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Patent quality determinants based on technology life cycle with special reference to solar-cell technology field

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Abstract: The purpose of this study is to illustrate the necessity of considering the technology life cycle when creating a distinct R&D strategy planning, if the aim is to enhance patent quality. The study also suggests an effective R&D strategy for the solar-cell technology field. It uses count data models to introduce the concept of technology life cycle and analyses the determinants of patent quality that depend upon the technology life cycle. Empirical results show that three variables influence patent quality in contrary manners, depending on the stage of the technology life cycle. This means that an R&D strategy for each of the three variables should be established while considering the technology life cycle. As a result, this study clarifies that the technology life cycle needs to be considered when establishing an R&D strategy that will enhance patent quality, and it suggests that distinct R&D strategy planning should be done for the solar-cell technology field in particular while bearing in mind the technology life cycle.

Keywords: technology life cycle, patent quality, count data model, solar-cell technology

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INTRODUCTION

Today's crises involving patent trolls, increased patent litigation and technology standards competition point to the importance of intellectual property rights, the possession of which can create economic value in a knowledge-based economy. There is a positive relationship between a patent's economic value and its citation counts, and the latter is used as a proxy to determine the quality of the patent [1–3]. In other words, a patent with high economic value will be cited more frequently [4–5].

Hence, R&D policymakers need to pay attention to the determinants of patent citation counts to establish R&D strategies that give rise to stronger R&D economic performance. On the other hand, technology is created so it can be further developed and introduced into a variety of R&D environments, until it eventually reaches a stage of decline. Therefore, to achieve stronger R&D economic performance, any R&D strategy should be differentiated by virtue of the technology life cycle. However, R&D strategies have generally been established through some experts' peer views, without due consideration for either the determinants of patent citation counts or the technology life cycle.

The current study offers an R&D strategy that bears in mind these considerations. In particular, the concept of the technology life cycle is initially introduced to identify the stage of technology development. Empirical analyses are used to emphasise differences in R&D strategies while taking into consideration the determinants of patent citation counts in terms of the technology life cycle. Moreover, with regard to technology development undertaken to improve patent quality, this study suggests an R&D strategy for the solar-cell technology field.

LITERATURE REVIEW

Patent data have been considered useful in analysing various trends including technological change, technological development, and economic growth [6–9]. In particular, patent citation counts data have been used in applied research fields to study patent quality, knowledge spillover, economic value and so on. Trajtenberg [10], Narin et al. [11] and Carpenter et al. [12] each attempted to put forward patent counts that are weighted by citations as indicators of the value of innovations and hence overcome the limitations of simple counts—limitations that have hindered assessments of technology importance or value in economic research. Moreover, Harhoff et al. [3] and Sampat and Ziedonis [13] each suggested that there is a positive relationship between patent citation counts and economic value, and the studies of Fung and Chow [14], Hu and Jaffe [15], and Jaffe et al. [16] each showed that patent citation data are a good proxy for knowledge flow into an industry.

The studies of Sampat [17] and Lee et al. [5] are representative pieces of work that discuss patent quality in relation to patent citation counts. Lee et al. [5] identified the factors that affect patent citation counts using US patents that belong to particular government-funded research institutes in South Korea. Sampat [17] meanwhile collected a large quantity of patent data issued between 2002 and 2003 and analysed patent quality and any patents (or published articles) related to an invention.

As shown above, most studies to date verify the relationship between patent citation counts and patent quality (or the economic value of a patent). However, few studies discuss R&D strategies that can be used to improve patent quality while using determinants of patent citation counts. Moreover, prior studies did not apply the concept of the technology life cycle in spite of changes in the technology development environment. To fill this research gap and address the importance of R&D strategies, this study addresses the concept of technology life cycle and analyses the determinants of patent citation counts.

MODELS FOR COUNT DATA

The most useful model for use with the count data is the Poisson distribution. It can be used to model the number of occurrences of a type of event such as the numbers of patent applications, patent citations or car accidents [18–19]. If the discrete random variable Y is Poisson distributed with an intensity or rate parameter μ (μ>0), then Y has the density [20–21]:

$$Prob(Y_i = y_i) = \frac{e^{-\mu}\mu^{y_i}}{y_i!} \qquad y = 1,2,3,.... \tag{1}$$

where μ is a positive real number equal to the expected number of occurrences during the given interval; e is the base of the natural logarithm; and y is the number of occurrences of an event. The mean of the Poisson distribution is equal to its variance, i.e. E(Y) = Var(Y) = μ, which is a unique feature of this distribution.

A regression model specifies the parameter μ as varying across individuals according to a specific function of regressor vector x and parameter vector β. The typical Poisson specification is $\mu = \exp(x^{'}\beta)$. The method of maximum likelihood is widely used to estimate the parameter. The log-likelihood function of the Poisson estimation models is as follows [20–21]:

$$\ln L_{Poisson} = \sum_{y_i}\left[-\mu_i + y_i \ln(\mu_i) - \ln(y_i!)\right] \tag{2}$$

The equidispersion property of Poisson distribution, *E(Y)* = *Var(Y)* = μ), is violated in many research studies because the overdispersion problem is common. Researchers have proposed many extensions for the count data model to improve the validity of the equidispersion assumption inherent in the Poisson model [22]. One of these is the negative binomial model—a model more general than the Poisson model because it accommodates overdispersion. The negative binomial distribution arises as a continuous mixture of the Poisson distribution, where the mixing distribution of the Poisson rate is a gamma distribution. In equation (1), by replacing μ with μv, where v is a random variable, $y \sim Poisson(y|\mu v)$. If v is specified, i.e. $E(v) = 1$, $Var(v) = \sigma^2$, v preserves the mean but increases the dispersion. In $v \sim Gamma(1,\alpha)$, α is the variance parameter of the gamma distribution. The gamma function, $\Gamma(\alpha)$, is defined by $\Gamma(\alpha) = \int_0^\infty e^{-t}t^{a-1}dt, \quad \alpha > 0$. Thus, a negative binomial distribution is denoted by $NB(\mu,\alpha)$, and its probability mass function is a mixture density [20–21]:

$$Prob(Y_i = y_i) = \frac{\Gamma(\alpha^{-1}+y)}{\Gamma(\alpha^{-1})\Gamma(y+1)}\left(\frac{\alpha^{-1}}{\alpha^{-1}+\mu}\right)^{\alpha^{-1}}\left(\frac{\mu}{\alpha^{-1}+\mu}\right)^{y}. \tag{3}$$

The moments of negative binomial distributions are $E(y) = \mu$, $Var(y) = \mu(1+\alpha\mu)$. The log-likelihood function of the negative binomial estimation model is as follows [20–21]:

$$\ln L_{NB} = \sum[y\ln(\frac{\alpha\mu_i}{1+\alpha\mu_i}) - \frac{1}{\alpha}\ln(1+\alpha\mu_i) + \ln\Gamma(y_i + \frac{1}{\alpha}) - \ln\Gamma(y_i+1) - \ln\Gamma(\frac{1}{\alpha})] \tag{4}$$

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TECHNOLOGY LIFE CYCLE

The technology life cycle comprises a pattern of dynamic characteristics pertaining to technology, in which its innovative and economic outcomes change over time. Ford and Ryan [23] developed the idea of technology life cycle and broke it into six distinct periods─technology development, application, application launch, application growth, technology maturity and degraded technology─from the viewpoint of technology selling, based on its position within the product life cycle [24].

Haupt et al. [25] pointed out a good reason for using the patent approach to measure the technology life cycle: patents inform the public about technological developments since they contain technological expertise and inform the public about the commercial potential of certain technologies. In its patent portfolio, the Japan Intellectual Property Association (JIPA) breaks the technology life cycle into five distinct periods using the trends pertaining to patent applications and growth rates: technology seed, growth, development, maturity and technology declining period (Figure 1) [26].

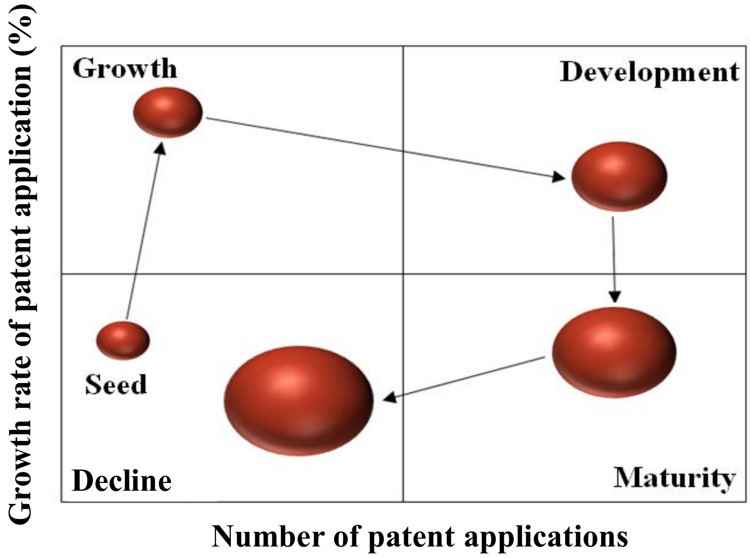

Figure 1. Characteristics of patent application in terms of technology life cycle period

A technology growth period is defined by an increase in its number of applications and in its growth rate. Similarly, an increase in the application number and in the static growth rate of applications are observed during the technology development period. In the technology maturity period the number of applications stagnates and the application growth rate decreases. A summary of the technology life cycle's characteristics vis-à-vis the number of applications and the growth rate of applications is provided in Table 1.

Table 1. Characteristics of the technology life cycle period

Life cycle period	Description	
Seed	No. of applications (↓),	Growth rate of applications (↓)
Growth	No. of applications (↑),	Growth rate of applications (↑)
Development	No. of applications (↑),	Growth rate of applications (→)
Maturity	No. of applications (→),	Growth rate of applications (↓)
Declining	No. of applications (↓),	Growth rate of applications (↓)

DATASET AND VARIABLES

Dataset

Solar-cell technology is a significant field that promises a new form of renewable energy. It has the characteristic of being widely distributed in other technology areas such as liquid-crystal displays, semiconductor and lighting. Its development is being promoted in various countries through government support, along with the commercialisation of the technology and rapid expansion into various markets. Therefore, a large quantity of patent applications in the last 20 years is available for analysis. Furthermore, one should bear in mind that in terms of the technology life cycle, solar-cell technology has already passed its maturity period [27].

The technology classes and technology ranges for patent searching in the solar-cell technology field are shown in Table 2, following the precedent set by the quasi-government institute–the Korea Institute for Advancement of Technology (KIAT) [28].

Table 2. Solar cell technology classes and ranges

Technology class	Technology range
Material	Silicon cell, inorganic compound cell, organic compound cell, dye cell
Manufacture	Manufacturing process (wafer, ingot, module, array)
Module	Thin-film type (CIGS), wafer type, flat-bed type, array
Electrode	Electrode for solar-cell structure, electrode for solar-cell manufacturing process

The patent search results show that the number of US patent applications has been in decline since 2001. However, there has been a rapid increase in the number of patent applications in South Korea and Europe, where patent applications were not very active in the 1990s. On the other hand, the number of patent applications in Japan did not change substantially, as shown in Table 3. Although patent application information related to the patent offices of South Korea (KIPO), Japan (JPO), and the European Union (EPO) would have various implications, this study was compelled to use US patent data because only the US Patent and Trademark Office (USPTO) provides patent citation information. Thus, after removing data noise, the 4,447 granted US patents found to be related to the solar-cell technology field yielded 1,466 valid data records, and then this valid data should be grouped by technology life cycle for empirical analysis in this study.

Table 3. Number of patent applications by year and patent office for solar-cell technology

Year	KIPO(KR)	USPTO(US)	JPO(JP)	EPO(EU)
1990	3	65	-	20
1991	1	80	29	33
1992	3	90	85	49
1993	2	58	75	43
1994	11	88	71	32
1995	16	81	86	36
1996	17	90	80	36
1997	29	91	110	44
1998	20	100	130	58
1999	33	116	110	86
2000	40	128	102	77
2001	58	143	98	79
2002	45	116	98	67
2003	75	87	106	56
2004	93	54	107	86
2005	126	37	105	92
2006	204	26	76	174
2007	347	14	113	218
2008	240	2	69	116
2009	44	-	22	21

However, when using patent data, it is not possible to classify all the life cycle periods therein in detail. Thus, the current study considers only the period of technology maturity and compares differences in patent quality determinants between the pre-technology and post-technology maturity periods. To classify the technology maturity period, a patent portfolio along with its number of patent applications and growth rate was constructed following JIPA's technology life cycle model (Figure 2). This patent portfolio data show that solar-cell technology matured in 2001. For empirical analysis, patent data are separated into pre-technology maturity and post-technology maturity periods, based on the year 2001. In its analysis this study uses 1,130 patents granted before 2001 and 336 patents granted after that year.

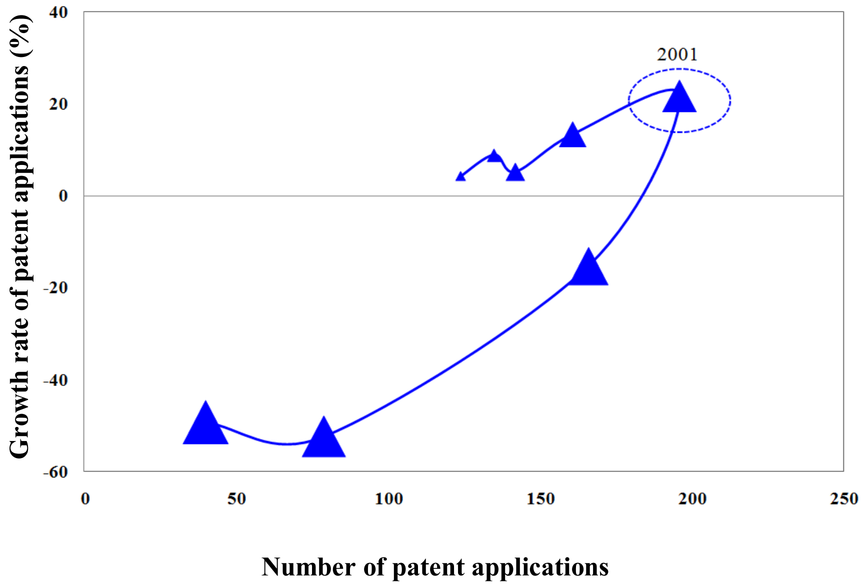

Figure 2. Patent portfolio of solar-cell technology (The size of the symbols ▲ represents the accumulated number of patent applications.)

Variables

The dependent variable for this study is the number of patent citation counts; this figure is a proxy of the patent quality as discussed in previous research [2, 5, 10]. The independent variables used in this study are listed in Table 4. A variety of information from the front pages of the patent documents were used to consider the strategies for R&D planning; in this sense the current study follows the lead of Lee et al. [5] and Daines [29].

Table 4. Description of independent variables

Variable	Measurement	Description
NA	No. of assignees	Size of research
DC	Domestic collaboration	Domestic joint research
INTC	International collaboration	International joint research
NINV	No. of inventors	Size of research team
2INV	Two or more nationalities of inventors	Linguistic problem
BCitation	No. of backward citations	Size of knowledge from outside
NNONP	No. of non-patent citations	Scientific linkage
NSELF	No. of self citations	Technological(knowledge) cumulativeness
USIC	No. of citations of US-invented patent	Degree of dependence on US technology
JPIC	No. of citations of JP-invented patent	Degree of dependence on JP technology
EUIC	No. of citations of EU-invented patent	Degree of dependence on EU technology
NCLAIM	No. of claims	Size of patent right
NFAM	No. of family patents	Size of potential market
NIPC	No. of international patent classification	Size of application range

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To examine how the size of the research project and joint research (i.e. collaboration) affects patent citation counts, the number of assignees (NA) was used as an independent variable and dummy variables were set up for domestic collaboration (DC) and international collaboration (INTC). In addition, this study used the number of inventors (NINV) as an independent variable to observe the effect of the size of the research team. A dummy variable of two or more nationalities of inventors (2INV) was set up to investigate any language-related effects—a variable discussed by Maurseth and Verspagen [30]. In addition, the numbers of cases that cited other patents (BCitation) and non-patent documents (NNONP) as well as the number of self-citations (NSELF) were set up as independent variables to examine the influence of the degree of technology dependence type and the accumulation of knowledge.

The variables USIC, JPIC and EUIC were set up to accurately analyse the degree of technology dependence on the US, JP and EU respectively, and the nationality of the referenced patent's assignee was investigated rather than the nationality of the patent itself. Besides these variables, NCLAIM, NFAM and NIPC were considered independent variables and they were used to measure the size of the patent rights, the size of the potential market and the possibility of application to other fields of technology respectively.

The basic statistics with respect to the independent variables are summarised in Tables 5 and 6. In terms of the mean statistics of NA, DC, INTC, NINV, 2INV and NIPC, no statistically significant difference was found between the pre-technology and post-technology maturity periods. On the other hand, in the post-technology maturity period the mean statistics for BCitation, NNONP, NSELF, USIC, JPIC and EUIC related to technology dependence were about twice those in the pre-technology maturity period. It is assumed that basic technologies related to solar cells

Table 5. Descriptive statistics of variables (pre-technology maturity period) for solar-cell technology

Variable	Mean	Std. dev.	Min.	Max.
NA	1.0	0.2	1	4
DC	0.0	0.2	0	1
INTC	0.0	0.1	0	1
NINV	2.8	1.7	1	10
2INV	0.0	0.1	0	1
BCitation	10.3	9.3	0	109
NNONP	2.6	4.4	0	43
NSELF	1.0	2.9	0	71
USIC	5.0	6.4	0	78
JPIC	4.0	5.0	0	100
EUIC	1.2	1.8	0	16
NCLAIM	19.3	16.8	1	236
NFAM	7.4	8.1	1	167
NIPC	1.8	0.9	1	5

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Table 6. Descriptive statistics of variables (post-technology maturity period) for solar-cell technology

Variable	Mean	Std. dev.	Min.	Max.
NA	1.1	0.3	1	5
DC	0.1	0.2	0	1
INTC	0.0	0.1	0	1
NINV	2.7	1.8	1	10
2INV	0.1	0.2	0	1
BCitation	22.9	31.6	0	210
NNONP	7.2	14.4	0	94
NSELF	2.1	5.4	0	63
USIC	11.5	17.9	0	125
JPIC	7.2	9.4	0	59
EUIC	3.2	7.7	0	77
NCLAIM	20.4	15.6	1	119
NFAM	10.3	13.0	1	78
NIPC	1.6	1.0	1	6

were validated on the basis of prior research during the pre-technology maturity period and that these technologies were put into practical use in the post-technology maturity period. Meanwhile, Tables 5 and 6 show that in the solar-cell technology field, more US-invented and JP-invented patents were used in technology development than were EU-invented patents, irrespective of the technology life cycle period. The mean statistics of NCLAIM and NFAM in the post-technology maturity period tended to be relatively higher than those in the pre-technology maturity period. It is reasonable to assume that these results stem from a consideration of technology commercialisation in the post-technology maturity period.

EMPIRICAL RESULTS AND DISCUSSION

The current study estimated parameters by using STATA statistical software version 10.0. According to the estimation results, the effect of the number of assignees (NA), which indicates the size of the research project, on the patent citation count differs by technology life cycle period. With a one-unit increase in NA comes a patent citation count decrease of 0.436 unit in the pre-technology maturity period, while with a one-unit increase in NA comes a patent citation count increase of 0.485 unit in the post-technology maturity period. Similarly, if domestic joint research (DC) takes place in the pre-technology maturity period, the patent citation count increases by 0.614 unit, whereas in the post-technology maturity period, it decreases by 1.006 unit. Likewise, the effects of NA and DC on the patent quality are sensitive to the technology life cycle period. In other words, these results show that the technology life cycle period is a crucial factor in establishing an R&D strategy that enhances patent quality. On the other hand, Table 7 shows that undertaking international joint research (INTC) enhances patent citation count, irrespective of the technology life cycle period involved.

Regarding the effect of the number of inventors (NINV)—a variable that indicates the size of the research team—on the patent citation count, it was found that a one-unit increase in NINV leads to an increase of 0.018 unit in patent citation count in the pre-technology maturity period. Especially, this study considers the effect of a multinational research team (2INV) and uses it as a variable. As a result, irrespective of the technology life cycle period involved, and all else being equal, if a research team comprises researchers from a number of different countries, the patent citation count decreases by 0.165 unit. This result is similar to that of the study of Maurseth and Verspagen [30], who suggested that patent citation count is higher if the citing region belongs to the same linguistic group. Therefore, an R&D planner needs to consider the size of the research team as well as linguistic issues therein as the R&D strategy is formulated.

Typically, there are two paths of technology knowledge inflow. One involves knowledge inflow from a patent (BCitation); the other involves knowledge inflow from a nonpatent (NNONP) such as a journal article or technology magazine. As described in Table 7, the effects of the two paths on patent citation count differ. With a one-unit increase in BCitation comes a patent citation count decrease of 0.196 units, while with such an increase in NNONP, the patent citation count increases by 0.013 unit. The citation of one's prior own patent (NSELF), a special path of technology knowledge inflow, affects patent citation count differently. Among studies that use a substantial amount of NSELF in the pre-technology maturity period, patent citation count increases while it decreases in the post-technology maturity period. Technology knowledge accumulation and the referencing of non-patent documents can serve as significant components of an R&D strategy in the early stages of technology development. These results point to the importance of the technology knowledge inflow path in enhancing patent quality.

Results pertaining to each of the models indicate that the use of US-invented patents (USIC), JP-invented patents (JPIC) and EU-invented patent (EUIC) as references is important to the patent quality in the pre-technology maturity period. In the post-technology maturity period, only the Poisson model shows any significant positive impact on patent quality. This result indicates that the US, JP and the EU are the leading countries in solar-cell technology, and we need to be mindful of their prior patents and research trends.

Table 7 shows that high numbers of claims (NCLAIM), family patents (NFAM) and international patent classifications (NIPC) can increase patent citation count, which is consistent with the viewpoint of Lee et al. [5]. Moreover, the coefficient values for NCLAIM, NFAM and NIPC are much higher in the post-technology maturity period than in the pre-technology one. This could be a natural result because each of these variables represents the size of the patent rights, the potential market and the application field, all of which are related to economic performance (e.g. technology licensing and commercialisation) in the post-technology maturity period.

Thus far, we have investigated the effects of the aforementioned variables on patent quality. In terms of the technology life cycle, three variables—NA, DC and NSELF—are especially noteworthy. Unlike other variables, these variables have differential effects on patent quality as per the technology life cycle period (Table 8). This means that small-sized research projects or those featuring low technology cumulativeness or domestic joint research values need to be encouraged to acquire a high patent quality in the pre-technology maturity period. While a large research project

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Table 7. Estimation results by technology life cycle period and model for solar-cell technology

Variable	Pre-technology maturity period		Post-technology maturity period	
	Poisson model	Negative Binomial model	Poisson model	Negative binomial model
NA	-0.436***	-0.389	0.485*	0.574
	(0.167)	(0.398)	(0.257)	(0.664)
DC	0.614***	0.551	-1.006**	-1.291
	(0.194)	(0.493)	(0.471)	(0.978)
INTC	0.721***	0.705	0.871*	1.132
	(0.218)	(0.588)	(0.457)	(1.367)
NINV	0.018***	0.017	0.048	0.055
	(0.006)	(0.018)	(0.031)	(0.067)
2INV	-0.165**	-0.126	-0.077	0.218
	(0.077)	(0.237)	(0.267)	(0.544)
BCitation	-0.196***	-0.167***	-0.077**	-0.037
	(0.022)	(0.055)	(0.035)	(0.066)
NNONP	0.013***	0.010	0.009**	-0.012
	(0.002)	(0.007)	(0.004)	(0.013)
NSELF	0.011**	0.008	-0.052***	-0.007
	(0.005)	(0.014)	(0.019)	(0.032)
USIC	0.202***	0.177***	0.067*	0.031
	(0.022)	(0.056)	(0.038)	(0.072)
JPIC	0.170***	0.141**	0.077**	0.040
	(0.023)	(0.056)	(0.036)	(0.070)
EUIC	0.211***	0.181***	0.074**	0.015
	(0.023)	(0.058)	(0.037)	(0.073)
NCLAIM	0.006***	0.008***	0.021***	0.026***
	(0.000)	(0.002)	(0.002)	(0.010)
NFAM	0.008***	0.013***	0.034***	0.038**
	(0.001)	(0.004)	(0.004)	(0.015)
NIPC	0.122***	0.117***	0.175***	0.241*
	(0.010)	(0.033)	(0.052)	(0.144)
constant	2.231***	2.126***	-1.498***	-1.862**
	(0.170)	(0.407)	(0.291)	(0.760)
Log-likelihood	-6884.6	-3673.9	-633.9	-431.3
lnalpha		-0.153***		1.149***
		(0.047)		(0.149)

Notes: 1) *** p<0.01, ** p<0.05, * p<0.1
2) Standard errors are in parentheses.
3) lnalpha is the log-transformed overdispersion parameter.

and the use of others' knowledge are both essential characteristics, domestic joint research needs to be avoided in the post-technology maturity period if patent quality is to be enhanced. In other words, this result highlights the importance of considering technology life cycle when developing an R&D strategy: an R&D planner within the solar-cell technology field needs to consider the size of a research project, the nature of its collaboration and accumulated knowledge in relation to the technology life cycle.

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Table 8. Noteworthy effects of variables on patent quality by technology life cycle period

Variable	Pre-technology maturity period	Post-technology maturity period
NA	Increased NA → Decreased patent quality	Increased NA → Increased patent quality
DC	Adopted DC → Increased patent quality	Adopted DC → Decreased patent quality
NSELF	Increased NSELF → Increased patent quality	Increased NSELF → Decreased patent quality

CONCLUSIONS

It is important to establish an appropriate plan for an R&D strategy in order to obtain strong R&D performance in relation to a technology's position within the technology life cycle. This is because the R&D environment is rapidly changing in terms of the technology life cycle. Such a change is caused by rapid fluctuations in market needs and the fact that technology is advancing at an ever-growing pace.

The primary aim of this study was to investigate differences in the determinants of patent citation counts. It also asserts that R&D strategies for solar-cell technology should be prepared while bearing in mind the technology life cycle. The empirical results of this study are in agreement with our intuitive expectations. When a technology develops in some R&D field, the accumulation of the technological knowledge generally reaches a certain level through development from independent basic studies; thereafter, the outcomes are grafted into various fields and disperse outwards.

This empirical analysis has confirmed the veracity of intuitive knowledge that is related to the technology life cycle. Thus, to enhance the R&D performance, every R&D programme should adopt a distinct R&D strategy based on the technology period within the technology life cycle.

Since this study focused solely on the solar-cell technology field, it does have some limitations. Thus, to improve the generalisability of the results, it is necessary to undertake similar analyses in other fields and compare and analyse the results obtained with those presented here. In addition, for a more specific R&D planning, the dynamic determinants of patent citation counts should be distinguished in greater detail by further refining the technology life cycle.

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