Reusing new or old knowledge combinations to generate short and long-term breakthrough innovations? Evidence from the wind energy industry

Abstract

Breakthrough innovations can either be influential in a short period after their creation (short-term) or require a longer time to gain influence (long-term). While exploration and exploitation contribute to breakthrough innovations, many studies claim that a firm's reuse of knowledge combinations reduces the likelihood of breakthrough innovations because they have limited opportunities for improvement. This argument is based on an overly strong assumption that firms excessively focus on reusing the same knowledge combination over extended periods. Differentiating between new and old knowledge combinations within the sector is essential to understand whether firms excessively focus on reusing the same knowledge combination. This study first distinguishes between new and old knowledge combinations by comparing the age of knowledge combinations to the length of sectoral technological cycle. By analysing granted patents in the global wind energy sector over the past 30 years, this study finds that reusing old knowledge combinations facilitates short-term breakthrough innovations (1-5 years after the patent is granted). Furthermore, generating long-term breakthrough innovations (6-10 years after the patent is granted) requires firms to explore more while reusing fewer new knowledge combinations within the sector. These findings underscore the importance of adopting distinct knowledge search strategies to generate short-term and long-term breakthrough innovations.

1. Introduction

Technological innovations are crucial drivers of technological changes (Schumpeter, 1934; Freeman, 1992). The influence of technological innovations is often assessed by the extent to which they serve as a basis for subsequent technological development (Trajtenberg, 1990; Ahuja and Lampert, 2001). Only a small subset of innovations achieves exceptional influence and is classified as breakthrough innovations (Rosenberg, 1994; Ahuja and Lampert, 2001; Datta and Srivastava, 2023). Some breakthrough innovations can be influential in a short period after creation, but some of them need a longer period to become influential (Chai and Menon, 2019). One possible explanation is that such innovations may be unfamiliar to firms, requiring time to learn how to integrate them (Capaldo et al., 2017). Accordingly, this study differentiates between short-term and long-term breakthrough innovations. Short-term breakthrough innovations exert significant influence in a short period after their creation, whereas long-term breakthrough innovations require more time to be influential.

The generation of breakthrough innovations arises from knowledge combinations (Fleming, 2001; Arts and Veugelers, 2015; Xiao et al., 2021; Capponi et al., 2022). In this context, a firm's ability to create breakthrough innovations is closely linked to its combinative capabilities. A firm's combinative capabilities encompass two key dimensions: exploration and exploitation (March, 1991; Kogut and Zander, 1992). Exploration allows firms to search various knowledge beyond their boundaries (March, 1991; Rosenkopf and Nerkar, 2001). On the other hand, exploitation enables firms to develop a deep understanding of specific technological fields (Katila and Ahuja, 2002). This understanding helps firms identify knowledge with high potential to enhance or even replace existing ones (Cohen and Levinthal, 1990; Fleming and Sorenson, 2004). Building on these

perspectives, Randle and Pisano (2021) emphasised that breakthrough innovations may result from an iterative process, including exploration and subsequent exploitation.

As one dimension of exploitation, the reuse of knowledge combinations is defined as the use of knowledge combinations already known to the firm to solve new problems and develop new applications (Carnabuci and Operti, 2013). While exploitation is crucial for breakthrough innovations, some studies argue that knowledge combination reuse leads to less influential innovations, as these combinations may eventually be irrelevant to current technological problems (Chen, 2023; Zhong et al., 2024). However, this argument relies on an overly strong assumption that firms reuse the same knowledge combinations over extended periods. Such an assumption contradicts the overarching hypothesis in the knowledge search literature, which posits that firms ought to maintain a balance between exploration and exploitation (Levinthal and March, 1991; Rothaermel and Alexandre, 2009).

This study proposes that one way to identify whether firms reuse the same knowledge combinations over extended periods is to differentiate between new and old ones within the sector. The reuse of new knowledge combinations within the sector reflects firms' engagement in exploration. Conversely, the reuse of old knowledge combinations within the sector suggests that firms may excessively focus on exploitation over extended periods.

A new knowledge combination within the sector (referred to as "a new knowledge combination" in this paper), defined as a pair of knowledge components that were previously unconnected in the sector, can provide novel functionalities and address previously unsolved technological problems (Arthur, 2007; Verhoeven et al., 2016), thereby facilitating breakthrough innovations (Arts and Veugelers et al., 2015). On the other hand, some studies argue that firms may struggle to fully understand how new knowledge combinations work, reducing the likelihood of achieving breakthrough innovations (Chai and Menon, 2019). In contrast, firms are generally more familiar with old knowledge combinations within the sector (knowledge combinations that exist in the sector for longer). This familiarity reduces the risk of producing useless innovations (Fleming, 2001; Capaldo et al., 2017). Nevertheless, old knowledge combinations may become less relevant to current technological problems (Sorenson and Stuart, 2000) and offer fewer opportunities for further improvement (Heeley and Jacobson, 2008). **Consequently, the impact of the reuse of new and old knowledge combinations within the sector on a firm's ability to generate short-term or long-term breakthrough innovations is not examined.**

This study proposes that whether a knowledge combination within the sector is classified as new or old depends on the speed at which it becomes obsolete, referred to as the sectoral technological cycle (Lee and Lim, 2001; Park and Lee, 2006). In a sector with a short sectoral technological cycle, knowledge becomes obsolete rapidly, and even recently emerged knowledge combinations may be replaced by newer ones. Accordingly, this study defines a 'new knowledge combination' as one whose age is shorter than the length of sectoral technological cycle. When the age of a knowledge combination exceeds the length of sectoral technological cycle, it is classified as an 'old knowledge combination'. In this way, this study proposes a typology of a firm's knowledge search strategies based on two criteria: whether the firm has previously used the knowledge combination and whether

its age exceeds the sectoral technological cycle length. The typology comprises four knowledge search strategies: exploring new or old knowledge combinations and reusing new or old knowledge combinations.

This study extracts granted patents held by firms (patent assignees are firms) within the global wind energy industry over 30 years (1991-2023) from the Derwent World Patent Index (DWPI) database. Subsequently, we identify firms that reuse knowledge combinations and discern new and old knowledge combinations based on patent classification codes (Fleming et al., 2007; Verhoeven et al., 2016; Pezzoni et al., 2022). Following this, this study identifies breakthrough innovations based on the number of forward citations a patent received (e.g., Singh and Fleming, 2010) in short-term (1-5 years after a patent is granted) and long-term periods (6-10 years after a patent is granted). Finally, this study examines whether reusing new or old knowledge combinations allows firms to create more short and long-term breakthrough innovations.

Our results reveal that the reuse of old knowledge combinations can positively affect a firm's ability to generate breakthrough innovations. The reason could be that some old knowledge combinations, although previously overlooked, can address current technological problems (Nerkar, 2003). Furthermore, we find that when firms reuse more new knowledge combinations, they generate fewer long-term breakthrough innovations. This may be because firms may not fully leverage their advantages in familiar fields (Wang et al., 2017) and need time to learn how to use these new knowledge combinations (Capaldo et al., 2017).

Our study has three contributions. First, it emphasises the importance of differentiating between new and old knowledge combinations within a sector for understanding a firm's knowledge search strategy. Second, it highlights that this differentiation depends on the length of sectoral technological cycle. Moreover, by categorising short-term and long-term breakthrough innovations, this study reveals that firms need to adopt distinct knowledge search strategies to generate each type.

The rest of the paper is organised as follows. Section 2 outlines the theoretical framework and formulates our research questions and hypotheses. Section 3 presents the research context, and Section 4 explains our methodological approach. Section 5 shows the descriptive analysis of our data. Section 6 presents the results of the regression analysis. Section 7 tests the robustness of the results. Section 8 provides a discussion and conclusion of the results.

2. Conceptual framework and hypotheses

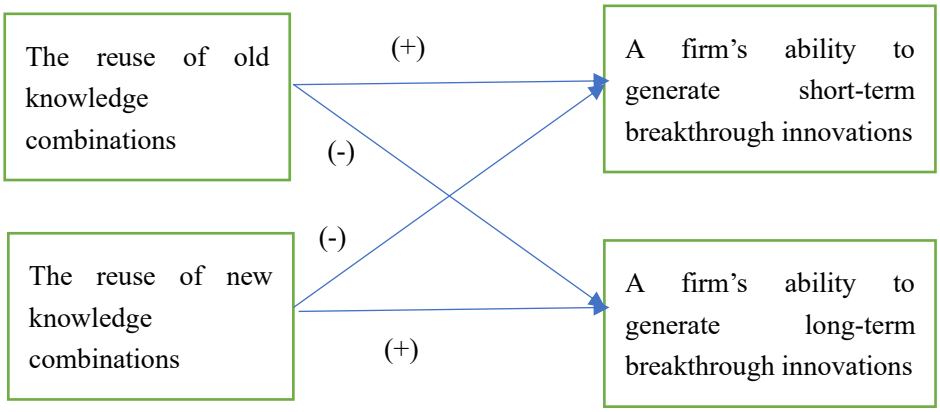


Figure 1 Conceptual model

The conceptual framework of this study is presented in Fig. 1. This paper examines the relationship between the reuse of new and old knowledge combinations within the sector and a firm's ability to generate short and long-term breakthrough innovations. Our hypotheses propose that reusing old knowledge combinations may positively influence a firm's ability to create short-term breakthrough innovations but negatively affect its ability to generate long-term ones. Additionally, we hypothesise that reusing new knowledge combinations may constrain short-term breakthrough innovations while facilitating long-term ones.

2.1 Breakthrough innovations: Short-term and Long-term

Breakthrough innovations have exceptional influence, serving as a basis for numerous subsequent innovations (Trajtenberg, 1990; Ahuja and Lampert, 2001). For example, patents that receive the top 5% number of forward citations are regarded as breakthrough innovations (Singh and Fleming, 2010). Breakthrough innovations play a crucial role in the process of "creative destruction", whereby existing innovations are replaced by new ones (Ahuja and Lampert, 2001; Singh and Fleming, 2010; Arts and Veugelers, 2015; Datta and Srivastava, 2023; Qu et al., 2023). Furthermore, breakthrough innovations enable firms to drive business growth, capture future markets, earn economic rents, and gain unique competitive advantages (Achilladelis et al., 1990; Harhoff et al., 1999; Datta and Srivastava, 2023). Thus, understanding the generation of breakthrough innovations is crucial for the development of a sector and the formulation of a firm's innovation strategy.

Breakthrough innovations often originate from new inventions within a sector (e.g., Ahuja and Lampert, 2001; Xiao et al., 2021; Capponi et al., 2022; Qu et al., 2023). New inventions contribute to breakthrough innovations because they differ from existing inventions and present opportunities to address previously unresolved technological problems (Ahuja and Lampert, 2001; Katila, 2002). For example, Arthur (2007) describes how the turbojet engine introduced the concept of generating thrust by expelling particles to create an opposite force, propelling the airplane forward. This represented a novel technological approach compared to conventional propeller engines, which create drag to drive the aircraft. Although new inventions are crucial for breakthrough innovations, they may not exert significant influence in a short period after their creation (e.g., Pezzoni et al.,

2022). One possible explanation is that firms require time to integrate new inventions into their existing knowledge bases (Katila, 2002; Chai and Menon, 2019).

However, many studies on breakthrough innovations assume that innovations become influential in a short period after creation. For instance, such studies often identify breakthrough innovations by the number of forward citations patents receive within five years of being granted (or applied) (e.g., Arts and Veugelers, 2015; Kaplan and Vakili et al., 2015; Qu et al., 2023). This methodology suggests that innovations exert their influence primarily within the first five years, with their influence diminishing thereafter. Nevertheless, Pezzoni et al. (2022) found that some innovations that are not influential within the first five years can still serve as a basis for subsequent innovations beyond this period. Considering that some breakthrough innovations may not be influential in a short period after creation (Pezzoni et al., 2022), this study distinguishes between short-term and long-term breakthrough innovations. Short-term breakthrough innovations exert a significant influence in a short period after creation, while long-term breakthrough innovations require more time to become influential.

2.2 Breakthrough Innovations and New knowledge combinations within the sector

Given the importance of new inventions and the assumption that knowledge components are fundamental constituents of an invention (Schumpeter, 1934; Nelson and Winter, 1982; Henderson and Clark, 1990; Fleming, 2001; Xiao et al., 2021), the innovation literature further emphasises that new knowledge combinations within the sector can contribute to breakthrough innovations (e.g., Arts and Veugelers, 2015; Jung and Lee, 2016). **A new knowledge combination within the sector** (referred to as "new knowledge combination" in this paper) **is defined as a pair of knowledge components that were previously unconnected within the sector** (Fleming et al., 2007; Strumsky and Lobo, 2015; Verhoeven et al.,2016). In other words, it consists of at least one knowledge component from outside the sector or introduces a new way of combining existing knowledge components within the sector.

Arts and Veugelers (2015) found that new knowledge combinations are more likely to lead to breakthrough innovations. Such combinations may introduce new functionalities (Castaldi et al., 2017; Xiao et al., 2021) and offer unique solutions to previously unsolvable technological problems within the sector (Verhoeven et al., 2016). For example, the CAT scanner, which earned the Nobel Prize in Physiology or Medicine, emerged from the combination of X-ray and computer technologies (Adner & Levinthal, 2002). Furthermore, Jung and Lee (2016) proposed that by searching new knowledge combinations within the sector, firms can identify technological opportunities to improve them and influence subsequent innovations. In summary, new knowledge combinations within the sector offer new solutions to technological problems and represent technological opportunities for improvement.

2.3 Breakthrough Innovations and Old knowledge combinations within the sector

Not all new knowledge combinations within the sector contribute to breakthrough innovations. First, whether they can solve current technological problems is uncertain (Wang et al., 2017). Thus, some

firms may avoid adopting them. Furthermore, Arts and Veugelers (2015) found that knowledge combinations comprising new components within the sector do not necessarily result in breakthrough innovations. One possible explanation is that firms may be unfamiliar with these new components and fail to fully understand how they interact (Chai and Menon, 2019). Consequently, some new knowledge combinations within the sector can also lead to extremely useless innovations (Fleming, 2001; Verhoeven et al., 2016).

Considering the drawbacks of new knowledge combinations within the sector, some studies implied that old knowledge combinations within the sector (those that have existed in the sector for a more extended period) may better promote breakthrough innovations. First, searching old knowledge combinations helps firms uncover previously neglected knowledge that can address current technological problems (Katila, 2002; Nerkar, 2003). Second, these knowledge combinations are more likely to have been proven useful in the past (Petruzzelli and Savino, 2014; Capaldo et al., 2017). By observing how other firms use these knowledge combinations, firms can avoid useless innovations and identify the most influential ones (Katila, 2002; Katila and Chen, 2008).

However, old knowledge combinations have been criticised for several reasons. First, they may no longer be relevant to current technological problems in the sector and often fail to align with market needs and expectations (Sorenson and Stuart, 2000). Second, old knowledge combinations within the sector may have been exploited by competitors, leaving limited opportunities for further improvement (Heeley and Jacobson, 2008). Finally, firms may forget how to apply old knowledge combinations correctly (Argote, 1999; Sorenson and Stuart, 2000).

In summary, both new and old knowledge combinations within the sector may or may not contribute to breakthrough innovations. This study proposes that one reason for these conflicting views could be that the differentiation between new and old knowledge combinations is influenced by the speed at which knowledge combinations become obsolete within the sector. In sectors where knowledge becomes obsolete rapidly, even recently emerged knowledge combinations can be replaced by newer ones (Lee and Lim, 2001; Lee, 2019). Conversely, in relatively stable sectors—where knowledge becomes obsolete more slowly—knowledge combinations that have existed for a long time may remain useful (Park and Lee, 2006). Hence, the differentiation between new and old knowledge combinations does not depend solely on their ages but is influenced by the speed at which knowledge combinations become obsolete within the sector.

2.4 Sectoral technological cycle

To differentiate new and old knowledge combinations within the sector, this study introduces the concept of the sectoral technological cycle. The sectoral technological cycle refers to the speed at which knowledge becomes obsolete within the sector (Lee and Lim, 2001; Park and Lee, 2006). A longer sectoral technological cycle indicates that firms tend to use knowledge that has existed for a longer period to develop innovations, reflecting fewer technological changes (Lee and Lim, 2001; Park and Lee, 2006). Conversely, a shorter sectoral technological cycle indicates that firms are more likely to adopt new knowledge within the sector. For example, the technological cycle of the IT or mobile phone sectors is short. It suggests that knowledge in these sectors is updated frequently (Lee,

2024).

This study assumes that when a knowledge combination first appears in the sector, its age is designated as 0. If the age of the knowledge combination is less than the length of the sectoral technological cycle, it is referred to as a "new knowledge combination". Once the age of a knowledge combination exceeds the length of the sectoral technological cycle, it is referred to as an 'old knowledge combination'.

This study proposes that using the sectoral technological cycle to differentiate between new and old knowledge combinations within the sector can provide valuable insights into a firm's strategy for generating breakthrough innovations. Firms that search more new knowledge combinations will likely seize opportunities to improve them (Verhoeven et al., 2016). Conversely, firms that use more old knowledge combinations may uncover previously overlooked knowledge that has become useful for addressing current technological problems (Nerkar, 2003).

2.5 The reuse of knowledge combinations: one dimension of a firm's combinative capabilities

2.5.1 A firm's combinative capabilities: exploration and exploitation

Invention is often conceptualised as a recombinant search process (Nelson and Winter, 1982; Fleming, 2001; Arthur, 2007). The process involves identifying knowledge components, discovering new relationships between them, and recombining them (Fleming, 2001; Schilling and Green, 2011). Recombinant search processes can be classified into two types based on whether firms once used the knowledge combination: exploration and exploitation. Exploration involves searching a knowledge combination never used by the firm, while exploitation refers to using a knowledge combination already existing in a firm's knowledge base (March, 1991). Building on this framework, Kogut and Zander (1992) defined a firm's combinative capability as its ability to exploit its existing knowledge and explore knowledge beyond its knowledge base.

Authors such as Randle and Pisano (2021) proposed that breakthrough innovations require an iterative process involving both exploration and exploitation. Initially, firms engage in exploration. Then, firms exploit selected knowledge cumulatively, gradually becoming more familiar with them. This increased familiarity enables firms to identify high-potential knowledge and avoid repeating past failures, thereby enhancing the influence of their innovations (Fleming, 2001; Fleming and Sorenson, 2004). In contrast, an excessive focus on either exploration or exploitation over extended periods will likely hinder the generation of breakthrough innovations. First, excessively focusing on exploration increases the difficulty of understanding and integrating diverse and unfamiliar knowledge (Katila and Ahuja, 2002; Schilling and Green, 2011). Firms that excessively focus on exploration may fail to leverage their advantages in specific technological fields, ultimately struggling to produce influential innovations (Wang et al., 2017). On the other hand, excessively focusing on exploitation locks firms into their existing knowledge (Levinthal and March, 1991; Schilling and Green, 2011; Kaplan and Vakili, 2015). Nevertheless, existing knowledge may no longer align with market needs or solve varied technological problems (Ahuja and Lampert, 2001; Rosenkopf and Nerkar, 2001; Petruzzelli and Savino, 2014). Moreover, excessively focusing on

exploitation limits opportunities for improvement, reducing the likelihood of breakthrough innovations (Katila and Ahuja, 2002; Schilling and Green, 2011; Lanzolla et al., 2020). Thus, firms are less likely to generate breakthrough innovations without a balance between exploration and exploitation.

2.5.2 The reuse of knowledge combinations

As one dimension of exploitation, the reuse of knowledge combinations is the use of knowledge combinations already known to the firm to solve new problems and develop new applications (Carnabuci and Operti, 2013). For instance, Vestas reused its existing knowledge of onshore wind turbine designs and aerodynamics to create offshore wind turbines (Awate et al., 2012; Dai et al., 2020).

Some studies suggest that reusing knowledge combinations diminishes the likelihood of breakthrough innovations. For instance, Zhong et al. (2024) argued that reusing knowledge combinations leads to an overdependence on existing knowledge, thereby constraining the ability to explore knowledge beyond the firm's knowledge base. Additionally, Chen (2023) argued that the limited opportunities for improving reused knowledge combinations further hinder the generation of breakthrough innovations. In summary, these studies draw on reasons similar to those regarding an excessive focus on exploitation over extended periods to support the view that reusing knowledge combinations negatively affects the generation of breakthrough innovations.

However, the overarching hypothesis in the knowledge search literature is that firms ought to maintain the balance between exploration and exploitation (Levinthal and March, 1991; Rothaermel and Alexandre, 2009). This balance can be achieved by exploring new knowledge combinations within the sector and then reusing them (O'Reilly and Tushman, 2013). In other words, reusing knowledge combinations does not necessarily imply that firms excessively focus on reusing the same combinations over extended periods.

This study proposes that one way to understand whether firms excessively focus on exploitation over extended periods is to differentiate between new and old knowledge combinations within the sector. Reusing new knowledge combinations within the sector implies that firms engage in exploration. Conversely, firms that reuse old knowledge combinations within the sector are more likely to rely on their existing knowledge bases with less exploration.

Building on this, this study creates a typology of a firm's knowledge search strategy, summarized in Figure 2. In Figure 2, four types of knowledge search strategies are identified based on two criteria: whether the age of the knowledge combination exceeds the length of the sectoral technological cycle (The x-axis: New VS Old) and whether the firm has previously used the knowledge combination (The y-axis: Exploration VS Reuse).

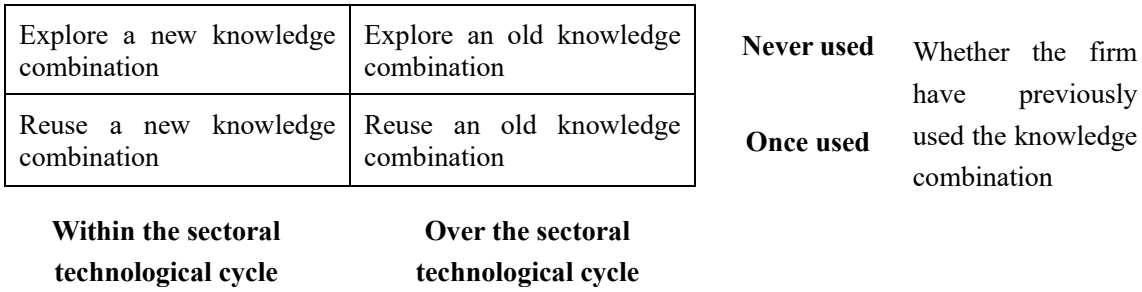


Figure 2 Four types of a firm's knowledge search strategy

2.5.3 The reuse of new knowledge combinations within the sector

This study argues that reusing new knowledge combinations within the sector may help firms generate long-term breakthrough innovations while potentially hindering short-term ones. First, new knowledge combinations represent emerging technological problems within the sector (Cohen and Levinthal, 1990; Ahuja and Lampert, 2001). Reusing new knowledge combinations within the sector indicates that firms recognise and try to solve new technological problems early. Consequently, firms can leverage the opportunity to improve new knowledge combinations, thereby providing a basis for subsequent innovations.

On the other hand, as defined earlier, new knowledge combinations within the sector are those with an age shorter than the length of the sectoral technological cycle. Hence, firms require time to train and learn how to use them (Capaldo et al., 2017). Consequently, this study argues that while reusing new knowledge combinations within the sector reduces the likelihood of short-term breakthrough innovations, it is more likely to promote long-term ones.

Hypothesis 1: Reusing new knowledge combinations within the sector negatively affects a firm's ability to generate short-term breakthrough innovations.

Hypothesis 2: Reusing new knowledge combinations within the sector positively affects a firm's ability to generate long-term breakthrough innovations.

2.5.4 The reuse of old knowledge combinations within the sector

On the contrary, reusing old knowledge combinations within the sector may enhance the likelihood of short-term breakthrough innovations but constrain long-term ones. First, since old knowledge combinations have existed over the length of sectoral technological cycle, they are more likely to have been explored and exploited within the sector (Katila, 2002). By observing how these combinations were previously used, firms can draw on previous experiences and avoid repeating the failures of earlier innovations (Katila and Chen, 2008; Xiao et al., 2021; Yang et al., 2021). In addition, old knowledge combinations are likely familiar to the sector, and they may require less

time to become influential (Pezzoni et al., 2022).

However, because the age of old knowledge combinations exceeds the length of the sectoral technological cycle, they are more likely to become less relevant to future technological problems and gradually replaced by new ones (Park and Lee, 2006). Consequently, this study argues that reusing old knowledge combinations within the sector enhances the likelihood of short-term breakthrough innovations but constrains long-term ones.

Hypothesis 3: Reusing old knowledge combinations within the sector positively affects a firm's ability to generate short-term breakthrough innovations.

Hypothesis 4: Reusing old knowledge combinations within the sector negatively affects a firm's ability to generate long-term breakthrough innovations.

3. Research context

Wind turbines are electro-mechanical devices consisting of multiple components. A typical wind turbine features three blades attached to a rotor mounted on a tall tower. Wind power is transferred from the blades to the rotor shaft and gearbox and finally to the generator, which converts the energy into electrical power for a connected power grid (Musgrove, 2010). Wind turbines must be adapted to the climate, wind speed, wind profile, and local regulations concerning grid connection, foundations, and noise. The design and development of wind turbines require knowledge of electronics, mechanics, advanced materials, aerodynamics, and other fields (Garud and Karnoe, 2003). Additionally, wind farm project design, installation, operation, and maintenance require specialised skills, training, and equipment. In summary, wind turbines are design-intensive products with a high degree of customisation, demanding high engineering and manufacturing capabilities (Awate et al., 2012).

In the late 1970s and early 1980s, firms experimented with different positions of the rotor relative to the tower (upwind and downwind), blade numbers, and rotor control mechanisms. By 1986, most firms in the market had adopted the three-blade, upwind rotor, known as the 'Danish design,' which is now used in grid-connected wind turbines. Subsequently, a series of incremental innovations allowed wind turbines to be scaled up to meet broader commercial demands (Zhou et al., 2016).

The advent of offshore wind turbines is a technological discontinuity in the wind energy sector. Since the early 2000s, companies have been developing and manufacturing larger wind turbines for the growing offshore market (Musgrove, 2010). The wind energy sector integrates technology from the maritime industry. In recent years, data analytics, machine learning, and artificial intelligence have represented the new technological frontier in the wind energy industry (Lema et al., 2020). Firms have begun collaborating with leading technological and digital consulting firms such as Apple, Microsoft, and Accenture.

The wind energy sector has traditionally been dominated by Western (mainly European) firms, such as Vestas (Denmark) and Siemens (Germany) (Nordensvard et al., 2018). However, after the 2000s,

Chinese firms such as Goldwind and Sinovel began offering turbines at considerably lower prices than leading firms (Zhou et al., 2016). These companies have displayed a high growth rate both domestically and internationally, and they have begun to catch up with and challenge the leaders in the sector.

In recent years, China has consistently led global wind energy installations, representing over half of the world's total additions (GWEC, 2024). This achievement arises from Chinese mass-producing advanced turbines at lower costs (Dai et al., 2020). Chinese domestic wind turbine manufacturers, such as Goldwind, have heavily invested in integrating cost-efficient designs that cater to market needs, developing larger-capacity turbines suited for both onshore and offshore applications (Quitzow et al., 2017). Furthermore, Chinese wind turbine manufacturers benefit from a vertically integrated supply chain, enabling them to produce turbines, components, and raw materials domestically (GWEC, 2023). In contrast, most European firms rely on global supply chains, which are more vulnerable to disruptions. Finally, the Chinese government's direct involvement in energy planning ensures alignment between industrial policies and renewable energy goals, facilitating faster project development (Binz et al., 2017; GWEC, 2024). In conclusion, China has caught up with European leaders through market dominance, technological advancements, and supply chain efficiency.

Wind turbines consist of numerous knowledge combinations of mechanical, electrical, and aerodynamic (Hain et al., 2020). The complexity of the knowledge base has evolved over time, especially as onshore and offshore turbines have different designs and installations (Rosiello and Maleki, 2021). Thus, firms in the wind energy sector are required to recombine knowledge components across various fields. The various knowledge components and complex knowledge bases increase the uncertainty of innovations. For example, offshore wind turbines require firms to understand specific geographic factors, such as wind speed and altitude, with mechanical and electrical to deal with unpredictable environmental changes and reduce higher installation and maintenance costs (Nordensvard et al., 2018). Furthermore, the length of the sectoral technological cycle shows a decreasing trend, mainly since the offshore wind turbine emerged (Rosiello and Maleki, 2021). The shorter sectoral technological cycle suggests that firms need to accelerate using complex and various knowledge combinations to remain competitive. Another reason for this intense competition is policies in the sector. Many international agreements, such as the Paris Agreement, have pushed countries to adopt green energies, promoting global demand and investment in the wind energy sector. Moreover, the growth of the wind energy sector is influenced by regional policies. For instance, in China, policies such as the Renewable Energy Law and Fedd-in Tariffs allow firms to expand their domestic market share (Dai et al., 2020).

This study chooses the wind energy sector for several reasons. First, the length of the technological cycle in the wind energy sector shows a decreasing trend (Rosiello and Maleki, 2021). This indicates that new knowledge in the wind energy sector is more likely to replace old knowledge. Consequently, although some firms in the wind energy sector have become market leaders, they still face the risk of technology lock-in based on outdated technologies (Hain et al., 2020). This risk is particularly significant because the wind energy sector is characterised by high asset specificity and large upfront investments. Second, some case studies have shown that some firms in the wind energy sector tend

to reuse old knowledge combinations. For instance, Dai et al. (2020) found that some firms in China relied on old technologies and ultimately fell behind technological leaders who exploited new technologies in the wind energy sector. This difference allows this paper to study whether reusing new and old knowledge combinations contributes to generating breakthrough innovations.

4. Data and Methodology

We begin this section by outlining our data and addressing three areas of interest: the identification of the reuse of new and old knowledge combinations within the sector and breakthrough innovations and the model specification regarding the variables to be included.

Building on related studies, this article uses granted patents to evaluate a firm's knowledge generation. Prior studies have shown that patents can be valuable indicators of knowledge creation and innovation capability (Ahuja and Lampert, 2001; Nerkar, 2003; Awate et al., 2012). Our empirical analysis utilises patents in 4-digit and 7-digit IPC codes in the wind energy sector over 30 years (1991 - 2023). The patent data is collected from the Derwent World Patent Index (DWPI) database, which includes data from forty-eight patent offices. The technological class of wind energy, as defined by DWPI codes, is X15B 'Wind Energy'. This study uses the patent assignee's country of address as a proxy for the location where the invention occurred. To avoid double counting, this article uses information concerning patent families.

4.1 Identification of the reuse of new and old knowledge combinations within the sector

Patent classification codes assigned to a patent are considered proxies for the specific knowledge components associated with the patented invention (Fleming, 2001). Following Verhoeven et al. (2016) and Li et al. (2023), a knowledge combination is identified when a new pair combination of IPC codes at the main group level (7-digit) appears in a patent within the sector. This study starts to identify knowledge combinations from 1980.

This study uses the length of the sectoral technological cycle to identify new and old knowledge combinations within the sector. Suppose a knowledge combination first appears in the sector, its age is 0. If the age of knowledge combinations is less than the length of the sectoral technological cycle, they are new knowledge combinations. In contrast, those exceeding the length of the sectoral technological cycle are deemed old within the sector. For instance, if the sectoral technological cycle is 6.5 years, knowledge combinations younger than or equal to 6 years are recognised as new within the sector, while knowledge combinations older than 7 years are identified as old.

For the measurement of the sectoral technological cycle, many studies use the time interval between the application (or publication) years of citing and cited patents (e.g., Park and Lee, 2006; Corrocher et al., 2021). However, this study proposes that the method may be inappropriate because it neglects the fact that firms can use knowledge outside the sector. This raises questions about its accuracy in capturing the sectoral technological cycle.

To address this problem, this study adopts the sectoral technological cycle at the knowledge

combination level to measure the speed at which knowledge becomes obsolete. The sectoral technological cycle at the knowledge combination level is measured by the mean of the age of knowledge combinations used in the sector. To calculate the length of sectoral technological cycle, we first collect granted patents in the wind energy sector. Then, we identify pairs of IPC codes (7 digits) of each patent. When a knowledge combination (a pair of 7-digit IPC codes) first appears in the sector, its age is 0. The age of a knowledge combination is the gap between the year when the focal patent was granted and the year when the knowledge combination was created. For instance, if a patent is published in 2010 and consists of a knowledge combination created in 2000, the age of the combination in the year the patent is published (2010) would be ten years.

Finally, the reuse of knowledge combinations is defined as the use of knowledge combinations already known to the firm to generate innovations (Carnabuci and Operti, 2013). Suppose a pair of 7-digit IPC codes appearing in a firm's patents within a given year had already appeared in its previously published patents. In that case, it indicates that the firm reuses the knowledge combination.

4.2 Identification of Breakthrough innovations

Breakthrough innovations have an exceptional influence on subsequent innovations (e.g., Ahuja and Lampert, 2001; Arts and Veugelers, 2015). This study follows the innovation literature by identifying breakthroughs based on the number of forward patent citations (e.g., Ahuja and Lampert, 2001; Kaplan and Vakili, 2015). The number of forward citations a patent receives correlates with its technological importance (Albert et al., 1991). As such, this study interprets the number of citations a patent receives as its influence on subsequent innovations.

Numerous studies use the number of forward citations received within five years after an innovation is created as the criterion to identify breakthrough innovations (e.g., Ahuja and Lampert, 2001; Kaplan and Vakili, 2015). This indicator works on the assumption that innovations begin to exert influence on technological development shortly after they are created, and their influence disappears after the initial five-year period. However, firms may not fully understand how new knowledge combinations work when created (Chai and Menon, 2019). Pezzoni et al. (2022) further supported this view, suggesting that some innovations, though not shortly influential within the first five years because firms are not familiar with them, may serve as a basis for subsequent innovations after this period.

This study categorises breakthrough innovations into two distinct periods: short-term and long-term. Suppose the age of a patent is 0 when it is granted (the publication year). The short-term refers to the period when its age is from 1 to 5 years, while the long-term refers to when it is from 6 to 10 years. We use five years as the borderline between short-term and long-term because Pezzoni et al. (2022) found that the influence of new knowledge combinations within the sector tends to increase significantly, on average, starting five years after they are created. Drawing on the study of Singh and Fleming (2010), if a patent is in the top 5% of all patents published in the same year in terms of the number of forward citations received from 1 to 5 years (or from 6 to 10 years) after being published, it is identified as a short-term (or long-term) breakthrough innovation. However, some

breakthrough innovations may remain exceptionally influential across both timeframes (1-10 years). Since these innovations do not require a long period to be influential, they are excluded from the long-term group and retained in the short-term breakthrough innovations.

4.3 Regression model

Here, we clarify our model's structure. We describe the index used to measure a firm's ability to generate short and long-term breakthrough innovations (the dependent variables), the extent to which a firm reuses new or old knowledge combinations (the independent variables), and the control variables.

4.3.1 Dependent variable: A firm's ability to generate short and long-term breakthrough innovations (BIS and BIL)

In this study, the dependent variable is a firm's ability to generate short and long-term breakthrough innovations. Breakthrough innovations are identified by the number of forward citations a patent receives, with more forward citations indicating greater influence. As discussed above, this study categorises breakthrough innovations into short-term and long-term. A patent is identified as a short-term (or long-term) breakthrough innovation if the number of forward citations it receives from 1 to 5 years (or from 6 to 10 years) after being granted is in the top 5% of all patents granted in the same year.

Because firms that generate a larger number of breakthrough innovations are considered to possess competitive advantages in exerting influence on the sector (Ahuja and Lampert, 2001), this study uses the number of short- or long-term breakthrough innovations created by a firm in a given year to represent its ability to generate short- or long-term breakthrough innovations.

4.3.2 Independent variables: The reuse of new and old knowledge combinations within the sector (Reuse_new and Reuse_old)

The variable 'Reuse_new' indicates the extent to which a firm reuses new knowledge combinations within the sector. It is measured by the share of reused new knowledge combinations out of all knowledge combinations used by the firm within a given year (See Appendix). A higher 'Reuse_new' value indicates that firms reuse more new knowledge combinations within the sector to create an innovation. Conversely, if 'Reuse_new' is 0, this implies that the firm does not reuse any new knowledge combinations. Similarly, the variable 'Reuse_old' is measured by the share of reused old knowledge combinations within the sector out of all knowledge combinations used by the firm within a given year (See Appendix).

4.3.3 Other related variables

Our models include other variables highly related to a firm's knowledge search strategy. First, this study introduces the variables 'Explore_new' and 'Explore_old' (See Appendix), representing the extent to which a firm explores new or old knowledge combinations within the sector.

In addition, given that the knowledge in the wind energy sector is diversified (Rosiello and Maleki, 2021), our study proposes that the variety of a firm's knowledge base can influence its ability to generate breakthrough innovations. A diversified knowledge base allows firms to recombine knowledge components broadly to solve different technological problems (Katila and Ahuja, 2002; Schilling and Green, 2011), improving the likelihood of breakthrough innovations (Randle and Pisano, 2021; Qu et al., 2023). The knowledge variety denotes the level of diversity among different technological classes, including related (RV) and unrelated varieties (UV) (Krafft et al., 2011). Related variety captures the diversification of knowledge within the sector, while unrelated variety refers to the diversification of knowledge across different sectors (Saviotti and Frenken, 2008; Krafft et al., 2011; Castaldi et al., 2017). Related knowledge, which can be easily recombined and built on established cognitive structures with less uncertainty, supports incremental innovations (Castaldi et al., 2017). On the other hand, unrelated knowledge represents low similarity to components in the sector and introduces entirely new functionalities, resulting in more breakthrough innovations (Antonelli et al., 2011; Boschma et al., 2023). Thus, our models include variables representing a firm's knowledge base in terms of related and unrelated variety to measure the extent of knowledge diversification, making our results more accurate and robuster. RV is the weighted sum of entropy for shares of seven-digit subclasses within each four-digit class, showing how diversified a firm's knowledge base becomes within the higher-level classes (Frenken et al., 2007). UV is measured as the entropy of the distribution of patents at a four-digit level of disaggregation (Frenken et al., 2007). The trend of UV over time indicates how diversified a firm's knowledge base becomes across distinct technological classes.

Furthermore, how knowledge components are recombined can significantly influence the likelihood of breakthrough innovations. For instance, knowledge combinations involving components from different technological classes tend to be more influential because they can be broadly used (Pezzoni et al., 2022). The strength of the interdependencies and interactions of knowledge components from different technological classes are represented by the knowledge base complexity (Complexity) (Krafft et al., 2011; Maleki and Rosiello, 2019). Considering that the knowledge in the wind energy sector is complex (Rosiello and Maleki, 2021), breakthrough innovations will likely arise from integrating knowledge components across different technological classes. To capture this, our models include the knowledge base complexity at a firm level to measure a firm's ability to integrate knowledge components from diverse classes (Yayavaram and Ahuja, 2008; Yayavaram et al., 2018). Following Krafft et al. (2011) and Rosiello and Maleki (2021), this paper uses the weighted average degree of centrality (WADC) to measure complexity, which reflects the volume of interdependencies and the degree of interaction between components of a firm's knowledge base (Saviotti, 2011).

4.3.4 Control variables

This study first controls the lagged dependent variable to capture a firm's ability to generate short and long-term breakthrough innovations. Moreover, firms that create more innovations are more likely to generate more breakthrough innovations. Consequently, this study controls the number of innovations (NI) the firm generates (the number of patents published by the firm within a given

year). Furthermore, this study controls the share of knowledge firms obtain from research institutions (Research) (See Appendix). Research institutions are critical sources of knowledge for firms (Laursen. 2012). Recombining research-based components allows firms to create more influential innovations (Pezzoni et al., 2022). In addition, this study controls the share of knowledge firms search from local knowledge sources (Local) (See Appendix). Local knowledge sources can bridge technological distance (Li et al., 2023) and contribute to breakthrough innovations (Kelley et al., 2013). Finally, the age of firms represents related experience in the sector and impacts the influence of innovations (Sørensen and Stuart, 2000; Kotha et al., 2011). Thus, our models control the age of firms.

Table 1 summarises the description of all variables and how to measure them.

Table 1 List of variables

Type	Label	Variable	Description
Dependent Variable	BIS_{it}	The number of short-term breakthrough innovations generated by the firm in a given year	The number of patents that receive the top 5% number of forward citations (Singh and Fleming, 2010) in the short term (1 – 5 years after the given year)
	BIL_{it}	The number of long-term breakthrough innovations generated by the firm in a given year	The number of patents that receive the top 5% number of forward citations (Singh and Fleming, 2010) in the short term (6 – 10 years after the given year)
Independent Variables	$Reuse_new_{it}$	The share of reused new knowledge combinations within the sector in a given year	The number of reused new knowledge combinations divided by the number of knowledge combinations used by the firm in a given year (See Appendix)
	$Reuse_old_{it}$	The share of reused old knowledge combinations within the sector in a given year	The number of reused old knowledge combinations divided by the number of knowledge combinations used by the firm in a given year (See Appendix)
Related Variables	$Complexity_{it}$	A firm's knowledge base complexity	WADC using relative frequency: the number of patents in each class to the total number at the firm level within the recent five years (Krafft et al., 2011)
	RV_{it}	A firm's knowledge base related variety	The entropy index used in information theory and thermodynamics to measure the degree of disorder and randomness at the firm level (7-digit disaggregated) (Frenken et al., 2007)
	UV_{it}	A firm's knowledge base unrelate	The entropy index used in information theory and

		variety	thermodynamics to measure the degree of disorder and randomness at the firm level (4-digit aggregated) (Frenken et al., 2007)
	$Explore_new_{it}$	The share of explored new knowledge combinations within the sector in a given year	The number of all explored new knowledge combinations divided by the number of knowledge combinations used by the firm in a given year (See Appendix)
	$Explore_old_{it}$	The share of explored old knowledge combinations within the sector in a given year	The number of all explored old knowledge combinations divided by the number of knowledge combinations used by the firm in a given year (See Appendix)
Control Variables	BIS_{it-1}	The number of short-term breakthrough innovations created by the firm	One-year lag of the dependent variable
	BIL_{it-1}	The number of long-term breakthrough innovations created by the firm	One-year lag of the dependent variable
	$Research_{it}$	The share of knowledge inflow from research institutions	The number of cited patents (backward citations) granted by the research institutions divided by the number of all cited patents (See Appendix)
	$Local_{it}$	The share of knowledge inflow from local knowledge sources	The number of cited patents (backward citations) granted by the local knowledge sources divided by the number of all cited patents (See Appendix)
	NI_{it}	The number of innovations generated by the firm in a given year	The number of patents granted by the firm in a given year
	Age_{it}	The age of the firm	The age of the firm is zero in the year when it starts to grant patents in the sector

4.3.5 Statistical diagnosis and model specification

Tables 16 and 17 show that all correlation coefficients in models 1 and 2 are not close to 0.8. Thus, all independent variables are not highly correlated. Furthermore, the VIF results for all variables in the two models are less than 5, suggesting that multicollinearity is not likely to be a problem (Tables 18 and 19). Subsequently, we use the Breusch–Pagan test to check for heteroskedasticity. The results indicate that the null hypothesis (H0 = constant variance) could be rejected (p > chi2 = 0.000) (Table 18). Then, we determine whether a fixed effect or a random effect model is more appropriate for

our data. The results of the Hausman test for two models (Table 19) ($p = 0.0000$) show that a fixed effect model is more appropriate than a random effect model for our dependent variable. Subsequently, we test for autocorrelation using Wooldridge's (2002; pp. 282–283) test, implemented through the xtserial program developed by Drukker (2003). This test indicated that the null hypothesis (H0 = no first-order autocorrelation) was rejected (Table 20). As we detect first-order autocorrelation and heteroscedasticity, we introduce lagged dependent variables and adopt cluster-robust standard errors in our models.

Our dependent variable is the number of breakthrough innovations a firm generates yearly, which is the non-negative integer. There are two regression models for non-negative integers: Poisson regression and Negative binomial regression model. The Negative binomial regression model is more appropriate when there is overdispersion in the data.

Table 21 illustrates that for the short-term breakthrough innovations model, the result of the LR test rejects the null hypothesis that there is no overdispersion in the data. Thus, we adopt the Negative binomial regression model. In contrast, the result of the LR test for the long-term breakthrough innovations model does not reject the null hypothesis. Hence, we adopt the Poisson regression model for long-term breakthrough innovations. Then, we need to determine whether using the zero-inflated model, which is appropriate when the dependent variable contains an excessive number of zeros. Table 2 shows that the percentage frequency of 0 is more than 90%, indicating that most firms never generate breakthrough innovations. Thus, the zero-inflated model is more appropriate. Further, Table 22 illustrates that the results of the Vuong test for models 1 and 2 reject the null hypothesis (the zero-inflated model and the standard count model are equally close to the true model). As a result, we adopted the zero-inflated Negative binomial regression model for short-term breakthrough innovations and the zero-inflated Poisson regression model for long-term breakthrough innovations.

Table 2 The percentage frequency of 0 in dependent variables

	The frequency of 0	The percentage frequency of 0
Short-term	2002	92.34%
Long-term	692	91.53%

As a result, our regression models are specified below:

Model 1 (Short-term breakthrough innovations):
$BIS_{it} = \beta1 * BIS_{it-1} + \beta2 * Reuse_new_{it} + \beta3 * Reuse_old_{it} + Control + Constant$
't' stands for year from 1992 to 2018
'i' stands for the id of a firm

Model 2 (Long-term breakthrough innovations):
$BIL_{it} = \beta1 * BIL_{it-1} + \beta2 * Reuse_new_{it} + \beta3 * Reuse_old_{it} + Control + Constant$

‘t’ stands for the year from 1992 to 2013
‘i’ stands for the id of a firm

5. Result: Descriptive Analysis

Using a longitudinal perspective, we present descriptive analysis concerning (1) the sectoral technological cycle, (2) the sectoral knowledge base variety, (3) the sectoral knowledge base complexity, (4) patents within the wind energy sector, (5) The generation of new knowledge combinations within the sector, (6) knowledge combinations in short and long-term breakthrough innovations and (7) the number of short and long-term breakthrough innovations generated by firms.

5.1 Sectoral technological cycle

Figure 3 illustrates the trend of the sectoral technological cycle at the knowledge combination level. The sectoral technological cycle exhibits a fluctuating pattern, with an increase in length until 2009, followed by a subsequent decline. This indicates a shift in the sector towards adopting newly emerged knowledge combinations after 2009. This finding diverges from those presented by the study of Rosiello and Maleki (2021), which calculates the sector technological cycle at the knowledge level. They observed a consistent decrease in the length of the sectoral technological cycle over time. This discrepancy suggests that while firms may increasingly use newly emerged knowledge, the knowledge combinations they use may not be new within the sector.

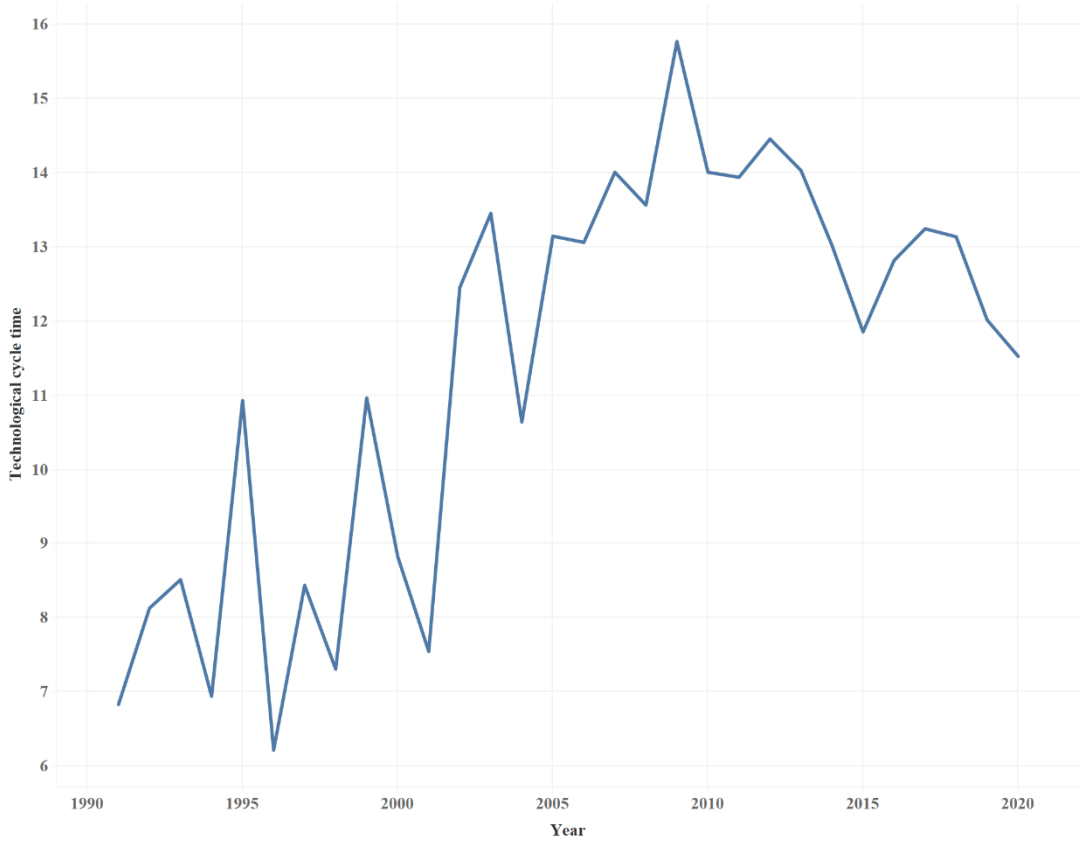


Figure 3 The length of the sectoral technological cycle

5.2 Sectoral knowledge base variety

As shown in Figure 4, the related and unrelated varieties of sectoral knowledge bases have gradually increased since 1991. The uptrend in unrelated variety is particularly significant, indicating that the knowledge base of the wind energy sector has become increasingly diversified (Rosiello and Maleki, 2021). The diversified sectoral knowledge base suggests that firms need to search broadly and absorb cross-sectoral knowledge flows to develop innovations (Dai et al., 2020).

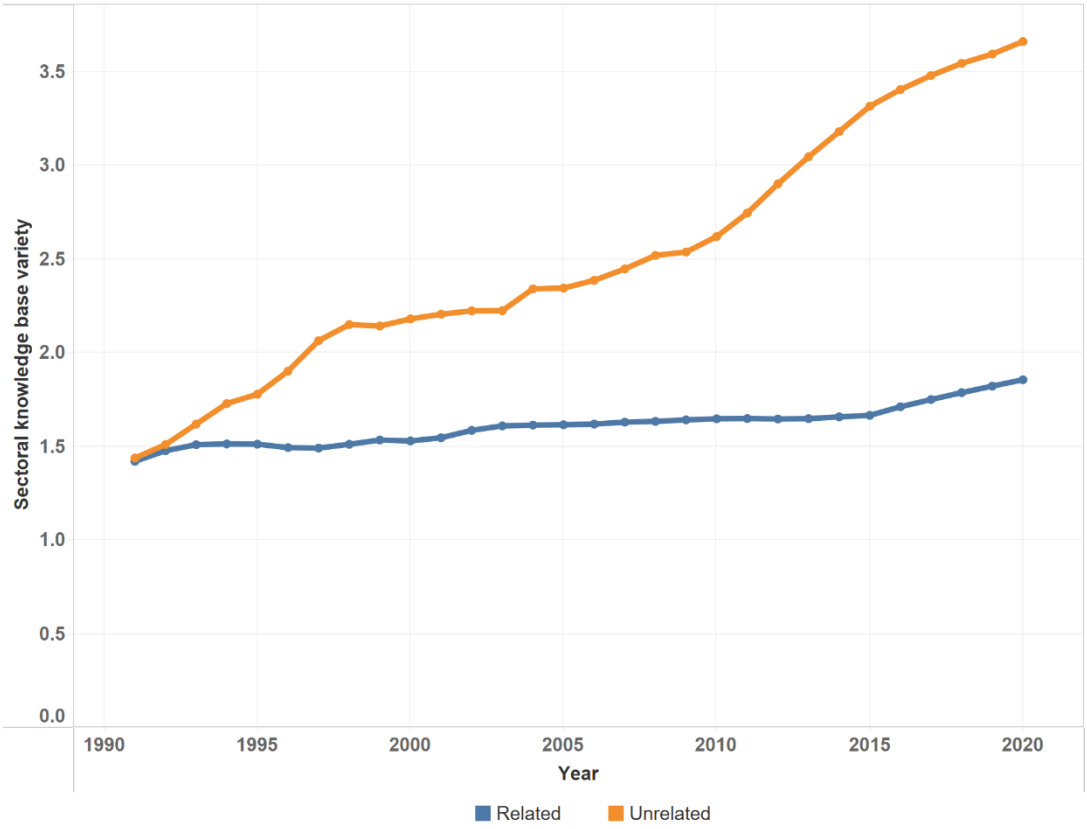


Figure 4 The knowledge base variety

5.3 Sectoral knowledge base complexity

Figure 5 illustrates a steady increase in the complexity of the sectoral knowledge base since 1991. This growing knowledge base complexity requires firms to deepen their understanding of interdependent knowledge components, thereby increasing the difficulty of generating innovations (Zhou et al., 2016; Rosiello and Maleki, 2021).

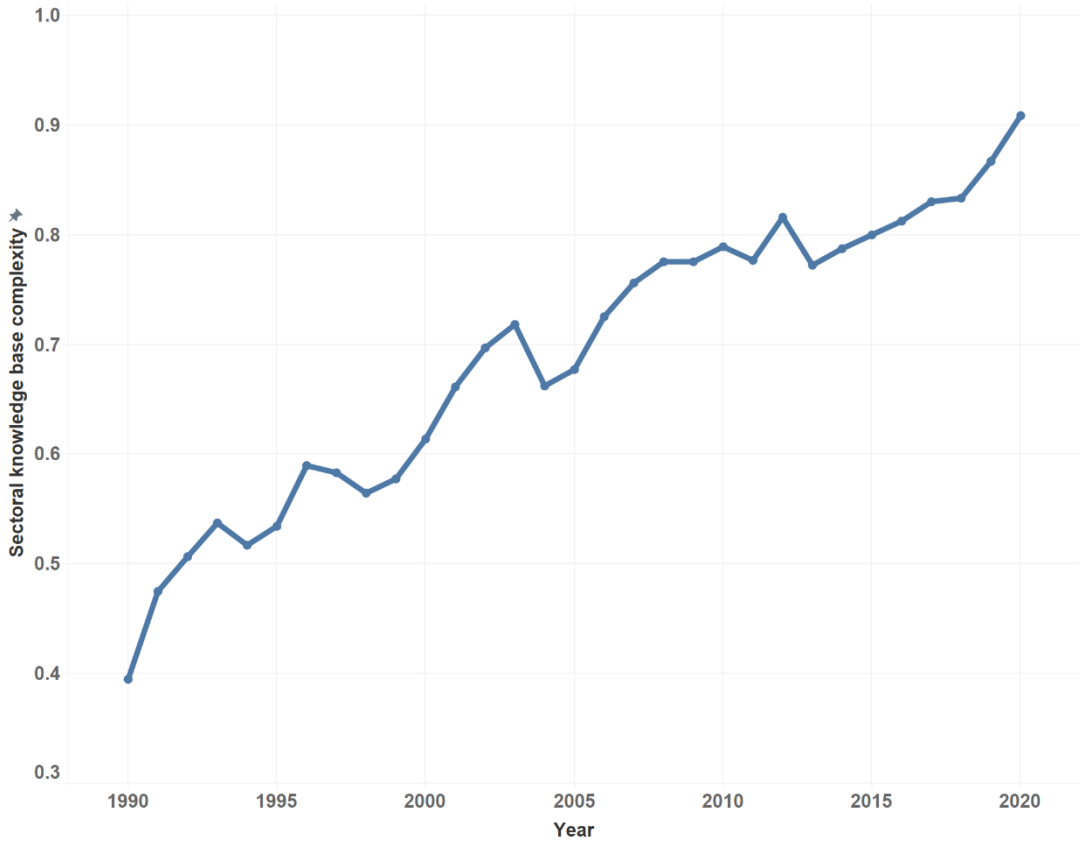


Figure 5 The knowledge base complexity

5.4 Patents in the wind energy sector

Given the increased variety and complexity of the sectoral knowledge base, we analyze the IPC codes of patents to identify the relatively important areas of knowledge within the wind energy sector over time. The International Patent Classification (IPC) system is a hierarchical framework for classifying patents based on their technological areas. Patent examiners assign IPC codes to individual patents according to the technological areas they represent. The IPC system is structured into multiple levels: sections (1 digit), classes (3 digits), subclasses (4 digits), groups (7 digits), and subgroups (9 digits). For this study, we focus on the section level (1 digit) and the subclass level (4 digits) to provide both a schematic overview and a detailed analysis.

Examining patents at the section level over time (Figure 6), IPC F (Mechanical Engineering; Lighting; Heating; Weapons; Blasting) consistently occupies the largest share, followed by IPC B (Performing Operations; Transporting) and IPC H (Electricity). Notably, as the number of patents increased significantly after 2010, these three sections became even more important in the wind energy sector. Additionally, patents in this sector also involve knowledge from IPC A (Human Necessities), IPC C (Chemistry; Metallurgy), IPC D (Textiles; Paper), IPC E (Fixed Constructions), and IPC G (Physics). Overall, the knowledge base of the wind energy sector is highly diversified, with mechanics, operations, and electricity serving as the dominant areas.

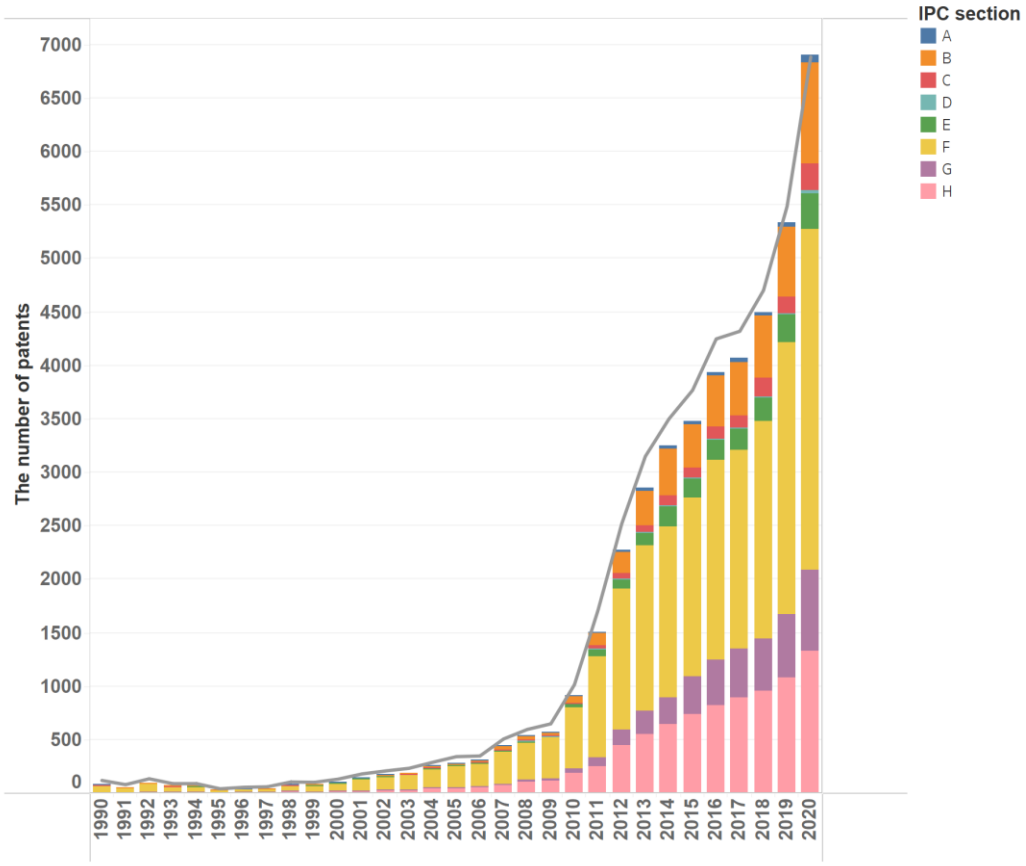


Figure 6 The number of granted patents each year at the section level

Here, we analyse our data further at the subclass level (4-digit IPC). The subclass level provides an appropriate balance by avoiding too narrow or broad analysis (Lee et al., 2024a). In general, a patent contains at least one IPC code. When a patent includes multiple IPC codes, it indicates the convergence and integration of knowledge from various areas within the patent (Curran et al., 2011). Consequently, comparing the structure of IPC co-occurrence provides insights into the connectivity and relationships among distinct knowledge areas. In an IPC code co-occurrence network, each node represents an IPC code, while each link represents a connection between two nodes. If two IPC codes co-occur in a patent, these two knowledge areas are considered interconnected (Breschi et al., 2003). Given the significant increase in patents granted after 2010, we divided our analysis into two periods: before 2010 (1991–2010) and after 2010 (2011–2020).

Table 3 shows the structural indicators of the IPC co-occurrence network before and after 2010. The number of IPC codes doubled after 2010, increasing from 226 to 486. This indicates an increase in the knowledge base variety within the wind energy sector. Additionally, the number of linkages between IPC codes increased significantly, from 1,076 to 8,188, suggesting a substantial rise in connections among different IPC codes. Furthermore, the increase in network density reflects more intensive interactions among IPC subclasses. These intensified interactions likely contribute to a more complex knowledge base within the wind energy sector.

Table 3 IPC co-occurrence network structural indicators

Period	The number of nodes	The number of linkages	Network density
Before 2010	226	1,076	0.04
After 2010	486	8,188	0.07

Furthermore, Figures 7 and 8 illustrate the structure of the networks before and after 2010. The size of each node is proportional to the degree of its corresponding IPC code over the entire period. Then, we focus on IPC codes with a high degree centrality to identify key IPC nodes. Degree centrality, one of the fundamental centrality indicators, is calculated by summing the number of links directly connected to a node and then dividing by the total number of nodes in the network (Son and Cho, 2020; Mazlumi and Kermani, 2022). Thus, IPC codes with a higher degree centrality are knowledge with greater importance and influence within the sector (Lee et al., 2024a).

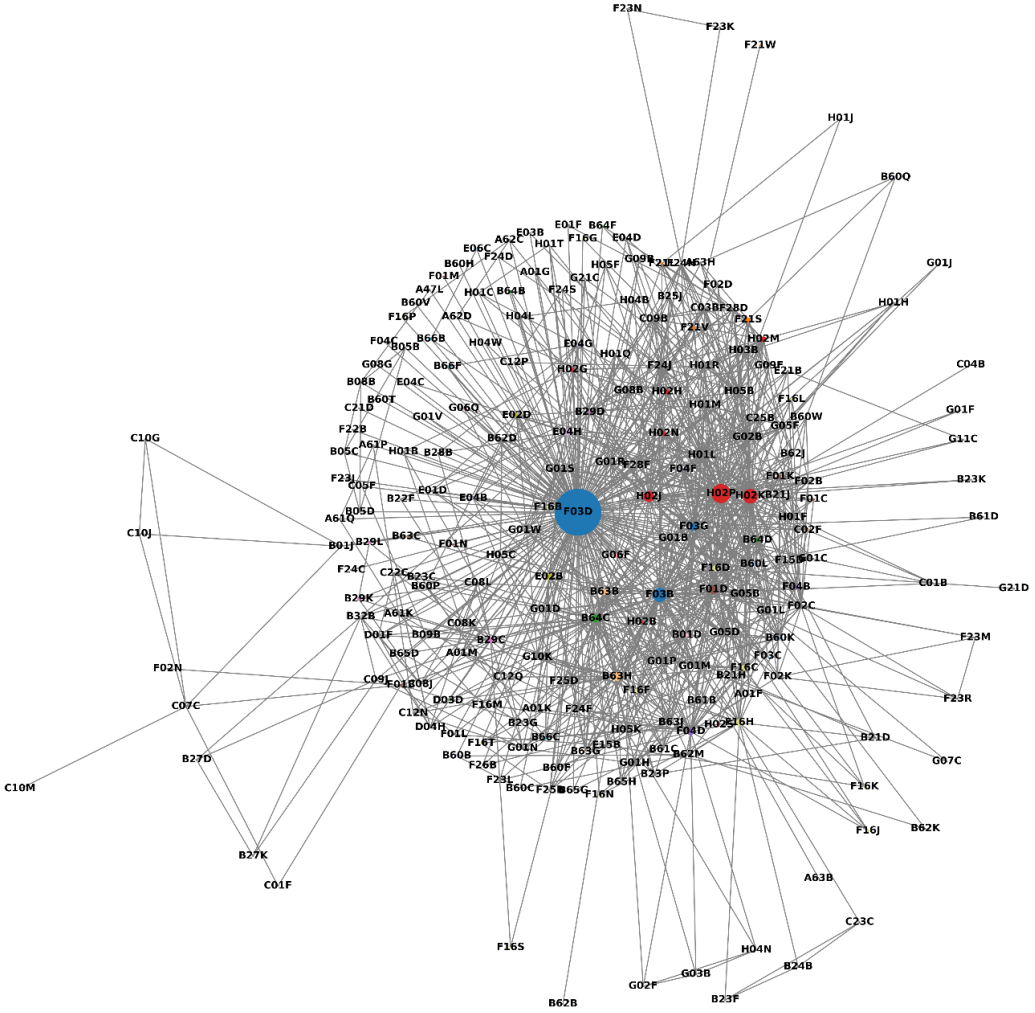


Figure 7 The IPC co-occurrence network before 2010 (1991-2010)

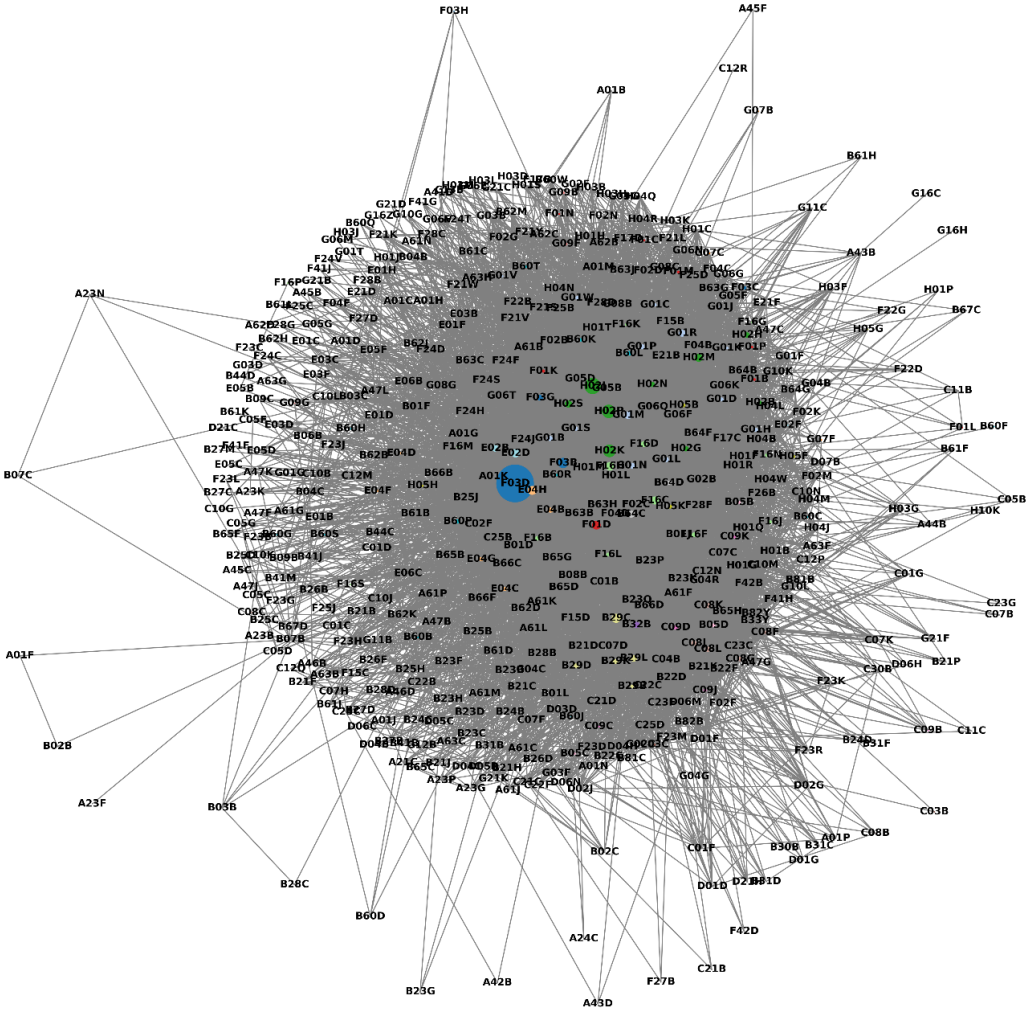


Figure 8 The IPC co-occurrence network after 2010 (2011-2020)

Tables 4 and 5 illustrate the key IPC codes with the highest degree centrality in the networks before and after 2010. Table 4 highlights that F03D, which refers to wind motors, is a dominant area within the sector. Additionally, H02P refers to control systems, considered critical complementary technologies for enhancing the electric capacity of wind turbines, with a degree centrality of 0.31 (Nordensvard et al., 2018; Zhou et al., 2016). For example, rotor control systems are designed to adjust the rotor and individual blades to optimise their alignment with wind conditions (Huenteler et al., 2016a). Furthermore, H02K and F03B indicate knowledge areas about improving energy output capacity. H02K encompasses knowledge related to dynamo-electric machines, such as generators or motors. F03B is knowledge concerning machines or engines for liquids. Finally, B64C represents knowledge about aerodynamics, which is essential for effectively capturing wind energy and controlling rotor speed (Huenteler et al., 2016a). Overall, technological innovations in the wind energy sector focus on improving electric capacity and conversion efficiency (Huenteler et al., 2016b; Zhou et al., 2016).

In the network after 2010, as shown in Table 5, F03D and H02K remain dominant, underscoring the

importance of improving the electric capacity and conversion efficiency in the wind energy sector. Meanwhile, F01D, knowledge about steam turbines becomes more important. Steam turbines play a key role in hybrid energy systems, where mechanical energy generated by wind turbines is integrated with other energy sources. They are particularly critical for mitigating the instability of wind turbines and enhancing overall energy output (Xiao-Ping et al., 2012). Additionally, knowledge about the distribution and storage of electric power (H02J) has become increasingly important in the wind energy sector. This shift can be attributed to the significant growth in electricity demand. Storage technologies enhance grid resilience by alleviating congestion, providing transmission services, and ensuring reliability, particularly during prolonged extreme weather events (GWEC, 2024). Finally, the rising importance of B29C reflects the demand for lightweight and durable materials, which are essential for reducing manufacturing costs and improving blade performance (Huenteler et al., 2016a). Specifically, the development of offshore wind turbines after 2010 highlights the critical role of lightweight and durable materials in enhancing resilience to extreme weather conditions and reducing costs associated with transportation, installation, and repairs (GWEC, 2024). Overall, after 2010, knowledge about enhancing electric capacity, improving energy storage, and utilising lightweight and durable materials has become critical in developing wind energy.

Table 4 Key IPC codes with the highest degree centrality in the network before 2010

Period	IPC code	Degree Centrality	Description
Before 2010	F03D	0.81	Wind motors
	H02P	0.31	Control or regulation of electric motors, electric generators, or dynamo-electric converters; controlling transformers, reactors, or choke coils
	H02K	0.27	Dynamo-electric machines
	F03B	0.26	Machines or engines for liquids
	B64C	0.22	Aeroplanes; Helicopters

Table 5 Key IPC codes with the highest degree centrality in the network after 2010

Period	IPC code	Degree Centrality	Description

	F03D	0.86	Wind motors
	F01D	0.42	Non- positive displacement machines or engines, e.g., steam turbines
After 2010	H02K	0.40	Dynamo-electric machines
	H02J	0.39	Circuit arrangements or systems for supplying or distributing electric power; systems for storing electric energy
	B29C	0.36	Shaping or joining of plastics; shaping of material in a plastic state, not otherwise provided for; after-treatment of the shaped

5.5 The generation of new knowledge combinations within the sector

Figure 9 presents the annual number of new knowledge combinations generated within the sector. It shows that more new knowledge combinations were generated after 2010, from 1,366 in 2011 to 9,982 in 2020.

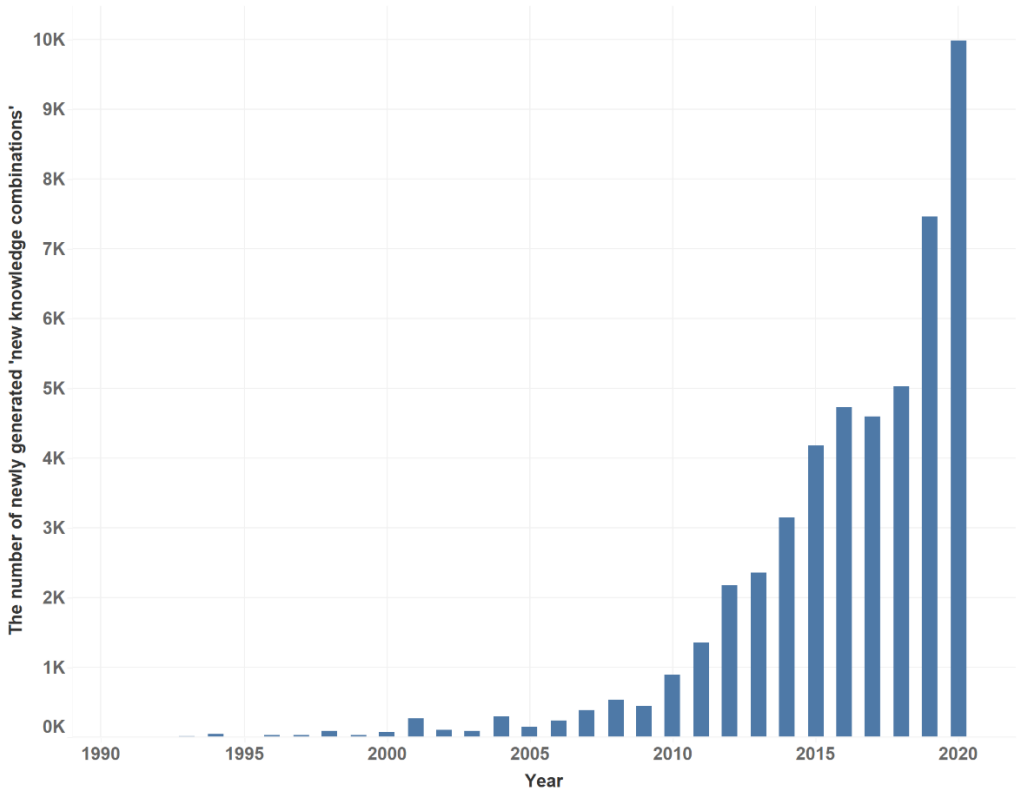


Figure 9 The number of newly generated 'new knowledge combinations' by year

Tables 6 and 7 further reveal key sources of new knowledge combinations within the wind energy sector at the subclass level (4-digit IPC) before and after 2010. Before 2010, dynamo-electric machines (H02K) and wind motors (F03D) were important sources of new knowledge combinations in the wind energy sector, as shown in Table 6. These knowledge components were primarily recombined with gearing (F16H), bearings (F16C), and control systems (H02P). This indicates a strong focus on improving the reliability and efficiency of converting mechanical energy from wind turbines into electricity.

Table 6 Key sources of new knowledge combinations within the wind energy sector after 2010

Period	IPC code	Share of all new knowledge combinations	Description
Before 2010	H02K & H02K	2.36%	Dynamo-electric machines
	F03D & H02K	1.56%	Wind motors & Dynamo-electric machines
	F03D & F16H	1.22%	Wind motors & Gearing
	F03D & F16C	1.14%	Wind motors & Bearing
	H02P & H02P	0.93%	Control or regulation of electric motors, electric generators, or dynamo-electric converters; controlling transformers, reactors, or choke coils

For new knowledge combinations generated after 2010 (Table 7), there is a clear shift toward advanced materials. For example, the combination of shaping or joining plastics and molding materials (B29C & B29K) reflects the growing importance of lightweight, durable materials in turbine manufacturing, particularly for blades. In addition, innovations in compositions of macromolecular compounds (C08L) and plastics & layered products (B29C & B32B) can enhance the strength and durability of wind turbine components, reducing maintenance costs and extending turbine lifespans. Moreover, innovations in lubrication (C10M) suggest that firms focus on reducing friction and improving efficiency.

To sum up, the generation of new knowledge combinations within the wind energy sector shifts from mechanics to materials. Before 2010, new knowledge combinations focused on critical components of wind turbines to enhance energy conversion efficiency. After 2010, the wind energy sector emphasises advanced materials to develop more durable and lightweight wind turbines with lower costs. Thus, knowledge components from fields like material science (e.g., B29C, C08L)

become key sources of new knowledge combinations. One driving factor is that the development of offshore wind turbines highlights the importance of lightweight and durable materials. In addition, firms need to reduce costs and improve durability to compete with other firms and even other energy sources.

Table 7 Key sources of new knowledge combinations within the wind energy sector after 2010

Period	IPC code	Share of all new knowledge combinations	Description
After 2010	B29C & B29K	0.50%	Shaping or joining of plastics & Moulding materials or to materials for reinforcements, fillers, or preformed parts
	C08L & C08L	0.42%	Compositions of macromolecular compounds
	B29K & B29K	0.40%	Moulding materials or materials for reinforcements, fillers, or preformed parts
	B29C & B32B	0.39%	Shaping or joining of plastics & Layered products, i.e., products built-up of strata of flat or non-flat, e.g., cellular or honeycomb, form
	C10M & C10M	0.38%	Lubricating, the use of chemical substances either alone or as lubricating ingredients in a lubricating composition

5.6 Knowledge combinations in short and long-term breakthrough innovations

Tables 8 and 9 illustrate key old and new knowledge combinations in short and long-term breakthrough innovations. For short-term breakthrough innovations before 2010, old knowledge combinations related to adapting wind motors for specific locations (F03D/9 & H02P/9) and controlling wind motors (F03D/7 & F03D/9 and F03D/7& H02P/9) are dominant. These old knowledge combinations reflect that the wind energy sector primarily focused on optimizing the reliability of wind turbines. Among new knowledge combinations, arrangements for cooling or ventilating (H02K/7 & H02K/9) played a significant role in short-term breakthrough innovations before 2010, suggesting that firms aimed to enhance efficiency and address heat dissipation issues (GWEC, 2023). After 2010, old knowledge combinations related to improving the energy output of wind turbines (F03D/1 & F03D/11, F03D/7 & F03D/9 and F03D/7 & F03D/11) remain dominant in short-term breakthrough innovations. In addition, some new knowledge combinations associated with advanced metal materials (B23P/15 & F03D/1 and B23P/15 & F03D/11) become important. This suggests a shift in short-term breakthrough innovations toward lighter and stronger turbine components after 2010.

Table 8 Key knowledge combinations in short-term breakthrough innovations

Period	New or Old	IPC code	Share in all short-term breakthrough innovations	Description
Before 2010	Old	F03D/9 & H02P/9	42.42%	Adaptations of wind motors for special use in particular locations & Arrangements for controlling electric generators for the purpose of obtaining a desired output
		F03D/7 & F03D/9	36.36%	Controlling wind motors & Adaptations of wind motors for special use in particular locations
		F03D/7& H02P/9	27.27%	Controlling wind motors & Arrangements for controlling electric generators for the purpose of obtaining a desired output
	New	H02K/7 & H02K/9	12.12%	Arrangements for handling mechanical energy structurally associated with dynamo-electric machines & Arrangements for cooling or ventilating
		F03D/9 & H02K/9	12.12%	Adaptations of wind motors for special use in particular locations & Arrangements for cooling or ventilating
		F03D/7 & H02K/9	9.09%	Controlling wind motors & Arrangements for cooling or ventilating
After 2010	Old	F03D/1 & F03D/11	37.32%	Wind motors with rotation axis substantially parallel to the air flow entering the rotor & Details, component parts, or accessories of wind motors
		F03D/7 & F03D/9	28.54%	Controlling wind motors & Adaptations of wind motors for special use in particular locations
		F03D/7 & F03D/11	25.35%	Controlling wind motors & Details, component parts, or accessories of wind motors
	New	B23P/15 & F03D/1	3.99%	Making specific metal objects by operations & Wind motors with rotation axis substantially parallel to the air flow entering the rotor
		B66C/1 & F03D/1	3.39%	Adapted for connection therewith for transmitting forces to articles or groups of articles & Wind motors with rotation axis substantially parallel to the air flow entering the rotor
		B23P/15 & F03D/11	2.79%	Making specific metal objects by operations & Details, component parts, or accessories of wind motors

For long-term breakthrough innovations before 2010, as shown in Table 9, old knowledge combinations related to adapting wind motors for specific locations (F03D/9 & H02P/9 and F03D/9

& F03D/11) and controlling wind motors (F03D/7& H02P/9) are essential, similar to short-term breakthrough innovations during the same period. Among new knowledge combinations, the importance of B63H/1 & F03D/1 suggests the application of aerodynamic technologies from marine engineering to wind turbines. After 2010, old knowledge combinations related to adapting wind motors for specific locations (F03D/1 & F03D/11) and controlling wind motors (F03D/7 & F03D/9 and F03D/7 & F03D/11) continue to play a major role. In terms of new knowledge combinations, integrating advanced material (B23P/15 & F03D/1) and aerospace-related technologies (B64C/9 & F03D/1) enables firms to generate long-term breakthrough innovations after 2010.

Overall, old knowledge combinations dominate short and long-term breakthrough innovations before and after 2010. Key old knowledge combinations in breakthrough innovations primarily focus on the energy output efficiency and reliability of wind turbines. Regarding new knowledge combinations, those related to materials are essential for short-term breakthrough innovations, while aerospace-related knowledge combinations play a more significant role in long-term innovations. One explanation is that material-related knowledge combinations aim to reduce production costs and improve the durability of wind turbine components, aligning with market demand and thus having a short-term impact. In contrast, aerospace-related knowledge combinations require multidisciplinary collaboration, and firms' unfamiliarity with these technologies makes their integration into existing knowledge bases more challenging.

Table 9 Key knowledge combinations in long-term breakthrough innovations

Period	New or Old	IPC code	Share in all long-term breakthrough innovations	Description
Before 2010	Old	F03D/9 & H02P/9	31.81%	Adaptations of wind motors for special use in particular locations & Arrangements for controlling electric generators for the purpose of obtaining a desired output
		F03D/9 & F03D/11	13.64%	Adaptations of wind motors for special use in particular locations & Details, component parts, or accessories of wind motors
		F03D/7& H02P/9	13.64%	Controlling wind motors & Arrangements for controlling electric generators for the purpose of obtaining a desired output
	New	B63H/1 & F03D/1	9.09%	Propulsive elements directly acting on water & Wind motors with rotation axis substantially parallel to the air flow entering the rotor
		F03D/1 & F04D/29	9.09%	Wind motors with rotation axis substantially parallel to the air flow entering the rotor & Details, component parts, or accessories
		F03B/15 & F04D/29	9.09%	Transmission of mechanical power & Details, component parts, or accessories

After 2010	Old	F03D/1 & F03D/11	32.69%	Wind motors with rotation axis substantially parallel to the air flow entering the rotor & Details, component parts, or accessories of wind motors
		F03D/7 & F03D/9	30.77%	Controlling wind motors & Adaptations of wind motors for special use in particular locations
		F03D/7 & F03D/11	21.15%	Controlling wind motors & Details, component parts, or accessories of wind motors
	New	B23P/15 & F03D/1	5.77%	Making specific metal objects by operations & Wind motors with rotation axis substantially parallel to the air flow entering the rotor
		B66C/1 & F03D/1	3.85%	Adapted for connection therewith for transmitting forces to articles or groups of articles & Wind motors with rotation axis substantially parallel to the air flow entering the rotor
		B64C/9 & F03D/1	3.85%	Adjustable control surfaces or members, e.g., rudders & Wind motors with rotation axis substantially parallel to the air flow entering the rotor

5.7 The number of short and long-term breakthrough innovations by firms

Tables 10 and 11 illustrate the number of short- and long-term breakthrough innovations before and after 2010, respectively. For short-term breakthrough innovations, Table 10 shows that the leaders in the wind energy sector before 2010 were General Electric Company, Mitsubishi Electric Corporation, Vestas, and Siemens. However, due to the relatively small number of patents granted before 2010, these companies produced only a limited number of breakthrough innovations. After 2010, some Chinese firms, such as the State Grid Corporation of China and Goldwind, began generating more breakthrough innovations, although they still lag behind established leaders.

Table 10 The number of short-term breakthrough innovations generated by firms

Period	IPC code	Country	Number of short-term breakthrough innovations
Before 2010	General Electric Company	US	4
	Mitsubishi Electric Corp	JP	3
	Vestas	DK	2

	Siemens	DE	1
After 2010	General Electric Company	US	160
	Vestas	DK	88
	Mitsubishi Electric Corp	JP	55
	Siemens	DE	28
	State Grid Corporation of China	CN	25
	Senvion	DE	18
	LW Wind Power	DK	13
	Goldwind	CN	13
	Siemens Gamesa	DE	13
	Hitachi	JP	12

Regarding long-term breakthrough innovations (Table 11), only a few firms could generate a limited number of such innovations before 2010. After 2010, more firms began producing long-term breakthrough innovations. Notably, while some Chinese firms have caught up in short-term breakthrough innovations, they have not achieved a similar catch-up in long-term ones. One reason is that the wind energy sector relies heavily on tacit knowledge, which is essential for understanding the high variety and complexity of knowledge components within a wind turbine (Zhou et al., 2016). Tacit knowledge is crucial in predicting technological changes (Hansen and Lema, 2019). Compared to established leader firms, Chinese firms are relatively younger and are likely to lack the accumulated tacit knowledge necessary for generating long-term breakthrough innovations.

Table 11 The number of long-term breakthrough innovations generated by firms

Period	IPC code	Country	Number of long-term breakthrough innovations
Before 2010	General Electric Company	US	2
	Nalco Holding Company	US	1
After 2010	General Electric Company	US	19
	Mitsubishi Electric Corp	JP	9
	Senvion	DE	7
	Vestas	DK	7
	Siemens Gamesa	DE	6
	Hitachi	JP	5
	Clipper Windpower	US	4
	LW Windpower	DK	4
	Nordex	DE	4
	Siemens	DE	4

6. Regression Results

Table 12 illustrates the regression results of short and long-term breakthrough innovations. In model 1 (short-term breakthrough innovations), the coefficient of 'Reuse_old' is positive (2.227) and statistically significant (p-value < 0.01). This suggests that reusing old knowledge combinations can facilitate the generation of short-term breakthrough innovations. Therefore, our hypothesis 3 is confirmed. However, the coefficient of 'Reuse_new' is positive (0.292) but not statistically significant (p-value > 0.1). Thus, the hypothesis 1 is not confirmed.

Furthermore, the coefficients of 'Explore_new' and 'Explore_old' are both positive (1.591 and 1.377) and statistically significant (p-value < 0.01). This implies that exploring knowledge combinations can enhance the firm's ability to generate short-term breakthrough innovations, regardless of whether the combination is new or old within the sector.

Moreover, the coefficient of 'Unrelated Variety' (UV) is positive (0.336) and statistically significant (p-value < 0.01). This result suggests that firms benefit from diversifying their knowledge base into fields unrelated to the focal sector. Knowledge from unrelated fields has new functionalities and may address previously unsolved technological problems (Castaldi et al., 2017).

Model 2 is for long-term breakthrough innovations. The coefficient of 'Reuse_new' is negative (-6.307) and statistically significant (p-value < 0.1). It implies that reusing new knowledge combinations negatively affects a firm's ability to generate long-term breakthrough innovations. Hence, the hypothesis 2 is not confirmed.

The coefficient of 'Unrelated Variety' (UV) is still positive (0.945) and statistically significant (p-value < 0.01), the same as the model 1. This result highlights that exploring knowledge from fields unrelated to the focal sector can contribute to short and long-term breakthrough innovations.

Combining the regression results on short and long-term breakthrough innovations, as presented in Table 12, we have several key findings:

Reusing old knowledge combinations enables firms to generate short-term breakthrough innovations. This argument contradicts the findings of Chen (2023) and Zhong et al. (2024), which claimed that reusing knowledge combinations reduces the likelihood of breakthrough innovations. The reason is that firms can draw on past experiences, avoid repeating failures, and uncover previously overlooked innovations that can address current technological problems (Nerkar, 2003; Katila and Chen, 2008; Yang et al., 2021). Regarding short-term breakthrough innovations, firms need to explore more but reuse fewer new knowledge combinations within the sector. Reusing more new knowledge combinations suggests that firms consistently operate in unfamiliar fields, resulting in useless innovations (Wang et al., 2017).

In summary, our findings support Randle and Pisano's (2021) conclusion that breakthrough innovations require an iterative process involving both exploration and exploitation. To generate short and long-term breakthrough innovations, firms need to explore new knowledge combinations within the sector and subsequently reuse some of them once they are old within the sector.

Table 12 Results of regression: Short and Long-term breakthrough innovations

	Model 1	Model 2
BIS_{it-1}	0.054	
	(0.058)	
BIL_{it-1}		0.059
		(0.121)
$Reuse_new_{it}$	0.292	-6.307*
	(0.689)	(3.707)
$Reuse_old_{it}$	2.227***	0.825
	(0.452)	(0.855)
NI_{it}	0.010**	0.121
	(0.004)	(0.080)
$Explore_new_{it}$	1.591***	0.486
	(0.548)	(1.357)
$Explore_old_{it}$	1.377***	0.772
	(0.474)	(1.119)
RV_{it}	0.074	-0.134
	(0.073)	(0.269)
UV_{it}	0.336***	0.945***
	(0.105)	(0.268)
$Complexity_{it}$	0.357*	0.542
	(0.205)	(0.670)
$Research_{it}$	1.218	-1.944
	(1.457)	(3.069)
$Local_{it}$	0.313	-0.491
	(0.388)	(0.676)
Age_{it}	0.021	0.047
	(0.020)	(0.032)
Log-Likelihood	-601.095	-111.745
R-squared	0.317	0.436
Adjusted R-squared	0.299	0.360
N	2,168	756

*p<0.1; **p<0.05; ***p<0.01

7. Robustness Tests

We performed two variations of the analysis to ensure the robustness of our results. First, we applied interval data with three different cutoff points to identify new and old knowledge combinations within the sector. Specifically, knowledge combinations were classified as "new" if their age was less than the sectoral technological cycle minus one, two, or three years (i.e., age < sectoral technological cycle - 1, -2, or -3). Conversely, they were categorized as "old" if their age exceeded the sectoral technological cycle plus one, two, or three years (i.e., age > sectoral technological cycle + 1, +2, or +3). By applying these three alternative cutoff points, the robustness test assesses whether the results remain consistent across varying classifications of new and old knowledge combinations. Table 13 illustrates the regression results with alternative cutoff points for new and old knowledge

combinations.

First, the positive impact of the reuse of old knowledge combinations on a firm's ability to generate short-term breakthrough innovations remains robust across three alternative models. Regarding long-term breakthrough innovations, the negative impact of the reuse of new knowledge combinations also remains robust.

In addition, we find that a firm's age positively impacts its ability to create long-term breakthrough innovations. This may be because innovations in the wind energy sector heavily rely on a firm's tacit knowledge (Zhou et al., 2016), which accumulates over time. Moreover, younger firms are more likely to prioritize meeting short-term market demand to gain competitive advantages. Consequently, they may be less inclined to invest in innovations that require a more extended period to become influential.

Table 13 The robustness test for the sectoral technological cycle

	New < Sectoral technological cycle -1 Old > Sectoral technological cycle + 1		New < Sectoral technological cycle -2 Old > Sectoral technological cycle + 2		New < Sectoral technological cycle -3 Old > Sectoral technological cycle + 3	
	Short-term	Long-term	Short-term	Long-term	Short-term	Long-term
BISit-1	0.054 (0.058)		0.054 (0.059)		0.054 (0.058)	
BIL_{it-1}		0.045 (0.080)		0.040 (0.079)		0.041 (0.079)
$Reuse_new_{it}$	0.126 (0.713)	-3.069* (1.582)	0.063 (0.759)	-2.779* (1.521)	0.230 (0.750)	-2.691* (1.670)
$Reuse_old_{it}$	2.224*** (0.454)	1.236** (0.509)	2.259*** (0.456)	1.225** (0.491)	2.214*** (0.452)	1.148** (0.473)
NI_{it}	0.010** (0.004)	0.009** (0.046)	0.011** (0.004)	0.009* (0.005)	0.010** (0.004)	0.008* (0.005)
$Explore_new_{it}$	1.579*** (0.602)	2.124** (1.039)	1.684*** (0.606)	2.271** (1.053)	1.657*** (0.609)	2.390** (1.075)
$Explore_old_{it}$	1.412*** (0.471)	1.136 (0.869)	1.490*** (0.459)	1.253 (0.849)	1.553*** (0.448)	1.243 (0.851)
RV_{it}	0.066 (0.072)	-0.133 (0.159)	0.067 (0.071)	-0.132 (0.152)	0.071 (0.073)	-0.129 (0.151)
UV_{it}	0.340*** (0.105)	0.727*** (0.150)	0.337*** (0.105)	0.721*** (0.146)	0.336*** (0.104)	0.727*** (0.149)
$Complexity_{it}$	0.362* (0.205)	0.753 (0.531)	0.361* (0.205)	0.727 (0.485)	0.352* (0.205)	0.723 (0.488)
$Research_{it}$	1.426 (1.476)	-0.323 (1.760)	1.374 (1.472)	-0.433 (1.766)	1.503 (1.566)	-0.379 (1.795)

$Local_{it}$	0.003	-0.189	0.005	-0.201	0.005	-0.202
	(0.388)	(0.428)	(0.382)	(0.427)	(0.388)	(0.416)
Age_{it}	0.023	0.073***	0.024	0.075***	0.024	0.077***
	(0.020)	(0.023)	(0.020)	(0.024)	(0.020)	(0.023)
Log-Likelihood	-601.763	-186.046	-601.104	-186.113	-601.410	-186.493
R-squared	0.318	0.391	0.319	0.390	0.319	0.389
Adjusted R-squared	0.300	0.342	0.301	0.341	0.300	0.340
N	2,168	756	2,168	756	2,168	756

*p<0.1; **p<0.05; ***p<0.01

To further validate the robustness of our findings, we examined whether the effects of the reuse of a knowledge combination vary with its frequency of reuse. Specifically, we hypothesize that initial reuse is less likely to deepen firms' understanding of a knowledge combination, potentially leading to different effects compared to subsequent reuse. To test this, we redefined the criteria for reuse by counting a firm's reuse of a knowledge combination starting from the second, third, or fourth time. By applying different thresholds, we aim to assess whether the results remain consistent when firms frequently reuse knowledge combinations over time.

For short-term breakthrough innovations, the positive impact of the reuse of old knowledge combinations remains statistically significant across the three alternative models. Additionally, the coefficient of Reuse_old exhibits an increasing trend, suggesting that greater reuse of old knowledge combinations within the sector enables firms to generate more short-term breakthrough innovations. Regarding long-term breakthrough innovations, the negative impact of the reuse of new knowledge combinations remains robust, though its coefficient decreases across the three models. This indicates that while the reuse of new knowledge combinations hinders long-term breakthrough innovations, its negative impact will likely diminish as its frequency increases.

Overall, these two tests confirm that our results remain robust when using interval data with different cutoff points to distinguish between new and old knowledge combinations within the sector and when applying stricter criteria for the reuse of a knowledge combination.

Table 14 The robustness test for the reuse of knowledge combinations

	Counting reuse from the 2nd time		Counting reuse from the 3rd time		Counting reuse from the 4th time	
	Short-term	Long-term	Short-term	Long-term	Short-term	Long-term
BISit-1	0.052		0.044		0.039	
	(0.058)		(0.060)		(0.061)	
BIL_{it-1}		0.068		0.008		0.024
		(0.132)		(0.143)		(0.138)
$Reuse_new_{it}$	-0.966	-11.080***	-3.613*	-7.77***	-5.124*	-6.326**
	(1.148)	(4.030)	(2.015)	(2.808)	(3.078)	(2.796)
$Reuse_old_{it}$	2.663***	0.787	3.199***	0.715	3.417***	1.044
	(0.738)	(0.917)	(0.986)	(0.885)	(1.152)	(0.003)

NI_{it}	0.011***	0.016**	0.014***	0.008**	0.015***	0.005
	(0.004)	(0.007)	(0.005)	(0.004)	(0.005)	(0.004)
$Explore_new_{it}$	1.220**	0.292	1.028**	0.249	0.954*	0.316
	(0.537)	(1.272)	(0.523)	(1.235)	(0.517)	(1.249)
$Explore_old_{it}$	1.205***	1.022	1.105**	1.195	1.055**	1.256
	(0.462)	(0.861)	(0.443)	(0.810)	(0.436)	(0.806)
RV_{it}	0.089	-0.084	0.096	-0.072	0.094	-0.082
	(0.083)	(0.225)	(0.085)	(0.216)	(0.093)	(0.213)
UV_{it}	0.289***	0.798***	0.255**	0.787***	0.236**	0.800***
	(0.107)	(0.251)	(0.105)	(0.251)	(0.107)	(0.251)
$Complexity_{it}$	0.366*	0.265	0.386*	0.226	0.402*	0.192
	(0.218)	(0.437)	(0.229)	(0.424)	(0.240)	(0.414)
$Research_{it}$	1.256	-2.411	1.333	-2.281	1.414	-2.244
	(1.519)	(2.903)	(1.537)	(3.129)	(1.587)	(3.183)
$Local_{it}$	0.193	-0.317	0.167	-0.281	0.131	-0.277
	(0.429)	(0.675)	(0.401)	(0.637)	(0.397)	(0.626)
Age_{it}	0.172	0.043	0.015	0.049*	0.015	0.048*
	(0.021)	(0.029)	(0.210)	(0.028)	(0.0208)	(0.028)
Log-Likelihood	-603.013	-113.164	-601.337	-114.284	-601.302	-114.485
R-squared	0.317	0.428	0.319	0.423	0.319	0.422
Adjusted R-squared	0.299	0.353	0.301	0.347	0.301	0.346
N	2,168	756	2,168	756	2,168	756

*p<0.1; **p<0.05; ***p<0.01

8. Discussion and Conclusion

Building on the literature about a firm's combinative capabilities (March, 1991; Kogut and Zander, 1992; Katila, 2002), this study focuses on firms in the wind energy sector and differentiates between new and old knowledge combinations based on the length of sectoral technological cycle. It examines whether reusing new and old knowledge combinations within the sector contributes to a firm's ability to generate short and long-term breakthrough innovation. Our findings reveal that reusing old knowledge combinations promotes long-term breakthrough innovations. On the other hand, firms need to reuse fewer new knowledge combinations to create long-term breakthrough innovations.

The positive impact of reusing old knowledge combinations on short-term breakthrough innovations contrasts with studies claiming that reusing knowledge combinations hinders breakthrough innovations (e.g., Chen, 2023; Zhong et al., 2024). This paper argues that these studies rely on an overly strong assumption that firms consistently reuse the same knowledge combinations over extended periods. Reusing diverse old knowledge combinations allows firms to identify those useful for addressing current technological problems, thereby increasing the likelihood of breakthrough innovations (Capaldo et al., 2017).

Furthermore, our study finds that reusing new knowledge combinations within the sector negatively

affects a firm's ability to generate long-term breakthrough innovations, contrary to our hypothesis. One possible explanation is that firms may not be familiar with new knowledge combinations, making it challenging to integrate them into their knowledge bases (Ahuja and Lampert, 2001; Katila and Ahuja, 2002; Lee et al., 2024b). Thus, firms may fail to fully leverage their advantages in familiar fields (Wang et al., 2017) and are likely to do superficial and incremental outcomes (Kaplan and Vakili, 2015). Although reusing new knowledge combinations within the sector may primarily promote incremental innovations and may constrain long-term breakthrough innovations, they are valuable. Huenteler et al. (2016a) and Binz et al. (2017) found that the development of the wind energy sector predominantly relies on sequential incremental innovations concerning specific sub-components. In a word, reusing new combinations within the sector is still essential for the development of the sector and a firm's competitive advantage.

Our results suggest that breakthrough innovations emerge from exploring new knowledge combinations within the sector and reusing them after they become old knowledge combinations within the sector. This implication extends the work of Randle and Pisano (2021), who argue that breakthrough innovations arise from an iterative process of exploration followed by exploitation. Our study further proposes that the time gap between exploration and subsequent exploitation is influenced by the length of sectoral technological cycle. This implies that maintaining the balance between exploration and exploitation highly depends on the speed at which knowledge becomes obsolete. This conclusion aligns with the argument of O'Reilly and Tushman (2013), who claimed that in a stable environment (a longer sectoral technological cycle), firms should alternate between exploration and exploitation. In such a context, firms have sufficient time to invest in exploration when opportunities arise and subsequently shift to exploitation. Conversely, in an environment with rapid technological changes (a shorter technological cycle), firms need to engage in both exploration and exploitation simultaneously to mitigate the risk of unanticipated challenges.

Our findings align with innovation studies that focus on firms in the wind energy sector. Suzlon, a firm from India, tends to reuse new knowledge combinations within the sector. It adopted a fast-follower strategy by acquiring companies with specific knowledge of wind turbines to leverage already available knowledge. While the knowledge base of Suzlon grew, it was shallow and narrow (Awate et al., 2012). Over time, knowledge in the wind energy sector has diversified significantly, expanding into previously unconnected domains (Rosiello and Maleki, 2021). Firms in the wind energy sector are increasingly required to search knowledge across various sectors. The failure to recognise the shift towards hybrid technologies and digital solutions early has hindered Suzlon's ability to generate breakthrough innovations.

In contrast, the Danish company Vestas is a firm that explores new knowledge combinations within the sector, particularly those unrelated to the wind energy sector, to create breakthrough innovations. For instance, Vestas was among the first companies to expand its knowledge of operating wind turbines in challenging environments and supply turbines for large-scale offshore wind farms in 2001, such as the Horns Rev project. Moreover, in 2014, Vestas began investing in digitalisation and integration, which are new knowledge within the wind energy sector. These investments enabled the integration of digital technologies, such as SaaS, advanced analytics, failure prediction, and other AI-based systems, into designing and operating Vestas-built wind parks (Dai et al., 2020).

Furthermore, Vestas explores cross-sectoral knowledge by establishing a global network of R&D centres. In 2017, it developed the world's first complete utility on-grid energy park in Australia, integrating solar, wind, and battery technologies. As a result, exploring new knowledge combinations within the sector has been crucial for Vestas in generating breakthrough innovations.

This study makes three main contributions. First, it highlights the importance of differentiating between new and old knowledge combinations within the sector in understanding a firm's knowledge search strategy. Firms that use more new knowledge combinations within the sector will likely recognise new technological problems and seize the opportunity to improve them (Jung and Lee, 2016). Conversely, searching more old knowledge combinations within the sector indicates that firms attempt to uncover previously overlooked knowledge that solves current technological problems (Nerkar, 2003).

Furthermore, this study highlights that whether a combination is new or old within the sector depends on the length of sectoral technological cycle. In sectors with shorter technological cycles, a recently emerged knowledge combination may no longer be classified as new within the sector, as it is likely replaced by an even newer one (Park and Lee, 2006).

Finally, existing studies on breakthrough innovations often emphasise the influence of innovations within a period shortly after their creation (e.g., Ahuja and Lampert, 2001; Arts and Veugelers, 2015). However, these studies may overlook that some innovations require time to become influential within the sector (Chai and Menon, 2019; Pezzoni et al., 2022). By differentiating between short-term and long-term breakthrough innovations, this study highlights that firms should adopt distinct knowledge search strategies for each. For short-term breakthrough innovations, firms can reuse old knowledge combinations within the sector to uncover previously overlooked innovations that address current technological problems. Regarding long-term breakthrough innovations, firms need to explore new knowledge combinations within the sector to recombine diverse knowledge components.

This study has some limitations. For example, there were fewer firms and patents before 2000 due to the slower development of the wind energy sector. Consequently, the number of breakthrough innovations and firms that reused knowledge combinations was limited during this period. Future studies should consider more extended periods to validate these conclusions.

This study highlights several promising directions for future research. While reusing old knowledge combinations is critical for short-term breakthrough innovations, the specific characteristics of the knowledge combinations that should be reused remain unclear. For example, have these combinations been used by competitors or remain unexplored by others? Should they comprise dissimilar or similar components? Additionally, firms that fail to explore new knowledge combinations within the sector may face limited access to high-quality external knowledge sources (Laursen, 2012). Future research could investigate how the quality of external knowledge sources influences the generation of breakthrough innovations.

Appendix

The measurement of the variables: 'Reuse_new','Reuse_old', 'Explore_new' and 'Explore_old'

Exploring a knowledge combination suggests that it is the first time a firm uses it. Thus, when a pair of IPC codes (7-digit) first appear in a patent published by the firm, the firm explores it. Therefore, if the firm explores a knowledge combination whose age is less than the length of sectoral technological cycle, the firm explores a new knowledge combination within the sector. Otherwise, firms explore an old knowledge combination within the sector.

A knowledge combination that exists in a firm's knowledge is explored or reused by the firm. Consequently, patents published by firms consist of four kinds of knowledge combinations: explore_new, explore_old, reused_new, and reused_old.

Suppose that the number of reused_new knowledge combinations is A, the number of reused_old knowledge combinations is B, the number of explore_new knowledge combinations is C, and the number of explored_old knowledge combinations is D. Additionally, we suppose that the total number of knowledge combinations used by the firm in a given year is N.

As a result, we have N = A + B + C + D.

The variable 'Reused_new' is the share of reused knowledge combinations out of all knowledge combinations used by the firm within a given year. Thus, '**Reused_new' = A / N = A/ (A+B+C+D)**.

Similarly, we have:
'Reused_old' = B / N = B / (A + B + C + D)
'Explore_new' = C / N = C/ (A + B + C + D)
'Explore_old' = D / N = D/ (A + B + C+ D)

The measurement of the variables: 'Research'

The variable 'Research' is the share of knowledge firms obtain from research institutions. To calculate this variable, we first identify the research institutions manually based on optimised assignee of cited patents, such as 'University' and 'Research centre'. Then, we calculated the share of knowledge inflow from these research institutions. Suppose that firms cited X patents in a given year, and the number of patents from research institutions is Y. Consequently, the variable 'Research' is equal to Y / X.

The measurement of the variables: 'Local'

The variable 'Local' is the share of knowledge firms search from local knowledge sources. We use the patent assignee's country of address as a proxy for the location where the invention occurred. If the country of a knowledge source matches that of the firm, the knowledge source is considered a local source. Suppose that firms cited X patents in a given year, and the number of patents from local sources is Y. Consequently, the variable 'Local' equals Y / X.

Table 15 Descriptive Statistics

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
BIS_{it}	2,168	0.253	1.822	0	36
BIL_{it}	756	0.653	0.470	0	9
$Reuse_old_{it}$	2,168	0.112	0.220	0	1
$Reuse_new_{t}$	2,168	0.047	0.134	0	1
$Explore_old_{it}$	2,168	0.137	0.242	0	1
$Explore_new_{it}$	2,168	0.140	0.220	0	1
NI_{it}	2,168	3.940	15.382	0	217
UV_{it}	2,168	3.269	1.905	0	11.416
RV_{it}	2,168	3.238	1.984	0	22.034
$Complexity_{it}$	2,168	1.478	0.832	0	7.5
$Research_{it}$	2,168	0.033	0.879	0	1
$Local_{it}$	2,168	0.285	0.344	0	1
Age_{it}	2,168	6.098	4.846	1	26

Table 16 Correlation table (Model 1)

	$Reuse_new_{it}$	$Reuse_old_{it}$	NI_{it}	$Explore_new_{it}$	$Explore_old_{it}$	$Research_{it}$	$Complexity_{it}$	$Related_{it}$	$Unrelated_{it}$	Age_{it}	$Local_{it}$
$Reuse_new_{it}$	1.000										
$Reuse_old_{it}$	.0533	1									
NI_{it}	.2073	.1636	1								
$Explore_new_{it}$	.0758	-.0239	.1017	1							
Explore Old_{it}	-.0849	.0867	-.0075	.0416	1						
$Research_{it}$	.0247	.0438	.1135	.2008	.1559	1					
$Complexity_{it}$	.0100	-.0604	-.0979	-.0858	-.0862	-.1267	1				
$Related_{it}$	.1857	.1322	.1754	.2219	.0590	.0383	.3237	1			
$Unrelated_{it}$	.1826	.1109	.3205	.2980	.0547	.1288	.1646	.6061	1		

Age_{it}	.0660	.0938	.2889	.0828	-.0132	-.0018	-.1222	.1763	.4195	1	
$Local_{it}$	.2171	.2865	.1222	.3446	.2755	.3155	-.1288	.1531	.2573	.0967	1

Table 17 Correlation table (Model 2)

	$Reuse_new_{it}$	$Reuse_old_{it}$	NI_{it}	$Explore_new_{it}$	$Explore_old_{it}$	$Research_{it}$	$Complexity_{it}$	$Related_{it}$	$Unrelated_{it}$	Age_{it}	$Local_{it}$
$Reuse_new_{it}$	1.000										
$Reuse_old_{it}$	.0979	1									
NI_{it}	.2060	.1553	1								
$Explore_new_{it}$	.0728	-.0336	.1885	1							
Explore Old_{it}	-.0574	.0384	.0542	.0827	1						
$Research_{it}$	.0527	-.0610	.1168	.2530	.1752	1					
$Complexity_{it}$	.0372	-.0369	-.1194	-.0946	-.0648	-.0758	1				

$Related_{it}$	.2045	.1598	.2471	.2385	.1066	.1107	.2446	1			
$Unrelated_{it}$	.1625	.0803	.3779	.2601	.0826	.1565	.0864	.5026	1		
Age_{it}	.0971	.0554	.2586	.0317	-.0182	-.0189	-.0966	.2073	.4766	1	
$Local_{it}$	.1314	.3656	.1748	.2616	.3412	.1988	-.1512	.1108	.2199	.097	1

Table 18 VIF tests for multicollinearity (Model 1)

VARIABLES	VIF	1/VIF
NI_{it}	2.44	0.410337
BIS_{it-1}	2.19	0.456898
UV_{it}	2.12	0.471798
RV_{it}	1.80	0.554222
$Local_{it}$	1.67	0.599139
Age_{it}	1.34	0.743928
$Explore_new_{it}$	1.29	0.777121
$Complexity_{it}$	1.28	0.782457
$Research_{it}$	1.17	0.855759
$Reuse_old_{it}$	1.16	0.862709
$Reuse_new_{it}$	1.15	0.873146
$Explore_old_{it}$	1.14	0.875482
Mean VIF	1.53	

Table 19 VIF tests for multicollinearity (Model 2)

VARIABLES	VIF	1/VIF
UV_{it}	1.91	0.524418
$Local_{it}$	1.63	0.615344
RV_{it}	1.56	0.641042
NI_{it}	1.50	0.665201
Age_{it}	1.40	0.715752
BLS_{it-1}	1.39	0.721245
$Explore_new_{it}$	1.28	0.779714
$Reuse_old_{it}$	1.25	0.797922
$Explore_old_{it}$	1.22	0.821239
$Complexity_{it}$	1.19	0.838920
$Research_{it}$	1.12	0.891173
$Reuse_new_{it}$	1.11	0.904070
Mean VIF	1.36	

Table 20 The test for Heteroskedasticity

Breusch–Pagan/Cook–Weisberg test for heteroskedasticity

Assumption: Normal error terms

Variable: Fitted values of BI_t

H0: Constant variance

Model 1	Model 2
Chi2 (1) = 47293.49	Chi2 (1) = 66819.65
Prob>chi2 = 0.0000	Prob>chi2 = 0.0000

Table 21 The Hausman test

H0: Difference in coefficients not systematic	Short-term breakthrough innovations	chi2(13) = 84.21	Pr>chi2 = 0.0000
	Long-term	chi2(13) = 60.64	Pr>chi2 = 0.0000

	breakthrough innovations		

Table 22 Wooldridge test for autocorrelation in panel data

H0: no first-order autocorrelation	Short-term breakthrough innovations	F(1, 250) = 10.334	Prob > F = 0.0015
	Long-term breakthrough innovations	F(1, 91) = 15.490	Prob > F = 0.0002

Table 23 The LR test

H0: no overdispersion	Short-term breakthrough innovations	chibar2(01) = 295.95	Prob >= chibar2 = 0.000
	Long-term breakthrough innovations	chibar2(01) = 0.0e+00	Prob >= chibar2 = 0.5

Table 24 The Vuong test for the Negative Binomial Regression

Vuong test of the zero-inflated Negative Binomial vs. standard Negative Binomial	Short-term breakthrough innovations	z = 4.15	Pr>z = 0.0000
Vuong test of the zero-inflated Poisson vs. standard Poisson	Long-term breakthrough innovations	z = 1.98	Pr>z = 0.0241

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