The dynamics of partner and knowledge portfolios in alternative energy field

Guan, JianCheng; Zhang, JingJing

Published in:
Renewable & Sustainable Energy Reviews

DOI:
10.1016/j.rser.2017.10.045

Publication date:
2018

Renewable and Sustainable Energy Reviews 82 (2018) 2869–2879

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

The dynamics of partner and knowledge portfolios in alternative energy field

JianCheng Guan[a,b,*,1], JingJing Zhang[a,c,1]

[a] School of Economics & Management, University of Chinese Academy of Sciences, 100190 Beijing, China
[b] School of Business Administration, South China University of Technology, 510640 Guangzhou, China
[c] Innovation Management and Strategy, University of Groningen, 9747 AE Groningen, The Netherlands

ARTICLE INFO

Keywords:
Collaborative diversity
Knowledge diversity
Partner portfolio
Knowledge portfolio

ABSTRACT

This study uses the patent applications of alternative energy organizations, including companies, universities and research institutions, to explain the dynamic evolutions of organizational resource portfolios. We study organizational resource portfolios from two dimensions: internal knowledge portfolio and external partner portfolio, and we capture the dynamic evolutions of two portfolios through the emergence of new partners and the growth of knowledge elements, and explain these from a diversity perspective. We propose inverted-U shaped relationships between diversities (collaborative and knowledge) and organizational portfolio dynamics (new partners and knowledge elements). Analyzing alternative energy patents from 3601 organizations during the time period 2000–2012, we find that organizations having too high or low collaborative diversity have less novel knowledge elements and new collaborative relationships than those having moderate collaborative diversity. We also suggest that knowledge diversity contributes to two types of portfolio dynamics. However, the positive effects of knowledge diversity on evolutions of partner and knowledge portfolios diminish, and even become negative and detrimental beyond certain levels of knowledge diversity. Our findings have theoretical implications for dynamic evolutions of organizational portfolios and diversity literature, and are also useful for firms' managers striving to develop valuable collaborative partners and pursuing novel innovations.

1. Introduction

Fossil fuels are considered as the world's dominant source of energy, and such dominance is related to public environmental objectives and climate challenges. The development of alternative energy technology—such as wind, solar, geothermal, ocean, biomass and so on-involves great efforts to fight with climate change and environmental issues [1]. Consequently, active global basic research or development of alternative energy resources sustains its growth, and alternative energy technology applications have risen considerably in recent years [2]. In this study, we focus on all the alternative energy technologies. First, alternative energy requires concurrent integration of mixed technologies. The knowledge elements of alternative energy are completely intertwined [3]. Most specific sub-technologies in one energy field are connected to technologies in other energy fields. Thus, considering all alternative energy technologies can enhance the reliability of the results. Second, our findings are not energy specific but may be generalized across different alternative energies. According to previous research [4], this made our findings interesting and filled an important void in the literature with its dominant focus on single alternative energy studies. As technological development and organizational routines are highly sector specific in the energy industry [5,6], the focus of the study and what criteria is adopted to select patent are vital. In this study, the criteria that we used to select alternative patent is a list of United States Patent Classification (USPC) assigned to alternative energy.[2] This list is developed for facilitating searches for alternative energy patent information. USPC is a complex hierarchical classification system that comprises of classes, subclasses and subdivisions. This system reaches an efficient and detailed categorization, and is intended to adopt an exhaustive definition of all patenting subject matter [7]. More in detail, this list has further subdivisions for alternative energy. For example, alternative energy comprises of solar energy, hydroelectric and geothermal, and further solar energy has subdivisions, such as photovoltaic and solar thermal energy. Based on the suggested USPC codes, we well identify and collect alternative energy patent documents. We can consider patent classification system as approximate

* Corresponding author at: School of Economics & Management, University of Chinese Academy of Sciences, 100190 Beijing, China.
E-mail address: guanjianch@ucas.ac.cn (J. Guan).
[1] Both authors contributed equally to this paper.
[2] https://www.uspto.gov/web/patents/classification/international/est_concordance.htm.

http://dx.doi.org/10.1016/j.rser.2017.10.045
Received 22 May 2016; Received in revised form 23 June 2017; Accepted 26 October 2017
Available online 06 November 2017
1364-0321/

knowledge elements, and further capture knowledge structure of alternative energy organizations [8]. Co-invention collaborations offer institutions opportunity to create novel or breakthrough inventions, exploratory knowledge elements or novel alternative inventions exhibiting greater technological potential [9]. Considering the accelerating pace, difficulty of alternative energy innovation and ever-increasing collaborations among energy institutions, it becomes important to explore their change patterns of collaborative partners and knowledge elements [10]. There are a rising number of studies dedicated to alternative energy. However, the dynamics of partner and knowledge portfolios of organizations in the alternative energy field have attracted little attention. This work can help managers to learn to formulate appropriate portfolio configuration and strategies.

According to the resource-based view (RBV), firms can be conceptualized as repositories of resource portfolios (sum of all controlled resources, such as tangible and intangible; internal and external), thus resource portfolios constitute crucial factors for firm development [11,12]. Meanwhile, structuring firms' resource portfolios is a dynamic process through which firms access valuable [13], accumulate strategic [14] and divest useless resources [15,16]. Consequently, there is a rich research literature in reasoning the dynamic change patterns of firms' resource portfolios [8,17–19]. Recent research has shown that some portfolio characteristics, such as diversity, may play key roles in firms' resource growth, yielding several mixed findings [20–22]. For example, for knowledge portfolio, resource-based view scholars argued that various partners provide non-redundancy knowledge, facilitating firms' knowledge exploration [23]. However, organizational economic theorists further suggested that overabundance accompanies some cost, hindering knowledge creation [24,25].

Our study aims to extend prior research and reconcile conflicting views on the effects of diversity on portfolio dynamics in three ways, and answer an important question in research on organizations: Do all kinds of diversities have alike influences on the dynamic changes of organizational portfolios? First, we explore firm resource portfolios from two dimensions: internal knowledge portfolio and external partner portfolio. Two resource-driven strategies, internal resource management through intra-organizational learning and external resource acquisition through inter-organizational linkages, comprise two essential facets of firms' resource development. Knowledge portfolio views firm's heterogeneous aggregations of knowledge elements as a portfolio [26,27], while partner portfolio considers firm's collaborative partners as a portfolio [28]. Further, we focus on what affects the dynamic evolutions of two portfolios, in terms of emergence of new knowledge elements and the addition of new collaborative partners.

Second, corresponding to two types of portfolios, we propose two kinds of diversities. Knowledge diversity, in this paper, indicates the diversity of technological domains in the firm's technological class portfolio [29]. It is related to a firm's expansion of its technological competence into a broader range of the technological domain. Similarly, collaborative diversity is defined as diversity of partners in the firm's partner portfolio [30]. It refers to the distribution of collaboration differences in partners. The collaborative diversity is related to partner number and collaboration times. There is a growing literature on firms' connections with diverse partners or diverse knowledge base [20,25]. We use an interesting approach from the social network perspective to analyze the extent of collaborative diversity and knowledge diversity of an organization. The analysis presented in this study relies upon the large relational information that inventors reported in their applied patent documents. In particular, we capture their collaboration relationships from co-inventing records to measure collaborative diversity. Based on the technological classifications records, we further acquire the affiliation relationships of knowledge elements with organization to measure knowledge diversity. Scholars have noticed that knowledge diversity and collaborative diversity may affect technological development, performance and partner selection [31–33]. For example, Ahuja [19] proposed that firms with high technical capital and various knowledge base are more likely to attract partners. However, it's far from being enough since most research considered collaborative and knowledge diversity separately. Cooperative relationships of organizations face a very natural tension [18]. On the one hand, organizations need the specific partners which are valuable to their particular needs. They need various partners who can effectively participate in different knowledge and innovation creation process. Such process is involved in combining and exchanging diverse knowledge resource and information, and identifying and selecting appropriate partners [34]. Building on this theme, we jointly explore the effects of two types of diversity (collaborative and knowledge diversity) on two kinds of organizational behaviors, i.e., the exploration of new knowledge elements and the addition of new collaborative partners, to fill the prior gaps.

Third, we argue that the influence of diversity on dynamic evolutions of organizational portfolio depends on the value of diversity. Having heterogeneous partner portfolio configurations or knowledge elements, however, may be challenging [35,36]. Although considerable perspectives of extant research may be favorable [37,38], the very nature of partner and knowledge diversity may make it difficult for partners to coordinately work, perform and mutually understand, and may bring cognitive stresses [39]. Some apparently conflicting perspectives suggest that diversity creates both benefits and vitiating effects for organizational behavior. Although positive impacts are driven by organizational access to diverse information and resource [40,41], potential problems of diversity are mainly caused by coordination cost and overloaded knowledge, which may reduce organizational ability to utilize information and manage resource portfolio [42]. Consequently, based on prior research [43,44], we outline nonlinear relations between two types of diversity and two types of dynamics of partner and knowledge portfolios, acknowledging that the effects of diversity on new knowledge elements and new partners may be nonlinear and more complex than previously thought.

Our contribution is to document the extent to which diversity influences firms' behavior and reconcile the abovementioned inconsistencies. We base our study on a panel of alternative energy industry patents that covers four successive five-year windows spanning the years 2000–2012. This study is at the organizational portfolio level as we focus on the firms' evolutionary dynamics of partner and knowledge portfolios in the alternative energy industry. The following paper is organized in four main sections. First, we review related literature and present our theoretical framework and hypotheses. After that, we provide research methodology. Second, we offer the results based on a sample of alternative energy firms using a longitudinal analysis. Third, we discuss the findings and explore the importance of our work. Fourth, the findings are concluded and directions of future research are described. In addition, we also present the main theoretical and policy implications of our work.

2. Literature review and hypotheses

2.1. Collaborative diversity on new partners/knowledge elements

The collaborative diversity of a firm is positively associated with its new partners because of several factors. On the one hand, according to transaction costs theory, under the relationship of mutual dependence among partners, some dissimilarity between partners may reduce the risk of knowledge spillovers and the cost of safeguard against opportunistic behaviors [45,46]. Further, due to the increasing collaborative diversity, firms can acquire learning benefits in cooperation skills [47]. Because of learning by doing, firms become more efficient in managing cooperation with new partners. On the other hand, as collaborative diversity increases, firms become linked with the diverse partners, who may possess complementary resources. Consequently these firms may have high potentialities of benefiting from synergies in dyadic relations and access to critical assets [28].

However, the association of collaborative diversity of firms with the addition of their new partners becomes negative beyond a specific threshold of collaborative diversity. Firstly, a high degree of collaborative diversity could create managerial challenges for firms in sharing resources across firm borders [48]. For example, diverse partners have to reconcile different objectives, timeframes and optimal network structures. Secondly, attention based view proposed that high levels of collaborative diversity could lead to information overload and overflow [39]. Firms may furthermore not only give up learning opportunities but may additionally fail to guard against knowledge spillovers to its diverse partners. Thus, beyond an optimum point of collaborative diversity, the negative effects on adding new partners outweigh the benefits gained, hence:

Hypothesis 1a. The collaborative diversity of a focal firm has an inverted U-shaped relationship with its added new partners.

As a firm's collaborative diversity increases, its added new knowledge elements tends to increase. Three main reasons can account for this. First, collaboration with different firms can increase breadth of knowledge search, learning capabilities, and diverse knowledge access [20,49]. Networks can help energy organizations to develop and explore new renewable energy knowledge and technology [50]. To develop renewable or alternative energy technology, priorities should be set in collaboration with partners in R & D activities, especially a variety of stakeholders in the alternative energy industry [51]. Therefore, collaborative diversity could enhance new knowledge element exploration due to the amount and variety of knowledge to be shared. Increasing collaborative diversity enables firms to combine knowledge, technology and skills [52], and overcome resource constraints [53], hence enhancing knowledge exploration prospects. Second, similarly with H1a, based on transaction costs theory, increasing collaborative diversity may reduce the risk of knowledge spillovers and the cost of preventing opportunistic behaviors, encouraging firms to explore new knowledge elements. Third, various partners may provide opportunities for the firm to choose among different technological directions, which help firms to achieve new knowledge elements.

However, the positive association between the collaborative diversity of a firm and its new knowledge elements turns negative, when the collaborative diversity grows too high. First, too high collaborative diversity may impede partner's communication, encumber knowledge acquisition, and raise coordination difficulty [20,48]. For instance, excessive and dispersive cooperation will result in cognitive stress [54], making the firm inefficient at advancing and promoting its new knowledge acquisition and exploration. Second, as discussed above, the higher the level of organizational collaborative diversity is, the higher the risk and possibility that partners may have obstacles to access to non-redundant resource will be [41]. Then the collaborative diversity could hurt the exploration of new knowledge elements. Thus, we therefore hypothesize that:

Hypothesis 1b. The collaborative diversity of a focal firm has an inverted U-shaped relationship with its added new knowledge elements.

2.2. Knowledge diversity on new partners/knowledge elements

Based on technological subclasses of organizational patents, scholars can acquire a much richer, reliable and complete picture of organizational knowledge or technological capabilities [7]. Patent classifications are oriented toward representing the knowledge elements or technological domain of the patent [8,55]. Recent years, it is widely acknowledged its appropriateness of using classifications to measure organizational knowledge or technological diversity [29,56,57]. In this study, we follow the prior approach and represent organizational knowledge diversity based on the subclass vectors of organizational patent applications. Especially, alternative energy-related technologies, which are involved in solving global warming problems are extraordinarily diverse, and intend to be developed by firms having diverse industrial sectors [58]. For example, hydrogen and fuel cells technologies can be utilized in transportation, distributed heating, power generation and energy storage systems industries [59,60]. Also, these technologies are highly related to diverse technologies, such as hydro, wind, solar, biomass and geothermal [59]. Thus, the development of hydrogen and fuel cells needs diverse collaborators and knowledge.

Several researches speak for the positive relationship of knowledge diversity of firms and the addition of their new partners. On the one hand, firms with high levels of knowledge diversity would have high ability and ease to communicate and exchange with others. They are likely to easily gain information and better understand what each other need, and they are more likely to discover more connection points with others' knowledge bases. We have enough reasons to assume that exchange convenience among firms may influence the likelihood of their collaborations in co-inventions, given those costs, hazards or obstacles associated with information access diminishes [61]. On the other hand, according to resource dependence theorists, underlying resource dependence is an important predictor of firms' propensity to form inter-organizational ties with each other [62]. Besides, prior studies argued that firms usually seek out collaborations with partners for complementary resources and tend to partner with organizations possessing the skills or ability that can contribute to the successful research and development [63]. Knowledge base are widely viewed as important resource and capabilities in generating competitive advantage [64]. Thus, heterogeneous knowledge base is a key factor to drive the formation of inter-organizational cooperation and the addition of new collaborative partners.

However, very high level of a firm's knowledge diversity is likely to negatively affect its new partners. For one thing, if firms have extremely diverse knowledge, there will be a finite opportunity and limited probability that they need collaborations with other firms for distinct knowledge. The knowledge of other firms may even be viewed as unvalued and risky. Therefore, they will not incline to seek for additional new relationships. This reason may dampen inter-organizational collaborations between two firms. For another, increased knowledge diversity will make the focal firm become reluctant to leverage external partners' diversity and confronted with significant challenges in pursuing both own and external explorations, consequently the benefits of external diversity diminish [11]. Therefore, the perceived decreased benefits of external knowledge and resource reduce the willingness of the focal firm to form collaborations with new partners.

Hypothesis 2a. The knowledge diversity of a focal firm has an inverted U-shaped relationship with its added new partners.

The relationship between knowledge diversity of a focal firm and its added new partners is nonlinear (inverse U-shaped).

We also argue that a firm's knowledge diversity is positively associated with its explorative potential of new knowledge elements. First, diverse knowledge base makes it easier for these firms to assimilate and utilize each partner's know-how, which means they generally have high absorptive capacities [65]. Thus, there is a greater ability for firms to absorb partners' resource and ideas to explore new knowledge elements. Second, exploratory technology is usually generated on a broad scope class of knowledge search activities [66]. The skills and experience those are available from multiple knowledge areas can help researchers in expanding extant knowledge bases and exploring new knowledge elements through the cross fertilization of information [67]. Moreover, theories of portfolio management argue that firms can reduce risk and grasp business opportunities through effectively managing a collection of different knowledge and resources [31].

On the negative side, we argue too high levels of firms' knowledge diversity negatively influence new knowledge elements. First, higher knowledge diversity implies too many and diverse ideas. Some costs may be involved in knowledge creation because of over diversification

[68–70]. To be specific, over diversification may generate negative synergy and result in diseconomies of scope. Increased costs, like massive costs of coordination, integrating or combining knowledge across multiple disciplines, may yield fewer new knowledge creations. In addition, this escalating knowledge dispersion would make the firms complex and much more difficult to handle technologically diversified portfolio. Firms may be difficult in creating the focus which is required to develop sufficiently strong competitive advantages in a specific knowledge domain. More diversified firms may easily fall into the competency trap, which means excessive exploitative knowledge but few exploratory knowledge [71]. Thus, these firms with high levels of knowledge diversity likely encounter more difficulties in exploring of new knowledge elements [72]. Similarly, we can propose the following hypotheses:

Hypothesis 2b. The knowledge diversity of a focal firm has an inverted U-shaped relationship with its added new knowledge elements.

3. Methods

3.1. Research background, sample, and procedures

Patent data on the alternative energy industry serves to examine the hypotheses in this article. Patents can be used to assess knowledge-based innovation [73,74]. This is an industry exemplifying a dynamic setting and firms in this industry are often characterized as competitive and knowledge intensive [3]. The alternative energy industry provides an appropriate setting for this study for two main reasons. On the one hand, the companies compete in dynamic environments, with generating new and plentiful knowledge elements. Therefore, events of new knowledge elements are easily observed, which is particularly important for the measure of explained variable in this study. On the other hand, this industry has witnessed increasing and improved energy collaborations among firms [75], and its dynamic environment makes partner changes continuous routine. The alternative energy industry thus offers an ideal setting for the observation of new partners.

We obtain data for the period 1976–2012 from United States Patent and Trademark Office (USPTO). To examine the hypotheses, we utilize a lag data structure and compile an unbalanced panel of firms from 2000 to 2012. To be specific, we use overlapping five-year windows to obtain the longitudinal data such that the explanatory variables are measured in the focal window (i.e., 2000–2004,… 2003–2007), and the explained variables are measured in the following specified window (i.e., 2005–2009, …2008–2012). This panel includes all institutions which filed at least one patent application during the analytic period in the alternative energy industry according to the official classification of USPTO. The final data sample consists of 3601 institutions and the total number of our longitudinal observations is 9855.

Fig. 1 shows the total number of patent applications, knowledge elements and active organizations per year. Patent applications grew dramatically after 2000s, and there has been continuous growth in

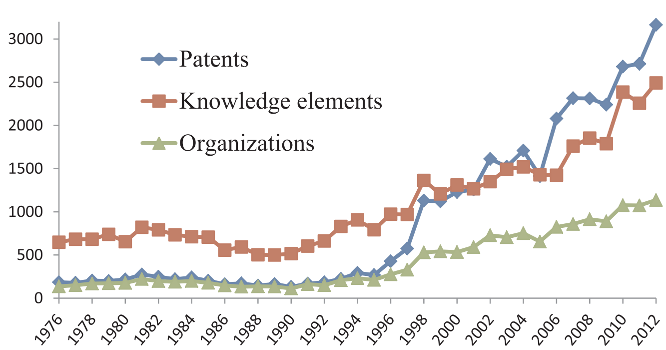

Fig. 1. Annual number of patent, knowledge elements and organizations.

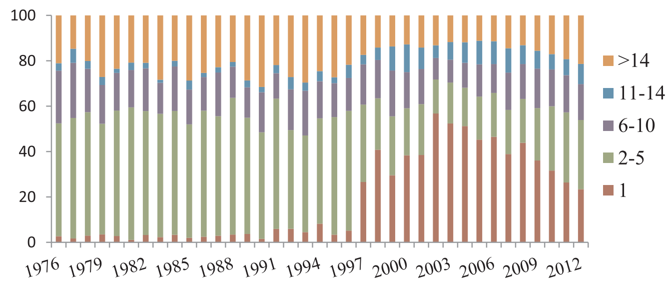

Fig. 2. Annual distribution of the number of knowledge elements.

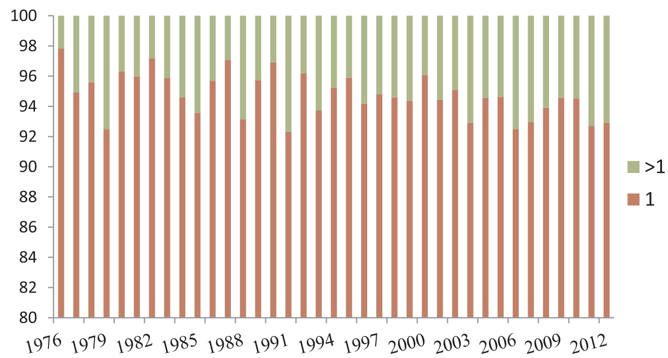

Fig. 3. Annual distribution of the number of organizations.

number of patent, knowledge elements and organizations.

In this paper, technological classifications are used to indicate knowledge elements. Fig. 2 provides a graphical representation of the annual distribution of the number of knowledge elements per patent in the alternative energy field. The patents categorized by 2–5 technology classifications keep the highest percentage before 1998. However, the percentage of patents having only one technology classification keeps a leader position after 1998.

Fig. 3 further provides a graphical representation of the annual distribution of the number of organizations involved in per patent in the alternative energy field. From this graph, we cannot observe apparent changing trends for the percentages of patents having only one organization assignee or more than one organization assignees. However, it is noticed that the patens having only one organization assignee dominate in the alternative energy field all the time, fluctuating around 90% over 1976–2012.

3.2. Measures

3.2.1. Dependent variable

3.2.1.1. New partners. As mentioned above, we rely on the partner portfolio in a specific period to assess the level of new partners. We construct two partner portfolios of all institutions in two different given periods: one is the partner portfolio from the 1976 (the first year of documents in USPTO) to the focal year, and the other is the partner portfolio in the subsequent period. We construct the measure of new partners by counting the number of new partners who never participate in the early portfolio but emerge in the second portfolio. For example, if we use patents applied during the period 2008–2012 to construct the explained variable (e.g., new partners), we would compare the partner portfolio of the focal firm in the period 2008–2012 with that in the preceding period 1976–2007 to determine which partner has newly added to collaborate with the focal firm.

To illustrate new partners clearly, we portray the partner portfolios of institutions in the time period from 2008 to 2012 in Fig. 4. We use one-mode network to capture the partnerships between two organizations and the partner portfolio of every organization. In the network, nodes represent the organizations and the ties among them are co-

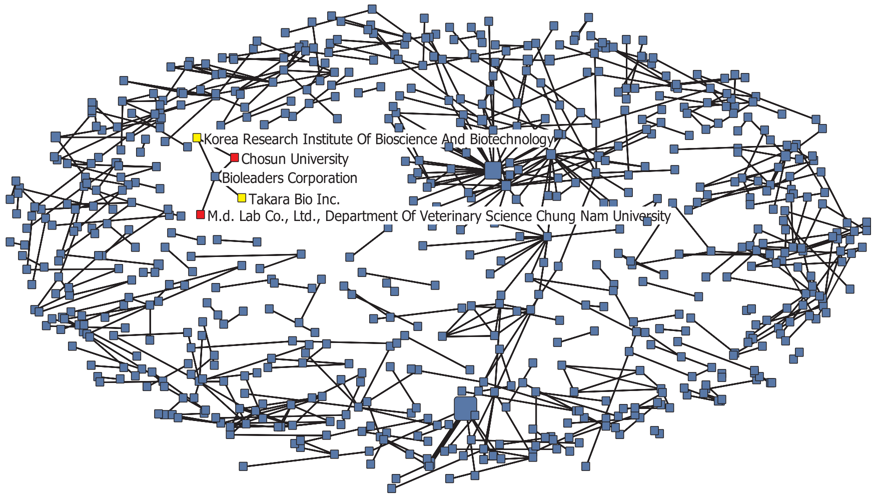

Fig. 4. partner portfolios of institutions in the period 2008–2012. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

authorships or co-patenting networks relationships. The size of the nodes means the number of applied patents of the institution, and the width of lines signifies the co-inventing times between the institution and its partner. For instance, the partner portfolio of BioLeaders Corporation in the period 1976–2007 is "Korea Research Institute of Bioscience and Biotechnology" and "Takara Bio Inc.", and that in the time period 2008–2012 is "Takara Bio Inc.", "M.D. Lab Co., Ltd., Department of Veterinary Science Chung Nam University", "Korea Research Institute of Bioscience and Biotechnology", and "Chosun University". By comparing these two portfolios, we identify "M.D. Lab Co., Ltd., Department of Veterinary Science Chung Nam University" and "Chosun University" (red color) are new partners, and the other institutions are old partners (yellow color). Thus, the value of new partners of BioLeaders Corporation is 2.

3.2.1.2. New knowledge elements. We use USPC defined by USPTO to represent knowledge elements [76]. For the new knowledge elements analysis, we also construct two knowledge portfolios of all firms in two different analytic periods: one is the knowledge portfolio from the 1976 to the focal year, and the other is the knowledge portfolio in the later period. We calculate new knowledge elements by identifying the number of new knowledge elements which are not included in the early portfolio but appear in the latter portfolio.

To illustrate new knowledge elements clearly, we draw knowledge portfolios of institutions in the time period 2008–2012 in Fig. 5. We use two-mode networks to obtain the bipartite relationships between organizations and knowledge elements, and acquire the knowledge portfolio of every organization. In those networks, nodes are divided into organizations and knowledge elements, and ties from an organization to a knowledge element indicate that the knowledge element is affiliation to the organization. Round nodes indicate institutions and square vertices display knowledge elements. The size of nodes means the number of applied patents of the institutions or knowledge elements, and the width of lines present the associated frequency between the institutions and knowledge elements. For instance, the knowledge portfolio of Driscoll Strawberry Associates, Inc. in the period 1976–2007 is "PLT/203", "PLT/204", and "PLT/209", and that in the time period 2008–2012 is "PLT/203", "PLT/204", "PLT/208", "PLT/209", and "PLT/157". By comparing these two portfolios, we identify "PLT/208" and "PLT/208" (red color) are new explored knowledge elements and the other three elements are old (yellow color). Thus, the value of new knowledge elements of Driscoll Strawberry Associates, Inc. is 2.

3.2.2. Independent variables

3.2.2.1. Collaborative diversity. We assess a firm's collaborative diversity using all patents that the firm applied in the analysis window. To calculate the diversity of partners associated with a firm's patents, we utilize firm's partner portfolio in the focal period. We index each partner by k, and let q_i denotes the number of patents that firm had at time period t. q_{ik} means the amount of patents the ith firm holds with partner k. Then we measure the collaborative diversity by the following equation:

$$collaborative\ \ diversity_i = 1 - \sum_k \left(\frac{q_{ik}}{q_i}\right)^2 \tag{1}$$

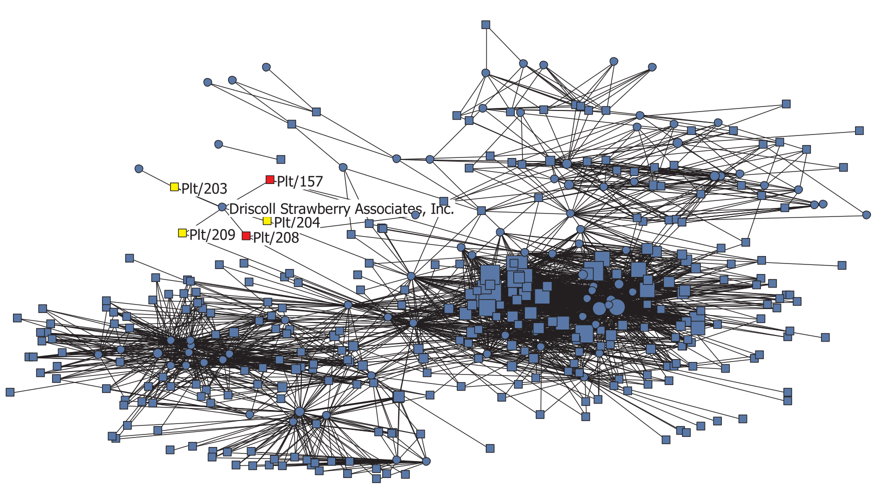

Fig. 5. knowledge portfolios of institutions in the period 2008–2012. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

For example, if the focal firm has applied 1 patent with firm A, 4 patents with firm B, the focal firm has a calculated collaborative diversity value: $1 - \left(\frac{1}{5}\right)^2 - \left(\frac{4}{5}\right)^2 = \frac{8}{25}$. This value varies from 0 (firm collaborates with the same partner) to 1. Higher value demonstrates more equally the focal firm collaborates with its partners.

3.2.2.2. Knowledge diversity. To calculate the diversity in knowledge elements associated with a firm's patents, we use USPC to index each knowledge element, and measure knowledge diversity by the following equation:

$$knowledge\ \ diversity_i = 1 - \sum_j \left(\frac{p_{ij}}{p_i}\right)^2 \tag{2}$$

where p_{ij} means the number of patents firm i holds in technological class j, and p_i denotes the number of patents that firm i had at the focal period. Knowledge diversity is measured by Herfindahl index [77], varying from 0 to 1. The value of zero implies all the firm's patents involve in a single technological class, and high value suggests that the focal firm is specialized in distinct technological classes.

3.2.3. Control variables

Several factors could also influence the dynamic of partners and knowledge. We control for those variables in our statistical analysis. These factors include firm characteristics and network structure variables.

Firm characteristics. Specifically, we include several productivity-related variables. *Patent family* represents the amount of patents weighted by patent family size, which is hold by the firm in the focal time period. *Partners* means the number of partners co-inventing with the firm in the focal period. *Knowledge* is measured as the amount of knowledge elements (i.e., US patent classes) in which a firm patents in the focal period. *Tenure* is calculated as the number of years the firm has participated in patent applications in the alternative energy industry.

Network characteristics. Because prior study has demonstrated that social network could influence the dynamics of collaborative relations and knowledge base [8,18], we also include some network structure characteristics as our control variables. According to prior research, organizations are double embedded in both collaboration networks and knowledge networks, which represent organization social-based and knowledge-based search capacity [78]. Besides, we examine two changes (the addition of new collaborative partners and knowledge elements) in this paper, thus we control network characteristics of two networks—collaboration network and knowledge network. In a collaboration network in our study, a node denotes a firm and a tie is a co-authorship in patents between two firms. We include *collaboration centrality,* which is measured as the normalized degree centrality of organizations in collaboration networks. The equation for degree centrality is as follows:

$$D_i = \frac{k_i}{n-1} \tag{3}$$

where k_i means the total number of actor i's direct connections, and n is the total number of actors in the network. We further include *collaboration structural holes*, which are calculated as the structural holes of organizations in the collaboration networks. The equation for structural holes is as follows:

$$S_i = 2 - \sum\nolimits_j \left(p_{ij} + \sum\nolimits_{q,q\neq i,q\neq j} p_{iq}p_{qj}\right)^2 \tag{4}$$

where p_{ij} is the ratio of actor i's relationships involved in interconnecting with j. We subtract the value in parenthesis from 2 since this value maybe bigger than 2.

In a knowledge network in this study, a node means a technological subclass and a tie is a co-occurrence or combination of two technological subclasses in patents [3]. Using the same formula displayed in Eqs. (3) and (4), we calculate the degree centrality and structural holes of each knowledge element in the knowledge network. After that, according to the knowledge portfolio of each firm, we measure *knowledge centrality/ knowledge structural holes* of the firm as the average value of degree centrality/structural holes of all the knowledge elements possessed by the focal firm. The equations are as follows:

$$d_i = \frac{\sum_{j=1}^m D_j}{m} \tag{5}$$

$$s_i = \frac{\sum_{j=1}^m S_j}{m} \tag{6}$$

In Eqs. (5) and (6), D_j means the degree centrality of knowledge element j in knowledge network, S_j means the structural holes of knowledge element j in knowledge network, and m means the total number of knowledge elements belong to firm i.

3.3. Statistical models

The seemingly unrelated regression method (SUR), which is also known as Zellner's method [79], accounts for heteroskedasticity. Comparing to ordinary least squares (OLS), SUR can contemporaneously estimate correlation of the errors across different equations, especially when estimated equations contain quite the same regress variables on the right side. In addition, the estimation technique, is particularly appropriate when equations contain several dependent variables and identical regress variables on the right side of estimated equations and when both equations draw from the same data set [18]. Because two explained variables (new partners and new knowledge elements) are correlated, SUR regressions are suitable to test our hypotheses. The estimation equations of our entire analysis are as follows:

$$\begin{cases} Newpartners = \beta_0 + \beta_1 Patent + \beta_2 Partners + \beta_3 Knowlegde \\ \quad + \beta_4 Collaborationcentrality + \beta_5 Knowledge\ \ centrality \\ \quad + \beta_6 Tenure + \ \beta_7 Collaborationstructuralholes \\ \quad + \beta_8 Knowledgestructuralholes + \beta_9 CD + \beta_{10}(CD)^2 \\ \quad + \beta_{11} KD + \beta_{12}(KD)^2 + \varepsilon_1 \\ New\ \ \ knowlegde = \lambda_0 + \lambda_1 Patent + \lambda_2 Partners + \lambda_3 Knowlegde \\ \quad + \lambda_4 Collaborationcentrality \\ \quad + \lambda_5 Knowledge\ \ \ centrality\ + \lambda_6 Tenure \\ \quad +\ \lambda_7 Collaborationstructuralholes \\ \quad + \lambda_8 Knowledgestructuralholes + \lambda_9 CD + \lambda_{10}(CD)^2 \\ \quad + \lambda_{11} KD + \lambda_{12}(KD)^2 + \varepsilon_2 \end{cases}$$

4. Results

In Table 1, we display the summary statistics, variance inflation factors (VIFs) and correlation coefficients among the variables in our models. VIFs of independent and control variables suggest that multicollinearity is not a big problem (highest VIF = 3.27).

Results of the SUR estimations are reported in Table 2. The results of models are arranged in two parts, with models 1–4 reporting the regression results for the new partners and models 5–8 reporting the regression results for the new knowledge elements. Corresponding models in two parts of Table 2 (i.e., models 1 and 5; 2 and 6; 3 and 7; 4 and 8) are run jointly for our dependent variables. Models 1 and 5 represent the results for baseline model, including the control variables.

Hypothesis 1proposes that collaborative diversity of a focal firm has U-shaped relationships with new partners and new knowledge elements. In order to test our Hypothesis 1, models 2 and 6 add the effect of collaborative diversity and the quadratic term for collaborative

Table 1
Means, standard deviations, and correlations.

Variable	M	SD	VIF	1	2	3	4	5	6	7	8	9	10	11
1. New partners	3.30	12.53	–											
2. New knowledge	0.09	0.65	–	0.321										
3. Patent Family	5.68	23.82	1.70	0.495	0.185									
4. Partners	0.26	0.79	3.27	0.114	0.433	0.443								
5. Knowledge	7.84	11.14	2.06	0.478	0.498	0.474	0.394							
6. Collaboration centrality	0.003	0.01	1.20	0.017	0.012	0.006	0.108	0.153						
7. Knowledge centrality	0.01	0.02	2.14	0.063	0.006	−0.016	0.177	0.308	0.406					
8. Collaboration structural holes	1.01	0.08	2.22	0.136	0.292	0.294	0.673	0.369	0.078	0.124				
9. Knowledge structural holes	1.56	0.39	3.17	0.142	0.022	−0.043	0.164	0.373	0.271	0.689	0.082			
10. Tenure	3.74	4.71	1.20	0.294	0.168	0.160	0.143	0.395	0.030	0.082	0.184	0.118		
11. Collaborative diversity	0.68	0.38	2.27	0.163	0.554	0.101	0.144	0.432	0.197	0.495	0.094	0.622	0.182	
12. Knowledge diversity	0.03	0.15	2.88	0.089	0.144	0.184	0.554	0.254	0.067	0.112	0.683	0.114	0.120	0.104

Note. All correlations with magnitude > 0.05 are significant at $p < 0.05$ level.

diversity. As shown in model 2, the coefficient of collaborative diversity is positive and significant ($r = 0.716$, $p < 0.05$), and its quadratic term is negative and statistically significant ($r = -1.906$, $p < 0.01$). The coefficient sign indicates collaborative diversity would first promote the new partners entries and then hinder the new partners after a threshold value. Thus, this provides supports for Hypothesis 1a. Meanwhile, the results of model 6 indicate that both the collaborative diversity and its squared term are statistically significant ($r = 15.30$, $p < 0.05$; $r = -17.29$, $p < 0.1$; respectively) and in the direction assumed in Hypothesis 1b. Thereby, Hypothesis 1b is supported.

Models 3 and 7 introduce knowledge diversity and its quadratic term to verify the Hypothesis 2, which states the inverted U-shaped relationships between knowledge diversity with new partners and new knowledge elements. As expected, the coefficients of knowledge diversity and its square term in model 3 are significant ($r = 0.702$, $p < 0.01$; $r = -1.030$, $p < 0.01$; respectively), supporting Hypothesis 2a. In addition, as shown in Model 7 and consistent with our Hypothesis 2b, the results demonstrate a curved effect of knowledge diversity on new knowledge elements ($r = 14.55$, $p < 0.01$; $r = -19.28$, $p < 0.01$).

Finally, we conduct full models (i.e., models 4 and 8) with two types of diversities and their quadratic terms jointly. The coefficient signs of the independent variables are still significant and demonstrate U-shaped relationships. The findings support that both collaborative and knowledge diversity have positive effects on new partners and new knowledge elements for linear terms, and negative effects for quadratic terms. These results provide further evidence of inverted-U shaped relationships mentioned in the hypotheses.

To evaluate the validity of the inverted-U relationships stated in our hypotheses, we have done several checks (see Table 3). We first verify the inverted U-shaped pattern by testing joint significance of the linear and squared terms of CD (collaborative diversity) and KD (knowledge diversity). Then, we utilize the method developed by Sasabuchi [80] to further test the presence of inverted U-shaped relationships. The

Table 2
Regression results.

	Model 1 New partners	Model 2	Model 3	Model 4	Model 5 New knowledge	Model 6	Model 7	Model 8
Patent Family	0.007**	0.007**	0.007**	0.007**	−0.033**	−0.031**	−0.036**	−0.0327**
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.006)	(0.006)	(0.006)	(0.006)
Partners	0.200**	0.294**	0.189**	0.278**	−0.929**	−1.133**	−1.087**	−1.380**
	(0.010)	(0.013)	(0.010)	(0.013)	(0.202)	(0.271)	(0.202)	(0.271)
Knowledge	0.011**	0.0107**	0.015**	0.015**	0.580**	0.580**	0.652**	0.654**
	(0.001)	(0.001)	(0.001)	(0.007)	(0.014)	(0.014)	(0.016)	(0.016)
Collaboration centrality	−0.960*	−1.041^{+}	(0.931)	−1.008^{+}	−29.86*	−29.49*	−29.32*	−28.87*
	(0.573)	(0.569)	(0.568)	(0.565)	(12.00)	(12.00)	(11.95)	(11.94)
Knowledge centrality	0.009	(0.283)	0.617	0.320	−73.72**	−73.08**	−61.88**	−60.86**
	(0.461)	(0.458)	(0.462)	(0.461)	(9.652)	(9.663)	(9.724)	(9.735)
Collaboration structural holes	0.660**	1.142**	0.651**	1.104**	(0.850)	(1.623)	(0.992)	−2.199
	(0.086)	(0.096)	(0.085)	(0.095)	(1.793)	(2.031)	(1.785)	(2.023)
Knowledge structural holes	(0.026)	(0.022)	0.123**	0.117**	0.581	0.552	2.436**	2.445**
	(0.019)	(0.019)	(0.024)	(0.024)	(0.404)	(0.404)	(0.497)	(0.497)
Tenure	0.001	0.001	0.001	0.001	0.311**	0.309**	0.320**	0.319**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.025)	(0.025)	(0.025)	(0.025)
Collaborative diversity		0.716*		0.684*		15.30*		14.89*
		(0.323)		(0.320)		(6.800)		(6.769)
Collaborative diversity squared		−1.906**		−1.804**		−17.29^{+}		−15.86^{+}
		(0.457)		(0.454)		(9.629)		(9.587)
Knowledge diversity			0.702**	0.684**			14.55**	14.66**
			(0.095)	(0.094)			(2.003)	(2.002)
Knowledge diversity squared			−1.030**	−0.995**			−19.28**	−19.47**
			(0.109)	(0.110)			(2.299)	(2.298)
Constant	−0.712**	−1.196**	−0.827**	−1.276**	−0.924	−0.140	−2.549	−1.360
	(0.091)	(0.101)	(0.091)	(0.101)	(1.909)	(2.136)	(1.910)	(2.131)
RMSE	0.515	0.512	0.511	0.508	10.797	10.791	10.748	10.741
R^2	0.368	0.376	0.378	0.386	0.257	0.258	0.264	0.267
Chi2	5746	5949	6005	6289	3424	3438	3545	3563

Note: $^{+}p < 0.1$; $^{*}p < .05$; $^{**}p < .01$. Standard errors are reported in parentheses.

Table 3
Test of inversely U-shaped relationships.

	Effect of CD on New partners	Effect of KD on New partners	Effect of CD on New knowledge	Effect of KD on New knowledge
Test of joint significance of independent variables (chi2(p-value))	69.33 (0.00)	87.12 (0.00)	4.41 (0.01)	44.51 (0.00)
Sasabuchi-test of inverse U-shape in independent variables (t(p-value))	2.42 (0.01)	7.80 (0.00)	1.73 (0.04)	7.40 (0.00)
Estimated extreme point (or, inflection point)	0.19	0.34	0.41	0.38
95% confidence interval (CI) –Fieller method	[0.06; 0.24]	[0.31; 0.36]	[0.35; 12.33]	[0.35; 0.40]
95% confidence interval (CI) – Delta method	[0.12; 0.26]	[0.32; 0.37]	[0.32; 0.51]	[0.36; 0.40]
Test of joint significance of control variables (p-value)	502.88 (0.00)	677.56 (0.00)	419.68 (0.00)	351.63 (0.00)
Test of joint significance of all variables in the model	572.11 (0.00)	577.66 (0.00)	346.42 (0.00)	357.26 (0.00)

Note: CD: collaborative diversity; KD: knowledge diversity.

Sasabuchi *t*-tests are observed significant, providing additional evidence for our hypotheses. After that, we report the estimated extreme value and calculate the 95% confidence interval (CI) for the estimated extreme value based on two methods (Fieller method and Delta method). Finally, we test the joint significance of control variables and all variables in the model, which indicates that models in our study are statistically significantly. All computations are conducted in Stata 11.0, which is provided by Lind and Mehlum [81].

5. Discussion

This study uses the patent applications of alternative energy organizations, including companies, universities and research institutions, to explain the evolutions of organizational knowledge base and collaborative partners. We predict and find that different kinds of diversity (collaborative and knowledge) of organizations influence organizational dynamic behaviors—exploring new knowledge elements and developing new partners. This work indicates that the relationships between diversity and organizational evolutionary progression may be more complex than it has been formerly viewed to be [82] and that seeing organizational innovation as static processes may obscure important differences [29]. According to the SUR regression and Sasabuchi test results (see Section 3), collaborative diversity is found to have inverted U-shaped effects on both new knowledge and partners, which means collaborative diversity is first positively, and then negatively associated with organizational dynamic behaviors. The study reveals that organizations with more diversity tend to produce more knowledge elements that are new to organizational extant stock of knowledge, but only up to a certain point. At high levels of collaborative diversity, further increases could result in a decrease in the capacities of acquiring new ideas and knowledge elements. And organizations with more collaborative diversity also exhibit more efficiency of attracting new collaborative partners. However, at too high levels of collaborative diversity, organizations won't feel as motivated to develop new partners.

The next set of relationships investigated in this article examines the effects of knowledge diversity. Our results suggest that knowledge diversity has inverted U-shaped relationships with new knowledge and partners. We find that diverse knowledge base implies the capability of synergy, and thus, increases the likelihood of new relationships formation. However, at very high levels, there may be some cost to too much knowledge base overlap between focal firms and others. Consequently, the marginal benefits of collaborations may decrease due to the risks of few learning opportunities from others. Meanwhile, diversity in knowledge may increase the amount of resource and information available to a firm, yet too much may make firms difficult to explore, utilize and process their knowledge.

Our findings support some findings in the research on innovation by Laursen and Salter in 2006 [83]. For example, to some extent, our results are consistent with Laursen and Salter's argument that the search depth and width from collaboration relationships with external actors have both positive and negative effects on innovation performance. Our argument that the diversity of external collaboration partners can both facilitate and hamper explored new knowledge elements is similar to Laursen and Salter's argument, which is, the variety of search enable a greater ability to the adaption of change and innovation, but the benefits of open search are subject to declining returns because of the absorptive capacity, timing and attention problems. What's more, compared with the study of Laursen and Salter [83], we make a substantial improvement and theoretical contribution. Particularly, besides studying the diversity of external collaboration portfolios, we also analyze the roles of the diversity of internal knowledge portfolios. We adopt a dynamic perspective to reason the dynamic change patterns of firms' resource portfolios, and build a dynamic model to link diversity with the growth of firms' resource portfolios.

6. Conclusion and policy implications

This study examines the factors that influence the exploration of new knowledge elements and the formation of new collaborations between organizations in the alternative energy industry. The following theoretical implications can be founded in this study. First, our analyses point to ways that collaborative diversity can both facilitate and constrain organizational ability to explore new knowledge elements or partners. These curvilinear relationships are consistent with prior argument on the benefits from diversity. For example, Cohen and Levinthal [65] concerned that when organizations reach a certain point above which the returns from diversity diminish. The most important thing is that future research can link our findings with the research on the relationships between partner profiles and innovation performance [84].

Second, we add to the diversity literature on that knowledge diversity plays crucial roles in both helping and hindering new knowledge creation [85]. Alternative energy organizations with moderate diverse knowledge are likely to form new collaborative relationships with other organizations. This finding is consistent with our hypothesis and some research [86,87], while inconsistent with some research [86]. We propose that organizations which have moderate diverse knowledge base tend to explore new knowledge elements, while those with too low or high levels of knowledge diversity may have difficulties in new knowledge creation.

Third, we contribute to the streams of dynamic phenomena, measuring the new addition of partners and knowledge elements. In this study, to capture the accurate growth of a firm's portfolio, we contrast its past partner or technology classifications portfolio and current ones in every period. Searching new partners could indicate the change of the firm's collaborative strategies, while exploring new technology classification may illustrate its exploratory ability or product innovation strategies, which are recognized by pervious literature [8]. The future research could continue the firm portfolio dynamics research from innovation capability, culture and geography perspectives, which will contribute the important implications on firms' technology innovation strategies.

Moreover, several important implications for management can be derived from our study. First, knowledge is widely viewed as crucial strategic resource to cope with the current competition. Previous studies have already highlighted that organizational resources and knowledge play important roles in firms' performance and decisions [88]. The prevalence of collaborations with diverse teams and pursuit of diverse knowledge-based resources to generate breakthrough innovations [11], which are attributed to rapid and uncertain changes in competitive environments, have become vital means by which organizations gain access to capabilities required to survive and grow fast [89,90]. Managers need to be aware of the firm' knowledge portfolio as it is determinant for attracting outside partners. Meanwhile, managers should reasonably increase investment in different inventions to help the cross-fertilization and ensure the combination of distant technologies [76].

Second, the findings suggest the need to not just regard firms as aggregations of knowledge resource, but also view firms in the context of their collaboration or knowledge exchange relationships with their partners. Essentially this study informs firm managers what certain types of managerial strategies to deploy partner and knowledge portfolios are most beneficial to implement. Thus, firms should focus not only on their unique knowledge elements, but also on their partner portfolio to leverage their knowledge with access to complementary resource of partners. The capability of firms to enhance their relational skills and foster cooperation with effective collaborative partners can strengthen their knowledge creation in alternative energy industry.

Third, the findings of our study urge firms' managers to consider collaborative diversity of their firms' partner portfolios as collaborative diversity may have both favorable and detrimental impacts on the dynamic evolution of their firms. To realize exploratory performance objectives, firms should pay enough attention to their firm's collaborative diversity – while diverse partners offer varied and complementary benefits, increasing collaborative diversity beyond a specific point may not 'play well' as a collaborative strategy in terms of exploring new and novel elements as targets for purchase. Thus, evolution of the partner portfolio should be strategically managed in a way that the partner configuration is consistent with focal firms' goals. For example, increasing firms have begun to emphasize exploration. Managers who adopt an exploratory orientation should pay more attention to treat own partners as a whole portfolio and not just in a dyadic way. Moving from the dyad perspective to the whole portfolio level perspective will sensitize managers to understand how partner configuration influences organizational performance and new relationship formations.

Several important limitations of our study point out possible directions for future research. First, using patent-based measures has some obvious drawbacks. For example, because of the varying patenting propensity, patent applications can't represent all innovation activities of the firms. Future work can explore other forms of collaboration relationships, such as knowledge exchange and alliance relationships. Besides, it is difficult to take into account the different extent of novelty and economic values of patent applications [91]. Another limitation is that the dataset of study is examined in alternative energy organizations with their particular industry characteristics, which may perplex the extrapolation of our findings to other industries. Thus, developing longitudinal data in different industries to test whether the relationships between diversities and organizational evolutive actions are contingent with the results under our empirical context can be one of the subjects of future research. Third, some scholars have suggested that the relationship between partner diversity and performance may be different over the technology life cycle [32]. Thus, future work can test the distinct effects of diversities on firms' new knowledge creation and new added collaborative partners during the technology life cycle. In addition, we did not consider the sources of knowledge development of these alternative energy technologies. Knowledge diversity of different energy technologies would be different for their technology maturity and capacity of attracting investors. For example, compared with other alternative energy, wind and solar technologies rank the highest for their technology maturity, scalability and commercial feasibility [92]. The important opportunity here is that future research could study the source of knowledge diversity in alternative energy firms, especially from technology maturity [93] and firm strategic perspectives.

Acknowledgements

This study is supported by the Grants from National Natural Science Foundation of China (Nos. 71673261 and 71373254) and from The Research Team of Natural Science Foundation of Guangdong Province in China (2016A030312005). The authors are very grateful for the valuable comments and suggestions from two anonymous reviewers and the Editors of the Journal, which significantly improved the quality of the paper.

Appendix A

TOPIC	USPC	IPC
Biofuel	44/605, 44/589	C10L 5/00
Genetically engineered organism	435/252.3 +, 254.11 +, 257.2, 325 +, 410 +;800/various	C12N 1/13, 1/15, 1/21, 5/10; A01H; A01K 67/027, 67/033
Fuel cell	429/12–46	H01M 8/00
Geothermal	60/641.2 +; 436/25 +	F24J 3/00; F03G 4/00
Harnessing energy from manmade waste	75/958; 431/5	B09B 3/00; F27D 17/00
Agricultural waste	44/589	C05F 17/00; C10L 5/00
Fuel from animal waste and crop residues	44/605	C10L 5/42, C10L 5/44
Gasification	48/197R +	C10J 3/02, C10J 3/46
Chemical waste	110/235 +, 346	B09B 3/00
Industrial waste	110/235 +, 346	C10L 5/48; F23G 7/00
Industrial waste anaerobic digestion	210/605	C02F 11/04; F23G 7/00
Industrial wood waste	44/589, 44/606	F23G 7/10
Hospital waste	110/235 +, 346	B09B 3/00; C10L 5/48

Landfill gas	431/5	B09B 3/00
Municipal waste	44/552	C10L 5/46
Refuse-derived fuel	44/552	C10L 5/46
Hydroelectric	405/76–78; 60/495–507; 415/25	F01B 25/00; E02B 9/00–9/08
Inertial (e.g. turbine)	290/51, 54; 60/495–507	F03B 13/00; F03B 17/06
Water level (e.g. wave or tide)	405/76–78; 60/495–507	F03B 13/00,13/14; E02B 9/06
Solar energy	126/561–714	F24J 2/00; H01L 31/00; F03G 6/00
Photovoltaic	136/243+	H01L 31/00
Solar thermal energy	126/561–713; 60/641.8+	F24J 2/00
For domestic hot water systems	126/634–680	F24D 17/00
For passive space heating	52/173.3	F24D 3/00
For swimming pools	126/561–568	F24J 2/42
Wind	290/44, 55; 415/2.1	F03D

References

[1] Panwar N, Kaushik S, Kothari S. Role of renewable energy sources in environmental protection: a review. Renew Sustain Energy Rev 2011;15:1513–24.
[2] Evans A, Strezov V, Evans TJ. Assessment of sustainability indicators for renewable energy technologies. Renew Sustain Energy Rev 2009;13:1082–8.
[3] Guan J, Zhang J, Yan Y. The impact of multilevel networks on innovation. Res Policy 2015;44:545–59.
[4] Duysters G, Vanhaverbeke W, Beerkens B, Gilsing V. Exploration and exploitation in technology-based alliance networks. United Nations University-Maastricht Economic and Social Research Institute on Innovation and Technology (MERIT); 2007.
[5] Sandén BA, Azar C. Near-term technology policies for long-term climate targets—economy wide versus technology specific approaches. Energy Policy 2005;33:1557–76.
[6] Azar C, Sandén BA. The elusive quest for technology-neutral policies. Environ Innov Soc Transit 2011;1:135–9.
[7] Aharonson BS, Schilling MA. Mapping the technological landscape: measuring technology distance, technological footprints, and technology evolution. Res Policy 2016;45:81–96.
[8] Wang C, Rodan S, Fruin M, Xu X. Knowledge networks, collaboration networks, and exploratory innovation. Acad Manag J 2014;57:484–514.
[9] Lee K, Lee S. Patterns of technological innovation and evolution in the energy sector: a patent-based approach. Energy Policy 2013;59:415–32.
[10] Mao G, Liu X, Du H, Zuo J, Wang L. Way forward for alternative energy research: a bibliometric analysis during 1994–2013. Renew Sustain Energy Rev 2015;48:276–86.
[11] Srivastava MK, Gnyawali DR. When do relational resources matter? Leveraging portfolio technological resources for breakthrough innovation. Acad Manag J 2011;54:797–810.
[12] Choe H, Lee DH, Kim HD, Seo IW. Structural properties and inter-organizational knowledge flows of patent citation network: the case of organic solar cells. Renew Sustain Energy Rev 2016;55:361–70.
[13] Grant RM. The resource-based theory of competitive advantage: implications for strategy formulation. Knowl Strategy 1991;33:3–23.
[14] Mahoney JT, Pandian JR. The resource-based view within the conversation of strategic management. Strateg Manag J 1992;13:363–80.
[15] Sirmon DG, Hitt MA, Ireland RD. Managing firm resources in dynamic environments to create value: looking inside the black box. Acad Manag Rev 2007;32:273–92.
[16] Moliterno TP, Wiersema MF. Firm performance, rent appropriation, and the strategic resource divestment capability. Strateg Manag J 2007;28:1065–87.
[17] Liu N, Guan J. Dynamic evolution of collaborative networks: evidence from nano-energy research in China. Scientometrics 2015;102:1895–919.
[18] Cannella AA, McFadyen MA. Changing the exchange the dynamics of knowledge worker ego networks. J Manag 2013. [0149206313511114].
[19] Ahuja G. The duality of collaboration: inducements and opportunities in the formation of interfirm linkages. Strateg Manag J 2000;21:317–43.
[20] Jiang RJ, Tao QT, Santoro MD. Alliance portfolio diversity and firm performance. Strateg Manag J 2010;31:1136–44.
[21] Lavie D, Miller SR. Alliance portfolio internationalization and firm performance. Organ Sci 2008;19:623–46.
[22] Parkhe A. Interfirm diversity, organizational learning, and longevity in global strategic alliances. J Int Bus Stud 1991;22:579–601.
[23] Goerzen A, Beamish PW. The effect of alliance network diversity on multinational enterprise performance. Strateg Manag J 2005;26:333–54.
[24] Das TK, Teng B-S. A resource-based theory of strategic alliances. J Manag 2000;26:31–61.
[25] Sampson RC. R & D alliances and firm performance: the impact of technological diversity and alliance organization on innovation. Acad Manag J 2007;50:364–86.
[26] Fang L-Y, Wu S-H. Accelerating innovation through knowledge co-evolution: a case study in the Taiwan semiconductor industry. Int J Technol Manag 2006;33:183–95.
[27] Barney J. Firm resources and sustained competitive advantage. J Manag 1991;17:99–120.
[28] Faems D, Van Looy B, Debackere K. Interorganizational collaboration and innovation: toward a portfolio approach. J Product Innov Manag 2005;22:238–50.
[29] Quintana-García C, Benavides-Velasco CA. Innovative competence, exploration and exploitation: the influence of technological diversification. Res Policy 2008;37:492–507.
[30] Guan J, Yan Y, Zhang J. How do collaborative features affect scientific output? Evidences from wind power field. Scientometrics 2015;102:333–55.
[31] Van de Vrande V. Balancing your technology-sourcing portfolio: how sourcing mode diversity enhances innovative performance. Strateg Manag J 2013;34:610–21.
[32] Stolwijk CCM, den Hartigh E, Vanhaverbeke WPM, Ortt JR, van Beers C. Cooperating with technologically (dis)similar alliance partners: the influence of the technology life cycle and the impact on innovative and market performance. Technol Anal Strateg Manag 2015;27:925–45.
[33] Subtil Lacerda J, van den Bergh JCJM. Diversity in solar photovoltaic energy: implications for innovation and policy. Renew Sustain Energy Rev 2016;54:331–40.
[34] Love JH, Roper S, Vahter P. Learning from openness: the dynamics of breadth in external innovation linkages. Strateg Manag J 2014;35:1703–16.
[35] Oerlemans LAG, Knoben J, Pretorius MW. Alliance portfolio diversity, radical and incremental innovation: the moderating role of technology management. Technovation 2013;33:234–46.
[36] Huang Y-F, Chen C-J. The impact of technological diversity and organizational slack on innovation. Technovation 2010;30:420–8.
[37] Wuyts S, Dutta S. Benefiting from alliance portfolio diversity: the role of past internal knowledge creation strategy. J Manag 2014;40:1653–74.
[38] Beers C, Zand F. R & D cooperation, partner diversity, and innovation performance: an empirical analysis. J Prod Innov Manag 2014;31:292–312.
[39] de Leeuw T, Lokshin B, Duysters G. Returns to alliance portfolio diversity: the relative effects of partner diversity on firm's innovative performance and productivity. J Bus Res 2014;67:1839–49.
[40] Belderbos R, Carree M, Lokshin B. Complementarity in R & D cooperation strategies. Rev Ind Organ 2006;28:401–26.
[41] Burt RS. Structural holes: the social structure of competition. Cambridge, Massachusetts: Harvard University Press; 2009.
[42] Koput KW. A chaotic model of innovative search: some answers, many questions. Organ Sci 1997;8:528–42.
[43] Raesfeld Av, Geurts P, Jansen M, Boshuizen J, Luttge R. Influence of partner diversity on collaborative public R & D project outcomes: a study of application and commercialization of nanotechnologies in the Netherlands. Technovation 2012;32:227–33.
[44] Duysters G, Heimeriks KH, Lokshin B, Meijer E, Sabidussi A. Do firms learn to manage alliance portfolio diversity? The diversity-performance relationship and the moderating effects of experience and capability. Eur Manag Rev 2012;9:139–52.
[45] Standifird SS, Marshall RS. The transaction cost advantage of guanxi-based business practices. J World Bus 2000;35:21–42.
[46] Hennart J-F. The transaction costs theory of joint ventures: an empirical study of Japanese subsidiaries in the United States. Manag Sci 1991;37:483–97.
[47] van Beers C, Zand F. R & D cooperation, partner diversity, and innovation performance: an empirical analysis. J Product Innov Manag 2014;31:292–312.
[48] Pandza K, Wilkins TA, Alfoldi EA. Collaborative diversity in a nanotechnology innovation system: evidence from the EU Framework Programme. Technovation 2011;31:476–89.
[49] Becker W, Dietz J. R & D cooperation and innovation activities of firms—evidence for the German manufacturing industry. Res Policy 2004;33:209–23.
[50] Alam Hossain Mondal M, Kamp LM, Pachova NI. Drivers, barriers, and strategies for implementation of renewable energy technologies in rural areas in Bangladesh—an innovation system analysis. Energy Policy 2010;38:4626–34.
[51] Dincer I. Renewable energy and sustainable development: a crucial review. Renew Sustain Energy Rev 2000;4:157–75.
[52] Ahuja G. Collaboration networks, structural holes, and innovation: a longitudinal study. Adm Sci Q 2000;45:425–55.
[53] Ang SH. Competitive intensity and collaboration: impact on firm growth across technological environments. Strateg Manag J 2008;29:1057–75.
[54] Bathelt H, Malmberg A, Maskell P. Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation. Progress Hum Geogr 2004;28:31–56.

[55] Fleming L. Recombinant uncertainty in technological search. Manag Sci 2001;47:117–32.
[56] Phelps CC. A longitudinal study of the influence of alliance network structure and composition on firm exploratory innovation. Acad Manag J 2010;53:890–913.
[57] Ardito L, Petruzzelli AM, Albino V. Investigating the antecedents of general purpose technologies: a patent perspective in the green energy field. J Eng Technol Manag 2016;39:81–100.
[58] Mowery DC, Nelson RR, Martin BR. Technology policy and global warming: why new policy models are needed (or why putting new wine in old bottles won't work). Res Policy 2010;39:1011–23.
[59] Edwards PP, Kuznetsov VL, David WI, Brandon NP. Hydrogen and fuel cells: towards a sustainable energy future. Energy Policy 2008;36:4356–62.
[60] Vazquez S, Lukic SM, Galvan E, Franquelo LG, Carrasco JM. Energy storage systems for transport and grid applications. IEEE Trans Ind Electron 2010;57:3881–95.
[61] Dahlander L, McFarland DA. Ties that last tie formation and persistence in research collaborations over time. Adm Sci Q 2013;58:69–110.
[62] Pfeffer J, Nowak P. Joint ventures and interorganizational interdependence. Adm Sci Q 1976:398–418.
[63] Rothaermel FT, Boeker W. Old technology meets new technology: complementarities, similarities, and alliance formation. Strateg Manag J 2008;29:47–77.
[64] Nag R, Gioia DA. From common to uncommon knowledge: foundations of firm-specific use of knowledge as a resource. Acad Manag J 2012;55:421–57.
[65] Cohen WM, Levinthal DA. Absorptive capacity: a new perspective on learning and innovation. Adm Sci Q 1990:128–52.
[66] Schilling MA, Green E. Recombinant search and breakthrough idea generation: an analysis of high impact papers in the social sciences. Res Policy 2011;40:1321–31.
[67] Cardinal LB. Technological innovation in the pharmaceutical industry: the use of organizational control in managing research and development. Organ Sci 2001;12:19–36.
[68] Zenger TR. Explaining organizational diseconomies of scale in R & D: agency problems and the allocation of engineering talent, ideas, and effort by firm size. Manag Sci 1994;40:708–29.
[69] Maskell P. Knowledge creation and diffusion in geographic clusters. Int J Innov Manag 2001;5:213–37.
[70] Guan JC, Yan Y. Technological proximity and recombinative innovation in the alternative energy field. Res Policy 2016;45:1460–73.
[71] March JG. Exploration and exploitation in organizational learning. Organ Sci 1991;2:71–87.
[72] Leten B, Belderbos R, Van Looy B. Technological diversification, coherence, and performance of firms. J Prod Innov Manag 2007;24:567–79.
[73] Kirkels AF, Verbong GP. Biomass gasification: still promising? A 30-year global overview. Renew Sustain Energy Rev 2011;15:471–81.
[74] Corsatea TD. Technological capabilities for innovation activities across Europe: evidence from wind, solar and bioenergy technologies. Renew Sustain Energy Rev 2014;37:469–79.
[75] Hackl R, Andersson E, Harvey S. Targeting for energy efficiency and improved energy collaboration between different companies using total site analysis (TSA). Energy 2011;36:4609–15.
[76] Guan J, Liu N. Invention profiles and uneven growth in the field of emerging nano-energy. Energy Policy 2015;76:146–57.
[77] Cooke H, Keppo I, Wolf S. Diversity in theory and practice: a review with application to the evolution of renewable energy generation in the UK. Energy Policy 2013;61:88–95.
[78] Guan J, Yan Y, Zhang JJ. The impact of collaboration and knowledge networks on citations. J Informetr 2017;11:407–22.
[79] Zellner A. An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias. J Am Stat Assoc 1962;57:348–68.
[80] Sasabuchi S. A test of a multivariate normal mean with composite hypotheses determined by linear inequalities. Biometrika 1980;67:429–39.
[81] Lind JT, Mehlum H. With or without u? The appropriate test for a U-shaped relationship*. Oxford B Econ Stat 2010;72:109–18.
[82] Gambardella A, Torrisi S. Does technological convergence imply convergence in markets? Evidence from the electronics industry. Res Policy 1998;27:445–63.
[83] Laursen K, Salter A. Open for innovation: the role of openness in explaining innovation performance among UK manufacturing firms. Strateg Manag J 2006;27:131–50.
[84] Oerlemans LA, Knoben J, Pretorius MW. Alliance portfolio diversity, radical and incremental innovation: the moderating role of technology management. Technovation 2013;33:234–46.
[85] Nieto MJ, Santamaría L. The importance of diverse collaborative networks for the novelty of product innovation. Technovation 2007;27:367–77.
[86] Suzuki J, Kodama F. Technological diversity of persistent innovators in Japan: two case studies of large Japanese firms. Res Policy 2004;33:531–49.
[87] Lin B-W, Chen C-J, Wu H-L. Patent portfolio diversity, technology strategy, and firm value. Eng Manag IEEE Trans 2006;53:17–26.
[88] Gu Q, Lu X. Unraveling the mechanisms of reputation and alliance formation: a study of venture capital syndication in China. Strateg Manag J 2014;35:739–50.
[89] Adams JD. Fundamental stocks of knowledge and productivity growth. J Political Econ 1990:673–702.
[90] Lechner C, Dowling M. Firm networks: external relationships as sources for the growth and competitiveness of entrepreneurial firms. Entrep Reg Dev 2003;15:1–26.
[91] Deyle H-G, Grupp H. Commuters and the regional assignment of innovative activities: a methodological patent study of German districts. Res Policy 2005;34:221–34.
[92] Umamaheswaran S, Rajiv S. Financing large scale wind and solar projects—A review of emerging experiences in the Indian context. Renew Sustain Energy Rev 2015;48:166–77.
[93] Moray N, Clarysse B. Institutional change and resource endowments to science-based entrepreneurial firms. Res Policy 2005;34:1010–27.