all with existing metrics, it is likely that our metric of knowledge accumulation is measuring a different construct. In addition, our metric is a leading indicator as it does not rely on future citations to the target patent to predict its value.

The objective of this method was not to predict the absolute value of a patent, but to identify a technically valuable patent amongst a cohort of other patents. The implications of this study show that knowledge accumulation can be a useful construct by which to evaluate the latest patents. Current patent valuation techniques based on forward citations or patent family fail to identify technically valuable inventions when the patent in question is new. Methods based on processing time can only be used on granted patents. Since our method attempts to take into account the knowledge structure that makes up an invention, the method is applicable as a leading indicator of technical value. Research at pre-patent level can also be analysed similarly if sufficient information on the prior knowledge is available. From a technology management perspective, the identification of valuable inventions at an early stage would lead to better planning and execution of the invention. Inventions with no technical value will have no commercial value; thus, identifying such inventions at an early stage would save resources and time.

Finally, we would like to point out certain omissions made in this study for the reason of simplification. We ignored the distinction made by other authors between inventor-references and examiner-references. The reason for this is that not every patent has these two types of references listed out separately. To maintain uniformity in our analysis, we counted both the references. We also excluded the non-patent references from our analysis in order to keep this analysis limited to patents at this stage.

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