

Article

Factors of Collaboration Affecting the Performance of Alternative Energy Patents in South Korea from 2010 to 2017

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Abstract: In recent years, innovation of alternative energy technologies to manage climate change has become an important goal worldwide. South Korea has been focusing on the innovation of alternative energy technologies through its investments and innovation systematic capabilities. This study quantitatively examines the effect of national innovation systems that are designed to improve the performance of innovation. To do so, this study analyzes the effects of financial support from the national research and development (R&D) project, and collaborations between institutions regarding the national innovation systems on patent performance based on citation count, which is a useful indicator of patent quality. Specifically, this study analyzes the effects of financial support from the national R&D project, as well as collaborations between universities, industries, and the government regarding patent performance using the patent data of South Korea. These data were used in congruence with a hurdle negative binomial model, using data from 2010 to 2017. Consequently, this study establishes that financial supports from national R&D project are generally inefficient. The relational aspects of the South Korean innovation systems are also generally inefficient, while collaborations between universities and industries contribute toward improving the performance of alternative energy patents.



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Keywords: alternative energy; technology; patent citation; collaboration; innovation system

1. Introduction

The development of technologies for managing the climate crisis is the most important global goal for a sustainable future. In many countries, alternative energy technologies have been developed as an approach to managing the climate crisis and improving innovative competition at the national level [1,2].

Despite the promotion of and incentives to create innovation systems at the global and national level [3,4], the extension of alternative energy rather than fossil fuel energy sources is beleaguered by several challenges, mainly owing to the relatively high production prices.

To overcome these barriers, various innovators, including individuals, universities, industries, and governments, have undertaken projects to develop alternative energy [5]. In fact, production costs have steadily decreased as a result of recent developments in alternative energy technologies [6–9]. However, there have been simultaneous technological developments related to fossil fuels in an effort to maintain competition in the future energy market [10–13]. To ensure a sustainable future, it is necessary to decrease production costs and gain advantage over fossil fuel energy through the technological development of alternative energy.

Today, technological development of alternative energy is driven by the promotion of global innovation systems and is hugely influenced by the national innovation system [2,3,5,6]. In this paper, we quantitatively examine the effect of national innovation systems on the performance of innovation in terms of technical knowledge development.

To reflect and include characteristics of the national innovation systems in the analysis, this study utilizes the theoretical perspective of the triple helix to analyze the relationship

between technological development performance and innovation system characteristics. The triple helix theory describes the innovation system by explaining the relationships between institutions, which dynamically change during the development of technology, and the economy. According to Leydesdorff and Etzkowitz [14], the coordination between institutions in some regions or industries actively and recursively recombines during development in a knowledge-based economy. Some previous studies have recognized collaborations between institutions based on the co-authorship of scientific papers [15–17]. Furthermore, previous studies [18,19] have utilized patent data to observe collaboration between institutions.

Many previous studies that analyzed the triple helix have focused on analyzing the status of the innovation system from a macroscopic [14–25] or microscopic perspective [6,26–30]. However, while many of the previous studies have conducted qualitative analysis of the effectiveness of the innovation system, empirical analysis on it is lacking. Therefore, this study attempts to elucidate the effects of collaborations between universities, industries, and governments on the patent performance of alternative energy technologies. This study suggests that efficient types of collaboration are the systematic source of a national innovation system, as this is shown to have positive effects on patent performance. Figure 1 outlines the empirical analysis of this study.

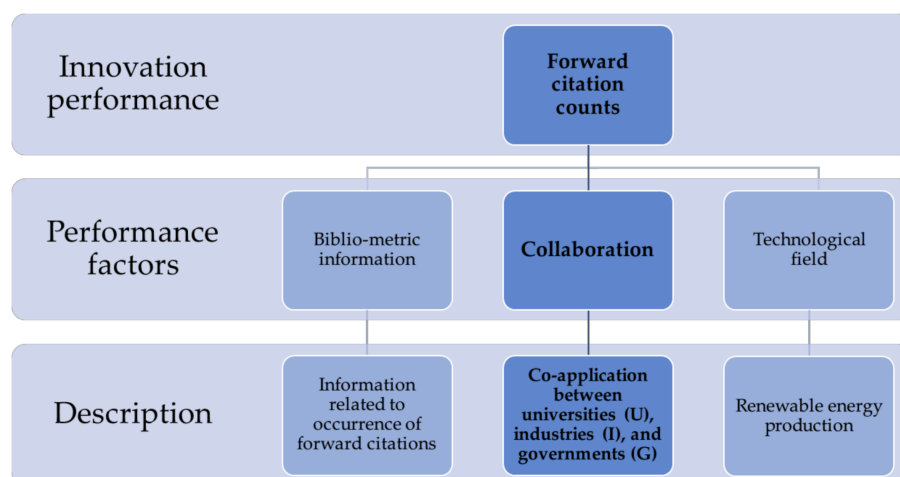


Figure 1. Theme of this study.

In Figure 1, the innovation performance of patents is represented by forward citation counts, which are determined by three categories of innovation performance factors. First, forward citation counts can be described using biblio-metric information, which reflects intellectual characteristics as being inventive. Second, as a focus of this study, forward citation counts can be defined as collaboration in invention activity. Characteristics of the collaboration can be divided into two sub-types: scale and type of cooperation networks. The scale of cooperation is reflected in the biblio-metric information through the size of inventors or applicants. The type of the cooperation network is measured by the composition of the inventors or applicants. In this study, research questions regarding the effect of collaboration on patent performance are analyzed in terms of the type of cooperation networks. Third, the forward citation counts may vary depending on the technological field. This is due to the difference in the size of the intellectual property market that occurs according to the intensity of technology development. Detailed information about performance factors will be explained in Sections 2 and 3.

To empirically analyze the effectiveness of collaboration on alternative energy patents, this study was conducted based on prior research in two fields: first, studies of the innovation system as an environmental factor in technological development; and second, studies on the performance of technological development. Previous works on the innovation system that are based on the triple helix theory are referenced in this study, as are studies

on the performance of technological development based on patent performance (forward citation counts of a patent).

The literature review is in Section 2 of this paper. Section 3 describes the data and methodology used in the study. The results of the regression analyses of the relationship between types of collaboration and the performance of patents are also presented in Section 3, followed by a detailed discussion in Section 4. Finally, Section 5 concludes the paper.

2. Literature Review

2.1. Innovation Modes of Alternative Energy

According to Jensen et al. [31], innovation of technology can be divided into two representative modes: science and technology innovation (STI) and doing, using, and interacting (DUI). These two modes of innovation represent how technological knowledge evolves over time. The STI mode refers to general knowledge that broadens understanding of object and phenomena. STI innovation is mainly achieved through experimentation and research by more human resources, including universities and research institutes. The DUI mode refers to region-, customer-, and operation-specific contextual knowledge. DUI innovation is based on the accumulation of knowledge through repetitive actions related to products. For example, knowledge used for innovation is accumulated through repeated actions related to a product, such as the production activities of producers, product uses by consumers, and repeated interactions between producers and consumers.

Binz and Truffer [2] argue that innovation for alternative energy includes characteristics of both the DUI and STI modes. For example, developments in wind power generation are due to DUI strategies rather than STI strategies. At the initial stage, wind power generation systems require customized design according to the local natural environment and develop through repeated installation and operation. In contrast, developments in solar photovoltaic power generation depend on advances in scientific knowledge about materials that convert sunlight into electricity [2].

Kim and Chang [32] analyzed the relationship between the price of generation and the cumulative generation of alternative energy sources in South Korea. In their study, the innovation of alternative energy sources, such as biofuel, fuel cell, and photovoltaic generation, are relatively less ascribable to DUI innovation. Meanwhile, small hydro, derived gas, landfill gas, and wind power generation are all ascribable to DUI innovation.

2.2. Innovation System

According to Leydesdorff and Etzkowitz [23], the triple helix theory elucidates co-operation between universities, industries, and governments. The theory also divides institutional cooperation forms into three types [23,25]: Triple helix I refers to institutional interaction across otherwise defended boundaries through the media, such as industrial liaison, technology transfer, and contract offices; triple helix II implies bilateral cooperation between universities, industries, and governments and different communication system interfaces compared to other cooperation types; finally, triple helix III refers to trilateral cooperation and means that each institutional sphere of a university, industry, and government shares a role and performs jointly. Ranga and Etzkowitz [24] describe three critical functions of triple helix collaboration: First, the triple helix can supply a knowledge space that both spreads and generates knowledge. Second, the triple helix can supply a space for innovation that accelerates entrepreneurship and innovative activity by promoting interactions between agents of innovation. Third, the triple helix can supply a space, meant for consensus, that helps innovation agents develop more sophisticated concepts by discussing and evaluating ideas for innovation with one another.

Yoon [18] analyzed co-patent data networks in South Korea from 1980 to 2012. The author suggests that the collaboration between industry and government research institutions was a type of triple helix collaboration from the mid-1980s to 1990s. Meanwhile, collaborations between universities and industries similarly constituted a majority of triple

helix collaborations from 2000 to 2012. Moreover, the study argues that South Korea's triple helix collaboration status was closest to the triple helix I from 1980 to 1990, in between triple helix II and triple helix III from 1990 to 2000, and closest to triple helix III from 2001 to 2010.

Yoon and Park [19] analyzed the triple helix theory by region within South Korea. They argue that collaboration activities are limited in some key regions and that the connections between key regions and surrounding regions are too weak to maximize the synergy effect. However, the collaboration between universities and industries are more distributed and less limited in the key regions as compared to other types of collaborations.

Lee and Kim [20] studied the patterns of the triple helix theory within South Korea by analyzing universities', industries', and governments' mutual information on national research and development (R&D) programs. They subdivided the category of "industry" into small, venture, and large companies according to company size and the characteristics of their R&D investment. The study reports lethargic longitudinal changes to the mutual information on national R&D programs, noting that they have generally decreased from 1997 to 2012. The authors argue that the South Korean R&D network is a point of weakness within national competition. For the study period, the government's political efforts pertaining to R&D were effective during the initial policy period but failed to sustain an effect on the active and dynamic R&D network interaction. Thus, the study supports the need to improve R&D network interaction to ensure qualitative development in R&D outputs.

Park and Leydesdorff [16] studied research policies regarding science and technology as well as changes in triple helix collaborations in South Korea. They found that the introduction of quantitative assessment-based science and technology research policies in the first decade of the 21st century, such as project-based systems for government research institutions and BK21 for universities, misled and discouraged sophisticated technology development and collaborative activity.

Lee et al. [30] analyzed the efficiency of triple helix collaborations between Korean firms. Their study suggests that government–industry collaborations are an efficient way to improve R&D outputs in the short term, while university–industry collaborations are a method to enhance R&D's knowledge base. In addition, they argue that university–industry–government collaboration can create a balanced synergy between output growth and R&D potential.

Yoda and Kuwashima [21] describe the developments and transitions in Japan's triple helix from 1973 to 2011. Their study argues that the deregulation of university–industry collaboration leads to the development of the triple helix and the growth of university–industry collaborations. The early versions of Japanese triple helixes were based on government–industry collaborations subject to stringent regulations instead of shock therapy. Therefore, the Japanese government began government-led developments through deregulation.

Lei et al. [17] analyzed Chinese patent applications in the United States (U.S.) and found that the application counts began to increase in the late 1990s, specifically growing from the mid-2000s on. The main patent application spheres in the U.S. came from universities and industries. Moreover, the most frequent type of collaboration was between universities and industries, as this occurred 10 times more frequently than other types of collaborations in the U.S.

Huang and Chen [22] studied the effect of collaboration between universities and industries. They argue that such collaborations facilitate improvements to universities' academic innovation performance. Brem and Radziwon [6] examined how to successfully initiate a socio-technical and local environmental innovation project through triple helix style collaborations in Denmark. They explain the role, benefit, and risks of the project's stakeholders and emphasize the importance of networking, win-win situations, and problem orientation. Networking helps project stakeholders act as boundary-spanners by improving collective awareness. A "win-win-situation" is one in which all project stakeholders share potential gains from the success of the project and can be motivated by

prospective benefits of the project. Problem orientation is defined when there is a focus on solving a specific problem across the project's organization.

Baier-Fuentes et al. [26] studied early internationalization in emerging economies by analyzing the interaction between new technology-based firms (NTBFs) and triple helix institutions. They argued that the interactions between triple helix institutions induced the early internationalization of NTBFs in Mexico. Universities supply technological knowledge, potential customers, markets, and internationalization strategies to NTBFs and business issues. Governments supply business consulting and public financing to NTBFs.

Czarnitzki et al. [27] studied the effects of innovation policies and R&D collaborations on firms' innovative performance. Their study argues that financially supported firms increase their innovative performance and investment in innovation activity when they are engaged in cooperative research.

Guerrero and Urbano [28] studied the effect of firms' collaboration with other triple helix agents on innovative sales performance. Their study suggests that collaboration positively affects performance by facilitating the firm's acquisition of knowledge and financial support through triple helix agents, while negatively affecting performance by allowing firms to obtain social knowledge through triple helix agents.

Kreusel et al. [29] studied the role of the incubator in the triple helix system by analyzing 11 German business incubators. They argue that the generic triple helix model is suitable for a business incubator center and that a university business incubator and triple helix with frequent interaction between government and industry is suitable for independent private incubators, corporate private incubators, and company builders. Moreover, a quadruple helix, which combines the triple helix with a social institution, is suitable for incubators focused on economic success, namely for-profit incubators.

2.3. Regression Model of Integer Count Dependent Variable

To perform empirical analyses, this study refers to a variety of previous studies on statistical estimation and independent variables related to the citation counts of a patent. Lee et al. [33] explored explanatory variables for the citation counts of a patent from a bibliometric perspective and suggested relationships between citation counts and variables such as the size of the research team, technological cumulativeness, research collaboration, size of invention, magnitude of international presence, scientific linkage, geographical localization, age of patent, and technological fields.

Adegbile et al. [34] suggested factors to consider in terms of managing the innovation portfolio, which, they argue, should take into account the market's potential and uncertainty, profitability, technology leadership, acceptance, and relationship with related technologies.

Several empirical studies on citation counts of a patent were analyzed based on models that assumed the Poisson distribution and negative binomial distribution of the dependent variable [35–38]. Citation counts of a patent are cumulative integer counts. However, Gardner [39] argues that the Poisson model can provide misleading inferences regarding the regression when count data are over-dispersed. Baccini et al. [40] suggests the hurdle negative binomial as the best fitting model for count data that include personal publication counts and h-index, by comparing the log-likelihood and Akaike information criterion (AIC) of eight models, namely, the Poisson, negative binomial, zero-inflated Poisson, zero-inflated negative binomial, hurdle Poisson, hurdle negative binomial, generalized Waring regression, and Sichel. This study employs the hurdle negative binomial to analyze the effect of collaborations on patent performance according to the results of Baccini et al. [40]. Further, Ehsan Saffari et al. [41] argued that the hurdle negative binomial model fits right-censored and excess-zeros better than the negative binomial model. The computation of the regression model is performed with the “pscl” package of the statistical software “R” [42,43].

3. Materials and Methods

3.1. Data

This study collected patents related to technologies that manage climate change based on the technological classification of alternative energy, also referred to as “green inventory” by the World Intellectual Property Organization (WIPO) [44]. We used two online patent database systems, including the Korea Intellectual Property Rights information Service (KIPRIS) [45] and Google Patents [46]. We found that 28,822 patents for alternative energy technologies had been granted by the property rights office in South Korea between 2010 and 2017. In this study, we utilized several pieces of information on forward citations, backward citations, applicants, inventors, family, priority, technological classification codes, application date, patent cooperation treaty (PCT) granted date, and claims in a patent.

3.1.1. Greentech Inventory

This study defines alternative energy technologies using WIPO’s green inventory [44], which was developed by the International Patent Classification (IPC) Committee of Experts to facilitate the retrieval of patent information related to environmentally sound technologies, as listed by the United Nations Framework Convention on Climate Change. There are seven topics in the green inventory, including: “alternative energy production,” “transportation,” “energy conservation,” “waste management,” “agriculture/forestry,” “administrative, regulatory or design aspects,” and “nuclear power generation.”

To retrieve alternative energy patents, this study utilized the technological classification code of 13 subtopics within “alternative energy production.” These 13 subtopics are: “bio-fuels (BF),” “integrated gasification combined cycle (IG),” “fuel cells (FC),” “pyrolysis or gasification of bio-mass (GB),” “harnessing energy from manmade waste (HE),” “hydro energy (HD),” “ocean thermal energy conversion (OT),” “wind energy (WE),” “solar energy (SE),” “geo-thermal energy (GE),” “other production or use of heat not derived from combustion, e.g., natural heat (OP),” “using waste heat (WH),” and “devices for producing mechanical power from muscle energy (DP).” This study utilized these 13 subtopics to distinguish between the technology fields. Notably, there are 1525 patents for identical hybrid technologies that include the same number of technological indexes for multiple subtopics in the dataset.

3.1.2. Collection

We performed data collection in three steps, as shown in Figure 1.

As shown in Figure 2, first, we chose search queries related to alternative energy production based on the technological indexes and the definition of alternative energy of WIPO [44]. Second, we retrieved Korean granted patent data from 2010 to 2017 using the KIPRIS online patent database system [45]. Finally, we collected additional information about citations using Google Patents [46].

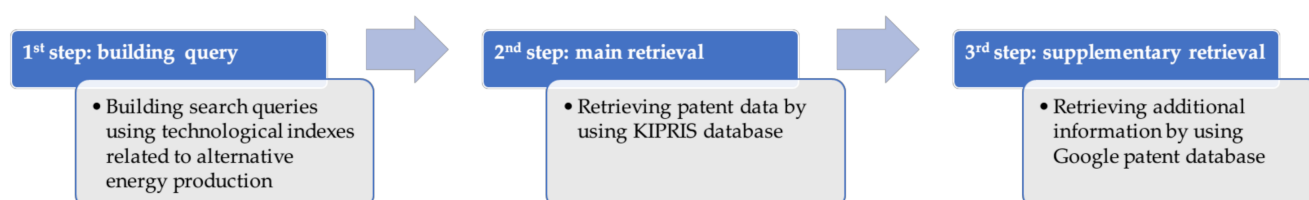


Figure 2. Data collection process.

We comprehensively collected patents with technological indexes (IPC: International Patent Classification; CPC: Cooperative Patent Classification) that were included in the 13 “alternative energy” subtopics of the green inventory. We also checked whether the patent had received funding from a national R&D project by retrieving the name of the related

South Korean ministry through KIPRIS. The relevant South Korean ministries include the following: Oceans and Fisheries; Agriculture and Forestry; Economy and Finance; Science and Technology; Environment; Education; Commerce, Industry and Energy; Small and Medium-sized Enterprises (SMEs) and Startups; Land, Infrastructure, and Transport; and National Defense. In this study, we assumed that if a patent contains the name of a South Korean ministry, it is funded by the national R&D project.

3.2. Methodology

Model

In this study, we analyzed the effects on patent performance by focusing on national R&D funding and collaboration between institutions, as shown in Equation (1). We conducted statistical analyses based on Equation (1) with the hurdle negative binomial model and maximum log-likelihood estimation. According to Baccini et al. [40], authors choose a model by comparing the information criterion and log-likelihood of various models for count data. The hurdle negative binomial model best fit the results when compared to other models according to [41]. More details regarding the information criterion and log-likelihood of models are shown in Table A1. The analyses were performed using the “pscl” package of the statistical computing program “R” [42,43].

$$Y = c + X\beta + C + \mu + \varepsilon, \quad (1)$$

In Equation (1), Y represents the total count of forward citations of a patent and its family, the dependent variable refers to patent performance, X represents the vector of interesting variables and their interaction terms, C represents the vector of control variables, and μ represents the vector of indicator variables regarding the types of technology and the control fixed effect according to the technological field.

In this study, empirical analysis concentrates on the effect of interesting variables regarding co-patent collaboration and financial support from a national R&D project in X . In Table 1, the abbreviations of interesting variables are described.

Table 1. Description of interesting variables.

Category	Description	Abbreviation	Description
Interesting variables (X)	Financial support from national R&D project	F	The variable equals 1 if the patent is financially supported from a national R&D project of a ministry of South Korea and 0 otherwise
	Co-patent collaboration	UIG	The variable equals 1 if a patent simultaneously includes a university, industry, and government as applicants and 0 otherwise
		UG	The variable equals 1 if a patent simultaneously includes a university and government as applicants and 0 otherwise
		UI	The variable equals 1 if a patent simultaneously includes a university and industry as applicants and 0 otherwise
		IG	The variable equals 1 if a patent simultaneously includes an industry and government as applicants and 0 otherwise
	Interaction of co-patent collaboration and the financial support	$UIG \cdot F$	The variable equals 1 if the patent is financially supported from a national R&D project of a ministry of South Korea and based on co-patent collaboration such as, UIG , UG , UI , and IG and otherwise 0
		$UG \cdot F$	
		$UI \cdot F$	
		$IG \cdot F$	

As shown in Table 1, the abbreviation F in X equals 1 if the patent contains information indicating it is part of a national R&D project funded by South Korean ministries; otherwise, it is 0. The co-patent collaboration abbreviations such as UIG , UG , UI , and IG in X equal

1 if the patent contains heterogeneous applicants that consist of a university, industry, and government as applicants.

$$X\beta = [F \text{ } UI \text{ } G \text{ } UI \text{ } IG \text{ } UI \text{ } G \text{ } F \text{ } UI \text{ } G \text{ } F] \begin{bmatrix} \beta_F & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \beta_{IG \text{ } F} \end{bmatrix}, \quad (2)$$

Equation (2) employs abbreviations for the interesting variables, which refer to financial support from the national R&D project and indicator variables regarding co-patent collaboration. This study deals with four types of co-patent collaborations: collaboration between a university, industry, and government (*UIG*); between a university and government (*UG*); between a university and industry (*UI*); and between an industry and government (*IG*) [14,23,25]. To ensure good fitness of regression analysis, this study used control variables and dummy variables. The control variables are related to technological novelty, as shown in Table 2.

Table 2. Description of control variables.

Category	Description	Abbreviation	Description
Biblio-metric control variables (C)	Information related to occurrence of forward citations	<i>P</i>	The variable equals 1 if a patent includes information about the PCT granted number and 0 otherwise
		<i>O</i>	Number of years since application date
		<i>CNP</i>	Cumulative number of patents in same technological field
		<i>NA</i>	Number of applicants
		<i>NI</i>	Number of inventors
		<i>NTI</i>	Number of IPC technological indexes
		<i>NTC</i>	Number of CPC technological indexes
		<i>NCL</i>	Number of claims
		<i>NBCF</i>	Number of backward citations of families
		<i>NBCP</i>	Number of backward citations of the patent
		<i>NBCN</i>	Number of backward citations to non-patent documents of the patent
		<i>NF</i>	Number of families
		<i>NFUS</i>	Number of families granted by U.S. patent office
		<i>NP</i>	Number of priority patents
		<i>NPUS</i>	Number of priority patents granted by U.S. patent office

C represents the vector of control variables that are related to the occurrence of forward citations. According to Lee et al. [33], a patent's biblio-metric information is divided into four categories: research team, invention, geographical localization, and technological field. These represent the characteristics of a patent. In this study, we similarly divided a patent's biblio-metric information into four categories and utilized that information as a control variable by referring to Lee et al. [33].

Conceptually, variables relating to the research team category represent a patent's human resource inputs. *NA* and *NI* are included in the research team category. For example, the number of applicants and inventors theoretically informs the amount of information used to invent patents through human resources. Variables of the invention category represent characteristics related to technological novelty. *CNP*, *NTI*, *NTC*, *NCL*, *P*, *NBCF*, *NBCP*, *NBCN*, and *NF* are included in the invention category. For example, a patent is a more pioneering invention if there are a smaller cumulative number of patents in the same technological field. The more technological indices a patent has, the more diverse and informative it is technologically. If a patent is internationally registered under the PCT, it is more versatile and valuable in terms of utilization. If a patent involves more claims, it has more originality. The more a patent and its family cite other patents and scientific papers, the more sophisticated it is technologically and scientifically. If a patent has priority, its novelty is already guaranteed. Variables of the geographical localization category represent geographical characteristics; *NFUS* and *NPUS* are included in this category. If a patent

involves priority and its family is granted by the U.S. patent office, its technology level is relatively high.

$$C = [P \ O \ CNP \ NA \ NI \ NTI \ NTC \ NCL \ NBCF \ NBCP \ NBCN \ NF \ NFUS \ NP \ NPUS], \quad (3)$$

Equation (3) employs certain abbreviations for the control variables, such as PCT granted patent (*P*), years since application date (*O*), cumulative number of patents in same technological field (*CNP*), number of applicants (*NA*), number of inventors (*NI*), number of IPCs (*NTI*), number of CPCs (*NTC*), number of claims (*NCL*), number of backward citations of family (*NBCF*), number of backward citations of patent (*NBCP*), number of backward citations to non-patent documents of the patent (*NBCN*), number of families (*NF*), number of families granted by the U.S. patent office (*NFUS*), number of priority patents (*NP*), and number of priority patents granted by the U.S. patent office (*NPUS*). The cumulative number of identical hybrid technology patents is calculated as the weighted average of the cumulative number of patents in each technological field. This study selected control variables related to forward citation counts by referring to a previous study [33]. Detailed information about the biblio-metric variables used in this study is shared in Table 2.

To control for fixed effect, this study used dummy variables regarding technological fields. Abbreviations of these are shared in Table 3.

Table 3. Description of dummy variables.

Category	Description	Abbreviation	Description
Fixed effect dummy variables (μ)	Technological field of alternative energy production	<i>DBF</i> ¹ , <i>DGC</i> ² , <i>DFC</i> ³ , <i>DGB</i> ⁴ , <i>DHE</i> ⁵ , <i>DHD</i> ⁶ , <i>DOT</i> ⁷ , <i>DWE</i> ⁸ , <i>DSE</i> ⁹ , <i>DGE</i> ¹⁰ , <i>DOP</i> ¹¹ , <i>DWH</i> ¹² , <i>DDP</i> ¹³	The variable equals 1 if the most relevant technological index for a technology of alternative energy production is included and 0 otherwise
		<i>DHB</i> ¹⁴	The variable equals 1 if numbers of the technological index are included and 0 otherwise

Note: ¹ BF: bio-fuels; ² GC: integrated gasification combined cycle; ³ FC: fuel cells; ⁴ GB: pyrolysis or gasification of bio-mass; ⁵ HE: harnessing energy from manmade waste; ⁶ HD: hydro energy; ⁷ OT: ocean thermal energy conversion; ⁸ WE: wind energy; ⁹ SE: solar energy; ¹⁰ GE: geothermal energy; ¹¹ OP: other production or use of heat not derived from combustion; ¹² WH: using waste heat; ¹³ DP: devices for producing mechanical power from muscle energy; ¹⁴ HB: devices for producing mechanical power from muscle energy.

The μ represents the vector of dummy variables regarding technological field and the control fixed effect according to the technological field. The abbreviations *DBF*, *DIG*, *DCF*, *DGB*, *DHE*, *DHD*, *DOT*, *DWE*, *DSE*, *DGE*, *DOP*, *DWH*, *DDP*, and *DHB* in μ are dummy variables indicating the types of technology. They are equal to 1 if the patent contains the highest number of technological indices of the technology that corresponds to the definition of the variable, and 0 otherwise. These dummy variables indicating types of technology control fixed effects related to types of technology. More detailed descriptions regarding the controlling fixed effect of these dummy variables related to types of technology are presented in Table 3.

$$\mu = [DBF \ DIG \ DCF \ DGB \ DHE \ DHD \ DOT \ DWE \ DSE \ DGE \ DOP \ DWH \ DDP \ DHB] \quad (4)$$

Equation (4) includes abbreviations of dummy variables for various types of technology, such as the dummy variables for patents of bio-fuels (*DBF*), integrated gasification combined cycle (*DIG*), fuel cells (*DCF*), pyrolysis or gasification of bio-mass (*DGB*), harnessing energy from manmade waste (*DHE*), hydro energy (*DHD*), ocean thermal energy conversion (*DOT*), wind energy (*DWE*), solar energy (*DSE*), geothermal energy (*DGE*), other production or use of heat not derived from combustion (*DOP*), using waste heat (*DWH*), devices for producing mechanical power from muscle energy (*DDP*), and iden-

tically hybrid technology (*DHB*). Detailed information about the codifying indicator variables used in this study is shared in Table 3.

4. Results

In this section, we present the empirical results via descriptive statistics and the results of our regression analysis. The descriptive statistics focus on showing the status of co-patent collaboration and developments in alternative energy technologies in South Korea from 2010 to 2017.

4.1. Descriptive Statistics

Figure 3 describes patent counts by the technological field of the data. The blue portion of the graph represents patents without co-patent collaboration or financial support of a national R&D project. The orange portion of the graph represents patents with financial support only. The grey portion of the graph represents patents with collaboration. The yellow portion represents patents with both collaboration and financial support. Detailed descriptive statistics of the data are shared in Appendix A. In Figure 3, the total observations comprise 28,822 patents, consisting of 1525 identical hybrid technologies and 27,297 non-identical hybrid technologies. The most frequent patents in non-identical hybrid technologies are (arranged from most to least frequent): solar energy (*SE*), fuel cells (*FC*), harnessing energy from manmade waste (*HE*), bio-fuels (*BF*), wind energy (*WE*), waste heat (*WH*), hydro energy (*HD*), geothermal energy (*GE*), pyrolysis or gasification of bio-mass (*GB*), other production or use of heat (*OP*), ocean thermal energy conversion (*OT*), integrated gasification combined cycle (*IG*), and devices for producing mechanical power from muscle energy (*DP*).

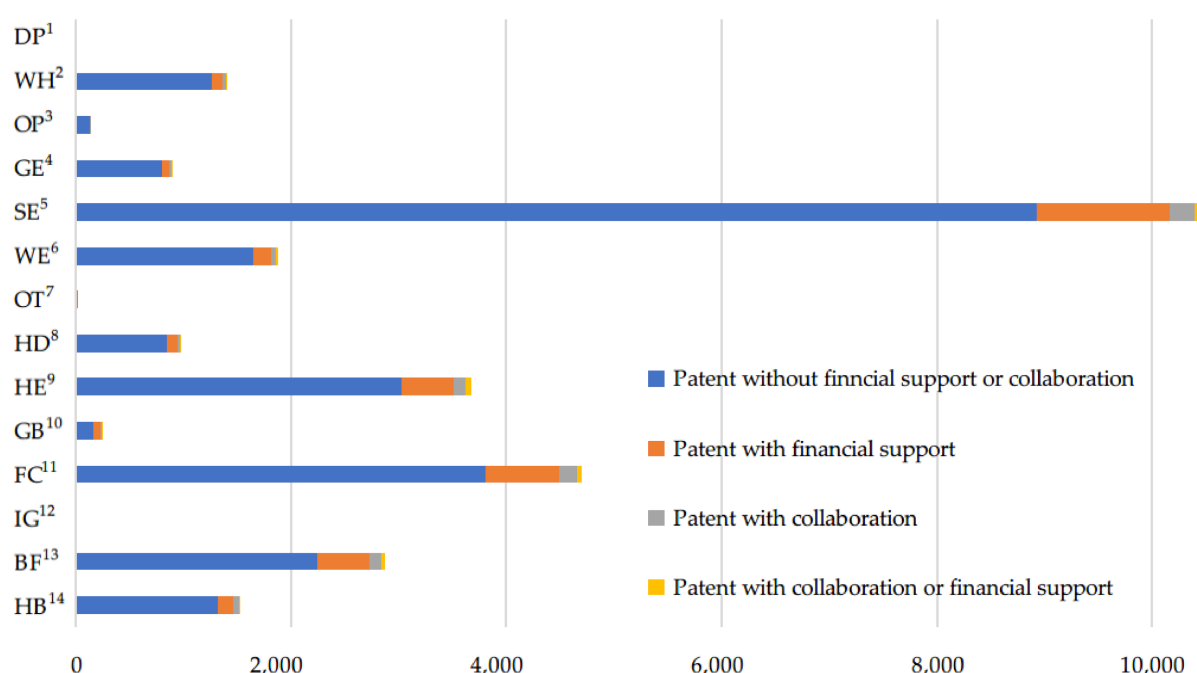


Figure 3. Patent counts by technological field. ⁽¹⁾ *DP*: technology of devices for producing mechanical power from muscle energy; ⁽²⁾ *WH*: waste heat technology; ⁽³⁾ *OP*: technology of other production or use of heat not derived from combustion; ⁽⁴⁾ *GE*: geothermal energy technology; ⁽⁵⁾ *SE*: solar energy technology; ⁽⁶⁾ *WE*: wind energy technology; ⁽⁷⁾ *OT*: technology of ocean thermal energy conversion; ⁽⁸⁾ *HD*: hydro energy technology; ⁽⁹⁾ *HE*: technology of harnessing energy from manmade waste; ⁽¹⁰⁾ *GB*: technology of pyrolysis or gasification of bio-mass; ⁽¹¹⁾ *FC*: fuel cell technology; ⁽¹²⁾ *GC*: technology of integrated gasification combined cycle; ⁽¹³⁾ *BF*: bio-fuel technology; ⁽¹⁴⁾ *HB*: identically hybrid technology).

Notably, 3824 patents received funding from the national R&D project, and 146 patents were identical hybrid technologies, while 3678 patents were non-identical hybrid technologies. Among the non-identical hybrid technology patents with financial support from the national R&D project, the most frequent patents are related to *SE*, *FC*, *HE*, *BF*, *WE*, *WH*, *HD*, *GE*, and *GB*. However, less than 10 non-identical hybrid technology patents, such as *OP*, *OT*, *IG*, and *DP*, have been granted.

A total of 1374 patent applications from collaborative applicants were made in a triple helix manner; 1085 patents did not receive any financial support from the national R&D project, of which 65 patents were identical hybrid technologies. The most frequent technologies in the remaining 1020 non-identical hybrid technology patents are (in descending order): *SE*, *FC*, *HE*, *BF*, *WE*, *WH*, *HD*, *GE*, and *GB*. However, fewer patents of non-identical hybrid technologies based on co-patent collaboration, such as *OP*, *OT*, *IG*, and *DP*, have been granted. Additionally, 289 patents were based on co-patent collaboration and received financial support from the national R&D project, of which 10 patents were identical hybrid technologies. The most frequent technologies in these 279 non-identical hybrid technology patents are: *SE*, *FC*, *HE*, *BF*, and *WE*. Fewer patents of technologies such as *WH*, *GB*, *GE*, *HD*, *OP*, *OT*, *IG*, and *DP* have been granted. Figure 4 describes patent counts by the data's collaboration type. The blue portion represents patents with co-patent collaboration and no financial support from the national R&D project. The orange portion represents patents with collaboration and financial support. Detailed descriptive statistics of the data are shared in Appendix A.

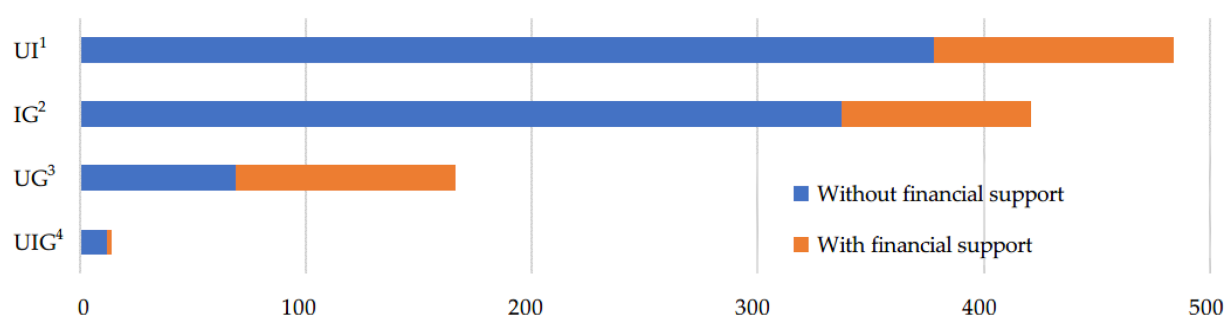


Figure 4. Patent counts by collaboration type. (¹ *UI*: co-patent collaboration between university and industry; ² *IG*: co-patent collaboration between industry and government; ³ *UG*: co-patent collaboration between university and government; ⁴ *UIG*: co-patent collaboration between university, industry, and government).

In Figure 4, the most common co-patent collaboration patterns were: *UI* (484), *IG* (421), *UG* (166), and *UIG* (14). The most frequent participants in the collaborations were: industry (1111), university (869), and government (784). In the absence of financial support, the most frequent collaborations were: *UI-F* (106), *UG-F* (97), *IG-F* (84), and *UIG-F* (2).

Figure 5 describes patent counts by collaboration type and technological field of the data. The color of Figure 5 represents different patent counts at the location as differentiated by the technology and collaboration types. Patent counts descend from greater to lesser in the following order: orange (200–250), yellow (150–200), green (100–150), blue (50–100), and grey (0–50). Detailed descriptive statistics of the data are shared in Appendix A.

In Figure 5, the patents of *SE* (30.57%), *FC* (18.92%), *HE* (15.57%), and *BF* (13.03%) show a relatively high proportion of collaboration-based invention without national R&D financial support. Interestingly, patents of *SE* (33.56%), *HE* (19.38%), *FC* (17.65%), and *BF* (11.75%) also show a relatively high proportion of having both collaboration-based invention and national R&D financial support. Moreover, universities are major institutions of co-patent collaboration in *SE* and *FC*. Industries are major institutions of co-patent collaboration in *HE* and *BF*.

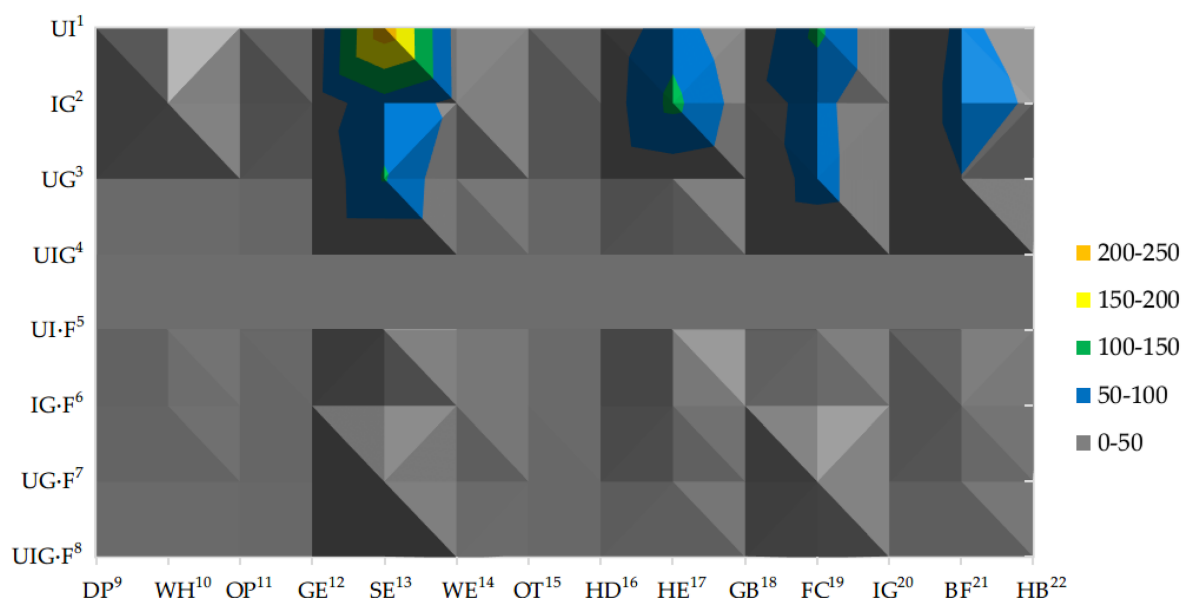


Figure 5. Patent counts with co-patent collaboration by collaboration and technology type. ¹ *UI*: co-patent collaboration between university and industry; ² *IG*: co-patent collaboration between industry and government; ³ *UG*: co-patent collaboration between university and government; ⁴ *UIG*: co-patent collaboration between university, industry, and government. ⁵ *UI·F*: the *UI* collaboration with the financial support; ⁶ *IG·F*: the *IG* collaboration with the financial support; ⁷ *UG·F*: the *UG* collaboration with the financial support; ⁸ *UIG·F*: the *UIG* collaboration with the financial support; ⁹ *DP*: technology of devices for producing mechanical power from muscle energy; ¹⁰ *WH*: waste heat technology; ¹¹ *OP*: technology of other production or use of heat not derived from combustion; ¹² *GE*: geothermal energy technology; ¹³ *SE*: solar energy technology; ¹⁴ *WE*: wind energy technology; ¹⁵ *OT*: technology of ocean thermal energy conversion; ¹⁶ *HD*: hydro energy technology; ¹⁷ *HE*: technology of harnessing energy from manmade waste; ¹⁸ *GB*: technology of pyrolysis or gasification of bio-mass; ¹⁹ *FC*: fuel cell technology; ²⁰ *GC*: technology of integrated gasification combined cycle; ²¹ *BF*: bio-fuel technology; ²² *HB*: identically hybrid technology).

In all technologies, the most frequent type of collaboration was *UI* or *IG*. In the case of collaboration-based inventions, *FC*, *SE*, and *OP* were most frequently invented based on *UI* collaboration, while *HB*, *BF*, *GB*, *HE*, *HD*, *WE*, *GE*, and *WH* were most frequently invented based on *IG* collaboration. Based on the results of the descriptive statistics, South Korea's national capability focuses highly on *SE*, *FC*, *HE*, *BF*, and *WE* technologies.

4.2. Empirical Analysis

The results of the analyses suggest that the type of collaboration used and the presence of financial support from the national R&D project both have effects the performance of alternative energy technologies.

Regression analyses were conducted using the control variables related to patent performance and the dummy variables regarding the technological field, which remove the fixed effect related to the types of alternative energy technologies.

In Table 3, the coefficients of the control variables are omitted because this study focuses on the effects of collaboration on patent performance. These coefficients are presented in Table A2. When summarizing the results of the control variables in the count portion of Model 3, it is important to note the coefficients of *P*, *O*, *NA*, *NI*, *NTI*, *NCL*, *NBCF*, *NBCP*, *NF*, *NFUS*, and *NP* are all positive and statistically significant. The coefficients of *NTC* and *NPUS* are negative and statistically significant, while the coefficients *NBCN* and *CNP* are statistically not significant. In summary, in the results of the control variables in the binomial portion of Model 3, the coefficients of *O*, *CNP*, *NA*, *NTI*, *NTC*, *NCL*, *NBCF*, *NBCP*, *NF*, *NFUS*, and *NP* are positive and statistically significant. The coefficient of *NPUS* is statistically not significant and negative. While the coefficients of *P*, *NI*, and *NBCN* are statistically not significant, variables such as, *O*, *NA*,

NTI, *NBCP*, *NFUS*, and *NP* are important factors that positively and significantly affect forward citation counts in the results of the binomial and count portions of Model 3.

In Table 4, there are three models. Models 2 and 3 involve control variables, whereas Model 1 does not. Model 3 includes both control and dummy variables of the technological field. The models were estimated in two parts: binomial and count. The binomial portion shows the relationships between collaboration type and whether a patent is cited, while the count portion shows the relationships between collaboration types and the performance of patents.

Table 4. Statistical analysis results.

Variables		Model 1		Model 2		Model 3	
		Binomial	Count	Binomial	Count	Binomial	Count
Intercept		0.759 *** (0.014)	−11.575 (106.434)	−2.583 *** (0.100)	−1.716 *** (0.075)	−2.258 (0.041)	−1.097 *** (0.173)
Financial support from national R&D project	F^1	−0.897 *** (0.036)	−1.628 *** (0.052)	−0.086 ** (0.041)	−0.235 *** (0.040)	0.066 (0.041)	−0.224 *** (0.039)
Collaboration	UIG^2	−0.066 (0.613)	−2.239 *** (0.730)	−0.121 (0.637)	−1.330 ** (0.566)	$−3.01 \times 10^{-4}$ (0.641)	−1.288 ** (0.565)
	UG^3	−0.555 ** (0.242)	−1.390 *** (0.325)	−0.470 * (0.260)	−0.550 ** (0.226)	−0.380 (0.261)	−0.507 ** (0.226)
	UI^4	0.277 ** (0.118)	−0.419 *** (0.125)	0.029 (0.131)	−0.180 ** (0.080)	0.054 (0.131)	−0.174 ** (0.080)
	IG^5	−0.586 *** (0.110)	−0.903 *** (0.151)	−0.560 *** (0.127)	−0.123 (0.102)	−0.537 *** (0.127)	−0.132 (0.102)
Interaction term of collaboration and funding	$UIG \cdot F^6$	10.770 (139.279)	2.438 (1.593)	9.848 (139.189)	1.008 (1.115)	9.795 (138.966)	0.989 (1.108)
	$UG \cdot F^7$	0.639 ** (0.318)	1.357 *** (0.440)	0.338 (0.334)	0.297 (0.309)	0.285 (0.336)	0.263 (0.307)
	$UI \cdot F^8$	−0.291 (0.231)	0.844 *** (0.317)	−0.298 (0.242)	0.464 ** (0.209)	−0.343 (0.242)	0.428 ** (0.207)
	$IG \cdot F^9$	0.963 *** (0.248)	1.057 *** (0.332)	0.609 ** (0.260)	−0.025 (0.229)	0.596 ** (0.261)	0.028 (0.035)
Control variables		X		O		O	
Fixed effect along technological field		X		X		O	
Pseudo R-squared		0.048		0.392		0.398	
Log-likelihood		$−6.365 \times 10^4$		$−5.72 \times 10^4$		$−5.706 \times 10^4$	
Wald test (probability)		22.5 (0.013)		388.69 (less than 0.001)		448.52 (less than 0.001)	
Observations		28,822		28,822		28,822	

Note: maximum log-likelihood estimations, standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ¹ F : financial support from national R&D project; ² UIG : co-patent collaboration between university, industry, and government. ³ UG : co-patent collaboration between university and government; ⁴ UI : co-patent collaboration between university and industry; ⁵ IG : co-patent collaboration between industry and government; ⁶ $UIG \cdot F$: the UIG collaboration with the financial support; ⁷ $UG \cdot F$: the UG collaboration with the financial support; ⁸ $UI \cdot F$: the UI collaboration with the financial support; ⁹ $IG \cdot F$: the IG collaboration with the financial support.

Based on the regression analysis results, the statistical significance of the coefficients in the binomial part was found to vary depending on the control and dummy variables of the technological field. In Model 1, the coefficients of F , UG , UI , IG , $UG \cdot F$, and $IG \cdot F$ are statistically significant, while in Model 2, the coefficients of F , UG , IG , and $IG \cdot F$ are

statistically significant; however, in Model 3, the coefficients of *IG* and *IG·F* are statistically significant.

In the binomial part of Model 3, the coefficient of *IG* is -0.537 , thereby showing that *IG* collaboration has a negative relationship with the first forward citation of patents. However, the coefficient of *IG·F* is 0.596 , while the total effect of *IG·F* is 0.069 ($0.596-0.537$). This positive value shows that *IG* collaboration with financial support from the national R&D project (*IG·F*) is positively related with the first forward citation, while the other collaboration types have no relationship with the first forward citation of patents. Even if *IG* collaboration with the national R&D project has a positive effect, the size and consequence of that effect are very slight.

The results of the count portion show that there are relatively few changes in the statistical significance of coefficients with the addition of control and dummy variables. The statistical significance of the coefficients of *UG·F* and *IG·F* disappear in the count portions of Models 2 and 3. In the count portion of Model 3, the coefficients of *F*, *UIG*, *UG*, and *IG* are -0.224 , -1.289 , -0.507 , and -0.174 , respectively. Thus, the financial support of the national R&D project, *UIG* collaboration, *UG* collaboration, and *IG* collaboration have a negative relationship with patent performance. While the coefficient of *UI·F* is 0.428 , *UI* collaboration with the financial support of the national R&D project (*UI·F*) has a positive relationship with patent performance. The total effect of *UI·F* is 0.030 ($0.428-0.174-0.224$) and is positive.

We compared the coefficient values and confirmed the statistical significance of the difference between coefficients. The comparative results of the Wald test for the hypothesis that differences between the coefficients of interesting variables equal to zero are presented in Tables 5–8. Table 5 presents the difference between the coefficients of collaboration terms of the count portion of Model 3 and the results of the Wald test for the hypothesis.

The value of the coefficient increases in the following order: *IG* (-0.132), *UI* (-0.174), *UG* (-0.507), and *UIG* (-1.288) in Table 4. In Table 5, only the coefficient of *UIG* is significantly different from the other coefficients of the collaboration terms of *UI* and *IG*. Therefore, *UIG* is a more inefficient way of collaboration compared to *UI* and *IG*.

Table 5. Wald test of differences between the coefficients of collaboration terms of the count portion of Model 3.

	<i>UIG</i> ¹	<i>UG</i> ²	<i>UI</i> ³	<i>IG</i> ⁴
<i>UIG</i> ¹				
<i>UG</i> ²	0.781			
<i>UI</i> ³	1.113 *	0.333		
<i>IG</i> ⁴	1.156 **	0.375	0.042	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ¹ *UIG*: co-patent collaboration between a university, industry, and government. ² *UG*: co-patent collaboration between a university and government; ³ *UI*: co-patent collaboration between a university and industry; ⁴ *IG*: co-patent collaboration between an industry and government.

Table 6. Wald test of differences between the coefficients of interaction terms of the count portion of Model 3.

	<i>UIG·F</i> ¹	<i>UG·F</i> ²	<i>UI·F</i> ³	<i>IG·F</i> ⁴
<i>UIG·F</i> ¹				
<i>UG·F</i> ²	-0.726			
<i>UI·F</i> ³	-0.561	0.165		
<i>IG·F</i> ⁴	-0.961	-0.235	-0.400	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ¹ *UIG·F*: co-patent collaboration between a university, industry, and government with financial support from national R&D project. ² *UG·F*: co-patent collaboration between a university and government with the financial support; ³ *UI·F*: co-patent collaboration between a university and industry with the financial support; ⁴ *IG·F*: co-patent collaboration between an industry and government with the financial support.

Table 7. Wald test of differences between the coefficients of collaboration and interaction terms of the count portion of Model 3.

	<i>UIG</i> ¹	<i>UG</i> ²	<i>UI</i> ³	<i>IG</i> ⁴
<i>UIG</i> · <i>F</i> ⁵	2.277	1.496	1.163	1.121
<i>UG</i> · <i>F</i> ⁶	1.551 **	0.770	0.438	0.395
<i>UI</i> · <i>F</i> ⁷	1.716 ***	0.935 ***	0.602 **	0.560 **
<i>IG</i> · <i>F</i> ⁸	1.316 **	0.535 *	0.203	0.160

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ¹ *UIG*: co-patent collaboration between a university, industry, and government. ² *UG*: co-patent collaboration between a university and government; ³ *UI*: co-patent collaboration between a university and industry; ⁴ *IG*: co-patent collaboration between an industry and government; ⁵ *UIG*·*F*: the *UIG* collaboration with financial support from a national R&D project; ⁶ *UG*·*F*: the *UG* collaboration with the financial support; ⁷ *UI*·*F*: the *UI* collaboration with the financial support; ⁸ *IG*·*F*: the *IG* collaboration with the financial support.

Table 8. Total effects of collaborations with financial support from the national R&D project.

Rows	Description	<i>UIG</i> ¹	<i>UG</i> ²	<i>UI</i> ³	<i>IG</i> ⁴
A	Financial support from national R&D project		−0.224 ***		
B	Collaborations	−1.288 **	−0.507 **	−0.174 **	−0.132
C	Interaction terms	0.989	0.263	0.428 **	0.028
D	Sum of A, B, and C	−1.512	−0.731	0.030	−0.224

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ¹ *UIG*: co-patent collaboration between a university, industry, and government. ² *UG*: co-patent collaboration between a university and government; ³ *UI*: co-patent collaboration between a university and industry; ⁴ *IG*: co-patent collaboration between an industry and government.

Table 6 presents the results of the Z-test of differences between the coefficients of the interaction terms of the count portion of Model 3.

The value of the coefficient increases in the following order: *UIG*·*F*(0.989), *UI*·*F*(0.428), *UG*·*F*(0.263), and *IG*·*F*(0.028) in Table 3. In Table 6, none of the differences between the coefficients of interaction terms are statistically significant.

The value of the coefficient increases in the following order: *UIG*·*F* (0.989), *UI*·*F* (0.428), *UG*·*F* (0.263), and *IG*·*F* (0.028) in Table 4. In Table 6, none of the differences between the coefficients of interaction terms are statistically significant.

Table 7 presents the difference between the coefficients of collaboration terms and interaction terms of the count portion of Model 3, and the results of the Wald test for the hypothesis.

The value of the coefficient increases in order from *UIG*·*F*(0.989), *UI*·*F*(0.428), *UG*·*F*(0.263), *IG*·*F*(0.028), *IG*(−0.132), *UI*(−0.174), *UG*(−0.507), to *UIG*(−1.288) in Table 4. Overall, the coefficients of interaction terms are bigger than the coefficients of collaboration terms. In Table 7, the coefficient *UG*·*F* is significantly bigger than *UIG*; *UI*·*F* is significantly bigger than *UIG*, *UG*, *UI*. and *IG*; and *IG*·*F* is significantly bigger than *UIG* and *UG*.

Table 8 presents the total effects of collaborations with the financial support of the national R&D project. It does so by summing up the effects of the financial support of the national R&D project, collaborations, and collaborations with the financial support of the national R&D project on patent performance. In Table 8, the rows A, B, and C are coefficients of the national R&D project variable, collaboration variables, and the interaction term of the count portion of Model 3 in Table 3, respectively. Row D is the sum of the values in rows A, B, and C of Table 8.

The values of row D in Table 8 show the total effects of the collaborations on patent performance. Values that are statistically insignificant are not included in the total effects. According to the results, the *UI* value of row D in Table 7 is higher than 0. The other values are less than 0. The collaborations are relatively efficient in the order of *UI* (0.030), *IG* (−0.224), *UG* (−0.731), and *UIG* (−1.512).

5. Discussion

The results of this study show the most frequent type and agent of collaboration. When the invention was not financially supported by the national R&D project, the types of collaborations occurred in the following order of frequency: *UI*, *IG*, *UG*, and *UIG*. However, *UG* collaboration appeared more frequently than *IG* collaboration when the invention was financially supported by the national R&D project. This major role of *UI* collaboration in the national invention network is consistent with the results of previous studies. In particular, financial support from the national R&D project seems to contribute to the major role of universities in the national invention network by relatively promoting cooperation between universities and government research institutes. In the absence of financial support, *UG* collaborations (69) occurred approximately four times less than *IG* collaborations (315). However, in the case of financial support, *UG* collaborations (97) occurred more frequently than *IG* collaborations (84). In addition, 58% of all *UG* collaborations were financially supported by national R&D projects. By contrast, 20% of all *IG* collaborations were financially supported by the national R&D project. These remarkable differences show how important financial support is for government research institutes that innovate with universities. Moreover, *UI* collaboration is the most effective according to results of Model 3. Therefore, South Korea's national innovation system operates as an environment wherein relatively effective collaboration can be achieved.

Alternative energy technologies such as *FC*, *SE*, and *OP* are more frequently invented through *UI* collaborations, while technologies such as *HB*, *BF*, *GB*, *HE*, *HD*, *WE*, *GE*, and *WH* are more frequently developed through *IG* collaborations. The role of *IG* collaborations in the alternative energy industry can be understood as an undeveloped aspect of the national innovation system. According to Yoda and Kuwashima [21], in the case of Japan, *IG* collaboration was the dominant type prior to the development of the national innovation system in terms of triple helix via deregulation. However, Yoon [18] argues that South Korea's national innovation system is close to triple helix III overall. In summary, South Korea's alternative energy industry of *HB*, *BF*, *GB*, *HE*, *HD*, *WE*, *GE*, and *WH* still shows undeveloped features of the innovation system in terms of the invention network. Brem and Radziwon [6] present a case in which R&D and commercialization of the *GE* technology are relatively less developed in Denmark through triple helix collaboration and they emphasize the importance of networking, win-win situations, and problem orientation. Government policymakers may need to consider the introduction of a coordination system that can compose a triple helix collaboration, with a focus on networking, win-win situations, and problem orientation, for the R&D and commercialization of a poor alternative energy such as *GE*.

Some technologies show a relatively high number of total patent counts, such as *SE* (36.39%), *FC* (16.32%), *HE* (12.75%), and *BF* (9.96%). These technologies also show a relatively high number of inventions based on collaborations. Therefore, we expect that development of the innovation system in terms of collaboration can be affected by the scale of technological invention.

As shown in Table 4, only *UI* collaboration shows a positive effect on patent performance when the invention is financially supported by the national R&D project. According to the results of Model 3 and Table 7, the net effect of *UI* collaboration with financial support from the national R&D project is 0.030 (0.428–0.224–0.174). The effect of *UI* collaboration is –0.174, and the net effect of funding on *UI* collaboration is 0.200 (0.424–0.224). This result is consistent with that of previous studies in terms of the efficient role of universities in triple helix studies. It also confirms that *UI* collaboration positively affects innovative performance [17,28]. Interestingly, the effects of co-patent collaborations with financial support from the national R&D project were not positive overall, with the exception of *UI* collaboration. In terms of the triple helix theory, these results could indicate that the knowledge and consensus space of a national innovation system did not work efficiently [24]. In other words, *UI* collaborations perform efficiently when financially supported. To increase national innovation performance, a political role that can promote innovative activities

through *UI* cooperation is necessary and important, as has been suggested by previous studies [22,28].

A few *UIG* collaborations were found during the research period. Patents based on *UIG* collaboration accounted for 1.16% of the total number of patents based on collaborations. According to Yoon [18], South Korea's collaborative aspects of the national innovation system have matured since the 2000s, while the effect of *UIG* collaboration shows a significantly negative and low value (−1.288). In actuality, this result seems to be related to the misleading science and technology research policy reported by Park and Leydesdorff [16].

In Table 4, *IG* collaboration with financial support from the national R&D project shows an insignificant low value. However, in Table 7, *IG* collaboration with financial support from the national R&D project was not significantly more efficient than *UI* collaboration without financial support, but *UI* collaboration with financial support from the national R&D project was significantly more efficient than *IG* collaboration without the financial support. This relatively inefficient result reinforces the argument that quantitatively promoting research policy induces discouraging activities, thereby qualitatively mitigating sound innovation. Moreover, government policymakers may need to consider increasing financial support to focus on university-based collaborations. However, *IG* collaboration is significantly positive in the binomial part of Model 3. These contradictory results regarding *IG* collaboration may mean that *IG* collaboration is effective for small-level technology development performance. The fact that patent performance is small can be understood as having occurred in a relatively short period. This is considered consistent with Lee et al.'s [30] finding that *IG* collaboration is effective for short-term achievement of technology development. In other cases, the national innovation system of Belgian biotech industries shows quite different results compared to those of South Korea. *UI* and *UG* collaborations have a positive effect on the qualitative innovation performance of patents (forward citation counts). However, *IG* collaborations do not have significant effects on the qualitative innovation performance of patents [47]. In the case of the U.S., all types of collaboration between universities, industries, and governments have a positive effect on the qualitative innovation performance of patents [48]. The effect of collaborations on the qualitative innovation performance varies by country because of differences in the maturity of different national innovation systems.

Until now, we have presented the innovation systematic characteristics of South Korea's invention network, demonstrating that South Korea's innovation network is immature and inefficient in the performance of technology development overall. However, according to Ranga and Etzkowitz [24], the effects of collaboration are not only upon the invention, but also upon knowledge dissemination and the development of ideas. In addition, according to previous studies [22,27,30], collaboration triggers the development of R&D potential. Moreover, *UI* collaborations generate various effects, such as helping companies expand the scope of the market [26]. The results of this study suggest that the majority of collaborations are ineffective. However, we assume that collaboration has a positive effect that is not reflected in the citation counts that represent the quality level of technology. For example, collaborations negatively affect the quality of patents, but they can positively affect the number of patent inventions. In addition, corporations can appropriately adjust the direction or strategies of their technological development through collaboration with other types of institutions. Due to this, we suggest that co-patent collaborations positively affect other aspects of the composition of patent pools, such as the relativeness of firm patents. For examples, collaborations between universities, industries, and governments generally positively affect product and process innovation in Spain [49]. In Mexico, collaborations between companies and universities have been found to have a positive impact on firms' sales [28]. However, only *UI* collaborations have a positive effect on the sale of green goods for small- and medium-size corporations in the U.S. [50].

This study has limitations in its estimation method. Referencing criticism by Jensen et al. [31], this paper includes a bias toward STI indications, such as citation counts.

STI innovation-based patents are more likely to record higher citation counts than DUI innovation-based patents, which are more likely to record zero or low citation counts. The dependent variable of this study is unlikely to reflect performance based on DUI innovation. STI innovation-based performance can be captured in citation counts of patent data, while the performance based on DUI innovation can be captured in an increase in market shares, and innovation application to the manufacturing process [51,52].

Furthermore, more than half of our data are related to technologies based on STI innovation such as solar energy (36.39%), fuel cell (16.32%), and biofuel (9.96%). According to Kim and Chang and Hong et al. [32,53], biofuel, fuel cell, and photovoltaic generation all display characteristics that show innovation performance is relatively less affected by DUI activity in South Korea.

Although the model includes control variables for fixed effects from the technology sector, the results of a full model can involve bias that is ascribable to the technological field. There can be implicit effects associated with the technological field such as those due to the size of a technology-specific patent market, and characteristics of innovation mode (STI or DUI) and so forth. The empirical analysis suggests that results are positively biased toward STI innovation performance and STI friendly collaboration pattern (e.g., UI collaboration).

In other words, the dependent variable reflecting innovation performance is likely to focus on outcomes, such as knowledge creation, oriented toward STI innovation mode. Moreover, most of the data are related to the technologies based on STI innovation. Therefore, the result of empirical analysis can favor collaborations involving universities which have advantages in STI innovation mode.

6. Conclusions

This study confirmed the effects of financial support from the national R&D project, as well as the effects of co-patenting collaboration on the performance of alternative energy patents between 2010 and 2017 in South Korea. The results provide evidence of inefficiency in South Korea's national innovation system. Specifically, only *UI* collaboration in congruence with financial support from the national R&D project efficiently affects patent performance. *UI* collaboration is relatively more efficient than other types of collaboration without financial support from the national R&D project. Furthermore, *UI* collaboration accounts for a significant proportion of all co-patent collaborations. In the Discussion, this study suggested some areas for improvement for South Korea's invention network. For example, except for *SE*, *FC*, *HE*, and *BF*, which are developed on a relatively large scale, the proportion of inventions based on collaboration is relatively low, and the scale of *UI* collaboration is relatively small except for *SE*, *FC*, and *OP*.

We thus establish the immature status of the invention network in South Korea. In particular, there is no evidence that the government's co-patent collaboration with other agents is efficient. Besides, financial support from the national R&D project is generally inefficient for increase in patent performance. Thus, South Korea's science and technology research policy needs to focus on an approach that promotes innovation activity to work toward attaining a qualitatively sound goal.

However, this study has data-oriented limitations. The dependent variable, which reflects patent performance (citation counts) has characteristics that suggests favorable results for STI-based innovations. The composition of patent data also concentrates on STI innovation-based technologies such as *SE*, *FC*, and *BF*. Due to these data-oriented limitations, the model of this study may be unsuitable for reflecting performances based on DUI innovation. Nevertheless, this study contains valuable points. As technology and industries advance, invention of key technologies may be dependent on STI innovation. Therefore, the results of this study at least suggest systematic characteristics suitable for suggesting critical aspects of alternative energy innovation.

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Abbreviations and Symbols

The following abbreviations and symbols used in this manuscript:

Abbreviations

AIC	Akaike information criterion
BF	Biofuels
CNP	Cumulative number of patents in same technological field
CPC	Cooperative Patent Classification
DBF	Dummy variable regarding biofuels
DDP	Dummy variable regarding devices for producing mechanical power from muscle energy
DFC	Dummy variable regarding fuel cells
DGB	Dummy variable regarding pyrolysis or gasification of biomass
DGC	Dummy variable regarding integrated gasification combined cycle
DGE	Dummy variable regarding geothermal energy
DHB	Dummy variable regarding hybrid technology of the alternative energy production
DHD	Dummy variable regarding hydro energy
DHE	Dummy variable regarding harnessing energy from man-made waste
DOP	Dummy variable regarding other production or use of heat not derived from combustion
DOT	Dummy variable regarding ocean thermal energy conversion
DP	devices for producing mechanical power from muscle energy
DSE	Dummy variable regarding solar energy
DUI	Doing, using, and interacting
DWE	Dummy variable regarding wind energy
DWH	Dummy variable regarding using waste heat
F	National research and development fund
FC	fuel cells
GB	pyrolysis or gasification of biomass
GC	integrated gasification combined cycle
GE	geothermal energy
HB	hybrid technology of the alternative energy production
HD	hydro energy
HE	harnessing energy from man-made waste
IG	Collaboration of industry and government
IPC	International Patent Classification
KIPRIS	Korea Intellectual Property Rights Information Service
NA	Number of applicants
NBCF	Number of backward citations of families
NBCN	Number of backward citations to non-patent documents of the patent
NBCP	Number of backward citations of the patent
NCL	Number of claims
NF	Number of families
NFUS	Number of families granted by U.S. patent office
NI	Number of inventors
NP	Number of priority patents
NPUS	Number of priority patents granted by U.S. patent office
NTBF	New technology-based firm

NTC	Number of CPC technological index
NTI	Number of IPC technological index
O	Years since application date
OP	other production or use of heat not derived from combustion
OT	ocean thermal energy conversion
P	PCT granted patent
PCT	Patent cooperation treaty
R&D	Research and development
SCC	Sum of co-patent collaborations, such as UIG, UG, UI, and IG
SE	solar energy
SME	Small and Medium-sized Enterprises
STI	Science and technology innovation
U.S.	United States
UG	Collaboration of university and government
UI	Collaboration of university and industry
UIG	Collaboration of university, industry, and government
WE	wind energy
WH	using waste heat
WIPO	World Intellectual Property Organization
Symbols	
C	Vector of control variables regarding biblio-metric information
X	Vector of interesting variables regarding collaboration and national R&D fund
β	Vector of coefficients of the interesting variable
μ	Vector of control variables for fixed effect related to types of technology

Appendix A

Table A1. Descriptive statistics of patent counts by technologies and collaborations.

Abbreviation	Total	Fund(F)	SCC ¹	UIG	UG	UI	IG	SCC ¹ F	UIG·F	UG·F	UI·F	IG·F
Total	100% (28,822)	13.27% (3824)	3.76% (1085)	0.05% (14)	0.58% (166)	1.68% (484)	1.46% (421)	1.00% (289)	0.01% (2)	0.34% (97)	0.37% (106)	0.29% (84)
HB ²	5.29% (1525)	0.51% (146)	0.23% (65)	0.00% (0)	0.01% (3)	0.07% (21)	0.14% (41)	0.03% (10)	0.00% (0)	0.00% (0)	0.02% (6)	0.01% (4)
BF ³	9.96% (2871)	1.77% (510)	0.50% (145)	0.01% (2)	0.14% (41)	0.17% (50)	0.18% (52)	0.12% (34)	0.00% (0)	0.03% (8)	0.03% (10)	0.06% (16)
GC ⁴	0.01% (2)	0.00% (1)	0.00% (0)	0.00% (0)	0.00% (0)	0.00% (0)	0.00% (0)	0.00% (0)	0.00% (0)	0.00% (0)	0.00% (0)	0.00% (0)
FC ⁵	16.32% (4704)	2.57% (741)	0.73% (209)	0.02% (7)	0.14% (41)	0.35% (100)	0.21% (61)	0.18% (51)	0.00% (1)	0.11% (31)	0.04% (12)	0.02% (7)
GB ⁶	0.86% (248)	0.23% (67)	0.07% (20)	0.00% (0)	0.00% (1)	0.01% (2)	0.06% (17)	0.03% (8)	0.00% (0)	0.00% (1)	0.00% (0)	0.02% (7)
HE ⁷	12.75% (3674)	1.90% (549)	0.55% (158)	0.01% (3)	0.03% (10)	0.18% (53)	0.32% (92)	0.19% (56)	0.00% (0)	0.03% (9)	0.09% (25)	0.08% (22)
HD ⁸	3.37% (971)	0.35% (100)	0.09% (26)	0.00% (0)	0.01% (2)	0.03% (9)	0.05% (15)	0.00% (1)	0.00% (0)	0.00% (1)	0.00% (0)	0.00% (0)
OT ⁹	0.03% (9)	0.01% (3)	0.00% (0)	0.00% (0)	0.00% (0)	0.00% (0)	0.00% (0)	0.00% (0)	0.00% (0)	0.00% (0)	0.00% (0)	0.00% (0)
WE ¹⁰	6.52% (1880)	0.63% (183)	0.22% (64)	0.00% (1)	0.03% (8)	0.09% (26)	0.10% (29)	0.06% (17)	0.00% (1)	0.00% (0)	0.03% (8)	0.03% (8)
SE ¹¹	36.39% (10,487)	4.62% (1333)	1.12% (323)	0.00% (1)	0.20% (58)	0.68% (195)	0.24% (69)	0.34% (97)	0.00% (0)	0.16% (46)	0.13% (38)	0.05% (13)
GE ¹²	3.13% (901)	0.28% (80)	0.10% (28)	0.00% (0)	0.01% (2)	0.03% (10)	0.06% (16)	0.02% (6)	0.00% (0)	0.00% (1)	0.01% (2)	0.01% (3)
OP ¹³	0.48% (138)	0.01% (2)	0.01% (2)	0.00% (0)	0.00% (0)	0.01% (2)	0.00% (0)	0.00% (0)	0.00% (0)	0.00% (0)	0.00% (0)	0.00% (0)

Table A1. Cont.

Abbreviation	Total	Fund(F)	SCC ¹	UIG	UG	UI	IG	SCC ¹ F	UIG-F	UG-F	UI-F	IG-F
WH ¹⁴	4.90% (1412)	0.38% (109)	0.16% (45)	0.00% (0)	0.00% (0)	0.06% (16)	0.10% (29)	0.03% (9)	0.00% (0)	0.00% (0)	0.02% (5)	0.01% (4)
DP ¹⁵	0.00% (0)	0.00% (0)	0.00% (0)	0.00% (0)	0.00% (0)	0.00% (0)	0.00% (0)	0.00% (0)	0.00% (0)	0.00% (0)	0.00% (0)	0.00% (0)

¹ SCC: the sum of co-patent collaborations, such as *UIG*, *UG*, *UI*, and *IG*; ² *HB*: identically hybrid technology; ³ *BF*: bio-fuel technology; ⁴ *GC*: technology of integrated gasification combined cycle; ⁵ *FC*: fuel cell technology; ⁶ *GB*: technology of pyrolysis or gasification of bio-mass; ⁷ *HE*: technology of harnessing energy from manmade waste; ⁸ *HD*: hydro energy technology; ⁹ *OT*: technology of ocean thermal energy conversion; ¹⁰ *WE*: wind energy technology; ¹¹ *SE*: solar energy technology; ¹² *GE*: geothermal energy technology; ¹³ *OP*: technology of other production or use of heat not derived from combustion; ¹⁴ *WH*: waste heat technology; ¹⁵ *DP*: technology of devices for producing mechanical power from muscle energy.

Table A2. Information criterion and log-likelihood of the candidate models.

Model	Akaike Information Criterion	Bayesian Information Criterion	Log-Likelihood
Poisson	183,970	182,492	−91,946
Negative binomial	115,094	115,424	−115,014
Zero inflated Poisson	168,770	169,415	−84,310
Zero inflated negative binomial	114,688	115,341	−57,260
Hurdle Poisson	168,763	169,408	−84,300
Hurdle negative binomial	114,271	114,924	−57,060

Table A3. Statistical analysis results with coefficients of control variables.

Variables		Model 1		Model 2		Model 3	
		Binomial	Count	Binomial	Count	Binomial	Count
Intercept		0.759 *** (0.014)	−11.575 (106.434)	−2.583 *** (0.100)	−1.716 *** (0.075)	−2.258 (0.041)	−1.097 *** (0.173)
Financial support from national R&D project	<i>F</i> ¹	−0.897 *** (0.036)	−1.628 *** (0.052)	−0.086 ** (0.041)	−0.235 *** (0.040)	0.066 (0.041)	−0.224 *** (0.039)
Collaboration	<i>UIG</i> ²	−0.066 (0.613)	−2.239 *** (0.730)	−0.121 (0.637)	−1.330 ** (0.566)	−3.01 × 10 ^{−4} (0.641)	−1.288 ** (0.565)
	<i>UG</i> ³	−0.555 ** (0.242)	−1.390 *** (0.325)	−0.470 * (0.260)	−0.550 ** (0.226)	−0.380 (0.261)	−0.507 ** (0.226)
	<i>UI</i> ⁴	0.277 ** (0.118)	−0.419 *** (0.125)	0.029 (0.131)	−0.180 ** (0.080)	0.054 (0.131)	−0.174 ** (0.080)
	<i>IG</i> ⁵	−0.586 *** (0.110)	−0.903 *** (0.151)	−0.560 *** (0.127)	−0.123 (0.102)	−0.537 *** (0.127)	−0.132 (0.102)
Interaction term of collaboration and funding	<i>UIG-F</i> ⁶	10.770 (139.279)	2.438 (1.593)	9.848 (139.189)	1.008 (1.115)	9.795 (138.966)	0.989 (1.108)
	<i>UG-F</i> ⁷	0.639 ** (0.318)	1.357 *** (0.440)	0.338 (0.334)	0.297 (0.309)	0.285 (0.336)	0.263 (0.307)
	<i>UI-F</i> ⁸	−0.291 (0.231)	0.844 *** (0.317)	−0.298 (0.242)	0.464 ** (0.209)	−0.343 (0.242)	0.428 ** (0.207)
	<i>IG-F</i> ⁹	0.963 *** (0.248)	1.057 *** (0.332)	0.609 ** (0.260)	−0.025 (0.229)	0.596 ** (0.261)	0.028 (0.035)

Table A3. Cont.

Variables		Model 1		Model 2		Model 3	
		Binomial	Count	Binomial	Count	Binomial	Count
Control variables	P^{10}			0.016 (0.093)	0.215 *** (0.035)	−0.005 (0.094)	0.241 *** (0.035)
	O^{11}			0.288 *** (0.008)	0.214 *** (0.006)	0.296 *** (0.012)	0.183 *** (0.008)
	CNP^{12}			0.016 *** (0.004)	0.037 *** (0.003)	0.022 * (0.011)	0.002 (0.008)
	NA^{13}			0.224 *** (0.035)	0.067 *** (0.024)	0.204 *** (0.035)	0.075 *** (0.024)
	NI^{14}			−0.018 *** (0.060)	0.022 *** (0.004)	−0.006 (0.007)	0.029 *** (0.004)
	NTI^{15}			0.075 *** (0.010)	0.046 *** (0.006)	0.073 *** (0.010)	0.048 *** (0.006)
	NTC^{16}			0.013 ** (0.007)	−0.010 *** (0.003)	0.014 ** (0.007)	−0.011 *** (0.003)
	NCL^{17}			0.003 (0.002)	0.009 *** (0.001)	0.004 ** (0.002)	0.009 *** (0.001)
	$NBCF^{18}$			0.038 *** (0.005)	0.005 *** (0.001)	0.035 *** (0.005)	0.005 *** (0.001)
	$NBCP^{19}$			0.070 *** (0.010)	0.036 *** (0.007)	0.060 *** (0.010)	0.033 *** (0.007)
	$NBCN^{20}$			−0.027 (0.026)	−0.004 (0.024)	−0.005 (0.024)	0.026 (0.024)
	NF^{21}			0.044 *** (0.008)	0.018 *** (0.002)	0.050 *** (0.008)	0.020 *** (0.002)
	$NFUS^{22}$			0.392 *** (0.035)	0.199 *** (0.010)	0.432 *** (0.036)	0.200 *** (0.011)
Fixed effect along technological field	NP^{23}			0.144 *** (0.030)	0.088 *** (0.012)	0.140 *** (0.030)	0.077 *** (0.011)
	$NPUS^{24}$			−0.139 *** (0.030)	−0.029 *** (0.011)	−0.138 *** (0.030)	−0.018 * (0.011)
	DBF^{25}					−0.650 *** (0.203)	−0.491 *** (0.149)
	DIG^{26}					−0.289 (0.314)	0.427 ** (0.190)
	DCF^{27}					−0.689 *** (0.201)	−0.448 *** (0.148)
	DGB^{28}					−0.656 *** (0.227)	−0.655 *** (0.171)
	DHE^{29}					−0.248 (0.201)	−0.316 ** (0.148)
	DHD^{30}					−0.120 (0.207)	−0.380 ** (0.153)
	DOT^{31}					−0.914 * (0.546)	−0.246 (0.315)

Table A3. Cont.

Variables	Model 1		Model 2		Model 3	
	Binomial	Count	Binomial	Count	Binomial	Count
DWE ³²					−0.377 * (0.202)	−0.255 * (0.150)
DSE ³³					−0.425 ** (0.209)	−0.127 (0.150)
DGE ³⁴					−0.308 (0.201)	−0.374 ** (0.150)
DOP ³⁵					−0.118 (0.232)	−0.221 (0.167)
DWH ³⁶					−0.493 ** (0.201)	−0.315 ** (0.150)
DDP ³⁷					−0.319 (0.559)	−0.475 (0.415)
DHB ³⁸					0.611 *** (0.218)	0.305 * (0.161)
Control variables	X		O			O
Fixed effect along technological field	X		X			O
Pseudo R-squared	0.048		0.392			0.398
Log-likelihood	−6.365 × 10 ⁴		−5.72 × 10 ⁴			−5.706 × 10 ⁴
Wald test (probability)	22.5 (0.013)		388.69 (less than 0.001)			448.52 (less than 0.001)
Observations	28,822		28,822			28,822

Note: maximum log-likelihood estimations, standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ¹ F: financial support from a national R&D project; ² UIG: co-patent collaboration between a university, industry, and government; ³ UG: co-patent collaboration between a university and government; ⁴ UI: co-patent collaboration between a university and industry; ⁵ IG: co-patent collaboration between an industry and government; ⁶ UIG·F: the UIG collaboration with the financial support; ⁷ UG·F: the UG collaboration with the financial support; ⁸ UI·F: the UI collaboration with the financial support; ⁹ IG·F: the IG collaboration with the financial support; ¹⁰ P: PCT granted patent; ¹¹ O: years since application date; ¹² CNP: cumulative number of patents in same technological field; ¹³ NA: number of applicants; ¹⁴ NI: number of inventors; ¹⁵ NTI: number of IPC; ¹⁶ NTC: number of CPC; ¹⁷ NCL: number of claims; ¹⁸ NBCF: number of backward citations of families; ¹⁹ NBCP: number of backward citations of the patent; ²⁰ NBCN: number of backward citations to non-patent document; ²¹ NF: number of families; ²² NFUS: number of families granted by U.S. patent office; ²³ NP: number of priority patents; ²⁴ NPUS: number of priority patents granted by U.S. patent office; ²⁵ BF: bio-fuels; ²⁶ GC: integrated gasification combined cycle; ²⁷ FC: fuel cells; ²⁸ GB: pyrolysis or gasification of bio-mass; ²⁹ HE: harnessing energy from manmade waste; ³⁰ HD: hydro energy; ³¹ OT: ocean thermal energy conversion; ³² WE: wind energy; ³³ SE: solar energy; ³⁴ GE: geothermal energy; ³⁵ OP: other production or use of heat not derived from combustion; ³⁶ WH: using waste heat; ³⁷ DP: devices for producing mechanical power from muscle energy; ³⁸ HB: devices for producing mechanical power from muscle energy.

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