Technological Diversification to Green Domains: Technological Relatedness, Invention Impact and Knowledge Integration Capabilities

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Abstract: Climate changes and ecological challenges often motivate firms to diversify into environmental domains. However, this does not guarantee impactful inventions. Therefore, this study investigates how firms can create impactful environmental inventions based on their technological relatedness and prior knowledge integration capabilities. Using a unique dataset of 1,990 high-tech Chinese firms between 2006 and 2016, our results reveal that diversifying firms' green technological relatedness has an inverted U-shaped relationship with invention impact. While the depth of firms' knowledge integration capabilities steepens this relationship, the breadth flattens it. Higher levels of depth capability result in a greater impact, while greater breadth leads to an early attainment of peak invention impact at a lower degree of green technological relatedness. Theoretical and policy implications are discussed.

Keywords: green innovation, environmental impact, technological value, technological relatedness, diversification, China

1. Introduction

With the increasing evidence of human environmental disruption outpacing the planet's adaptive capacity, environmental degradation and climate change are currently recognised as the greatest global challenges of our time (Wiedmann et al., 2020). One possible response through which organisations can accelerate and scale up their environmental actions is to engage in green technological innovation, which refers to the development of technologies with the potential to reduce, prevent, and even revert the negative environmental impacts of industries, while enabling a more efficient and responsible use of natural resources (Barbieri et al., 2020; Rennings, 2000). However, compared with the 'end-of-pipe' solutions geared towards complying with regulatory standards, environmental innovation (hereafter 'eco-innovation') is often associated with additional costs and uncertain financial returns (Berrone et al., 2013). Eco-innovation is conventionally believed to erode firms' revenues by diverting resources and managerial attention from its core business activities (Porter and Van der Linde, 1995; Adams et al., 2016). However, several scholars have challenged this perspective and consider eco-innovation as a novel source of firms' competitive advantage. By opening up business opportunities for new sustainable materials, product design, and efficient manufacturing methods, eco-innovation can enable direct cost savings in production with an increase in firms' value alignment with today's customers and stakeholders (Berrone et al., 2013; Hart and Dowell, 2011).

Despite the growing consensus on the socio-economic value of eco-innovation, the conditions and mechanisms through which established firms can transform themselves to develop impactful green innovation while utilising their competence are still unclear. Unlike *de novo* firms that are founded with an environmental mission, established firms need to rely on redeploying their pre-existing resources and capabilities to explore green opportunities (Driessen et al., 2013). The process of matching internal competence with green opportunities can be complex and challenging. Thus, diversifying firms would need to embark on radical structural changes, departing from existing businesses and technological portfolios (Adams et al., 2016; Barbieri et al., 2020; Driessen et al., 2013). The previous literature examining firms' diversification patterns is rooted in the 'relatedness' or the so-called synergy hypothesis. It suggests that firms' entry decisions are not random, but involve pursuing a technologically related pattern to leverage their current knowledge bases sharing potential with multiple businesses (Breschi et al., 2003; Miller, 2006; Kim et al., 2016). Firms can capture value that is unrealised by their counterparts diversifying for less strategic reasons or into unrelated technological domains (Miller, 2006; Teece, 1980; Ceipek et al., 2019). However, this line of inquiry does not explicitly consider the attributes of *de alio* firms' existing technological repositories and the heterogeneity of their knowledge integration capabilities in shaping their technological expansion and ex-post impact (Yayavaram et al., 2018; Kotha et al., 2011). Thus, business leaders and policymakers aiming to facilitate a smoother transition into green domains require greater understanding of the firms' pre-entry resource endowment and technological capabilities.

Drawing insights from the technological diversification literature, this study investigates how diversifying firms' ability to develop an impactful green invention depends on the degree of their technological relatedness to the green domains they seek to enter. Such green technological relatedness is measured by the frequency of patent citations between the technological domains of the focal firms' existing technological portfolios and that of their first green patents (see Section 3.3). Forward citations are used as a proxy for the impact of the focal firms' existing technological patents. We predict a concave relationship between green technological relatedness and the ex-post invention impact and suggest that the green invention impact is contingent upon the depth and breadth of diversifying firms' knowledge integration capabilities. The depth captures a firm's pre-entry knowledge combination expertise in a technological domain (George et al., 2008), whereas the breadth reflects a firm's cross-domain knowledge recombination experience (Helfat and Raubitschek, 2018, Helfat and Campo-Rembado, 2016). We hypothesise that firms with a high depth of capability can accelerate the benefit of technological relatedness on the impact of inventions, leading to an overall higher impact, whereas the breadth flattens the concave relationship and generates an impact peak at a lower level of technological relatedness. We test our hypotheses using a sample of 1,990 firms from the Zhongguancun Science Park (ZSP), China's Silicon Valley, which have developed green patents for the first time between 2006 and 2016.

Our study makes two main contributions to the literature. First, we elucidate the extent to which diversifying firms' pre-entry green technological relatedness contributes to their ex-post invention impact. We emphasise the resource-based view in understanding the firms' technological diversification into green domains to illustrate its underlying mechanisms. Thus, we depart from previous studies that primarily focus on identifying the entry propensity or determinants of eco-innovation, including regulatory compliance, stakeholder pressures, proactive firm strategies, and adoption of environmental standards (De Marchi, 2012; Adams et al., 2016; Barbieri et al., 2020; Berrone et al., 2013). Second, we draw attention to the diversifying firms' endogenous capabilities in integrating and enhancing their transformation into green domains. We enrich the concept of firms' pre-diversification integration capabilities by distinguishing between their depth and breadth, which have different contingent effects on the impact of their inventions (Lieberman et al., 2017; Maritan and Lee, 2017). Overall, by responding to George et al. (2016) call for research on global 'Grant Challenges', we extend the diversification literature by explaining why some firms develop more impactful green inventions than others while entering green domains for the first time.

2. Theory and hypotheses development

2.1 Technological relatedness in firm diversification to green domains

Prior research has heavily drawn upon the resource-based view in studying the outcomes of firms' technological diversification. Following the notion of relatedness, it argues that *de alio* firms can create value by leveraging their unique knowledge resources and capabilities to enter additional business and technological segments (Kim et al., 2016; Miller, 2006; Ceipek et al., 2019; Schommer et al., 2019). Technological relatedness refers to the degree to which a focal technology shares a common knowledge base with firms' existing technology and derives from mutual scientific principles or 'heuristics' of search (Leten et al., 2007; Breschi et al., 2003). This concept suggests that industries are endogenously linked by underlying technologies and reflect the extent to which technological knowledge overlaps across domains (Leten et al., 2016; Miller, 2006; Tanriverdi and Venkatraman, 2005)[1].

Firms are expected to obtain value when diversifying into technologically related industries (Sliverman, 1999; Miller, 2006; Sakhartov, 2017). By sharing technological resources such as expertise and human capital, firms can achieve inter-temporal economies of scope while avoiding the cost of duplicating or transferring knowledge across organisational boundaries (Breschi et al., 2003; Tanriverdi and Venkatraman, 2005). Synergies in firms' knowledge bases are critical in reducing costs and risks through the frugal use of firms' resources (Granstrand, 1998). Subsequent empirical research confirming the relatedness hypothesis have analysed the outcomes of technological diversification from the perspective of innovation quality, quantity, and finance, and the firms' propensity to enter new domains in the context of mergers and acquisitions or the firms' own technological portfolios (See recent reviews e.g. Ceipek et al. (2019) and Schommer et al. (2019)).

These prior studies have delineated an overall pattern for technological diversification; however, not every firm conforms to such a pattern to generate an invention impact. We contend that firms need to address two main concerns to diversify into new domains. The first concern is the characteristics of the target domain they intend to enter. For example, considering the green innovation setting, previous literature argues that eco-innovation is vastly different from innovation in other domains. First, eco-innovation is complex and multi-purpose, requiring diverse competences and knowledge inputs to satisfy regulatory requirements, stakeholder expectations, and customer demands (Ardito et al., 2019; Porter and Van der Linde, 1995; Berrone et al., 2013).

Second, it requires considerable systematic change towards an environmentally compatible design to disposal production process while simultaneously preserving the firms' core product offerings (De Marchi, 2012; Barbieri et al., 2020; Marzucchi and Montresor, 2017). Third, eco-innovation exhibits 'double externalities' by creating technological externalities that benefit non-green competitors at the innovation stage, and environmental externalities enjoyed by the wider society during the diffusion phases (Rennings, 2000; Ning and Wang, 2018). These characteristics suggest that firms may not be able to fully appropriate the value from additional efforts or costs incurred in developing these eco-characteristics (Marzucchi and Montresor, 2017; Barbieri et al., 2020). They may also experience slower returns, bear higher R&D costs and market failure risks, and have fewer incentives and higher opportunity costs than in other technological areas. Therefore, further elucidation is required to determine the extent to which firms' recombination of related knowledge resources to diversify into specific settings (such as the green domain) can improve their technological impact.

The second concern is the characteristics of firms' technological resources and capabilities before diversifying into new domains. Previous studies suggest that high-impact inventions stem from a unique combination of knowledge components (Fleming, 2001; Yayavaram et al., 2018). This calls for a greater understanding of firms' resources and capabilities. Following the work of Helfat and Campo-Rembado (2016), we define resources as stocks of production factors owned and controlled by firms, whereas capabilities refer to the firms' ability to productively utilise resources in a routine fashion. Resource attributes are generally associated with the efficiency and flexibility of firms' internal markets in redeploying resources when entering new industries (Lieberman et al., 2017; Speckbacher et al., 2015; Maritan and Lee, 2017; Lee, 2008). Although closely related businesses have a high potential for resource redeployment, the underlying mechanisms of value creation are still not well understood (Moeen, 2017; Lieberman et al., 2017). Moreover, firms require more than resources with related attributes to achieve superior performance, as they also need to process heterogeneous capabilities while managing diversification (Mackey et al., 2017). Prior research typically distinguishes between pre-entry capabilities of *de alio* (diversifying) and *de novo* (new venture) firms and argues that the latter are more flexible in facilitating resource redeployment (Chen et al., 2012; Ceipek et al., 2019). Given the adjustment cost of diversification, firms are more likely to rely on pre-existing capabilities from other industries that do not require much reconfiguration or tailoring to suit the development of their new target domains (Moeen and Agarwal, 2017; Speckbacher et al., 2015). However, the specific role of technological capability in utilising related resources to create valuable inventions in new industries remains unclear (Cefis et al., 2020; Helfat and Raubitschek, 2018).

In the following sections, we examine the two aforementioned concerns by exploring the extent to which firms' green inventions can create the requisite technological impact through redeploying related knowledge resources and previously accumulated knowledge integration capabilities. We focus on home-grown technologies rather than acquisitions, as firms continue to invest in knowledge to maintain their technological capabilities even after outsourcing some parts of their business (Leten et al., 2007).

2.2 Technological impact of green inventions and relatedness of technological repositories

The technological impact of inventions is determined by their technological value or usefulness, which is reflected in the number of times an invention is recombined to create subsequent inventions (Schillebeeckx et al., 2020; Keijl et al., 2016). As discussed in Section 2.1, considering the cost perspective, previous literature argues that firms diversifying into more related segments can create financial value through synergies raised from sharing existing knowledge resources and avoiding costly knowledge development (Sakhartov, 2017; Breschi et al., 2003; Tanriverdi and Venkatraman, 2005). Therefore, redeploying resources to related technological domains should engender technological value creation opportunities when firms exploit similar knowledge resources across multiple business segments. To elucidate how firms' green technological relatedness affects the ex-post impact of their first green inventions, we hypothesise a concave relationship between them. Following Haans et al. (2016) theoretical study, we discuss the two underlying latent mechanisms of positive invention applicability and negative novelty functions (See Figure 1 for the theoretical framework).

INSERT FIGURE 1 ABOUT HERE

Regarding the first latent mechanism of applicability, with increasing invention applicability, firms redeploying their existing related technological repositories would improve their invention impact (see Figure 1a). Applicability refers to the extent of knowledge being perceived as useful or relevant to its recipients (Papazoglou and Spanos, 2018; Rosenkopf and Nerkar, 2001). Inventions with more widespread potential applicability can increase invention impact. Such inventions provide a general solution to firms with heterogeneous technical problems and can thus influence how other inventors adopt and build upon new knowledge to continue evolving technologically beyond the focal invention's domain (Rosenkopf and Nerkar, 2001; Valentini and Di Guardo, 2012; Papazoglou and Spanos, 2018). Moreover, the recipients' perception of invention applicability is often based on similarity with past usage in the current context (Hicks and Hegde, 2005). Firms' technological relatedness to a domain implies that they predominantly use the same basic science which has a wider application beyond a single science domain (Klevorick et al., 1995; George et al., 2016). Consequently, these firms tend to develop a similar understanding of comparable technological challenges and rely on similar sets of scientific theories to resolve technological bottlenecks (Makri et al., 2010; Leten et al., 2016). Diversifying into related domains enables firms to recombine existing but related knowledge components. This makes the focal inventions more relevant and appealing to broader range of firms, thus engendering high inventions applicability and impact.

As green domains are still nascent, the best environmental practices and technological paradigms are yet to be established (Markman et al., 2004; De Marchi, 2012). The superiority of green technologies may not be apparent to existing customers and other users. Therefore, firms without adequate technological relatedness need to divert significant resources to establish a common ground and bridge their existing knowledge with new domains (George et al., 2008). Conversely, firms redeploying existing related knowledge to enter new domains are more likely to temporarily generate a consistent pattern of inventions that can be understood by users (Capaldo et al., 2017). Thus, green technological relatedness is likely to enhance invention applicability and impact. Moreover, redeploying existing and familiar knowledge can create linkages between existing and new domains and reduce uncertainty in new technologies by rejuvenating previously used components (Fleming, 2001; Yayavaram and Chen, 2015). Even if potential users are unfamiliar with the inventions, the product information and complementary components available in the original industries can assist user adoption (Turner et al., 2013; De Marchi, 2012). An example of eco-innovation illustrating this diversification pattern is the Norwegian energy company Equinor. It redeployed its familiar technologies in deep-water oil and gas drilling infrastructure to develop an offshore floating wind farm system. This extended the scope of the wind power industry, which had hitherto relied on conventional fixed-bottom platforms (Equinor, 2020).

Regarding novelty, the second latent mechanism, an increase green technological relatedness would be detrimental to the impact of green invention if the novelty of the invention is under a decline (see Figure 1b). Novelty is often depicted as an eventual output of innovation arising out of the unique recombination of pre-existing knowledge (Arts and Veugelers, 2015; Wang et al., 2014). Firms recombining their knowledge based on exploratory and distant searches are more likely to create novel inventions that denounce current technological and scientific models. Eventually, such inventions have the scope to become highly cited and impactful (Phene et al., 2006; Rosenkopf and Nerkar, 2001; Kaplan and Vakili, 2015). Conversely, firms relying on local search through an exploitation of technologically related or similar components would experience incremental inventions with low novelty and thus low impact (Fleming, 2001; Rosenkopf and Nerkar, 2001).

Accordingly, firms with high technological relatedness entering green domains through the recombination of components from existing repositories could suffer from potential novelty deterioration. First, the persistent use of technologically related or similar mature knowledge components can lead to an overly local search in the 'neighbourhood' of older solutions (Katila and Ahuja, 2002). Knowledge overlap and technology redundancy increase with technological relatedness, diminishing opportunities to develop radically new knowledge or to create novelty (Makri et al., 2010; Fleming, 2001). Second, the persistent use of related or similar mature knowledge components can dwindle invention novelty, since technological paradigms tend to shift over time (Capaldo et al., 2017). This exacerbates the risk of invention obsolescence and the risk of exhausting the possible combinations of creative components (Yayavaram and Chen, 2015). Third, with technological relatedness, firms are more likely to adopt an exploitation trajectory based on existing knowledge, which increases their likelihood of being locked in the dominant logic, encountering difficulties in altering established knowledge bases, and in exploring emerging technologies (Leten et al., 2007). Similarity within the underlying science domains further precludes the need for substantial knowledge exploration (Makri et al., 2010). Inventions could take the form of simple and low-impact substitutes for existing solutions with mature components from firms' original domains (Dibiaggio et al., 2014).

Moreover, such a status quo is self-reinforced. Firms that have already accumulated skills and deployed multiple resources for exploitative activities tend to have significantly high sunk and switching costs for radical changes, eventually resulting in a 'familiarity trap' and low novelty (Katila and Ahuja, 2002; Kok et al., 2019). Consequently, it hampers the feasibility of redeploying existing knowledge resources that are highly related to a targeted domain to create novel and high technological impact. We expect this mechanism to be applied to firms' green invention processes.

When the above positive and negative latent mechanisms are combined multiplicatively following the theoretical framework of Haans et al. (2016), an inverted-U relationship can be expected between firms' green technological relatedness and invention impact (see Figure 1c). Firms with moderate levels of relatedness are likely to have the best chance of creating more novel and applicable green inventions with the greatest overall impact than in other cases. Firms can redeploy and exploit existing green-related knowledge resources to increase applicability and explore various relatively distant knowledge areas to improve their novelty potential. This echoes the ambidexterity paradox, in which firms achieve the best performance when they simultaneously pursue both incremental and discontinuous innovation (Raisch et al., 2009; Wang et al., 2014; O'Reilly III and Tushman, 2013). On both sides of the concave curve, the overall impact of the inventions is low. As discussed above, firms with low levels of green technological relatedness can demonstrate a lesser extent of technological deployment from existing knowledge repositories to warrant high applicability of their invention, while a high novelty potential is possibly achieved via this unrelated knowledge recombination. Similarly, in the opposite spectrum, firms with high green technological relatedness have a higher tendency to reuse technologically similar components, resulting in high invention applicability. However, these firms have low invention-novelty potential due to technology overlap and substitution. Figure 1(c) depicts all parts of the concave curve, leading to the following hypothesis.

Hypothesis 1 (H1): *Firms' technological relatedness to green domains and the technological impact of their green inventions have an inverted U-shaped relationship.*

2.3 Moderating effect of pre-entry knowledge integration capability on the technological impact of green invention

As discussed in Section 2.1, owning related technological repositories provides vital and immediate knowledge input for firms to diversify into a new domain. However, this does not necessarily guarantee high-impact inventions (Lee, 2008; Keijl et al., 2016; Mackey et al., 2017). The concept of capabilities is particularly relevant here as it refers to organisations' abilities to reliably perform repetitive tasks (Helfat and Campo-Rembado, 2016). Some prior studies suggest that organisational capabilities affect firms' resource-utilisation routines and processes to achieve competitive advantages (Wuyts and Dutta, 2014; Helfat and Raubitschek, 2018; Helfat and Campo-Rembado, 2016; Moeen, 2017). Firms are also viewed as knowledge-integrating institutions that generate value after acquiring the requisite resources (Kotha et al., 2011; Speckbacher et al., 2015).

Therefore, we contend that firms' realisation of inventions may hinge on their heterogeneous technological capabilities for recombining and utilising knowledge components within or across technological domains. This process is path-dependent. It reflects firms' deliberate organisational learning efforts and demonstrates their accumulated expertise, experiences, and adaptation of relevant organisational processes and routines in vertical and horizontal combinations to achieve innovation (Helfat and Raubitschek, 2018; Lee, 2008; Boh et al., 2014; Leten et al., 2016). Following the work of Haans et al. (2016), we hypothesise that technological capabilities influence the two latent mechanisms of invention discussed earlier and reshape the curvilinear relationship between green technological relatedness and the impact of inventions (see Figure 2).

INSERT FIGURE 2 ABOUT HERE

2.3.1 Depth of knowledge integration capability

Depth of knowledge integration capabilities (thereafter 'depth') refers to the level of a firm's pre-entry knowledge combination expertise in a single or small number of technological domains (George et al., 2008). We expect firms to intuitively and strategically rely on their idiosyncratic core competencies or search their domains to exploit existing knowledge resources. Depth would moderate the two latent mechanisms by raising the positive slope of invention applicability upward while pushing the negative slope of novelty downward. Multiplicatively combining these two latent mechanisms would steepen the inverted U-shaped curve, as shown in Figure 2(a).

Greater depth of pre-entry capability has three experience-based advantages that would enable firms to further improve their innovation applicability. First, depth improves firms' understanding of component specificities and complex combinatory linkages based on past usage. This amplifies their internal absorptive capabilities and lowers their discovery hurdles in accurately identifying promising components and in extending application areas of technological inventions (George et al., 2008). Second, depth developed through repeated use of the same knowledge elements can foster firms' competence in recombining existing domain components, learning from past limitations, and sharing it across firms based on deep collective knowledge creation experience (Moeen, 2017). It can greatly reduce the likelihood of errors when applying knowledge to different contexts (Kok et al., 2019; Katila and Ahuja, 2002; Cohen and Levinthal, 1990; Helfat and Raubitschek, 2018). Third, combining and applying existing knowledge components to a new domain is consistent with firms' current organisational routines. It can lead to more predictable and efficient technological search and production process, while strengthening and extending the usefulness of inventions to different contexts (Arts and Veugelers, 2015).

Contrastingly, depth can hinder firms' novelty potential. First, it limits firms to improve along their current technological trajectories, restraining their exploration of distant knowledge. This lowers their scope for potential knowledge integration or redeployment of novel combinations, making them likely to overlook trajectories in other domains that can complement and facilitate their own domain development (Miller, 2006; Papazoglou and Spanos, 2018). Second, depth encourages within-domain linkages. This can lead to further organisational inertia, limiting firms' capability to modify existing knowledge structures and create novel combinations (George et al., 2008). Because of cognitive information filters and normative beliefs, departures from firms' current knowledge repertoires are more likely to be considered unnecessary and risky (Yayavaram and Chen, 2015; Nerkar, 2003). As argued in Section 2.1, the cost of incorporating distant knowledge is also higher for non-green firms (Diestre and Rajagopalan, 2011). The augmented deepening of firms' capabilities can thus hamper their incentive to search for and combine new components. These behaviours reinforce local search and increase firms' challenges in altering existing organisational, cognitive, and normative routines in learning and problem solving (Kaplan and Vakili, 2015; Henderson and Clark, 1990). Hence, we argue that depth is likely to boost the applicability potential of firms' eco-innovation while dampening its novelty. When these two latent effects are combined, the above arguments lead to the following hypothesis:

Hypothesis 2 (H2): *The depth of firms' technological capability steepens the curvilinear relationship (an inverted U-shaped) between firms' green technological relatedness and green invention impact.*

2.3.2 Breadth of knowledge integration capability

We make a related argument for the moderating effect of the breadth of firm's knowledge integration capabilities (hereafter 'breadth'), which represent firms' diversity of cross-domain integration capability (Helfat and Raubitschek, 2018; Helfat and Campo-Rembado, 2016). When firms' technological capabilities spread across several technological domains by adding new domain areas, the breadth of knowledge integration capability would moderate the two latent mechanisms. It pushes the positive slope of applicability downward while raising the negative slope novelty upward. Combining the two latent effects would result in a flattened inverted U-shaped curve, as shown in Figure 2(b).

We expect green invention applicability to suffer further for firms with high breadth capabilities. First, technological capability development is often a time-consuming and resource-intensive process (George et al., 2008). Firms with multiple domains are less likely to invest in and establish expertise in all domains simultaneously. They often face challenges in leveraging cross-domain knowledge to build cohesive ties and transfer tacit knowledge between their business units (Wuyts and Dutta, 2014). Thus, few firms are likely to develop sufficient knowledge depth to absorb knowledge across all their domains. This can hinder accurate identification and evaluation of internal and external knowledge sources to bridge different domains, further rendering invention-applicability uncertain (Capaldo et al., 2017). Second, the complexity of technological search and integration exponentially increases with additional dimensions (Fleming, 2001; Yayavaram and Chen, 2015). The lack of a common knowledge interface makes it costly for firms with high breadth capabilities to increase their scope of integration. These firms can experience information overload and diseconomies of scales in knowledge dissemination and production (Katila and Ahuja, 2002). They also face 'time-to-build' costs due to the necessity of conducting extensive experiments to combine diverse knowledge components (Kaplan and Vakili, 2015; Sakhartov, 2017). This decreases the possibility of finding valuable new components, resulting in excessive cognitive load and applicability impairment.

Conversely, breadth can enhance invention novelty in two ways. First, prior experience in boundary spanning across different domains reveals new perspectives to assess problems. This increases the likelihood of novel linkages between domains, reinvigorating existing knowledge (Nerkar, 2003; Capaldo et al., 2017). Breadth can also increase the scope of knowledge search for distinctive variations in problem solving (Leten et al., 2016). Second, superior innovations rely on accurate matching of components within and across domains (Carnabuci and Operti, 2013).

Broader capabilities help firms better evaluate unfeasible paths and loosen internal structures with greater flexibility to adjust their knowledge combination trajectories (Moeen, 2017). The ability to combine technologically distant knowledge also provides firms with opportunities to create novel links. This increases the uniqueness of combinations through creative thinking across diverse technological fields (Wuyts and Dutta, 2014). Hence, we hypothesise that breadth capabilities decrease firms' green invention applicability while enhancing its novelty. When combining these two latent effects, we expect

Hypothesis 3 (H3)*: The breadth of firms' technological capability flattens the curvilinear relationship (inverted U-shaped) between their green technological relatedness and green invention impact.*

3. Data and Method

3.1 Empirical context

To test our hypotheses, we obtained data on technological diversification and eco-innovation from firms located in China's Silicon Valley, Zhongguancun Science Park (ZSP). This was an ideal setting for several reasons. First, although China has experienced unprecedented economic and technological growth within a short period, its success comes at a colossal environmental cost (Ning and Wang, 2018). This context provides us with an opportunity to understand firms' intensified responses to rapid environmental degradation. The selection of regional samples also helps to reduce the possible impact of the heterogeneous local environmental regulations on firms' innovation performance across different authorities. Second, our sample not only provides us with a rich pattern of firms' green diversification, but also allows for a long observation period for our analysis. This is largely due to the uneven distribution of technological growth in China (Tong et al., 2018; Ning et al., 2016). The ZSP was China's first science and technology cluster directly established by the State Council in 1988. Most of China's renowned high-tech giants, such as Lenovo, Baidu, Xiaomi, and Sohu, were founded in the ZSP. Third, the ZSP is China's foremost high-technology community with top research institutions such as Tsinghua, Peking University, and the Chinese Academy of Sciences, apart from 251 research institutions and 62 key national laboratories, all of which contribute to the firms' active investment in R&D activities to pursue patenting and the region's rapid technological development. As we rely on patent data to trace the firms' technological diversification and eco-invention activities, the ZSP provides us with a suitable sample to easily track patents from the State Intellectual Property Office (SIPO) of China.

3.2 Data source and sample

Our sample firms' registration and annual financial information were collected from the annual census of the ZSP Administrative Committee between 2005 and 2015. To calculate our patent-based indices, we tracked 36,376 firms in the ZSP census between 2000 and 2020, including a five-year window before and after the sample period. From the SIPO, we retrieved information on a total of 565,201 patents granted to 12,511 firms (see Section 3.3 for more detail). While patent-based indicators have well-known limitations in capturing their full economic and technical value (Griliches, 1998), they provide us with extensive and standardised information on international patent classifications (IPCs) and citations for tracing firms' inventions.

To test our hypotheses, we examined *de alio* firms' diversification to green domains for the first time and the consequential impact of their first green inventions. Because we needed to lag our dependent variable by one year to mitigate potential endogeneity, we identified 1,990 firms from the above sample that received their first green patents from 2006–2016. Data on firms' financial information and main measurements included are from 2005–2015, which are used as independent variables. All firms with missing values and those with less than three-year financial information was excluded. We identified firms' green patents using the IPC classifications by the

World Intellectual Property Organization (WIPO), which lists six categories of eco-innovations: alternative energy production; efficient transportation; energy conservation; waste management; agriculture-forestry; and administrative regulatory aspects (see Table 1).

3.3 Variables

3.3.1 Dependent variable

Invention impact: To measure the technological impact of firms' first eco-innovation, we relied on the count data on the number of forward citations received within five years. Forward citations are widely used in the literature to capture the technological impact of patented inventions and have been used synonymously with technological value, usefulness, and quality (Katila and Ahuja, 2002; Capaldo et al., 2017; Keijl et al., 2016; Fleming, 2001). They also reflect the economic and technological information of the patents. High citation count indicates that a patented invention is regularly used by subsequent inventions as knowledge input, signifying its importance and impact (Capaldo et al., 2017). In line with the prior literature (Miller et al., 2007; Nerkar, 2003), we excluded self-citations and applied a fixed five-year window to filter forward citations and to account for the potential time effects of the impact of invention.

3.3.2 Explanatory variable

Technological relatedness: To measure the firms' level of technological relatedness to a green domain during their first-time entry, we first measured the relatedness between each pair of technology domains. Following Leten et al. (2007), we considered two domains as related if patents in these domains frequently cite each other. The higher the technological relatedness, the more common the underlying knowledge base shared among the technological development in each domain (Leten et al., 2016). To construct a systematic pair-wise technological relatedness measure, we retrieved 640,960 forward and backward citations from 1990–2020 for 565,201 patents granted to 12,511 ZSP firms identified in Section 3.2. We compared O_{ij} , the number of observed patents in domain *j* cited by patents in domain *i* with the expected number E_{ij}. The total number of observed citated patents in domain *j* with citations from domain *i* is calculated as:

$$O_i = \sum_j O_{ij} \quad (1)$$

The total number of expected citations in domain *j* with citations from domain *i* is expressed as

$$E_{ij} = O_i * \left(N_j/T\right) \quad (2)$$

N_j represents the number of patents in domain j. The total number of patents that can be cited by all other domains is calculated as $T = \sum_j N_j$. The systematic relatedness of two domains *i* and *j* (R_{ij}) is subsequently computed as the ratio between the observed ($O_{ij} + O_{ji}$) and the expected number of citations $\left(E_{ij} + E_{ji}\right)$, as shown below.

$$R_{ij} = (O_{ij} + O_{ji})/\left(E_{ij} + E_{ji}\right) \quad (3)$$

We interpret that a high value of R_{ij} (if $R_{ij} > 1$) indicates a high relatedness between technologies *i* and *j* and implies more than expected citations based on random citation patterns.

Finally, to calculate a firm's green technological relatedness, we consolidated individual patents at the firm level. A firm's total number of patents (*P*) in the past five years represents the firm's technology portfolio in year *t*. If P_j represents the total number of patents in the portfolio classified in domain j, we expressed the level of technology relatedness of a firm's existing technological repositories to a new green domain *g* as

$$Relatedness = \sum_j \left(\frac{P_j}{P}\right) * R_{gj} \quad (4)$$

3.3.3 Moderating variables

Knowledge integration capabilities: Knowledge integration capabilities are proxied by the total number of IPC co-occurrence at the four-digit level (subclass) in a focal firm's patent portfolio. This approach was adopted from Carnabuci and Operti (2013). We focused on firms' inter- and intra-knowledge domain integration capabilities for various technological combinations. The SIPO assigns all patents with IPCs, which provides us with a standard method of identifying the knowledge components firms have successfully combined for their prior innovation from different domains. Drawing on the work of George et al. (2008) and Kotha et al. (2011), we further classified the firms' integration capabilities into depth and breadth capabilities. The depth capability captures a firm's depth of knowledge integration expertise within a domain. It is calculated as the maximum number of pairwise within-subclass combinations in a firm's technological portfolio P (a pool of patents during the last five years) prior to its technological diversification to the green domains[2].

$$Depth = \max_{j \in P}(combinations\ within\ an\ IPC\ subclass\ j) \tag{5}$$

Likewise, the breadth capability captures the firms' broad and cross-domain knowledge integration expertise. It is measured as the total number of pairwise cross-subclass combinations in a firm's technological portfolio.

$$Breadth = \sum_{j \in P} \sum_{k \in P} combinations\ cross\ IPC\ subclasses\ j\ and\ k \tag{6}$$

These two variables are in their natural logarithm form to reduce the initial skewness.

3.3.4 Control variables

First, we controlled for firm characteristics that might affect the impact of green inventions. These included firm *size*, measured by its total assets in million Chinese Yuan; firm *age* included the number of years from a firm's establishment to the current year. A firm's *R&D intensity* is measured by its R&D expenditure over its total number of employees. Firms with large technological portfolios are more experienced and are likely to have a greater innovation impact. We proxied this accumulated *knowledge stock* effect using the total number patents produced by a firm during the last five years (Schillebeeckx et al., 2020). Second, to control for the effects of the external business environment, we included *domain competition* following Leten et al. (2016). It captures the degree of competition in green domains and is measured using the Herfindahl index:

$1/\sum_i (N_i/N)^2$. N_i represents the number of patents that an incumbent firm i owns in its technology domain, and N represents the total number of patents in the focal domain. We also controlled for *collaboration,* measured by the percentage of co-patenting against a firm's total patents to capture the firms' knowledge exchange with their external partners (Carnabuci and Operti, 2013). The regulatory pressure for firms' engagement in green technology investment is captured by the regional *environmental stringency*, measured by the total number of local environmental staff enforcing environmental regulations (Ning and Wang, 2018). Following Filatotchev et al. (2011), we controlled for the potential local *knowledge spillovers* using the ratio of the total R&D expenditure to the total number of employees in an industry (excluding the focal firm's R&D expenditure and employees) to proxy this effect. Finally, we included *industry, green IPC,* and *year dummy* variables to respectively control for the effects of sectoral differences, heterogeneity of green IPC classes (Perruchas et al., 2020), and the temporal trends in patent citations. All the control variables were in the natural logarithm, except for the dummy variables.

3.4 Estimation methods

Firms' diversification into new green domains is unlikely to be completely random. These firms may be systematically different from firms that do not enter green domains and may self-select into eco-innovation activities. We followed the Heckman two-stage procedure to account for the potential selection bias (Heckman, 1979). In the first stage, we estimated a probit model of a firm's entry into the green domain using the entire sample of 36,376 firms (see Section 3.2). After excluding firms with less than three-year financial information or those with missing registration details, we obtained 23,677 firms with 162,360 firm-year observations for the probit estimation. We considered several potential factors affecting a firm's propensity to enter green domains. These included firm size, age, R&D intensity, state-ownership, profitability, knowledge stock, collaborative intensity, local knowledge spillovers, and regional environmental stringency. We then calculated the inverse Mill's ratio (IMR), which is included as a control variable in the second stage of the Heckman correction model.

To test our hypotheses, we employed a zero-inflated negative binomial (ZINB) model with robust standard errors. This approach is appropriate for estimating models with a non-negative, count-dependent integer variable containing excess zeroes. As 64.32 % of patents in our observations did not have citations, they potentially violated the normality assumption (Cameron and Trivedi, 2013). We further performed Vuong tests across our models ($P < 0.01$), which indicates a preference for zero-inflated estimations (Vuong, 1989). Furthermore, the main assumption of a zero-inflated Poisson model is that the mean equals the variance. In our sample, the coefficient of the variance shows that the standard deviation is 1.896 times greater than the mean. However, the ZINB model allows the sample variance to be different from the mean to correct the sample's over-dispersion from excess zeros (Cameron and Trivedi, 2013). Therefore, we adopted the ZINB model for our estimations and presented the zero-inflated Poisson (ZIP) estimations for comparison. Our model is expressed as follows:

$$\begin{aligned} Impact_t = \exp(&\alpha_0 + \gamma X_{t-1} + \beta_1 Relatedness_{t-1} + \beta_2 Relatedness_{t-1}^2 + \beta_3 Depth_{t-1} \\ &+ \beta_4 Relatedness_{t-1} \times Depth_{t-1} + \beta_5 Relatedness_{t-1}^2 \times Depth_{t-1} \\ &+ \beta_6 Breadth_{t-1} + \beta_7 Relatedness_{t-1} \times Breadth_{t-1} \\ &+ \beta_8 Relatedness_{t-1}^2 \times Breadth_{t-1} + IMR_{t-1} + \sigma_i) \end{aligned} \tag{7}$$

where X denotes all the control variables previously defined. *IMR* (Inverse Mill's Ratio) is obtained from the probit estimation. All explanatory variables are lagged by one year.

4. Empirical results

4.1 Descriptive statistics and regression results

Table 1 presents the distribution of our sample firms as per the WIPO green IPC classifications. Table 2 presents four selected company cases with the most citations for their first green patent to illustrate how our sample firms diversify into the green domains. Firm A applied its prior communication technologies to create a traffic signal transmission system, which resulted in an improved transportation efficiency and a reduction in traffic emission. Firm B is an Internet-based firm that entered the telecommunications industry based on prior data management technologies. Firm C applied oil lubricant production technologies to invent new energy reservation techniques. Firm D developed a newly shaped building element by recycling solid waste using its cement production technology. These cases provide some examples for firms' entry into a new green domain based on their previous knowledge.

INSERT TABLE 1 &2 ABOUT HERE

INSERT TABLE 3 & 4 ABOUT HERE

Table 3 reports the descriptive statistics and the pairwise correlations of our variables. On an average, our sample firms were 9.968 years old and had 6 patents. To examine the potential multicollinearity issues, we calculated the variance inflation factors, which was below the threshold value of 10 and had a mean value of 2.58. The results confirmed a lack of multicollinearity in our estimation. Table 4 presents the coefficients and the corresponding significance of the first-stage Heckman selection probit model. The IMR was calculated to correct the possible selection bias in our second-stage model. Table 5 presents the results of our baseline NB estimations in Models 1, 3, 5, 7, and 9. The alternative Poisson estimates are shown in Models

2, 4, 6, 8, and 10 as robustness checks. We first included our control variables and then added in our main explanatory variables. The IMR was significant across all models, indicating that the potential selection bias had been controlled for. The significant *LnAlpha* statistics further indicated our dependent variable's over-dispersion issue. The ZINB model was more suitable for our estimations and showed more robust results than the ZIP models. Concerning the control variables, our results suggest that regional stringency is significantly and positively associated with green invention impact, whereas firm size is significantly and negatively associated it.

INSERT TABLE 5 ABOUT HERE

H1 proposed an inverse U-shaped relationship between green technological relatedness and green inventions. In Model 3, we find a negative and significant quadratic effect, indicating the existence of a concave relationship between the firms' green relatedness and the impact of inventions ($\beta = -0.067, p < 0.01$). These results were consistent across all the models. Figure 3 provides a graphical analysis of the predicted values of patent impact based on Model 3, showing the range of relatedness values. Following Lind and Mehlum (2010), we further verified the marginal effect of the relatedness by checking the steepness of the slope at both ends of the relatedness data range. When relatedness equals 0, the slope is positive and statistically significant ($0.145, p < 0.05$). This implies that a 1% increase in technological relatedness translates into a 0.145-unit marginal increase in firms' green invention impact. When the relatedness equals 4.032 (the maximum value), the slope becomes negative and statistically significant ($-0.207, p < 0.01$). A 1% increase in relatedness leads to a 0.207-unit marginal decrease in the impact of green inventions. Next, we examined the location of the inverted U-shaped inflexion point. Our results show that the curvilinear relationship turns when technological relatedness equals 1.453 with a 95% confidence interval (interval = [0.929, 1.978]). All the above results are within the relatedness data range, thus supporting H1.

INSERT FIGURE 3 ABOUT HERE

H2 contends that firms' depth of technological capability steepens the curvilinear relationship proposed in H1. In Model 9, the interaction term $Relatedness\ squared * Depth$ is statistically significant ($\beta = -0.014, p < 0.05$). We plotted the positive moderating effects of depth in Table 4(a). However, this result only partially supported H2 because the nonlinearity of the ZINB model required further testing. Therefore, following Haans et al. (2016), we examined the slopes of ZINB regression at a different distance 'a' from the inflexion point. For simplicity, we compared these slopes at distance 'a' (between 0 and 1) at a depth of 0.5 standard deviations below and above the mean level. Figure 5(a) confirms the depth's steepening effect as the line is significantly steeper at a high depth level than at a lower one. This supports H2. We repeated this process to analyse H3. In Model 9, the interaction term $Relatedness\ squared * Breadth$ is statistically significant ($\beta = 0.004, p < 0.01$). Figure 4(b) depicts the flattening effect of the breadth capability. This effect is further confirmed in Figure 5(b), as the line is significantly flatter at high than at low levels of breadth. The larger the breadth, the flatter the concave relationship between technological relatedness and green invention impact, thus supporting H3.

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INSERT FIGURE 4 & 5 ABOUT HERE

4.2 Post-hoc analysis

To draw policy and managerial implications, we inspected the movements of the inflection points resulting from the moderating effects of depth and breadth capabilities. Regarding depth, we first visually inspected whether the inflection point in Figure 4(a) shifted to a higher level of invention impact with an increase in depth. Following Haans et al. (2016), we inspected this variation by calculating the vertex coordinates when the depth was at a 0.5 standard deviation below and above its mean, and the statistical significance of the shift. We found that the coordinates respectively moved from ($x = 1.699$; $y = 0.832$) to ($x = 1.703$; $y = 0.947$) towards higher values of invention impacts, but the shift of the level of technological relatedness was statistically insignificant ($z = 0.42, p > 0.1$ for depth at mean-0.5 standard deviation; $z = 0.28, p > 0.1$ for depth at mean +0.5 standard deviation). These results complement H2 on the steepening moderation effect of depth, suggesting that firms' depth capability increases the optimal level of green invention impact, but without a corresponding shift in the level of technological relatedness.

Concerning breadth capability, Figure 4(b) shows that as the breadth increases from a lower to a higher value, the inflection point moves from ($x = 2.092$; $y = 1.056$) to ($x = 1.712$; $y = 0.831$), respectively. The coordinates shift towards the left of the lower level of technological relatedness and are statistically significant ($z = -3.10, p < 0.01$ for breadth at mean -0.5 standard deviation; $z = -2.02,\ p < 0.05$ for breadth at mean +0.5 standard deviation). The breadth capability also exhibits a lower level of the optimal green invention impact. It moderates the inverted U-shaped relationship between green technological relatedness and invention impact by shifting the point of balance towards a lower level of technological relatedness and invention impact. Regarding the flattening moderation effect proposed in H3, these additional results imply that a firm can achieve its peak green invention impact earlier at a lower level of technological relatedness than at a high level. However, the level of the overall invention impact is also lower for firms with a greater breadth of technological capability.

4.3 Robustness tests

We conducted several robustness checks for our results. First, we explored whether our results were sensitive to firms with different levels of knowledge stock. We ran additional analyses on firms where patents in the last five years ranged from at least one to at least six (see Table 6). Consistent with our hypotheses, these subsamples did not show a deviation from our main results.

Second, we adopted the linear spline model suggested by Greene (2003), as an alternative method to test the non-linear effect of technological relatedness. Third, we considered alternative patent accumulation windows using three, four, and six years to calculate our patent-based measurements in Section 3.3. Fourth, we lagged the explanatory variables by two and three years to further control for potential dynamic endogeneity. Finally, we included alternative measurements of our explanatory variables, including R&D intensity, measured by the ratio of R&D expenditure scaled by total sales; firms' size, proxied by the total number of employees; and local knowledge spillovers, proxied by industrial R&D per employee at a two-digit level. Our estimates remained materially unchanged. We present the results of the linear spline model, alternative 3-year accumulation windows of dependent variable and alternative measurements of control variables in Appendix Table A1. For brevity, the remaining robustness test results are available upon request.

INSERT TABLE 6 ABOUT HERE

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5. Conclusion and discussion

This study aimed at exploring how diversifying firms can develop impactful green inventions by redeploying their pre-existing related technological resources, and how this process is shaped by their integration capabilities. To shed light on these issues, we drew upon the resource-based view of technological diversification to suggest that *de alio* firms' technological relatedness to green domains would have a curvilinear relationship with the impact of eco-invention. We further explored two conflated but different knowledge integration capabilities on firms' green invention impact. Using patent data of 1,990 Chinese firms that diversified into green domains for the first time between 2006 and 2016, our empirical results provide compelling evidence that the green-related attributes of firms' pre-existing technological resources contribute to their invention impact, up to a point where these resources are moderately related to the target green domains.

Beyond that point, the impact declines. Thus, the ‘related’ technological diversification presents a paradox that can facilitate and hinder the exploitation of existing resources in creating impactful green inventions, depending on the degree of technological relatedness of firms’ knowledge resources to the targeted green domains. Moreover, we found that having a depth of knowledge integration capability hastens the utilisation of related technological resources to create more impact of green inventions. The breadth of the capability decreases this relationship and reduces the overall impact. However, it enables firms to reach their potential peak impact at an earlier time with lower degrees of green technological relatedness.

5.1 Contributions to the literature

The contributions of our study are twofold. First, we theorised a concave-shaped relationship between firms’ green technological relatedness and the impact of inventions due to a multiplicative combination of two underlying latent mechanisms, invention applicability and novelty. This allowed us to provide a fine-grained explanation of firms’ diversification in specific eco-innovation settings and followed the best theoretical practices in depicting the observed quadratic effects, based on the work of Haans et al. (2016). We highlight the importance of considering the related attributes of firms’ existing technological resources. Technological relatedness is often positively associated with invention applicability derived from the firms’ prior familiarity with related knowledge domains (Zhou and Wu, 2010; Capaldo et al., 2017). It can also enhance the usefulness and relevance of inventions by bridging existing knowledge with green domains (Capaldo et al., 2017). However, firms relying overly on green technological relatedness can impair novelty creation due to their tendency to favour familiarity over distant knowledge while engaging in radical improvements (March 1991). Together with organizational learning rigidity, firms can exhibit limited scope of invention novelty to create impact. Green technological relatedness determines firms’ synergetic knowledge potential between the existing domains and the newly targeted green domains. Thus, our study enriches the understanding of the extent to which firms' prior technological relatedness to green domains contributes to the ex-post invention impact.

Second, we contribute to the technological diversification literature by elucidating why some established firms are better at creating impactful eco-innovation based on their knowledge integration capabilities. We contend that firms' green technological relatedness provides opportunities to exploit existing resources to create an invention impact. While it is a necessary condition, the extent to which firms can redeploy existing related knowledge is contingent on their prior knowledge integration capabilities. Our study substantively complements prior research exploring the antecedents of firms' recombining capabilities in innovation (Carnabuci and Operti, 2013). In contrast with most previous studies that regard technological capabilities as a determinant for diversification into new domain (Ceipek et al., 2019; Moeen, 2017), our study sheds light on the role of firms' differing technological capabilities. Since innovation comes from technological recombination (Fleming, 2001; Sliverman, 1999), we argue that the cumulated breadth and depth of firms' prior knowledge integration capabilities can provide them with various experience-based advantages to achieve invention impact. This distinction clarifies the ambiguous role of firms' pre-diversification resources and capabilities in contributing towards the creation of impactful inventions.

5.2 Policy and managerial implications

In terms of policy, the acceleration of eco-innovation and its effective diffusion are relevant to both public and private sectors to address the growing concerns of human-induced climate change and environmental degradation. Our study provides policymakers with a better understanding of how firms pursue environmental innovation and its consequential technological usefulness. Eco-innovation is not firms' simple response to regulatory pressures, but a result of firms' past efforts in accumulating technological resources and developing their capabilities (Breschi et al., 2003). Thus, an effective policy intervention design should not only target the reconfiguration of firms' existing technological resources but also foster their knowledge integration capabilities. Our study recommends placing policy focus on facilitating diversification into those green domains to which firms' technological profile is moderately related. Moreover, firms' pre-entry breadth capabilities in integrating cross-domain knowledge enable them to achieve optimal impact at lower levels of green relatedness, while depth capabilities in niche areas raise the overall levels of invention impact when firms exploit their existing knowledge base. Thus, by attentively evaluating firms' technological attributes and integration capabilities, policymakers can provide more tailored support to enable firms to maximise their eco-invention impact and bring greater benefits to the wider society.

Regarding managerial implications, our study helps firms to refocus their eco-innovation efforts based on the degree of their technological resource relatedness to their target green domains and their knowledge integration capabilities. For established firms that previously only made conventional offerings, diversifying into green domains for the first time is not straightforward. This requires additional effort and investment to overcome organisational inertia (Barbieri et al., 2020). Our study shows that the dependence on resources excessively related to the target green domains reduce the impact of consequential innovation efforts, making their green transition trajectories ineffective. We show that there is an optimal level of green technological relatedness, beyond which the consequential invention impact starts depreciating. Investing in depth capabilities can provide firms with a more comprehensive understanding of causal relationships in a domain. Firms can further raise the overall impact of their inventions when exploiting the existing, green-related technological resources. Conversely, fostering breadth capabilities allows firms to develop broad cross-domain integration capabilities and lowers required extent of green relatedness to reach optimal impact, even though the overall impact becomes smaller than before. Thus, managers are advised to systematically evaluate their firms' green technological relatedness and integration capabilities before choosing to target green domains to maximise both financial and technological value.

5.3 Research limitations and direction for future research

In closing, we acknowledge our research limitations and identify some areas for further research. First, we chose China's leading science park as our empirical setting. Firms based in this unique emerging market context have demonstrated unprecedented technological advancements over a short period. While we assure a rich pattern of diversification into green domains, our results might be more pronounced in other countries or in less prominent clusters. Consequently, the generalisation of our results can be restricted to the Chinese context or to clusters with rapid expansion. We invite future studies to explore the proposed mechanisms in other contexts or in a cross-country setting. Second, due to data limitations, we could not control for the effects of internal R&D teams, external collaboration networks, paradigm shifts in industrial technology, or the specificities of stakeholder pressures or government subsidy programs (Schillebeeckx et al., 2020; Ceipek et al., 2019). Third, our study was exclusively based on firms' patents and citations data for assessing their resources and capabilities. This may underestimate firms' full eco-invention impact (Ning et al., 2016). Fourth, prior research has undertaken a dynamic analysis of firms' resources and capability for value creation (Helfat and Raubitschek, 2018). Future research can consider disentangling the effects of depth and breadth capabilities on inventions and explore their diminishing returns. Fifth, future research can explore other contingencies that might moderate the relationship between firms' technological relatedness and green invention impact. These include non-market factors such as reputation, the complexity of industrial competition, internal organisational and managerial strategic changes (Ceipek et al., 2019) and the impact of regional capabilities (Neffke et al., 2011; Santoalha, 2019; Boschma, 2017)[1]. In doing so, future research can provide a more holistic understanding of how different resource attributes influence the impact of firms' green inventions. Nevertheless, our study opens avenues for research into the technological diversification of established firms in developing impactful green inventions.

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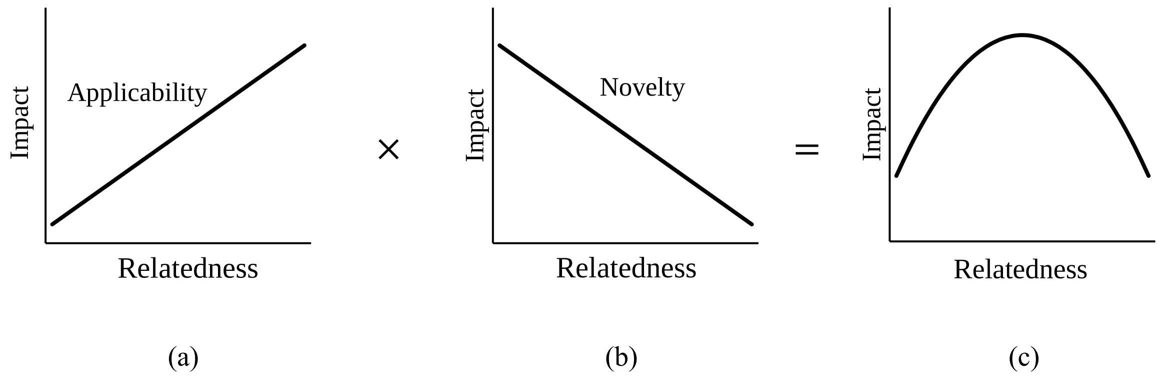


Figure 1 The multiplicative combinations of latent mechanisms resulting in an inverted U-shaped relationship

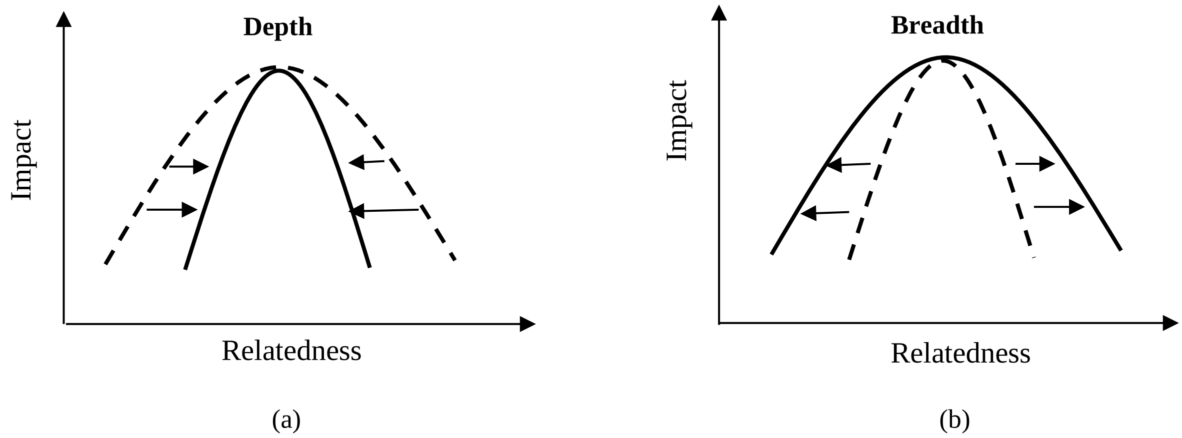


Figure 2 The hypothesized moderating effects of depth and breadth capabilities on the concave relationship between technological relatedness and green invention impact

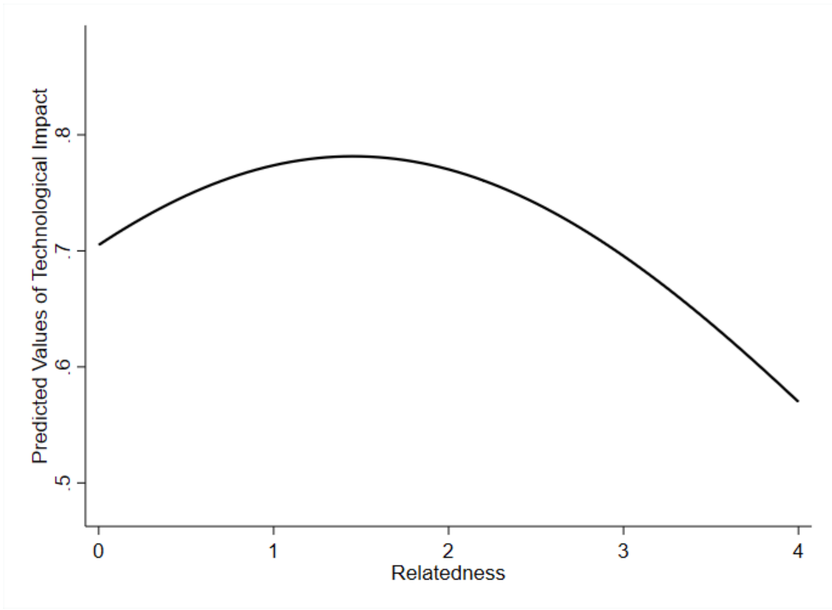
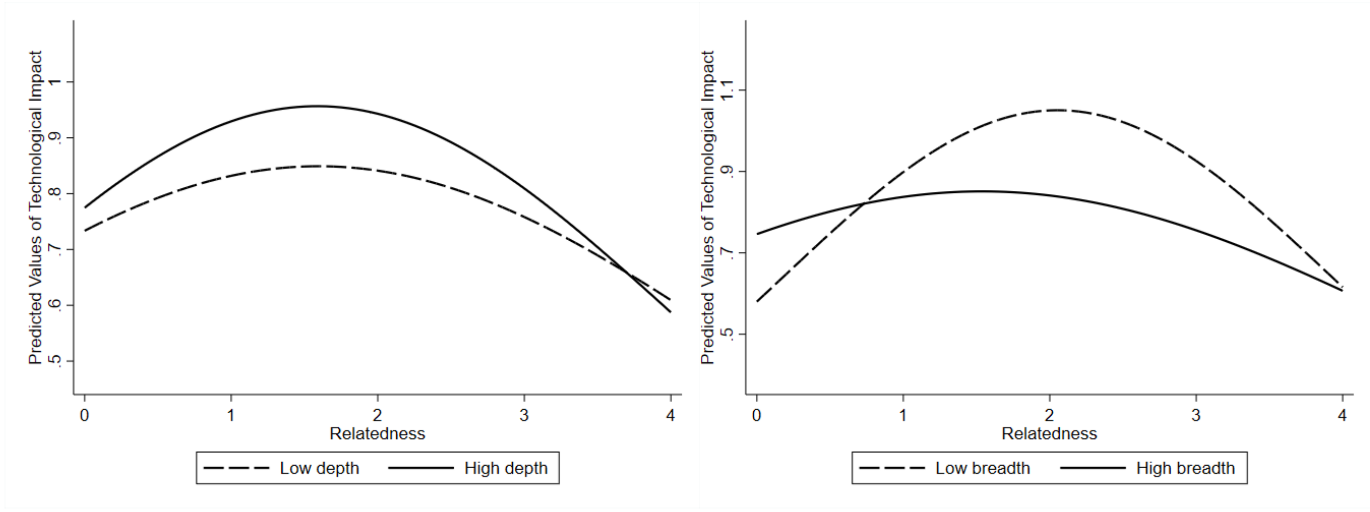
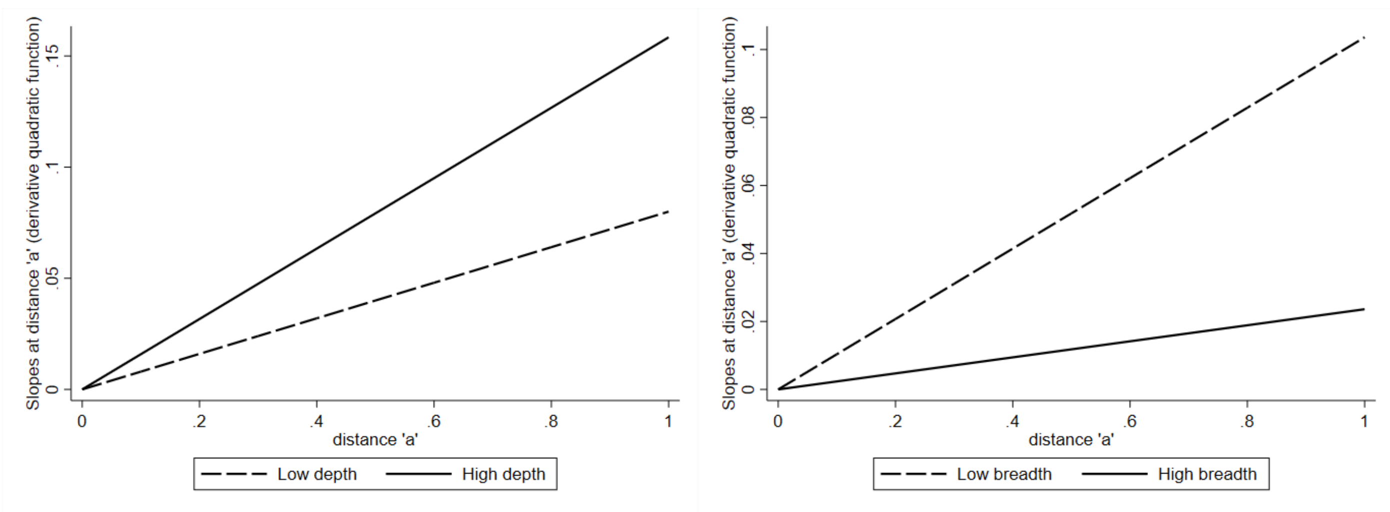


Figure 3 Technological relatedness and invention impact



(a) (b)

Figure 4 The moderating effect of capability depth and breadth on the relationship between technological relatedness and invention impact



(a) (b)

Figure 5 Analyses of the slopes from the inflection point at distance 'a'.

Table 1 WIPO Green IPC Classifications and Patent Sample Distribution

Innovation types	Sub-innovation types	IPC classifications	Share. of Patents
Alternative energy production	Integrated gasification	C10L 3/00	1.73%
		F02C 3/28	0.25%
	Fuel cells	H01M [4/86-4/98, 8/00-8/24, 12/00-12/08]	1.09%
	Pyrolysis	C10B 53/00	0.69%
		C10J	0.59%
	Ocean energy	F03G 7/05	0.10%
	Wind	F03D	1.43%
	Solar	F24S	0.05%
		H02S	0.74%
	Nuclear	G21	1.14%
		F02C 1/05	0.20%
	Other use of heat	F24T [10/00-50/00]	0.00%
		F24V [30/00-50/00]	0.00%
		F03G [5/00-5/08]	0.05%
Transportation	Rail vehicles	B61	3.46%
	Cosmonautic vehicles	B64G 1/44	0.15%
Energy conservation	Storage of electrical energy	B60K 6/28	0.94%
		B60W 10/26	0.25%
		H01M [10/44-10/46]	1.48%
		H01G 11/00	0.39%
		H02J [3/28, 7/00, 15/00]	1.38%
	Power supply circuitry	H02J	8.98%
		B60L 3/00	0.54%
		G01R	16.19%
	Storage of thermal energy	C09K 5/00	1.48%
		F24H 7/00	2.37%
		F28D [20/00, 20/02]	3.41%
		E04B [1/62, 1/74-1/80, 1/88, 1/90]	3.21%
	Recovering mechanical energy	F03G 7/08	0.05%
Waste management	Waste disposal	B09B	1.92%
		B65F	0.30%
	Consuming waste by combustion	F23G	1.58%
Agriculture/forestry	Forestry techniques	A01G 23/00	1.53%
		A01G 25/00	1.09%
	Pesticide alternatives	A01N [25/00-65/00]	2.27%
	Soil improvement	C09K 17/00	2.07%
		E02D 3/00	3.46%
Administrative regulatory or design aspects	HOV, teleworking	G06Q	25.27%
		G08G	4.84%
	Static structure design	E04H 1/00	3.36%

Notes: (1) total number of sample patents: 1,990. (2) Sources: World Intellectual Property Organization (WIPO), Green IPC inventory, November 2020, accessed at www.wipo.int/classifications/ipc/en/green_inventory/

Table 2 Four Selected Cases of Technological Diversification into the Green Domains

Firms	A	B	C	D
Industries	Software Application Services	Computer, software and auxiliary equipment	Crude oil processing and petroleum products manufacturing	Cement product manufacturing
Year of Establishment	2006	2005	2002	2002
First green patents	Traffic instruction system	Teleworking	Heat-transfer, exchange and storage materials	Disposal of solid waste
Green IPC	G08G 1/01	G06Q 10/06	C09K 5/00	B09B 3/00
IPC subclasses of knowledge stock	H04Q, H04M, G10L	G06F, G11B, H04L, H05K	C10M, C10N, C23C, C23G	B28B, E03F, E04C, C04B
Entry year	2008	2011	2011	2009
Previous technologies.	Software systems in telephonic communication.	Digital data processing and information storage, including transmission of digital information and cloud storage systems.	Core technologies in chemical lubricating compositions; cleaning or pickling metallic material with solutions or molten salts.	Core technologies in cement manufacturing and other building materials.
Green innovation	Applied the core technology to develop an intelligent transportation solution & service system with applications for improving travel efficiency and reducing traffic emissions.	Used data management technologies to develop a teleworking system that reduces commuting costs and energy consumption.	Developed new materials that improves the energy reservation application of their lubrication products that reduce the heat-loss in manufacturing equipment.	Developed a technology that breaks down solid waste and transforms it into recycled building materials.

Note: firms' names are anonymized for data protection purposes.

Table 3 Descriptive statistics and correlation matrix

Variables	Mean	Std.Dev.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12
Impact	0.807	1.530	0	8	1.000											
Relatedness	1.116	1.566	0	4.032	-0.016	1.000										
Depth	1.047	1.148	0	4.220	0.005	0.111	1.000									
Breadth	1.256	1.476	0	5.193	0.051	0.233	0.319	1.000								
Firm size	587.9	3850	0.025	130000	-0.018	-0.002	0.056	0.073	1.000							
Firm age	9.968	9.719	1	116	-0.082	0.027	0.063	0.078	0.054	1.000						
Firm R&D intensity	0.059	0.090	0	0.620	0.023	0.001	0.050	0.052	0.011	-0.009	1.000					
Knowledge stock	6.135	18.560	0	443	-0.056	0.281	0.322	0.378	0.071	0.107	0.064	1.000				
Domain competition	10.150	3.205	1.751	16.50	-0.093	-0.044	0.055	0.036	0.024	0.076	0.021	0.073	1.000			
Collaborative patent	0.037	0.164	0	1	0.002	0.018	0.084	0.071	0.059	0.055	0.002	0.131	0.007	1.000		
Knowledge spillovers	0.057	0.044	0	0.920	0.023	-0.028	0.020	0.016	0.075	0.007	0.054	0.006	0.094	0.061	1.000	
Environmental stringency	87185	8391	70400	99200	0.205	0.045	0.085	0.158	0.055	0.212	0.035	0.225	0.377	0.059	0.094	1.000

Notes: (1) N=1,990; (2) All absolute correlation coefficients greater than 0.008 are significant at the 5 percent level.

Table 4 Green Domain Entry Propensity: The First-Stage Heckman Probit Model

	Green domain Entry (0=No, 1=Yes)	
VARIABLES	Estimate	SE
Firm size	0.124***	(0.006)
Firm age	-0.007***	(0.002)
R&D intensity	0.043***	(0.006)
State-ownership	0.047	(0.047)
ROA	0.494***	(0.097)
Knowledge stock	0.369***	(0.009)
Collaboration	0.456***	(0.060)
Environmental stringency	0.164**	(0.081)
Knowledge spillovers	0.062	(0.076)
Relatedness	0.028***	(0.000)
Constant	-3.623***	(1.283)
Year dummies	Included	
Industry dummies	Included	
LR Chi^2	26957.40	
Pseudo R^2	0.575	
Log likelihood	-9960.87	

Notes: (1) Estimations are based on a panel of 23,677 sample firms; (2) state-ownership is a dummy variable; ROA is the average ratio of firms' total profit over total assets at the two-digit industry level; all other variables are defined in section 3.1; (3) Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5 Zero Inflated Negative Binomial and Poisson Analyses with Heckman corrections for Green Technological Impact

VARIABLES	(1) Impact ZINB	(2) Impact ZIP	(3) Impact ZINB	(4) Impact ZIP	(5) Impact ZINB	(6) Impact ZIP	(7) Impact ZINB	(8) Impact ZIP	(9) Impact ZINB	(10) Impact ZIP
Firm size	-0.027	-0.029*	-0.045**	-0.045**	-0.055***	-0.059***	-0.041**	-0.041**	-0.058***	-0.055***
	(0.017)	(0.016)	(0.018)	(0.018)	(0.016)	(0.020)	(0.018)	(0.018)	(0.022)	(0.021)
Firm age	-0.005*	-0.005	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
R&D intensity	0.004	0.007	0.004	0.003	0.003	0.000	0.001	0.002	0.003	0.008
	(0.017)	(0.015)	(0.017)	(0.017)	(0.015)	(0.018)	(0.017)	(0.017)	(0.020)	(0.020)
Knowledge stock	-0.047	-0.063*	-0.095*	-0.090*	-0.135***	-0.150***	-0.130**	-0.127**	-0.183***	-0.168***
	(0.039)	(0.032)	(0.050)	(0.050)	(0.043)	(0.054)	(0.057)	(0.058)	(0.058)	(0.058)
Domain competition	0.034***	0.033***	0.024**	0.024**	0.018*	0.019	0.025**	0.024**	0.020*	0.021*
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.012)	(0.010)	(0.010)	(0.011)	(0.011)
Collaboration	0.221	0.218	0.153	0.167	0.132	0.105	0.189	0.204	0.126	0.168
	(0.199)	(0.145)	(0.205)	(0.210)	(0.147)	(0.178)	(0.203)	(0.207)	(0.209)	(0.209)
Environmental stringency	0.039***	0.022***	0.038***	0.037***	0.018***	0.019***	0.039***	0.039***	0.019***	0.019***
	(0.007)	(0.004)	(0.007)	(0.007)	(0.004)	(0.004)	(0.007)	(0.007)	(0.004)	(0.004)
Knowledge spillovers	0.935	0.915	0.894	0.911	0.745	0.674	0.884	0.902	0.683	0.798
	(0.790)	(0.775)	(0.803)	(0.802)	(0.768)	(0.932)	(0.795)	(0.792)	(0.883)	(0.887)
Relatedness			0.197**	0.195**	0.186**	0.199**	0.262***	0.262***	0.301***	0.294***
			(0.094)	(0.095)	(0.086)	(0.96)	(0.100)	(0.101)	(0.112)	(0.103)
Relatedness square			-0.067***	-0.071***	-0.051**	-0.058*	-0.080***	-0.079***	-0.075**	-0.084***
			(0.025)	(0.026)	(0.025)	(0.031)	(0.028)	(0.028)	(0.034)	(0.029)
Depth					0.023***	0.022***			0.016**	0.015**
					(0.006)	(0.007)			(0.008)	(0.007)
Relatedness*Depth					0.026**	0.028*			0.032***	0.028***
					(0.012)	(0.015)			(0.011)	(0.008)
Relatedness squared*Depth					-0.011**	-0.013**			-0.014**	-0.013**
					(0.006)	(0.007)			(0.007)	(0.006)
Breadth							0.036***	0.037***	0.059***	0.044**
							(0.010)	(0.010)	(0.022)	(0.021)
Relatedness*Breadth							-0.025***	-0.026***	-0.023***	-0.021**
							(0.009)	(0.009)	(0.005)	(0.009)

Relatedness squared*Breadth							0.004**	0.006***	0.004***	0.007**
							(0.002)	(0.002)	(0.001)	(0.003)
IMR	-0.240***	-0.259***	-0.238***	-0.225***	-0.223***	-0.268***	-0.243***	-0.230***	-0.279***	-0.238***
	(0.053)	(0.051)	(0.090)	(0.083)	(0.064)	(0.094)	(0.089)	(0.082)	(0.102)	(0.083)
Constant	1.407***	1.410***	1.132**	1.174**	1.857***	1.993***	1.224***	1.226***	1.831***	1.987***
	(0.509)	(0.475)	(0.549)	(0.531)	(0.470)	(0.518)	(0.435)	(0.429)	(0.451)	(0.466)
Year dummies	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Industry dummies	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Green IPC dummies	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
LnAlpha	-2.384***	N/A	-2.450***	N/A	-1.695***	N/A	-2.546***	N/A	-1.724***	N/A
Vuong test	56.17***	29.73***	55.48***	29.81***	62.98***	30.09***	55.45***	30.18***	62.52***	30.98***
LR Chi2	276.18	82.59	309.20	321.77	118.01	180.83	359.17	401.88	172.53	219.81
Log likelihood	-1306.904	-1367.399	-1301.723	-1346.176	-1349.688	-1304.086	-1332.92	-1294.490	-1301.002	-1344.969
Observations	1,990	1,990	1,990	1,990	1,990	1,990	1,990	1,990	1,990	1,990

Notes: (1) Vuong test is to test the standard negative binomial (Poisson) model v.s. Zero inflated negative binomial (Poisson) model. (2) Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 6 Zero Inflated Negative Binomial Analyses with Heckman Corrections for Green Technological Impact – Subsample Analysis by Knowledge Stock

	Patent ≥ 1	Patent ≥ 2	Patent ≥ 3	Patent ≥ 4	Patent ≥ 5	Patent ≥ 6
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Firm size	-0.054**	-0.052**	-0.058*	-0.055**	-0.053**	-0.043**
	(0.025)	(0.026)	(0.030)	(0.023)	(0.025)	(0.021)
Firm age	-0.007	-0.011*	-0.011	-0.007	-0.006	-0.005
	(0.006)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
R&D intensity	0.015	0.001	0.004	0.023	0.037	0.059
	(0.024)	(0.028)	(0.031)	(0.034)	(0.036)	(0.039)
Domain competition	0.024	0.021	0.022	0.041**	0.033*	0.055**
	(0.016)	(0.018)	(0.020)	(0.021)	(0.019)	(0.025)
Collaboration	0.572***	0.548**	0.575**	0.605**	0.662**	0.671**
	(0.187)	(0.237)	(0.293)	(0.296)	(0.300)	(0.307)
Environmental stringency	0.021***	0.020***	0.022***	0.023***	0.023***	0.023***
	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Knowledge spillovers	0.995	0.949	0.961	0.887	0.762	0.791
	(1.131)	(1.252)	(1.395)	(1.465)	(1.565)	(1.655)
Relatedness	0.273**	0.397***	0.260**	0.206**	0.280***	0.496**
	(0.113)	(0.134)	(0.125)	(0.099)	(0.091)	(0.217)
Relatedness square	-0.092***	-0.128***	-0.060**	-0.079**	-0.118**	-0.173***
	(0.036)	(0.041)	(0.026)	(0.033)	(0.058)	(0.063)
Depth	0.015***	0.022**	0.020**	0.021**	0.019**	0.032*
	(0.003)	(0.010)	(0.010)	(0.010)	(0.010)	(0.017)
Relatedness*Depth	0.028**	0.025***	0.040**	0.040**	0.038**	0.041**
	(0.013)	(0.008)	(0.018)	(0.018)	(0.018)	(0.019)
Relatedness squared*Depth	-0.007**	-0.006**	-0.011**	-0.010**	-0.010**	-0.013**
	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.006)
Breadth	0.053**	0.052**	0.050**	0.050**	0.049**	0.036*
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.020)
Relatedness*Breadth	-0.038**	-0.039**	-0.032*	-0.034**	-0.038**	-0.038**
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)
Relatedness squared*Breadth	0.006**	0.006**	0.006**	0.006**	0.007**	0.009**

	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
IMR	-0.396***	-0.530***	-0.459***	-0.457**	-0.631***	-0.671***
	(0.142)	(0.162)	(0.178)	(0.205)	(0.223)	(0.241)
Constant	1.408***	1.365***	1.327***	1.301***	1.413***	1.374***
	(0.513)	(0.474)	(0.429)	(0.491)	(0.422)	(0.507)
Year dummies	Included	Included	Included	Included	Included	Included
Industry dummies	Included	Included	Included	Included	Included	Included
Green IPC dummies	Included	Included	Included	Included	Included	Included
lnalpha	-3.143***	-4.122***	-4.821***	-2.829***	-2.877***	-2.739***
Vuong test	43.13***	36.72***	33.35***	37.10***	33.37***	32.83***
LR Chi2	51.26	46.54	53.48	49.16	53.36	48.24
Log likelihood	−573.218	−498.186	-414.445	-349.716	-242.227	−165.371
Observations	1,118	921	762	659	579	512

Notes: (1) Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Appendix

Table A1 Robustness checks

VARIABLES	Alternative 3-year window of dependent variable			Alternative control variables			Linear spline
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Firm size	-0.028	-0.023	-0.023	-0.046*	-0.040*	-0.039*	-0.047***
	(0.020)	(0.020)	(0.020)	(0.024)	(0.024)	(0.024)	(0.018)
Firm age	-0.002	-0.002	-0.002	-0.004	-0.004	-0.004	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
R&D intensity	0.006	0.005	0.002	0.004	0.006	0.005	0.005
	(0.018)	(0.018)	(0.018)	(0.011)	(0.011)	(0.011)	(0.017)
Knowledge stock	-0.149***	-0.181***	-0.211***	-0.110***	-0.150***	-0.155***	-0.104**
	(0.045)	(0.059)	(0.057)	(0.042)	(0.055)	(0.052)	(0.048)
Domain competition	0.024**	0.024**	0.024**	0.028***	0.027***	0.028***	0.023**
	(0.012)	(0.012)	(0.012)	(0.010)	(0.010)	(0.010)	(0.011)
Collaboration	0.182	0.159	0.166	0.122	0.139	0.151	0.151
	(0.199)	(0.200)	(0.201)	(0.165)	(0.164)	(0.164)	(0.201)
Environmental stringency	0.009**	0.009**	0.009**	0.022***	0.022***	0.022***	0.036***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)
Knowledge spillovers	0.675	0.684	0.621	1.088	1.087	0.928	0.783
	(0.426)	(0.425)	(0.414)	(1.191)	(1.188)	(1.184)	(0.794)
Relatedness	0.175**	0.172**	0.214**	0.215**	0.224**	0.277***	
	(0.086)	(0.088)	(0.107)	(0.088)	(0.101)	(0.098)	
Relatedness square	-0.068**	-0.052*	-0.064**	-0.076***	-0.065**	-0.082***	
	(0.029)	(0.032)	(0.030)	(0.025)	(0.029)	(0.027)	
Depth		0.040**			0.042**		
		(0.018)			(0.018)		
Relatedness*Depth		0.014			0.017		
		(0.023)			(0.021)		

Relatedness squared*Depth		-0.015**			-0.014**		
		(0.007)			(0.006)		
Breadth			0.045***			0.039***	
			(0.013)			(0.012)	
Relatedness*Breadth			-0.019**			-0.025**	
			(0.009)			(0.012)	
Relatedness squared*Breadth			0.003***			0.004***	
			(0.001)			(0.001)	
Low Relatedness							0.429***
							(0.138)
High Relatedness							-0.295***
							(0.075)
IMR	-0.310***	-0.299***	-0.306***	-0.230***	-0.223***	-0.233***	-0.239***
	(0.085)	(0.087)	(0.087)	(0.078)	(0.078)	(0.078)	(0.082)
Constant	1.171**	1.191**	1.138**	2.293***	2.369***	2.381***	1.900**
	(0.522)	(0.521)	(0.521)	(0.499)	(0.472)	(0.477)	(0.867)
Year dummies	Included	Included	Included	Included	Included	Included	Included
Industry dummies	Included	Included	Included	Included	Included	Included	Included
Green IPC dummies	Included	Included	Included	Included	Included	Included	Included
lnalpha	-3.112***	-4.013***	-4.316***	-2.798***	-2.936***	-2.765***	-3.659***
Observations	1,990	1,990	1,990	1,990	1,990	1,990	1,990

Notes: (1) The dependent variables for Models 1-3 are measured by the accumulation windows three years; (2) Models 4-6 use alternative measurements of our control variables, including R&D intensity, measured by the ratio of R&D expenditure scaled by total sales; firms' size, proxied by the total number of employees; and local knowledge spillovers, proxied by industrial R&D per employee at a two-digit level; (3) Model 7 is estimated using the linear spline model. As shown, at low level, the technological relatedness has a significantly positive impact of patent citation; while at high level, the technological relatedness has a significantly negative impact. The results further confirm the non-linear relationship between a firm's technological relatedness and green technological impact. (4) Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

[1] This paper focuses exclusively on firms' innovation management literature in understanding how technological relatedness affects the diversification of firms' technological portfolios. It is rooted in the work of (Breschi, Lissoni, & Malerba, 2003; Leten, Belderbos, & Van Looy, 2007). At the aggregated industry or regional level, a strand of economic geography literature on relatedness deliberates how the heterogeneity of local capabilities such as infrastructure, natural resources, institutional conditions, and pre-existing local knowledge or skills can lead regions to diversify into new industrial activities (Boschma, 2017; Neffke, Henning, & Boschma, 2011; Santoalha, 2019). Although our contribution is limited to the firm-level literature, it provides a micro perspective on possible reconfigurations for firms' resources and capabilities to pursue impactful green innovation in new technological domains. Future research can build on our work and bridge the relatedness research to enrich our understanding on how the regional capabilities can influence firms' green technological diversification.

[2] We adopt the absolute IPC combination numbers rather than a concentrated or scaled index, following the previous research by George, Kotha, and Zheng (2008), Kotha, Zheng, and George (2011), and Xu (2015) Compared with the index based on the absolute IPC numbers, the latter two types of indices may underestimate firms' depth or breadth capabilities. Regarding depth, for example, consider two firms A and B. Firm A has 10 patents in 2 IPC subclasses with 6 within-subclass combinations each. Firm A's score scaled by its patent portfolio size is 0.6, calculated as [6/10]. Firm B has 15 patents in 7 IPC subclasses, including 9 within-subclass combinations in one single subclass and 1 within-subclass combination each in the rest of the 6 subclasses. Firm B's score scaled by portfolio size is 0.6, calculated as [9/15]. When calculated by the concentration index, firm A's score is 0.72, calculated as $[0.6^2+0.6^2]$, whereas Firm B's score is 0.387, calculated as $[0.6^2+6*(1/15)^2]$. In both cases, firm B has greater depth, but smaller scores. This causes underestimation of Firm B's depth capabilities. The breadth scores also suffer from similar distortion. Therefore, we have decided to follow the previous literature and use the absolute count of combination numbers. This also allows for comparison and consistency with the previous literature.