THREE ESSAYS ON FIRM INNOVATION STRATEGY: INNOVATION OF INTERNET OF THINGS AND GREEN TECHNOLOGIES

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Doctor of Philosophy

ASTON UNIVERSITY
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THESIS SUMMARY

The last few decades have seen an accelerating pace of fundamental transformations in the business environment driven by digital technologies and the emergence of the green agenda. These are known as the digital and green transitions, largely pushed by technological advancements and innovation. Given the profound impact of such two transitions on the business operations and environment, it is crucial for both researchers and policy makers to improve their understanding of what these big trends mean for businesses and how market players should strategise for responding to these technological transformations to maximise the benefits and mitigate the risks. We attempt to tackle these big problems by probing into the fundamental technological trends underlying these two transitions.

This thesis is developed to investigate how companies react to the ongoing economic and societal challenges during the digital and green transitions by searching for answers to three related research questions. In particular, we intend to understand how businesses develop their technological competence or capacity for creating ground-breaking innovation within Industry 4.0 as well as environmental innovation under the current global endeavour to achieve SDGs. We also propose to analyse how the wave of green technology influences economic performance of businesses in the wider economy through the diffusion of green innovation.

The work is composed of three empirical chapters, mainly drawing upon patent information from the Bureau van Dijk's Orbis Intellectual Property (Orbis IP) database, Environmental, Social and Governance (ESG) practices from the Thomson Reuters ASSET4 database, and firm-level information from the Orbis database.

The first empirical study focuses on the innovation of Internet of Things (IoT) technologies and advances our understanding of the route towards pathbreaking innovation activities undertaken by the UK firms. Firms often face a tension between innovation persistence in their technological core competence and technological diversification that typically expands the boundary of knowledge. This tension is especially acute in the case of pathbreaking technologies such as the IoT, a core infrastructure element of Industry 4.0. Centring on the factors that drive firms' creation of ground-breaking IoT technologies, we investigate how companies' technology trajectory in terms of their core-technology competence, technology diversification, and innovation persistence affects pathbreaking innovation, as measured by IoT patenting. We develop theory suggesting that technological core competence is inimical to engagement in IoT patenting, whereas possessing a technological related and unrelated knowledge base is positively linked to IoT innovation.

Multinational enterprises (MNEs), especially those from the developed economies, present an important context for studying sustainability related issues (e.g., environmental innovation) for they possess resources and abilities to promote social and environmental values, potentially leading on global economic and environmental development. Drawing on the global connectedness of MNEs and knowledge-based perspective, the second empirical chapter conceptually develops the theory of the diverse antecedents of environmental innovation from the perspective of MNE connectivity through networked relationships for production and innovation. Employing Environmental, Social and Governance (ESG) data from Thomson Reuters ASSET4 database of developed country MNEs whose headquarters are in France, Germany, the United Kingdom, and the Netherlands, our empirical tests support our conjectures. Wider global linkages built on production networks, and intra- and inter-MNE innovation co-production linkages contribute to a MNE's capability to produce environmental innovation. However, intra-organisational linkages motivated by traditional control and coordination mechanisms do not play an important role in environmental innovation capacity. Our findings

emphasise that specific types of ties related to knowledge connectivity and innovation collaboration matter more for environmental innovation than general control and coordination linkages. As such, this chapter enriches the international business (IB) literature by understanding MNEs' internationalisation strategies and cross-border innovation management in the light of the contemporary challenges and opportunities presented by the need to respond to the climate emergency. To put it another way, we contribute to an important intersection between IB literature and the environmental innovation field by explaining its determinants from a novel IB and management perspective. Policy implications are drawn for practitioners and policymakers to effectively foster and stimulate organisations' environmental innovation capacity.

The third empirical study focusses on the wider impacts of green innovation and the dynamics pertaining to its diffusion within a UK context. Research on environmental innovation has largely focused on the determinants of such innovation development, its internal impacts on the focal firm, and external impacts on the sectoral environmental performance. Despite this, we still lack understanding of how green technology interacts with the local economy and thus affects other firms' economic performance. By connecting the environmental innovation literature with economic geography arguments on agglomeration externalities, we fill the knowledge gap by investigating the economic relevance of green innovation spillovers on the performance of other related businesses within the same locality and revealing the conditions under which the spillovers can happen. Moreover, we consider how different dimensions of absorptive capacity affect firms' ability to leverage green innovation externalities and absorb such spillovers. To the best of our knowledge, this is the first study to investigate the spillover effects of green innovation via both horizontal and vertical linkages in driving firm-level productivity and employment growth, which tends to offer important implications for both practitioners and policy makers.

Key words: Industry 4.0, Pathbreaking IoT technologies, Innovation persistence, Environmental innovation, Developed country MNEs, Global connectedness, Intra- and inter-organisational linkages, Agglomeration externalities, Green innovation diffusion, Core-technology competence, Technological diversification

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CHAPTER 1: INTRODUCTION

1.1 Research context

The overarching aim of the thesis is to study how businesses are responding to the contemporary economic and societal challenges that have led to fundamental transformations in the business environment during the digital [1] and green transition [2]. Specifically, it investigates pathbreaking innovation and environmental innovation[3]. It looks at how companies can develop the capacity or technological competence for generating (i) pathbreaking innovation within the fourth industrial revolution, and (ii) environmental innovation that addresses the global sustainability challenge. It also explores how the wave of green technology affects businesses in the wider economy through different channels of diffusion.

In the early 21st century, businesses are pressed for transformations driven by digital technologies and the emergence of the green agenda. These are known as the digital and green transitions. Accordingly, Zhan (2021) identifies five forces[4] driving the transformation of global value chains (GVCs) in the coming decade. Of these, technology/Industry 4.0 and the sustainability imperative appear to be the two most important, with their key elements creating long-term social and economic challenges and opportunities, effecting a GVC transformation that will reshape global trade trends and the investment landscape. A common feature of Industry 4.0 and the sustainability imperative is that they are largely driven by technological advancements and innovation.

The current wave of technological advancement amounts to a digital technological revolution (Ghobakhloo, Iranmanesh, Grybauskas, Vilkas and Petraitė, 2021; Li, Fast-Berglund and Paulin, 2019), which is commonly known as the fourth generation of industrial revolution (Industry 4.0)[5]. We have witnessed radical changes to real world operations, with production systems becoming incorporated with business intelligence (Choi, Kumar, Yue, and Chan, 2021). In the Industry 4.0 era, technological advances in a variety of ground-breaking disruptive technologies are revolutionising business operations by using machines for knowledge work (e.g., smart manufacturing and intelligent

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[1] This concept denotes the transition from analog to digital processes which enables digital tools to model processes and activities, thus improving performance and productivity (Rosário and Dias, 2022).

[2] It represents a process towards a new development model that ensures environmentally sustainable and fairer societies. It is a necessity to address the human-induced climate change emergency, environmental degradation (water, land, forests, atmosphere) as well as the loss of biodiversity (European Training Foundation, 2022).

[3] Environmental innovation refers to products, processes, or management practices designed to reduce and prevent harm to the environment, in which we follow Beise and Rennings (2005) and Rennings and Zwick (2002).

[4] The five driving forces suggested are economic governance realignment, technology and the new industrial revolution, the sustainability imperative, corporate accountability, and resilience-oriented restricting.

[5] It is a term created to represent the digitalisation of industries. A number of related terms are used in different countries, such as ‘smart manufacturing’, ‘industrial internet’, ‘intelligent manufacturing’, ‘advanced manufacturing’, and ‘smart factory’. Typical Industry 4.0 technologies include redistributed manufacturing, additive manufacturing, digital twins, autonomous robots, Big Data, and IoT.

production), and transforming traditional mass production into flexible production wrought by digital means (Choi *et al*, 2021). By means of these technological-push transformations, businesses can enjoy a range of economic benefits in terms of improved manufacturing agility, operational efficiency, product quality, and overall profitability (Dalenogare, Benitez, Ayala and Frank, 2018). To successfully realise the enormous potential of Industry 4.0 and respond to the paradigm shift, it is crucial to understand the characteristics of the underlying technologies and to be conscious of the potential issues and risks presented by the revolution (Choi *et al*., 2021).

The sustainability imperative is a by-product of the green transition triggered by numerous ecological crises and stricter environmental regulations (Lampikoski, Westerlund, Rajala and Möller, 2014). Indeed, related environment issues are pressurising management teams to rethink their business models, driving enterprises to view corporate sustainability as a matter of strategy (Lampikoski *et al*., 2014). Given the increasingly crucial role of sustainable thinking in business management, scholars and practitioners are attempting to figure out how sustainability can be introduced into business practices and products, with a view to prioritising environmental concerns and securing social wellbeing (Awan, Arnold and Gölgeci, 2020). To reach the mounting sustainability expectations of various stakeholders, businesses are turning to environmental innovation to promote energy-conscious production, create cleaner technologies, produce eco-friendly and customized products, and build their industries that are, overall, sustainable (Chiarini, 2021). That being said, the process of exploration is challenging because green innovation is risky and can result in failure, and more importantly, corporate sustainability does not provide managers with clear guidelines for effective management (Lampikoski *et al*., 2014). Thus, the transition towards corporate sustainability warrants investigation, particularly with regard to the factors that will drive and facilitate businesses to successfully act on the mission. Firms can thereby gain valuable insights on how to capitalise on the opportunities provided by environmental innovations, grow their businesses in line with the principles of sustainability, and mitigate the destructive impacts of market turbulence.

The role of businesses in mitigating environmental harm and effecting a green transformation has been widely recognised both in academic and practitioners' discussions (Przychodzen, Leyva-de la Hiz, and Przychodzen, 2019). Businesses make strategic choices and act to become the first movers in green-oriented innovative activities, with a view to improving their existing capabilities and competitive positions (Berrone, Fosfuri, Gelabert and Gomez-Mejia, 2013). Companies at the forefront of green innovation may create technological advances, influence consumers' cognitive positions, and trigger creative destructions derived from new solutions. In turn, they can exert enormous impacts on the rest of the related firms within their geographic locality. As such, there is a need to get a sense of how the strategic choices made by the first movers affect the remaining companies. Businesses in the wider economy may encounter a situation where they can either act on and benefit from the wave of green technology, or take a hit from having a less competitive market position. Understanding the wider impacts of the green technology enabled transformation provides information about not only how other firms should react more constructively to its related opportunities and challenges, but also how the efforts of policy makers can be devoted to supporting this transformation.

Given the profound impacts of the above digital and green transitions on the business operations and business environment, Zhan (2021) advises both researchers and policy makers to improve their understanding of what these big trends mean for businesses; such understanding will shed light on the policy implications of the two driving forces. In other words, in order to fully appreciate the influences of the digital and green transitions, we must probe into the fundamental technological trends underlying them. We can thus reveal what kind of impacts the big trends will have on the economy, and how market players should respond to these technological transformations to maximise the benefits and mitigate the risks.

Building on the two pillars of Industry 4.0 technological revolution and environmental innovation in the context of green transition, the three empirical chapters in the thesis attempt to address these two related topics by searching for answers to three specific sets of research questions.

The first question focuses on businesses that engage in innovating Internet of Things (IoT)[6] technologies within Industry 4.0. Specifically, what are the characteristics of the firms that innovate IoT technologies, and what factors related to their innovation trajectory contribute to their innovation in IoT technological domains?

Moving on to the green transition, we switch our focus to a specific type of corporation, multinational enterprises (MNEs)[7], and ask why some MNEs in the developed countries have a higher capacity than others to undertake environmental innovation, and how their global linkages built on production networks, and intra- and inter-MNE innovation co-production linkages contribute to their capability to produce environmental innovation.

Finally, focusing on green innovation and the dynamics pertaining to green technology diffusion within the wider local economy, we then ask how the externalities generated by green-tech companies affect other firms' economic performance via both horizontal and inter-sectoral linkages? How does a firm's heterogeneous absorptive capacity, measured by intangible assets and technological competences, affect its ability to absorb such spillovers?

[6] IoT describes the network of physical objects that are embedded with sensors, software, and other technologies for the purpose of connecting and exchanging data with other devices and systems over the internet. For more details, see https://www.oracle.com/uk/internet-of-things/what-is-iot/

[7] An MNE is defined as a shareholder with at least one foreign subsidiary during the observation period.

1.2 Brief overview of Chapter 2 – Innovation of IoT technologies

1.2.1 Research question

As a core infrastructure component of Industry 4.0, IoT technologies represent a new paradigm for the information networks. Such technologies possess ground-breaking and boundary-spanning properties because they represent a complex set of infrastructural enabling technologies. They are disruptive in terms of challenging both the conventional business model (Osterwalder and Pigneur, 2011) and how people conceptualise the nature of data, products, and services (Schwab, 2018). Indeed, the complex and disruptive characteristics of IoT make it an exemplar for studying the pathbreaking technologies within Industry 4.0.

The process of innovation tends to be path-dependent with persistence[8] (Cefis and Orsenigo, 2001). The cumulative nature of internal and external knowledge affects the dynamics of the processes through which a firm's knowledge base shapes its new knowledge creation (Antonelli, Crespi and Scellato, 2015). Innovative firms with strong specialised technological competence can be subject to knowledge inertia. This creates knowledge lock-in situations, such that these firms become less likely to produce ground-breaking innovation (Molina-Morales, García-Villaverde and Parra-Requena, 2014). This implies that firms frequently face a tension between innovation persistence in their core-technology competence[9] and technological diversification[10] that usually requires expanding the boundary of knowledge to less competent domains.

However, the existing literature offers limited understanding of the above tension. This is particularly unfortunate in the case of pathbreaking technologies such as the IoT, where the tension may become especially acute. In spite of the significant impacts of IoT technology within this round of technological revolution, we have limited knowledge about the characteristics of the underlying technologies or about which factors will facilitate businesses' participation in attempts to create such technologies and exploit their enormous potential.

As a result, the first chapter of the thesis aims to advance our understanding of the routes for innovating in specific pathbreaking fields within Industry 4.0. Specifically, we investigate how the determinants of IoT innovation differ from those of the more established technologies.

1.2.2 Contribution

The first empirical chapter advances our understanding of the actors who are defining the IoT technology landscape within Industry 4.0 and the route they follow to create pathbreaking IoT

[8] Further discussion can be seen in paragraph 1-2 of Section 2.3 Theory and hypotheses.
[9] Detailed definition and description can be seen in Section 2.4.2.2 Independent variables.
[10] Detailed definition and description can be found in Section 2.4.2.2 Independent variables.

innovation. By integrating the notion of core-technology competence with that of technological diversification in hypothesis testing, we challenge the innovation management literature's concepts of innovation persistence and path dependence within the context of ground-breaking innovation. Based on the negative impacts of core-technology competence on the possibility of innovating IoT technologies, consequently, we develop a theoretical framework suggesting that firms may experience knowledge inertia and knowledge lock-in during knowledge accumulation; these render ground-breaking IoT innovation less likely. By contrast, a diversified technology portfolio enhances the likelihood of engaging in ground-breaking innovative activities.

Empirically, even though three predictors of firm's technological trajectory – innovation persistence, innovation intensity and experience in patenting – all fail to predict innovation propensities in the IoT field, innovation persistence does play a role in enhancing the positive effect of unrelated technological diversification on IoT innovation. Such result offers empirical support to the positive association between persistence and innovation activities.

The fact that previous innovation patterns and experience are not prerequisites for cultivating ground-breaking technologies in Industry 4.0 throws light on the strategic management of innovation. Management teams and policy makers who wish to be ready for this round of technological revolution, whether by planning or stimulating related innovative activities, can gain valuable insights from our findings.

1.2.3 Conceptual framework

In the innovation management literature, the concepts of path dependence and innovation persistence have contributed to a conceptual framework that is commonly employed to explain why some firms can maintain consistently high rates of knowledge creation and innovation. The cumulability, indivisibility, and non-exhaustibility of the knowledge generation process (Antonelli and Colombelli, 2013) and the fact that knowledge stock is a crucial input for knowledge creation play central roles in interpreting the path-dependent character of knowledge generation and the effect of persistence in innovation activities (Crespi and Scellato, 2014).

However, counterarguments may also be found in the extant literature. While knowledge accumulation is important, innovative firms with strong technological competence in specific domains may also experience knowledge inertia and knowledge lock-in, rendering ground-breaking innovation less likely (Boschma, 2005). In such cases, companies face a tension between the innovation persistence in their core competences, and the technological diversification that usually requires expanding the boundary of knowledge to less competent domains (Molina-Morales *et al*., 2014).

Unfortunately, the existing literature offers limited understanding of this tension and its complexities. We therefore investigate it in order to understand better what drives innovation, especially breakthrough innovation in completely new technologies such as the IoT.

1.2.4 Data sources and empirical setting

This empirical work draws on patent information from the Bureau van Dijk's Orbis Intellectual Property (Orbis IP) database to identify Industry 4.0 technologies. Note that in all our empirical chapters, we draw on patent records owned by all UK firms[11], i.e., not only those registered through the UK IPO but also those registered via other patent authorities. This data is then linked with information about UK owners taken from Orbis, a firm-level database provided by Bureau van Dijk. This gives us a final sample of 235,796 patents published by 5,455 UK firms over the period 2008-2017. Following the search strategy suggested by the existing informatics literature (e.g., Martinelli, Mina and Moggi, 2021), patent records can be identified as IoT-related by a set of designated International Patent Classification (IPC) codes belonging to the technological domains of the IoT.

Our dependent variable is a multinomial categorical indicator of firm's different innovation activities. Given that firms may patent in any type or types at one point in time, we design three mutually exclusive and exhaustive set of patenting options: firms with IoT patents (choice 1), firms with information and communications technology (ICT) patents other than IoT ones (choice 2), and firms with non-ICT patents only (choice 3, base group).

In terms of independent variables, we measure firm's core-technology competence following Kim, Lee and Cho (2016), based on its revealed technology advantage (RTA) (Patel and Pavitt, 1997). Next, technological related and unrelated diversification are employed to measure the firm's technological diversity. Following the strategic management literature which has established to use entropy index for quantifying technological relatedness and unrelatedness (e.g., Chen and Chang, 2012; Kim *et al*., 2016; Zander, 1997), our work adopts the method introduced by Kim *et al*. (2016). According to Demirel and Mazzucato (2012) which uses a minimum of five consecutive years of patenting as the criterion to define a persistent patentee, in the present case, we select the idea of an innovation spell implying a firm's innovation state for the last consecutive five years.

Our choice of control variables is guided by the existing literature on innovation outputs and limited by the availability of the data. Essentially, we include two indicators of firm's overall innovativeness: accumulated innovation intensity and patenting experience. We also consider a set of firm characteristics including firm age, firm size, productivity, cash holding, intangible assets ratio,

[11] UK firms are defined as those which are registered and located within the geographical scope of the United Kingdom.

average wage, and foreign ownership, to control for their potential influences on firm's patenting choices.

To identify the key determinants of firms' IoT patenting activities, we adopt a multiple choice modelling approach to model the likelihood of firm's engagement in patenting in three types of technological fields: IoT technologies, ICT technologies more broadly, and other non-ICT technologies. Accordingly, a multinomial logit model is specified given that our dependent variable is a multinomial categorical indicator of firm's different innovation activities and that the three technological pathways are mutually exclusive and exhaustive among all the patenting firms.

We find consistent support for the hypotheses, and they are robust to a number of sensitivity tests. We first consider the measurement issues of the time dimensions of core-technology competence and technological diversification and alternative definition of innovation persistence. More importantly, we adopt an instrument variable strategy for the variation in technological varieties to tackle potential endogeneity by constructing more aggregate variables which are exogenous to firm's strategic innovation choices by construction. The instruments include three region-specific and industry-specific variables[12]. Last but not least, we extend the analysis by considering the extent of patenting in IoT technologies, with the number of IoT patents owned by each firm used as the dependent variable for robustness testing.

1.2.5 Summary of empirical findings

The primary aim of Chapter 2 is to examine the effects of firms' core-technology competence, technological diversification, and innovation persistence on ground-breaking innovation, as measured by IoT technology patenting. It shows that core-technology competence is actually inimical to firms' involvement in IoT patenting. However, having a diversified technological portfolio—both technologically related and technologically unrelated—is strongly positively linked to IoT innovation. Furthermore, we find that innovation persistence, based on the path-dependent nature of the knowledge creation process, fails to directly predict firms' propensity to innovate in IoT. However, it does exert a positive moderating effect, boosting the positive impact of unrelated technological diversification on IoT innovation.

[12] The first variable is the current level of total public R&D related to the IoT and Big data technology in a region, defined by log-transformed R&D grant value (£). The second variable is total number of patentees of the patents registered within a sector, while the last variable is total number of patentees of the patents registered within in a region. Section 2.6.2 provides detailed descriptions and explanations of these three variables.

1.3 Brief overview of Chapter 3 – Connectivity and environmental innovation of developed country MNEs

1.3.1 Research question

The global economy is in the nascent stage of green transformation. In order to meet the sustainability requirements of various stakeholders, companies have undertaken a variety of sustainable innovative initiatives and green innovations; these are crucial to firms' competitiveness while also contributing to an overall environmentally sustainable society (Chiarini, 2021). Clearly, such innovative initiatives and activities also challenge the way companies have always strategised and operated.

MNEs, especially those from the developed economies, present an important context for studying sustainability related issues (e.g., environmental innovation) because MNEs possess the resources and abilities to promote social and environmental values, making them major players in global economic and environmental development (Marin and Zanfei, 2019). They have a crucial role in developing and disseminating environmental innovations through their global research and development (R&D) facilities (Noailly and Ryfisch, 2015), and MNEs that develop a socially responsible attitude and innovative green practices can also influence and put pressure on other organizations through their GVCs and production networks (Aguilera-Caracuel, Aragón-Correa and Hurtado-Torres, 2011; Chang and Gotcher, 2020).

Compared with domestic players, MNEs engage in international business activities by organising and arranging their productions globally. They can arrange and organise internationally integrated production networks and value chains as well as participate in international networks for technological accumulation (Cantwell and Marra, 2022). The related literature on MNEs' global connectedness is rich, but it has not been fully developed and tested in the context of environmental innovation. Considering that MNEs have advantages in undertaking innovation and R&D based on their firm-specific advantages, we still know little about if this is also the case with the creation of environmental innovation under the emerging sustainability context. In the intersection of the knowledge-based view of MNEs and the environmental innovation literature, prior literature neglected to consider whether the MNEs' knowledge advantages (derived from global connectedness) could provide them with competitive advantage in terms of environmental innovation, particularly from the perspective of the parent company.

Hence, Chapter 3 aims to address such gaps by exploring the determinants of environmental innovation through an international business (IB) and management research lens. Specifically, we seek to analyse how an MNE's different types of international and inter-organisational networks contribute to its capacity to generate environmental innovation. We investigate the multifacets of MNEs' global linkages, including organisational linkages, production linkages, and, most importantly, cross-border innovation networks. In addition, we extend the existing theoretical framework of determinants of environmental innovation at the level of the parent firm by our incorporation of intra- and inter-MNE linkages of different kinds, and geographically diversified organisational spaces. Lastly, based on a large-scale secondary dataset, our work provides concrete empirical evidence and practical implications for the specificities of environmental innovation and how it is conceived and realised.

Answers to the aforementioned questions are of vital importance not only in terms of advancing the existing conceptual framework of environmental innovation's determinants by analysing such innovation from the global connectedness lens, but also guiding actions of practitioners and policymakers who strive to engage in and drive the green transformation.

1.3.2 Contribution

Chapter 3 aims to provide insights into the interplay between the global connectedness of MNEs and their capacity for environmental innovation capacity. Our investigation enriches the IB literature by understanding MNEs' internationalisation strategies and cross-border innovation management in the light of the contemporary challenges and opportunities presented by the need to respond to the climate emergency.

As such, we contribute to an important intersection between IB literature and the environmental innovation field in the following ways. First and foremost, we bring the topic of environmental innovation into the IB and management research arena and explain its determinants from a novel IB and management perspective. Second, we contribute to the literature on the drivers of environmental innovation by focusing on how the cooperative arrangements of MNEs contribute to their eco-innovation R&D. We explore multiple facets of MNEs' global linkages: organisational, production, and more importantly, cross-border innovation networks. To the best of our knowledge, this is the first study to reveal diverse antecedents of environmental innovation from the perspective of MNE connectivity. Third, our incorporation of cross-border intra- and inter-organisational networks into environmental innovation research extends the existing theoretical framework for analysing the determinants of environmental innovation at the level of the MNE parent firm. This idea aligns with Kolk and van Tulder's (2010) proposal that a consideration of the drivers related to institutional, industry and organisational aspects is appropriate for understanding the MNE's approach to gaining sustainable competitive advantage and its role in advancing sustainable development. Finally, we provide concrete evidence and practical implications based on a large-scale secondary dataset, which supplements the limited empirical evidence about the specificities of environmental innovation and how it is conceived and realised.

Practically speaking, this chapter also offers valuable managerial and policy implications. The insights obtained can inform practitioners to foster environmental innovation capacity by promoting and facilitating diversity in their firms' internationally-integrated production networks and their internal and external innovation networks. Additionally, we offer valuable insights for policymakers on how to plan initiatives in response to the ‘sustainability imperative’ (Zhan, 2021).

1.3.3 Conceptual and theory framework

In the current competitive business environment, the innovation activities of companies tend to be organisationally and geographically dispersed (Castellani, Perri, Scalera, and Zanfei, 2022), resulting in interconnected networks of organisations and individuals (Castellani and Zanfei, 2006; Scalera, Perri, and Hannigan, 2018). Such collectives involve a wide range of actors, including partner companies, suppliers, and the MNE’s foreign subsidiaries (Choudhury and Kim, 2019; Marino, Mudambi, Perri, and Scalera, 2020; Papanastassiou, Pearce, and Zanfei, 2020). This increased connectivity has important implications for knowledge combination in terms of more dispersed innovation activities and higher knowledge complexity across both technological scope and geographical space (Cantwell and Marra, 2022).

MNEs govern and nurture the flow of knowledge within their dispersed and interconnected internal and external networks that traverse both organisational and geographical spaces (Castellani *et al*., 2022). The organisational space is populated by intra- and inter-organisational networks composed of MNEs’ foreign subsidiaries, partner companies, suppliers, and customers. The geographical dimension denotes the various locations across the globe where knowledge and competences are generated as inputs for cross-border innovation (Castellani *et al*., 2022). Based on the perspective of place and organisational space, our key theoretical argument centres on the idea that MNEs are able to enhance their ability to innovate by leveraging heterogenous external environments (Almeida and Phene, 2004) and by utilising and recombining knowledge obtained from within and without the organisation’s boundaries.

Compared with domestic players, MNEs engage in international business activities by organising and arranging their productions globally. Their global production networks allow them to organise and orchestrate operation activities to optimise the different location-specific advantages as a means of acquiring competitive advantage. This type of enterprise opts for various governance modes to obtain technological knowledge and inputs from overseas (Contractor, Kumar, Kundu, and Pedersen, 2010). MNEs can arrange and organise internationally integrated production networks and value chains as well as participate in international networks for technological accumulation (Cantwell and Marra, 2022). Specifically, their knowledge search can take the shape of global production networks (GPNs), GVCs (Gereffi, Humphrey, and Sturgeon, 2005; Pietrobelli and Rabellotti, 2011), and R&D collaborations that feature a high degree of connectivity (Cantwell and Marra, 2022).

In this chapter, we focus on two broad types of networks identified by Cantwell (2017) and Cantwell and Marra (2022). The first type is the intra-MNE network. These are networks of international production, including international research and R&D facilities, that are owned by the

MNEs themselves. The second is the inter-organisational network. These result from MNEs joining strategic alliances with external partners (Cantwell and Marra, 2022). Intra- and inter-organisational networks lay the foundation for the internal and external networks for innovation, through which MNEs can access diverse knowledge bases that are distinct from those in their home countries. They thus enrich their own knowledge bases and foster knowledge diffusion across actors and countries, which ultimately leads to the increased potential for knowledge recombination (Cantwell and Marra, 2022). The key to this strand of research is that MNEs strive to connect and orchestrate international networks, thereby increasing their potential for knowledge recombination and development, from which they can create solutions for complex problems (Cantwell and Marra, 2022). The emphasis that Cantwell and Marra (2022) place on resource accumulation and technological capability in MNEs builds upon the literature of dynamic capabilities (Athreye, 2022). Focusing on environmental innovation, Orsato (2006) proposes that firms' capabilities can be deployed and arranged so as to create competitive advantages in environmental innovation.

Building on the above discussion, we employ a theoretical framework that integrates both strands of thinking. That is, we explore MNEs' sustainable competitive advantages by focusing on the global connectedness of multinationals and their cross-border innovation networks. The following section discusses the hypothesis development, which draws on arguments related to global connectivity and the internationalisation of innovative activities.

1.3.4 Data sources and empirical setting

To formulate the empirical study, we extract data on Environmental, Social, and Governance (ESG) practices over the period 2009 to 2020 from the Thomson Reuters ASSET4 database. This database compiles annual and sustainability reports, as well as proxy filings for companies subject to integrated ESG monitoring (Thomson Reuters, 2011). To link the firms in ASSET4 database located in five developed countries with those in Bureau van Dijk's Orbis main database, we employ a string-matching approach, in which the strings of company names and the country code of the company's location are taken into account. We obtain information on MNEs' patents records from the Orbis IP database from 1808 to 2019. A unique advantage of this data is that patent records can be matched to their current direct owners' detailed corporate and financial information using the unique firm identifier. This means that patents owned by the parent company or its foreign subsidiaries can be identified from the unique identifier of direct owner(s), from which one can tell whether the patent is co-produced by the parent and any of its affiliates, or by the parent and its foreign partners. Another source of information comes from the Executive Opinion Survey managed by the World Economic Forum on the stringency and enforcement levels of environmental regulation. The final sample is an unbalanced panel of 4,510 firm-year observations from 622 unique developed country MNEs (DMNEs, hereafter) across France, Germany, the United Kingdom, Netherlands, and Sweden over the period 2009-2017.

Our dependent variable, the environmental innovation score, is directly extracted from Thomson Reuters ASSET4 database. In line with the definition provided by Thomson Reuters, this score reflects a firm's capacity to reduce the environmental costs and burdens for its customers and thereby create new market opportunities through new environmental technologies and processes, or eco-designed products.

Turning to the independent variables, we adopt a similar method to that suggested by Maksimov, Wang and Yan (2019) to measure international diversification of MNEs' global production networks, which derives from the diversity of total assets' distribution across different foreign countries. To measure the strength of an MNE's intra-organisational linkages, we depict its ownership structure through its control and coordination over both physical and knowledge capital, which is believed to be a channel through which MNEs maintain intra-relationships with their foreign affiliates and exert influence on them. Hence, we first collect the share of an MNE's total participation in each of its foreign subsidiaries. Each share is weighted by the proportion of that subsidiary's total assets to the total amount of all the foreign subsidiaries in a given year, from which the mean value is then calculated. The resulting average weighted ownership stake of foreign subsidiaries captures how strongly an MNE and its affiliates are, on average, linked and associated with each other. Due to information constraints on patent inventors in our data, we capture organisational innovation networks by exploiting information on the direct owner(s). We contend that a patent is co-produced by different partners if multiple owners are listed as its direct owners, based on which the intra- and inter-organisational innovation co-production networks are established. Indeed, to capture the strength of intra-organisational innovation co-production between the parent firm and its foreign subsidiaries, we compute the extent to which an MNE's patents are co-produced with its foreign subsidiaries. This is the ratio of co-owned patent publications between headquarter and the affiliates to the total number of the parent company's patents. In similar vein, we gauge an MNE's inter-organisational innovation co-production network from its patent co-ownership with foreign collaborators. Following the method of constructing international diversification, we again employ 1 minus the Herfindahl index to measure the geographical diversification of a MNE's inter-organisational innovation co-production network. This is derived from the geographical distribution of its patents co-owned with other foreign companies across different foreign countries.

Our choice of control variables is guided by theoretical considerations and existing empirical evidence on the determinants of environmental innovation, and limited by data availability. Prior research emphasises the particularity of environmental innovation in terms of its externalities and the drivers of its introduction (De Marchi, 2012), highlighting the crucial contributory role of regulation (e.g., Jaffe, Newell and Stavins, 2002; Marin and Zanfei, 2019). Here, we consider environmental policy in the context of both host and home countries. Firm age and size by employees (both in logarithm form) are included as controls to account for the resources and capacity of the enterprise. Labour productivity (revenue per employee) is taken into account to reflect the efficiency of the workforce, given the literature's acknowledgement that productivity plays a positive role in the innovativeness of organisations (Chiarvesio, De Marchi and Di Maria, 2015). In the innovation literature, R&D activities are expected to be crucial inputs for a firm's knowledge production and innovation process. Patents are generally regarded as an alternative measure of innovation capacity (e.g., Costantini, Crespi, Martini and Pennacchio, 2015), but they play a different role in the knowledge creation process because not all R&D commitments or research successes will lead to patents (Popp, Hafner and Johnstone, 2011). Here, we use the natural logarithm value of the number of green patent publications to account for existing knowledge stocks and the outputs related to environmental innovation. Our green patents are identified by a set of designated IPC codes related to environmentally sound technologies (ESTs) in numerous technical fields listed in the IPC Green Inventory[13]. Finally, heterogeneity at the levels of sector (one-digit section level) and country are controlled for by their respective dummies.

To identify the antecedents of MNEs' environmental innovation capacity in terms of role played by the different types of international intra- and inter-organisational linkages and networks, we formulate a pooled Tobit model of environmental innovation capacity as the empirical approach estimated by maximum likelihood, considering that the dependent variable, environmental innovation score, ranges from 0 to 1. As a robustness check, we employ panel Tobit random effects estimation to re-estimate the model. These results lend further support to our main hypotheses.

1.3.5 Summary of empirical findings

The primary aim of Chapter 3 is to examine the factors that facilitate the firm's environmental innovation capacity. Specifically, we draw on the knowledge-based view (Grant, 1996; 1997) to explain why some MNEs can be more environmentally innovative than others. We therefore analyse antecedents related to their internationally networked relationships for production and innovation, as well as their firm characteristics. We draw on theoretical arguments about the global connectedness of MNEs and their cross-border innovation connectivity to develop and test hypotheses concerning the antecedents of environmental innovation. The lessons drawn can help guide the actions of practitioners and policymakers in home and host countries.

It indicates that developed country MNEs are in an advantageous position to develop such innovation capability and sheds light on their potential contribution to achieving the Sustainable

[13] IPC Green Inventory can be accessed at https://www.wipo.int/classifications/ipc/green-inventory/home

Development Goals (SDGs). Specifically, we focus on the effects of different types of intra- and inter-organisational production and innovation networks, and show that wider global linkages built on production networks, and intra- and inter-MNE innovation co-production linkages contribute to MNE's capability to produce environmental innovation. However, intra-organisational linkages motivated by traditional control and coordination mechanisms do not play an important role in environmental innovation capacity. This emphasises that specific types of ties related to knowledge connectivity and innovation collaboration matter important for environmental innovation than general control and coordination linkages. MNEs' arrangements for international production and innovation activities are grounded in their cross-border organisational linkages. These appear to be important channels for facilitating knowledge transfer and recombination, cultivating high levels of knowledge development and environmental innovation capacity.

1.4 Brief overview of Chapter 4 – Agglomeration externalities of green innovation

1.4.1 Research question

Given the increasingly critical role of sustainable thinking in business management, scholars and practitioners seek out ways in which sustainability can be introduced into business practices and products in an effort to prioritise environmental concerns and secure social wellbeing (Awan *et al*., 2020). Companies that need to meet the escalating sustainability expectations of various stakeholders are turning to environmental innovation to promote energy-conscious production, create cleaner technologies, produce eco-friendly and customized products, and build sustainable industries (Chiarini, 2021). This explains why the analysis of eco-innovations or green innovations and their impacts have gained momentum in the last few years.

The existing literature concerning green innovation has focused on the relationship between having a green business strategy and firm performance (e.g., Lin, Chen, Yu, Li, Lampel and Jiang, 2021), the determinants of green innovation development (e.g., Perruchas, Consoli and Barbieri, 2020), its internal impacts on the focal firm's performance (e.g., Horbach, 2010; Marin, 2014), and its external impacts on sectoral environmental performance (e.g., Costantini, Crespi, Marin and Paglialunga, 2017).

What is missing is how green innovation interacts with the local economy to affect other firms' economic performance, given the ability of such innovation to create both positive knowledge externality effects and environmental spillover effects (Ben Arfi, Hikkerova and Sahut, 2018). So far, there has been just one study that touches on the idea that green innovation spills over onto economic growth in terms of company market values, but we still have no clear answer about the economic relevance of green innovation spillovers to the performance of other firms in terms of productivity and growth. More importantly, we lack understanding about the channels through which the impacts of green innovation externalities may take place.

Therefore, in this chapter, we intend to bridge the literatures on environmental innovation and agglomeration externalities, filling a knowledge gap by examining the external impacts of green innovation on the wider local economy. Specifically, we study how variations in such agglomeration externalities affect the productivity and employment growth of other industrially related and geographically adjacent non-green-tech companies via horizontal and inter-sectoral linkages, and we reveal the conditions under which this can happen. Moreover, we consider how a firm's absorptive capacity affects its ability to leverage green innovation externalities and absorb such spillovers, by considering the aspects of firms' intangible assets and technological competence, namely core-technology competence and technological diversification.

1.4.2 Contribution

In Chapter 4, we step beyond the state of the art by bridging the environmental innovation literature with economic geography theories. This allows us to analyse the agglomeration externalities of green innovation and its wider economic values. To the best of our knowledge, this is the first study to investigate the spillover effects of green innovation via both horizontal and vertical linkages, and how these drive firm-level economic performance.

Specifically, we contribute to the existing literature in the following ways. First, our firm-level analysis of green innovation diffusion is much finer grained than the usual national, regional, or sectoral level analysis. Second, this chapter augments the currently limited empirical evidence of green innovation's effects on economic performance through inter-sectoral linkages by studying its influences on firm productivity and employment growth. Third, instead of focusing on the internal impacts of green innovation on the focal firm, we propose to extend the state of the art by analysing green innovation's externalities and its wider economic values. Investigating this issue is critical in terms of empirically validating the increasing focus of policy on environmental innovation, and the considerable resources and efforts devoted to stimulating sustainable endeavour.

1.4.3 Conceptual and theory framework

To investigate the spillovers arising from the co-location of green-tech firms and other companies in agglomerated regions and industries, this chapter connects the green innovation literature to economic geography theory on agglomeration externalities, which introduce different mechanisms for the spillovers to take place (Iammarino and McCann, 2013). We mainly focus on the Marshall-Arrow-Romer (MAR) externalities in this chapter. This stream of theory sets out three mechanisms through which location-specific economies of scale may come into being: access to skilled labour, input-output linkages, and intra-industry knowledge spillovers (Marshall, 1920; Arrow,1962; Romer, 1986). By applying these mechanisms to the green innovation context, we suggest that the agglomeration of green-tech firms within a given region and industry may create both positive and negative externalities for other spatially proximate and industrially related non-green-tech companies.

How much an organisation can benefit from externalities depends on its absorptive capacity, which is defined as a firm's ability to learn and improve performance by internalizing and assimilating knowledge generated outside itself (Cohen and Levinthal, 1989). This notion is incorporated in our theorising as it connects the pieces of knowledge generated outside of the organisation to those created inside it (Gluch, Gustafsson and Thuvander, 2009). This implies that external, complex, and cross-disciplinary environmental knowledge can be transformed and integrated into organisational capabilities (Dzhengiz and Niesten, 2020) that further enable the development of competences and capabilities. In short, heterogenous absorptive capacity allows us to explain the learning of individuals and organisations through both intra- and inter- organisational processes, given the agglomeration externalities.

1.4.4 Data sources and empirical setting

This chapter is the last empirical one. It extracts from the Orbis IP database the patent records of UK manufacturing firms. We employ the IPC of the patent records to identify green patents, which reflect green innovation. Our strategy for assigning green patents to their relevant sectors relies on matching green patents to their owners, from which we can extract information about the firms' sectors. The individual records are then structured in a panel setting to match with the UK firms from Orbis, giving us in total 18,106 green patents published by 5,964 firms over the period 2008-2017. By exploiting and aggregating firm-level linked green patents to the division level (2-digit) of the UK Standard Industrial Classification (SIC 2007) and the NUTS-2 region, we construct sectoral and regional green innovation indicators as exogenous explanatory variables. The Office for National Statistics (ONS) input-output table is used to estimate vertical backward and forward linkages across all the sectors (at the 2-digit level of SIC 2007) in the UK.

As far as the dependent variables are concerned, we employ the Wooldridge estimator implemented in Stata's *prodest* command (Rovigatti and Mollisi, 2018) to estimate total factor productivity within each industrial sector. This measure is based on a revenue-based Cobb-Douglas production function with production factors of labour, capital, and materials. The second dependent variable, employment growth, is defined as the annual rate of growth of employee numbers (e.g., Jung and Lim, 2020) and is generated by taking the difference of the natural logarithm value of number of employees between t and t-1.

Following the established empirical literature developed since Javorcik (2004) on identifying agglomeration externalities, we generate three proxies for spillovers from green-tech companies, which are green innovation industrial externalities at the horizontal level and two measures of the vertical externalities at the upstream supply and downstream customer sectors[14].

As we assume that firms' ability to exploit and internalise external technological opportunities rests on the knowledge and capabilities held within the organisations, we employ intangible assets intensity and two important characteristics of firms' technological knowledge, core-technology competence and technological diversification, as proxies for absorptive capacity. In view of Marrocu, Paci and Pontis (2011), we compute the ratio of intangible to tangible fixed assets to account for the effects of knowledge capital on the spillovers to firms' economic performance. Our index of core-technology competence is measured following Kim *et al*. (2016), based on the revealed technology advantage (RTA) (Patel and Pavitt, 1997). Then, core-technology competence is the maximum value of the product of RTA index and the number of patent publications in the corresponding technological domain. Following the strategic management literature on using the entropy index to quantify technological relatedness or unrelatedness (e.g., Chen and Chang, 2012; Zander, 1997), our index of technological diversification is constructed based on the method introduced by Kim *et al*. (2016).

The selection of control variables is directed by the extant literature on the determinants of firm performance, albeit somewhat limited by data availability. We take account of the factors including patent stock in line with the method in Guellec and van Pottelsberghe de la Potterie (2004), average wage considered as a proxy for overall labour quality, as well as firm age and size to account for the experience and resources owned by the company.

We specify a set of models to test impacts of green innovation externalities on the productivity and employment growth of other non-green-tech firms separately, controlling for both firm and industry heterogeneity. To examine the related spillovers of green-tech companies, we estimate those equations using panel fixed-effects with standard errors clustered at the firm level. Adopting a fixed-effects model here allows us to remove unobserved heterogeneity between the different firms in the data. Moreover, clustered standard errors are considered when there is some unexplained variation in the dependent variable that is correlated across time. Besides firm-level control variables, we also introduce aggregated industry dummies and year dummies, to control for industry and year specific effects.

The empirical results show interesting heterogenous effects of green externalities across firm characteristics and different sectors. Our baseline results tend to be robust after relaxing the restriction of regional boundary from the NUTS-2 to NUTS-1 region within the UK.

[14] For the detailed methods on how to produce these three measures, see Section 4.3.3.2.1 Green innovation externalities.

1.4.5 Summary of empirical findings

Our results show that, overall, non-green-tech manufacturers in downstream sectors can benefit from their green-tech suppliers in terms of both productivity and employment growth. Small and medium-sized enterprises (SMEs)[15] show potential for benefiting from the externalities of upstream green innovators in both productivity and employment growth. For large enterprises, only those with core-technology competence and diversified technological competence can gain positive upstream productivity spillovers. In addition, technological diversification allows SMEs and low-tech businesses to exploit the upstream productivity gains.

The positive impacts of the horizontal productivity spillovers are mainly captured by businesses with technological core competence. In particular, core-technology competence and technological diversification within both SMEs and low-tech firms allow them to gain efficiency improvements sparked by fierce intra-industry competition. On the other hand, large firms that are intangible-intensive tend to experience negative horizontal productivity spillovers, which can be regarded as a sign of competition led crowding-out effects.

Turning to forward linkages, we observe market disruption effects on the productivity of large-sized and high-tech upstream suppliers, while for employment growth, there is an overall negative forward spillover effect from green-tech consumers. However, other firms with core-technology competence and technological diversification can more easily manage innovation investments and react to the related technological risks and challenges, mitigating the induced demand shocks.

1.5 Structure of the thesis

The thesis is organised into five chapters. Chapter 1 provides an overview of the research context and our empirical chapters. This is followed by three individual empirical chapters. By examining the characteristics of IoT innovators and their innovation pathways, Chapter 2 investigates the factors related to firms' innovation trajectory which contribute to the creation of IoT technology. In Chapter 3, we examine green innovation capacity from the perspective of MNEs in developed countries, and investigate how factors related to their global linkages built on production networks, and intra- and inter-MNE innovation co-production linkages contribute to their capability to produce environmental innovation. Chapter 4 focuses on the dynamics pertaining to the diffusion of green innovation within the local economy. Specifically, we explore how agglomerated externalities of green innovation affect other firms' economic performance via both horizontal and vertical linkages, and how heterogeneous absorptive capacity within companies affects their ability to absorb such spillovers. The final chapter

[15] We employ the OECD definition of business size: SMEs have fewer than 250 employees, while large enterprises employ 250 or more.

concludes with a summary of the key points made and implications expressed in each of the empirical chapter. Tables and Appendices are provided at the end of each chapter.

CHAPTER 2: PATHBREAKING TO INNOVATE: PATENTING IN INTERNET OF THINGS (IOT) TECHNOLOGIES

2.1 Introduction

The innovation literature frequently suggests that innovation tends to be path-dependent, with both non-innovative and highly innovative firms exhibiting a propensity to remain in their respective states (Cefis and Orsenigo, 2001). In the case of highly innovative firms, this can lead them to being persistently innovative. The persistent innovation pattern is built on the idea that firms explore a process of learning and discover new ideas by recombining (re-arranging) old ones (Weitzman, 1996). The cumulative and non-exhaustible characteristics of knowledge as an economic good have clear implications for the path-dependent nature of the knowledge generation process (Le Bas and Scellato, 2014), allowing scholars to identify and interpret persistence phenomena in innovation activities (Crespi and Scellato, 2014). Thus, firms that have innovated in the past are likely to be in a better position to innovate again, since their accumulated knowledge and competence amount to advantages over their competitors (Antonelli, Crespi and Scellato, 2012). More importantly, a firm's current level of research effort tends to decide the rate and direction of innovations within a context (Antonelli, 2011).

However, there is a counterargument that innovative firms with strong technological competence can fall victim to knowledge inertia, which creates knowledge lock-in situations, and that as a result those firms become less likely to generate ground-breaking innovation (Boschma, 2005; Molina-Morales *et al*., 2014). In addition, apparently strong incumbent firms can experience difficulties when a radical or disruptive product 'architecture' or technology emerges (Henderson and Clarke, 1990), such as digital tools for design and collaboration (Marion and Fixson, 2021). Firms thus face a tension between clinging to their technological core competence and venturing into technological diversification that usually expands the boundary of knowledge to domains where they are less competent. This tension could be mitigated if firms knew the optimal level of core-technology competence, and how far they should diversify to maximise their opportunities for innovation, issues upon which the existing literature offers limited understanding.

This question has become even more relevant in the era of Industry 4.0. Widely considered as something quite unprecedented in terms of its scale, speed, scope, and complexity (Schwab, 2016), Industry 4.0 technologies are expected to be the most powerful driver of the next wave of innovation (Kaggermann, 2015). In particular, the Internet of Things (IoT) technologies are a novel paradigm of information networks, bringing physical objects into internet networks and facilitating information collection and transmission among actors. As such they are a core infrastructure element of Industry 4.0 (Trappey, Trappey, Govindarajan, Chuang and Sun, 2017).

Originating from the broad field of ICT, IoT technologies possess ground-breaking and boundary-spanning properties that go beyond the conventional ICT technologies. They present an opportunity to study the driving forces of IoT technological inventions in a relatively homogeneous context. We postulate that firms' core-technology competence may not be a helpful driving force towards innovation in Industry 4.0 technologies. By contrast, technological diversification and openness to new technologies and competence domains may prove to be beneficial. Drawing from appropriate theory, this chapter hypothesises, and confirms empirically, that the determinants of innovation in IoT differ substantially from those of the more established technologies. We find that firm-specific core-technology competence is negatively related to innovation in the technological fields of IoT relative to other traditional ICT areas. Contrary to the view that innovation is a process of persistence that relies on firms' learning experience over time, we find that three common predictors of firms' technological trajectory, namely, innovation persistence, innovation intensity, and experience in patenting, all fail to predict innovation propensities in the IoT field. These findings do not offer support for the premise that continuity of innovation, scope of accumulated experience, and previous performance in the forms of innovative intensity help to generate creative accumulation and creative destruction (Malerba, Orsenigo and Peretto, 1997). However, innovation persistence does play a role in enhancing the positive effect of unrelated technological diversification on IoT innovation.

These apparently counterintuitive results may be due to the distinctive natures of Industry 4.0 technologies. As a new revolution of the Internet, the IoT is built on novel combinations of various enabling technologies, providing technological solutions that overturn the conventional understanding of information networking and communication. This gives rise to opportunities for new entrants and the smaller, less experienced innovators who are able to keep pace with the technological revolution. Rather than being a game open only to the technological giants or advanced innovative incumbents, IoT innovation opens up opportunities for newcomers to get in on the act and equip themselves with the necessary knowledge to transform from Industry 3.0 to Industry 4.0.

The empirical work draws upon the Bureau van Dijk's Orbis Intellectual Property (Orbis IP) database, which gives the most comprehensive coverage of patent records. We use informatics methodologies and text analytics to identify Industry 4.0 technologies from two data sources[16]. This data is then linked with the owners of patents collected by Orbis firm-level database, giving us a final sample of 235,796 patents published by 5,455 UK firms over the period 2008-2017. In measuring the innovation activities through patenting, we specify a discrete choice model to unpick characteristics that explain firm's innovation in IoT (as opposed to standard ICT and non-ICT field) field. The three pathways are mutually exclusive and exhaustive among all the patenting firms. We find consistent support for the hypotheses, and they are robust to a number of sensitivity tests.

[16] A detailed discussion can be found in Section 2.4.1 Data sources.

The contribution of this chapter is to advance understanding of the route to innovate in specific pathbreaking fields within Industry 4.0. Specifically, it develops theory suggesting how core-technology competence is actually inimical to involvement in IoT patenting, whereas having a diversified technological portfolio—both technologically related and technologically unrelated—is strongly positively linked to innovation in IoT. We then demonstrate empirically that this is the case. We find that persistence in innovation, often considered to be a major advantage in innovation, does not assist IoT innovation, but it does have a positive moderating effect on enhancing the positive effect of unrelated technological diversification on IoT innovation. These findings offer valuable insights for management and policy makers who wish to plan and stimulate related innovative activities in a rapidly emerging field. The fact that previous innovation patterns and experience are not prerequisites for cultivating the ground-breaking technologies in Industry 4.0 sheds light on the strategic management of innovation.

The current chapter is organised as follows. The next section introduces the context of this research, outlining the special features of Industry 4.0 and IoT technologies. In section 3, we establish the conceptual foundations of innovation persistence, outline the arguments related to knowledge inertia, and propose hypotheses on technological competence and diversification. Section 4 describes the data sources and research method. Section 5 reports the baseline model results. These are followed in section 6 by a discussion of potential empirical issues and further analysis related to the robustness of our results. Section 7 discusses and concludes.

2.2 Context

'Industry 4.0' is a term created in 2011 at German's Hannover Fair to represent the digitalisation of industries. It has been widely adopted and expanded to capture how the fourth generation of the industrial revolution can transform the structure of global value chains through digitalisation: this has involved the use of a number of related terms in different countries, such as 'smart manufacturing' (Thoben, Wiesner and Wuest, 2017), 'industrial internet', 'intelligent manufacturing', 'advanced manufacturing', and 'smart factory' (Hermann, Pentek and Otto, 2016).

Industry 4.0 technologies, including redistributed manufacturing, additive manufacturing, digital twins, autonomous robots, Big Data, and IoT, have profoundly transformed marketing, product development and planning, procurement, production processes, operations (Lopes de Sousa Jabbour, Jabbour, Godinho Filho and Roubaud, 2018; Mangla *et al*., 2018; Ménière, Rudyk and Valdes, 2017), and distribution, and have led to more advanced manufacturing systems (Li, 2018; Sung, 2018). These technologies allow business organisations to use ICT systems to build real-time capability and interoperability, and to integrate production systems horizontally and vertically. This is all crucial to staying competitive in an increasingly globalised and competitive world, which is characterised by volatile market demands, shortened innovation and product life cycles, and increasingly complex products and processes (Arnold, Kiel and Voigt, 2016).

Vermesan and Friess (2014) summarise a couple of fundamental characteristics of the IoT, among which interconnectivity, heterogeneity, dynamic changes, enormous scale, and connectivity are prominent ones. As a core infrastructure component of Industry 4.0, IoT technology is not only rapidly changing the inherent nature of products, but also redesigning firms' internal processes and value chains, transforming business models, and in turn, changing the nature of market competition and industrial structures (Iansiti and Lakhani, 2014). These emerging solutions are featured by high technological complexity in respect to different technologies and protocols, variety of devices (Ma, 2011), and the participation of various actors connected in value creation activities who need to be coordinated in ecosystems (Rong, Hu, Lin, Shi and Guo, 2015). As pointed out by Ehret and Wirtz (2017), IoT solutions open up new systematic paths to the exploration and exploitation of business opportunities, including higher efficiency or reliability of existing businesses as well as advantages of differentiated product and service offerings. For instance, Roe, Spanaki, Ioannou, Zamani and Giannakis (2022) summarise a couple of IoT applications in smart stores, with such technologies being able to offer customers personalised promotions to manipulate their path through the store (Hui, Inman, Huang and Suher, 2013) and to induce an increase in the value of their baskets. Another vivid example of a provincial ambulance management system is described by Schwab (2016) in one of his recent books. The equipment usage pattern of each ambulance driver is collected and analysed to optimise routes and minimise the time needed to access services and return to hospital. The real-time location data of the ambulance is further linked with emergency call data and geographic information of coffee shops in order to save time for lives and make drivers free to take time off between emergency calls. That is why IoT is regarded as a fast-evolving, potentially disruptive technological innovation, which expands the scope of conventional internet networks, for many industries (Li, Xu and Zhao, 2015).

Following this line of reasoning, IoT solutions differ from other Industry 4.0 technologies for three important reasons. First, IoT becomes a ground-breaking artefact being invented by combining or reorganising existing or new technologies in novel and different ways (Schwab, 2018). According to Richard Soley, the chairman and chief executive officer of Object Management Group in the USA, IoT is deemed to bring about a revolution even though the components of this transition are not specifically new. Essentially, they are not the usual standalone technologies, but rather a complex set of enabling infrastructural technologies. More specifically, they can be understood as three groups of technologies: (i) technologies enabling things to obtain contextual information, (ii) technologies allowing things to process contextual data, and (iii) technologies that can improve privacy and security (Vermesan and Friess, 2013). Patel and Patel (2016) also regard IoT as a new revolution of the Internet, building on a range of enabling technologies and components, including machine to machine communication, sensor networks, 2G/3G/4G, general packet radio service (GPRS), global system for mobile communications

(GSM), wireless fidelity (WI-FI), radio frequency identification devices (RFID), microcontroller and microprocessor, etc. In light of the argument put forward by Richard Soley, Schwab (2018) summarises that when entirely uncorrelated pieces of information stay connected, completely novel and unexpected business opportunities can be discovered in the strangest places for making the utmost of this revolution.

Second, IoT can be operated on an unprecedented enormous scale. This revolution brings about a larger opportunity of the "internetisation" of industry, which reveals that application of IoT to industry is not limited to manufacturing and production but to those relying on ICT, which are essentially every major industry.

Last but not the least, IoT technology is considered a radical technological paradigm among these technologies (Kim, Lee and Kwak, 2017), as they have the potential to radically transform business models (Ceipek, Hautz, Petruzzelli, De Massis and Matzler, 2021b). Typically, IoT solutions are disruptive and require changes in the business model (Osterwalder and Pigneur, 2011). The smart devices of IoT technologies can deliver value by changing the way objects are produced, anticipating consumer needs, and providing new perspectives on business models through their three core capabilities (Schwab, 2018). Their first core capability is to allow rich data to be combined with smart analytics, offering contextual information reflecting real-time events or states. Their second derives from IoT devices' capacity for communication and coordination, which can improve life efficiency and productivity. Their third capability is to generate intelligent-interactive objects and synergistic opportunities from linking with other distributed emerging technologies, such as artificial intelligence (AI) and blockchain. These abilities stimulate radical changes in business models and trigger structural shifts across various industries, such as manufacturing, agriculture, transportation, and healthcare. Ultimately, they challenge current institutions and how people conceptualise and think about the nature of data, products, and services (Schwab, 2018). Indeed, the complexity and disruptive characteristics of IoT technologies are borne out by the rapid digitalisation in the business world, which has broken down traditional industry barriers. Therefore, it requires firms to rethink their existing business models (Gerlitz, 2016).

By reasons of the foregoing, one can expect that IoT can be viewed as a pathbreaking technology. This argument is also connected to the reasons behind the focus of this Chapter. Firms usually face a tension between clinging to their technological core competence and venturing into technological diversification that usually expands the boundary of knowledge to domains where they are less competent. However, the extant literature offers limited understanding on the relationship between the two ends and on how to mitigate such tension in terms of knowing the optimal level of core-technology competence and degree of technological diversification. These questions have become even more relevant in the era of Industry 4.0, within which Industry 4.0 technologies are widely considered as something quite unprecedented in terms of their scale, speed, scope, and complexity (Schwab, 2016). In particular, IoT technologies represent a radical paradigm of information networks, and possess ground-breaking and boundary-spanning properties that go beyond the conventional ICT technologies. Hence, this chapter aims to examine the abovementioned tension in the context of pathbreaking technological field, such as the IoT technology, to fill the above knowledge gaps.

2.3 Theory and hypotheses

Over the last two decades, the concepts of innovation persistence and path dependence have contributed to the development of a comprehensive conceptual framework that can explain why some firms have maintained consistently high rates of innovation. This topic is of importance in the research fields of economics of knowledge, economics of organisation, and economics of innovation, and innovation management (Antonelli *et al*., 2012; Cefis and Orsenigo, 2001; Clausen and Pohjola, 2013; Malerba *et al*., 1997; Peters, 2009).

To explain the phenomenon of persistent knowledge production, the earlier economics literature highlights the role of sunk costs in non-redeployable R&D investment and entry barriers (Manez, Rochina-Barrachina, Sanchis and Sanchis, 2009). Theories and evidence depict successful innovation feeding into high profitability and reduced financial constraints; these then allow firms to fuel R&D investment, creating a virtuous circle of 'success breeds success' (Le Bas and Scellato, 2014). Running parallel to this, the innovation management literature recognises the existence of innovation persistence. This places an emphasis on the role of knowledge cumulativeness and the relevance of strategic decisions to leveraging internal and external knowledge, leading to path dependence in innovation (Antonelli and Colombelli, 2013). In turn, the cumulative nature of internal and external knowledge affects the dynamics of the processes through which a firm's knowledge base shapes its new knowledge generation (Antonelli *et al*., 2015). This perspective implies that persistent innovation is a result of knowledge accumulation and the development of dynamic capabilities.

However, recent literature has presented counterarguments to both these factors. While knowledge accumulation is important, innovative firms with strong technological competence may also experience knowledge inertia and knowledge lock-in, which render ground-breaking innovation less likely (Boschma, 2005). In such a case, firms face a tension between innovation persistence in their technological core competences, and the technological diversification that usually requires an expanded boundary of knowledge (Molina-Morales *et al*., 2014).

Further, it is less clear what dynamic capabilities matter most for innovation. Conceptually, the resource-based view contends the importance of collective learning in the organisation; this occurs through coordinating various production skills and integrating multiple sources of technologies (Hamel and Prahalad, 1994). These integrated and harmonised capabilities strategically differentiate a company in the marketplace and constitute the enterprise's competitive advantages (Wind and Mahajan, 1988). In practice though, dynamic capability could mean a wide range of firm characteristics and activities.

To innovate technologies that are of a different nature, the knowledge and dynamic capabilities required must diverge from previous patterns.

Unfortunately, the existing literature offers limited understanding of these tensions and complexities. This chapter therefore seeks to develop them in order to understand better what drives innovation, especially breakthrough innovation in completely new technologies such as the IoT.

2.3.1 Core-technology competence and innovation

Effective knowledge accumulation is the underlying basis of a firm's core competence. The resource-based view uses the concept 'core competence' to capture a firm's integrated and harmonised capabilities that first strategically differentiate it in the marketplace and then constitute its competitive advantages (Wind and Mahajan, 1988). Gökkaya and Özbağ (2015) conceptualise a framework that links together technological core competence, firm innovativeness, and firm performance, demonstrating that a firm's core competence enhances its capability to innovate. In addition, a firm's core competence and innovation may be dynamically reinforcing, as innovation may enhance core competence, which then further drives innovation (Han and Huang, 2012).

However, the notion of core technology has a drawback. Successful firms tend to do the 'right thing'; they focus on better products, the best procedures, and the most profitable clients. Nevertheless, it is a 'wrong thing' that blinds them to future competitive threats, and it can eventually cause even great firms to fail to foresee disruptive invention. This happens not because of their stupidity but because of their supreme rationality (Christensen, 2013). In fact, management scholars have long recognised the tensions between core competence and knowledge inertia. Knowledge inertia refers to the common tendency of individuals and organisations to resort to prior knowledge and past experience when they encounter problems, through which they formulate a routine strategy (Sharifirad, 2010; Sternberg, 1985). This tendency may maintain the organisation's status quo, while a reliance on personal commitment, financial investment, and institutional mechanisms will keep the firm moving in a predictable trajectory (Huff, Huff and Thomas, 1992). This is also in line with the evolutionary perspectives which argue that owing to the cumulative, localised, and tacit nature of technological knowledge, proximity in the cognition dimension can impose negative effects on innovation due to the lock-in mechanisms (Boschma, 2005).

Similarly, 'core rigidities' can lead to the institutionalisation of knowledge and thus inhibit new information creation and innovative progress (Leonard-Barton, 1992). The essence of core rigidity lies in its feature of path dependence, a characteristic stemming from the cognitive inertia of corporate members and the general risk aversiveness of human nature (Liu, Chen and Chen, 2003).

Further, competence in the core technological field can affect innovation differently, depending on the nature of innovation. Some innovations are incremental (i.e., continuity), while others can be breakthrough (i.e., discontinuity) innovations (Johannessen, Olsen and Lumpkin, 2001; Song and Di Benedetto, 2008). Different organisational environments and capabilities, along with different elements within the organisation's core competence, may be required to foster different types of innovations (Xu, Zhao, Wanyan and Chin, 2000).

The IoT is considered to be revolutionary and ground-breaking, thanks to its high degree of newness and considerable impacts on the existing usage patterns. Its network goes way beyond computers, evolving to include devices of all types and sizes, making objects recognisable by equipping them with intelligence to communicate information about themselves (Patel and Patel, 2016). Owning to its fundamental characteristics (e.g., interconnectivity and heterogeneity), it is plausible to infer that this ground-breaking technology is built on diverse knowledge disciplines and novel combinations of technological components.

Patel and Pavitt (1997) suggest viewing technology competences in terms of a firm's commitment and position across a range of technological areas. The core-technology competences show cognitive proximity within knowledge bases and present high technological interdependence. Benner and Tushman (2003) indicate that when firms become efficient at utilizing existing core knowledge and capabilities, the self-reinforcing nature of learning is prone to creating innovations that are incremental rather than breakthrough. This argument is supported by the findings of Song and Di Benedetto (2008) that, generally speaking, substantial novel knowledge bases and innovation capabilities are needed for breakthrough innovation.

Moreover, technology lock-in theory (Arthur, 1989) indicates that technological interdependence is one of the drivers of inertia in technological systems (Arthur, 1994). As this sort of structural inertia intensifies, change and innovation—especially breakthrough innovation— are likely to be hindered. The IoT is representative of the kind of breakthrough innovation that requires novel knowledge bases and diverse innovation capabilities. Considering that cognitive proximity and technological interdependence of core-technology competence impede ground-breaking innovation, we expect the following:

H1. The higher the core-technology competence of a firm, the less likely it will be to innovate in IoT technologies relative to more traditional technological domains.

2.3.2 Technological diversification and innovation

Technology diversification refers to a corporation's extension of its technological capability into a wider variety of technical fields (Granstrand and Oskarsson, 1994). Technological diversification might bring about diversification risks that hinder exploratory innovation activities. Specifically, technological diversification usually requires changes in company routines and also incurs increased R&D costs (Leten, Belderbos and Van Looy, 2007) which firms find difficult to cover with financial capital. It can also create over-diversification issues that can prevent firms from recognising the most valuable idea and can thus cause resource allocation problems (Ceipek, Hautz, De Massis, Matzler and Ardito, 2021a). For example, Ceipek *et al*. (2021a) indicate in a recent work on IoT innovations that a high degree of technological diversification might hinder exploratory innovation activities in firms with high family involvement in the top management team.

That being said, here are three ways in which firms can also benefit from technological diversification. First, technological diversification has direct implications for a firm's technological evolution in respect of economies of scale, scope, speed, and space (Granstrand, 1998). In particular, by diversifying technological bases, an enterprise's R&D and technological knowhow can reap economies of scope by making the most of the available resources (Miller, 2006; Teece, 1982). Second, diversification reduces the risks involved in innovation by strengthening a firm's adaptability (Garcia-Vega, 2006) and helping it to extract larger rents in the product market by creating complex product lines (Kim *et al.*, 2016). This has received empirical support, suggesting that technological diversification has positive effects on innovative performance (e.g., Garcia-Vega, 2006) and firm growth (e.g., Kim *et al*., 2016). The third benefit lies in the opportunity for firms to improve their absorptive capacity and firm-specific technological competences through the assimilation of external knowledge. This can take place when firms widely search for and connect to new knowhow (Katila and Ahuja, 2002), which can mitigate the core rigidities and path dependency nature of knowledge (Quintana-Garcia and Benavides-Velasco, 2008), thus providing novel solutions that depart from the firm's past activities and accelerate the possibility of innovation.

In addition to these positive impacts of diversified technologies on a firm's innovative competence, diversification tends to exert stronger effects on exploratory (as opposed to exploitative) innovative capability (Quintana-Garcia and Benavides-Velasco, 2008). Using a cross-sectional sample of pharmaceutical firms, Cardinal (2001) demonstrates that scientific diversity has a stronger positive association with the creation of radical innovation than with the creation of incremental innovation. Abernathy and Clark (1985) also demonstrate that because such technological diversification facilitates novel combinations and knowledge transformation, the possibility of fostering radical innovative capabilities is increased. As firms' existing knowledge provides a critical ingredient of their competitive advantage and corporate success, they utilise technological diversification as a strategy to enter into new technological areas (Breschi, Lissoni and Malerba, 2003; Garcia-Vega, 2006; Granstrand, 1999).

In this respect, Sadowski, Whalley and Nomaler (2019) hypothesise and prove that broader technological diversification strategies are expected in those technological areas where firms expect more rapid technological change. Overall, technological diversification tends to be even more necessary for revolutionary technological change than it is for ordinary technological change (Patel and Pavitt, 1997).

To further understand the nuances of technological diversification, we adapt the concepts of related and unrelated technological diversification (Chen and Chang, 2012; Kim *et al*., 2016). These two components of total technological diversification are introduced to account for the relatedness of different technological fields. Related technological diversification addresses distinctions within the same technological field, while unrelated technological diversification focuses on variety across different technological fields. Here, we speculate that both related and unrelated diversification are useful for innovation in IoT technologies.

From an evolutionary perspective, companies are considered as behaviourally constrained seekers of competitive advantages (Estolatan and Geuna, 2019). Firms generally rely on established principles or routines embedded in their existing technical knowledge bases for directing their actions when they are accessing unknown risky marketplaces (Nelson and Winter, 1982). Similarly, drawing from the arguments of Dosi, Nelson and Winter (2000) and Estolatan and Geuna (2019), firms are likely to select knowledge combinations that are close to their existing bases, a phenomenon that leads to the accumulation of a particular group of related capabilities within organisations. Because related technologies are rooted in the same fundamental knowledge and tend to share common science principles, related technological diversification is characterised by the high extent of technological relatedness in knowledge base (Breschi *et al*., 2003; Chen, Shih and Chang, 2012). For this reason, related technological diversification can not only enable organisations to learn knowledge from related technological areas to enhance their R&D competences, but also lower R&D costs owning to economies of scope (Cantwell and Piscitello, 2000). One might expect such diversification to create opportunities in a wider scope of technological innovation. The possible advantage of technological diversification mainly lies in its acceleration of spillovers across related technological domains. This argument is akin to the claim of Frenken, Van Oort and Verburg (2007) about knowledge spillovers within a region, which mainly occur among related sectors based on firm-level economies of scope.

From another perspective, a firm that extends its technological boundaries into adjacent fields, as in the case of related technological diversification, enables it to build stronger core capabilities, from which it can benefit by making full use of them (Zook and Allen, 2003). Recently, Suzuki and Kodama (2004), investigating the patent data of Canon, reveal several successful cases in which core technologies are diversified into adjacent fields; for instance, Canon's semiconductor manufacturing machinery (specifically, its mask aligner) has a close relationship with cameras, one of its core technologies. Generating such technological trajectories allows organisations to offer a wider spectrum of products, which directly links to new product development and market penetration. Hence, a plausible deduction can be made that related technological diversification exerts a positive influence on corporate innovations where adjacent technologies are relevant.

From an alternative perspective, portfolio theory (Montgomery, 1994) considers unrelated technological diversification to be a strategy designed to protect enterprises from external technological shocks by using uncorrelated chances and spreading risk over unrelated fields. This is consistent with the argument in Garcia-Vega (2006) that firms apply unrelated technological diversification to seize R&D opportunities cross different technological areas and to share R&D risks. For instance, in the case of Takeda, exotic technologies are imported and combined with the company's existing knowledge base, allowing it to consistently supply a broader spectrum of products that are in the same vein but are nevertheless new (Suzuki and Kodama, 2004). Directing resources to a wide variety of technological fields, in other words unrelated technological diversification, alleviates the scarcity of innovation opportunities from a narrowly defined domain and thus equips firms with the capability to explore new technological opportunities by using the knowhow generated by diversification (Katila and Ahuja, 2002). Following this reasoning, unrelated technological diversification is also expected to enhance technological innovation.

Within the network of the IoT, those emerging solutions are featured by high technological complexity in respect to different technologies and protocols, variety of devices (Ma, 2011), and the participation of various actors connected in value creation activities who need to be coordinated in ecosystems (Rong *et al*., 2015). Earlier presented arguments indicate that diverse fields of technological knowledge in terms of hardware and software infrastructural platforms are, together with electronic systems for communication, crucial to the smooth running of interconnected networks. IoT, being characterised by diversified knowledge bases, a high degree of newness, and considerable impacts on the existing pattern of information networks, can be viewed as an ideal embodiment of discontinuity innovation. As a result, it is plausible to infer that companies involved in such a paradigm shift ought to expand their knowledge bases with novel technological solutions and adopt broader technological diversification strategies. This argument is corroborated by the existing empirical studies. For instance, Sadowski, Nomaler and Whalley (2016) provide evidence that technological diversification into IoT technology has been a common strategy for ICT companies over the past twenty years. They also argue that a higher degree of technological diversification can lead to technological specialisation in the new emerging technological field of IoT (Sadowski *et al*., 2016; Sadowski *et al*., 2019). In line with above theoretical arguments and evidence, we hypothesise that both related and unrelated technological diversification are beneficial to innovation in this ground-breaking technology.

H2a. The higher the related technological diversification, the more likely it is that a firm will participate in innovating in IoT technologies.

H2b. The higher the unrelated technological diversification, the more likely it is that a firm will participate in innovating in IoT technologies.

2.3.3 The role of innovation persistence

The tension between core-technology competence and diversification suggests that the persistent accumulation of knowledge and learning may not drive innovation in all types of technologies. In the cases of incremental and developmental innovation, persistent technological learning and accumulation of knowledge over time should support firms to sustain innovation (Leten *et al*., 2007), since innovation is itself a cumulative process of incremental problem-finding and problem-solving activities (Rosenberg, 1982). Hence, its path-dependent nature is driven by three elements: knowledge cumulability, external knowledge, and the firm's dynamic capabilities (Crespi and Scellato, 2014).

However, innovation persistence may become a barrier for breakthrough innovation such as IoT technologies. First, if a firm largely relies on its existing knowledge stock to generate new ideas (Weitzman, 1996), it may be limited by path dependence and therefore miss important new opportunities. Further, firms' existing internal knowledge shapes how they seek out external knowledge, given the importance of knowledge generation from internal knowledge stock to external knowledge sourcing (Antonelli, 2011). External conditions in terms of knowledge externalities and rivalries act on internal knowledge bases, imposing localised impacts on innovation persistence (Crespi and Scellato, 2014).

However, while the direct effect of persistence may be ambiguous, there is also evidence that innovation persistence and technological diversification can be mutually reinforcing (Pavitt, Robson and Townsend, 1989). Suzuki and Kodama (2004) use the cases of two large Japanese corporations to show how they were able to experience sales growth for a prolonged period through persistence and technological diversity. Similarly, Crespi and Scellato (2014) also suggest a positive loop between knowledge accumulation, dynamic capabilities development, and continuous innovation activities. Firms that command larger internal knowledge stocks and have more capabilities to exploit the knowledge bases from other external agents will find it easier to introduce further innovations (Antonelli, 2011). Shim, Kwon, Moon and Kim (2016) conceptualise two dimensions to investigate the mechanism of technology convergence, explaining it as a continuous process in which diversity and persistence are constantly interacting with each other. In their framework, diversity captures the capabilities for assimilating diverse technologies, while persistence refers to continuity in using accumulated technologies.

Thus, persistent innovation, as a network of firms' technological competences, can modify companies' knowledge bases (Colombelli and Quatraro, 2014). This modification occurs along three dimensions: coherence, similarity, and variety. Coherence refers to the extent to which knowledge elements within the sector, which are used for new knowledge creation, are complementary to each other. Similarity is defined as the degree of closeness among knowledge pieces within the knowledge space (Colombelli and Quatraro, 2014). The nature of variety is connected with technological differentiations within knowledge bases, specifically concerning the diverse feasible combinations of knowledge pieces within the sector (Colombelli and Quatraro, 2014). Organisations improve their knowledge bases by increasing the degrees of knowledge complementarity, similarity, and variety in their technological portfolios. Such dynamics also prove the cumulative character of knowledge creation process. These properties of knowledge bases are closely related to firms' ability to pursue a given innovation strategy of 'exploration' or 'exploitation' (March, 1991).

Firms appear to be more technologically diversified as time goes by (Granstrand, Patel and Pavitt, 1997; Patel and Pavitt, 1997). The relatedness or unrelatedness of technical knowhow at a specific point of time is a cross-section of dynamic relatedness or unrelatedness in the technology across time (Kim and Kogut, 1996). Further, the path dependence dynamics of innovation persistence can benefit firms that consistently engage in knowledge creation based on internal and external knowledge stocks because related and unrelated technological diversification tend to be continuously accumulated. Here, a self-reinforcing mechanism along the path of capability formation can be inferred, with a high accumulation of diversified knowledge bases giving rise to the development of an organisation's dynamic capabilities, a virtuous outcome that subsequently drives innovation activities (Crespi and Scellato, 2014). When firms consistently exploit knowhow bases and create new pieces of knowledge, a high level of accumulation of diversified knowhow and development of dynamic capabilities can be expected. In this respect, one could expect that the positive effects on innovation, stemming from technological varieties of knowhow, will be strengthened. Taken together, persistent innovators should be in a better position than their non-persistent counterparts to obtain benefits from both related and unrelated technological diversification. Thus:

H3. Innovation persistence strengthens the positive role of related and unrelated technological diversification in driving innovation in IoT technologies.

2.4. Data, variables and empirical specifications

2.4.1 Data sources

This research employs patents data to capture firm innovation in the IoT-related technological domains. The limitations of using patent statistics as a proxy for innovation have been recognised in academic and practitioner-oriented literature. Not all inventions can meet the patentability criteria (Choi, Kim and Park, 2007) and the preference for patents as a means of protecting technologies may vary across firms, industries (Hasan and Tucci, 2010), and countries (Gold and Baker, 2012). In particular, the IoT may encounter a subject-matter eligibility issue, considering that this technology usually includes computer-implemented functionality and that abstract ideas implemented on a computer are not patent eligible.[17] Yet patents are still one of the most standardised and reliable indicators of innovation and the dynamic technological trend, given their consistent statistical features, comparability, and the strong correlation between technology development and patents (Sheikh and Sheikh, 2016). Applying for a patent in a certain technological field implies an advancement in the corresponding knowledge space and an accumulation of relevant knowhow (Suzuki and Kodama, 2004). More importantly, patents are specifically regarded as the most widely accepted gauge for measuring the innovative activities of IoT-related technologies (Kshetri, 2016a) in both academic and practitioner-oriented literature.

To measure firm's innovation performance in the IoT domains, relevant literature has suggested several approaches for capturing the development progress from different dimensions, including IoT-related products or services, adoption and diffusion of IoT-related products or services, standards setting, and creation of IoT-related patents (Kshetri, 2016b). We adopt the method that draws on patent data. The IPC system administered by the World Intellectual Property Organization (WIPO) offers a systematic hierarchy for classifying patents' technological domains and for subdividing technologies into different levels of sections, classes, subclasses, main groups, and sub-groups (WIPO, 2015). This enables each firm's technological trajectory to be traced. Following the search strategy suggested by the existing informatics literature (e.g., Martinelli *et al*., 2021), patent records can be identified as IoT-related by a set of designated IPC codes belonging to the technological domains of the IoT. Drawing on the classification symbols documented in Trappey *et al*. (2017) and publications by the UK IP Office (2014b), we classify a patent as IoT-related if its IPC symbol is identified as such, with the full list of relevant IPCs being provided in Appendix Table 2.A1. Of the existing academic literature and official reports that have been examined, these two works, to the best of our knowledge, present the most comprehensive lists of IPCs for defining the scope of IoT-related technologies. Similarly, to identify innovation activities in the wider ICT technology sector, a list of IPC codes belonging to the ICT technological fields published by OECD in 2011 (see Appendix Table 2.A2) is used in the search for

[17] For more details, see https://henry.law/blog/internet-of-things-patent-challenges/

related patent records. It is worth mentioning that under the current research setting, the IoT-related technology is a subset of the entire ICT field based on the collected IPC symbols.

Following this search strategy, a IoT technology landscape of UK firms is built by extracting information from the Bureau van Dijk's Orbis IP database, which covers historical patent records (1808-2019). Orbis IP covers all filings made through the Patent Cooperation Treaty (PCT) from the WIPO, PATSTAT data from the European Patent Office (EPO) as collected by Lexis Nexis, and additional national filings not covered by PATSTAT. This database provides detailed patent records with their publication date, current direct owner(s), and complete symbol of the primary IPC. Compared to other sources of patent data, the advantage of Orbis IP is that patent records can be matched to their current direct owner's corporate and financial information using a unique firm identifier. Note that in this empirical work, we draw on records of patents owned by UK firms, including not only those registered through the UK IPO but also those registered via other patent authorities. This can raise concerns about double counting inventions that are registered in more than one patent office, when individual records are used instead of the patent family. The aim of this research is not to count IoT patents but rather to model the probability of a firm patenting in the IoT fields. Therefore, this issue is therefore less of a concern.

For the sake of data aggregation, the publication date of each patent record is chosen to capture the time when the technological knowledge was created; this creates far fewer missing values than if the application date had been used (only 714 out of 2,984,750 patent records have been dropped for lacking the publication date). The individual record is organised in a panel setting using its current direct owner's firm identifier and patent publication year. We then match the patent records with Bureau van Dijk's Orbis database using the identifiers of UK firms and publication years for the period from 2008 to 2017. Here, the UK firms are defined as those which are registered and located within the geographical scope of the United Kingdom. The linked data generate a total of 95,666 patents of any classification symbol owned by 2,707 firms. Over the examined period, 1,417 IoT-related patents are owned by 150 firms, 21,231 non-IoT ICT patents are owned by 905 firms, and 73,018 non-ICT patents are owned by 2,707 firms. As expected, patents are concentrated among a small number of firms, with half of the firms in the sample having four (or more) patents. A range of company characteristics including age, size, type of corporation, sector, location, and various financial indicators are taken into consideration, totalling 9,175 firm-year observations.

2.4.2 Measurement of variables

2.4.2.1 Dependent variable

The dependent variable is a multinomial categorical indicator of a firm's different innovation activities. Given that firms may publish patents of any type or types at some point in time, we design three mutually exclusive and exhaustive set of options: firms with IoT patents (choice 1), firms with ICT patents other than IoT ones (choice 2), and firms with non-ICT patents only (choice 3, base group).

If a firm has at least one patent in the IoT field in a given year regardless of any other type of patent, we classify this firm-year observation as the first category (choice 1, IoT patenting), which takes value of 1. If a firm has at least one patent in the ICT domains but without any IoT, it will be assigned to the second group (choice 2, ICT patenting), taking value of 2. The last category covers companies that patent in other non-ICT technological domains only (choice 3), taking value of 3. In this multi-choice modelling setup, the last category is defined as the reference group. Using this way of modelling, the assumption we make (and test through the hypotheses) is that firms that possess IoT patents are somehow different from those that have ICT but no IoT patents, while firms with ICT or IoT patents differ from those who have only non-ICT patents. Empirically, the exhaustiveness of above 3 options and the independence of irrelevant alternatives (IIA) can be tested. What one needs to ensure is that the relative probability of IoT patenting over ICT patenting is not affected when an additional alternative of non-ICT patenting is considered simultaneously. A statistical test is adopted to test this assumption and the Hausman-McFadden test reports no violation.

2.4.2.2 Independent variables

We measure a firm's ***core-technology competence*** by following Kim *et al*. (2016) in drawing on the RTA (Patel and Pavitt, 1997). Technology competence captures a firm's commitments and positions across a range of technological areas. The main intention is to derive the relative importance to each technological field of the firm's different kinds of patenting, after taking account of the share of the firm's total patenting in the entire patent sample across all the fields. The RTA method creates an index for firm *i* within the field *q*:

$$RTA_{ijt} = \frac{P_{iqt}/P_{qt}}{P_{it}/P_t} = \frac{P_{iqt}/P_{it}}{P_{qt}/P_t}$$

Where P_{iqt} is firm *i*'s number of publications in technological field *q* at time *t,* and P_{qt} refers to the number of publications within field *q* owned by the sampled organisations at time *t*. The number of publications owned by firm *i* at time *t* is marked as P_{it}, and P_t sums up the total number of publications for the entire sample across all fields at time *t*. By comparing the patent share of field *q* in firm *i*'s patent portfolio (i.e., P_{iqt} /P_{it}) to the patent share of field *q* in the entire sampled patents (i.e., P_{qt}/P_t), the RTA index in effect sheds light on the extent of firm *i*'s specialisation in field *q*. We then compute the product of the RTA index and number of publications for the corresponding field across 1,085 technological domains. The maximum value is the measure of the firm's core-technology competence:

$$coretec_{it} = ln\left[max\left(RTA_{iqt} \times P_{iqt}\right)\right]$$

This metric depends on two dimensions, which are the dominance in a given technological field defined by the RTA and the quantity of patents in that field. On one hand, the RTA index captures the extent of a firm's specification or dominance in a given technological field. On the other hand, the number of patents in such field represents a firm's strength in the corresponding technological knowledge field. Only when both the RTA and quantity of patents in a given field are high can we have the largest value of core-technology competence. Since the index is calculated by taking the maximum value of the product of the RTA and number of publications for the corresponding field across a firm's all the technological fields, this measure captures the degree to which the firm has the highest level of such competence. Grounding on the concept and measurement, it is worth noting that the technological field in which a company has the core-technology competence will not make a difference to the index value itself.

Given the assumption that the accumulated knowledge base affects a firm's capability of performing certain types of innovation in subsequent time periods, core-technology competence is lagged two years behind the dependent variable following Kim *et al*. (2016).

Next, ***Technological related and unrelated diversification*** are created to capture firm's technological diversity. Following the strategic management literature, which has established the use of the entropy index for quantifying technological relatedness and unrelatedness (e.g., Chen and Chang, 2012; Kim *et al*., 2016; Zander, 1997), we adopt the method introduced by Kim *et al*. (2016). One of the advantages of the entropy index is that it can be easily decomposed at different levels as required, such that it will not cause collinearity in the regression analysis (Sadowski *et al*., 2016).

The entropy measure evaluates firm's patent shares across technological fields. The four-digit Subclass of the IPC symbol is used for classifying technological fields, and each field can be subdivided into the Main group or Subgroup levels (most detailed). Such classification method yields 1,085 different technological fields and 68,537 different Main groups or Subgroups in the sample. Then two entropy indices for related and unrelated technological diversification are constructed. The equations show as follows:

$$rv_{it} = \sum_{q=1}^{n} PS_{iqt} \left(\sum_{r \in q} PS_{irt} ln(1/PS_{irt}) \right)$$

$$uv_{it} = \sum_{q=1}^{n} PS_{iqt} \, ln(1/PS_{iqt})$$

where PS_{iqt} denotes firm i's patent share of technological field q at time *t* and is derived from P_{iqt} and P_{it} (PS_{iqt}=P_{iqt}/P_{it}). P_{iqt} is the number of patent publications of firm i in field q at time t, and *r* stands for the main groups or subgroups within the field q. Similarly, P_{irt} is derived from number of patents of firm i within r at time t, whereas P_{it} counts the total number of patents published by firm i at time t (i.e., $P_{it} = \sum_{r=1}^{68537} P_{irt}$). The first equation evaluates the weighted average of related diversification across 68,537 main groups or subgroups within 1,085 fields (n=1085) while the second measures unrelated diversification across 1,085 technological fields (n=1085). Again, related and unrelated technological diversification are lagged two years behind the dependent variable.

Turning to ***innovation persistence***, despite abundant discussion of this concept, verifying and quantifying the existence of innovation persistence still proves elusive (Bianchini and Pellegrino, 2019). Intuitively, the term 'persistent innovator' refers to an organisation that has consistently applied patents in a certain domain of technology (Malerba and Orsenigo, 1999) or has introduced new products or processes consecutively over a certain period of time (Bianchini and Pellegrino, 2019). Previous literature has employed the transition probability matrix (e.g., Cefis, 2003; Cefis and Orsenigo, 2001) and other econometric analysis methods to quantify the persistence in innovation. These include random effect probit models (Antonelli *et al*., 2012; Ganter and Hecker, 2013; Huang, 2008), and hazard models for innovation spells (Fontana and Vezzulli, 2016; Geroski, Van Reenen and Walters, 1997). Another method for measuring the degree of innovation persistence is to construct an indicator by counting the frequency with which an organisation innovates in a given time window. However, this measure turns out to be sensitive to the number of years observed for each firm, especially when the panel data set is unbalanced. Most importantly, a simple count of the frequency of innovation activities is unable to capture interruptions over a number of time-steps, which represents a feature of discontinuous innovators (Bianchini and Pellegrino, 2019). The concept of 'innovation spell' refers to the number of successive years during which a firm introduces at least one patent per year without interruption or gaps (Geroski *et al*., 1997), and it is considered able to overcome the drawbacks described above (Bianchini and Pellegrino, 2019). In line with the notion of consecutive innovation spell, Guarascio and Tamagni (2019) regard persistent innovators as those who have participated in a certain type of innovation for at least 7 consecutive years within a 10-year-period. Similarly, Demirel and Mazzucato (2012) use a minimum of five consecutive years of patenting as the criterion to define a persistent patentee. In the present case, we use the idea of innovation spell, which implies a firm's innovation state for the last consecutive five years. For a certain firm, the variable takes value of 1 in a given year if at least one patent has been published in the last five years consecutively.

2.4.2.3 Control variables

Our choice of control variables is guided by the existing literature on innovation outputs and limited by the data availability. Essentially, two indicators of a firm's overall innovativeness are included: accumulated innovation intensity and patenting experience. A firm's past innovation output and its accumulation of innovation experience have been found to have a positive impact on its current intensity of innovation output (Córcoles, Triguero and Cuerva, 2016; Kim and Kogut, 1996), especially in the high-tech category (Raymond, Mohnen, Palm and Schim Van Der Loeff, 2010). Penrose (2009) also notes that firms learn to take advantage of their resources, such as technical knowhow and R&D capabilities, to create favourable conditions for engaging in other promising technological fields (Leten *et al*., 2007). Innovation intensity is captured by the ratio of accumulative number of patents for the last five years to the number of employees at time *t*. Patenting experience is measured by the log-transformed value of number of years since a firm gained its first patent.

Firm age and size (natural log value of number of employees) are included as controls to account for a firm's resources and capacity. A recent study of 128 IoT adoption cases across 500 production sites in Germany shows that the deeper users and more advanced buyers of IoT tend to be large businesses, while small and medium-sized enterprises lag behind (Martinelli *et al*. 2021). Total factor productivity (TFP) is also included, estimated by a revenue-based Cobb-Douglas production function using production factors of labour, capital, and materials.

Investment in innovation requires sustainable long-term financing (Teece, 1986), and one can expect it to play an important role in driving IoT technologies. Thus, we include firm's cash flow (the log-transformed value of cash and cash equivalents). Intangible assets, including goodwill, brand recognition and various forms of intellectual property, can be viewed as a proxy for organisational creativity and innovation strength. Therefore, a ratio of intangible fixed assets to the firm's total assets is computed to account for invisible assets' influence on the possibility to innovate. Further, average wage (the ratio of cost of employees to number of employees) is added as a proxy for labour quality, with higher labour quality being generally associated with stronger capabilities to absorb external knowhow and create new knowledge.

Prior research suggests that multinationals exploit technological capabilities and knowledge globally by means of exporting, establishing subsidiaries, and licensing (Iammarino and Michie, 1998). According to Kshetri (2016b), the Chinese IoT sector has benefited substantially through various mechanisms associated with multinationals' technological globalisation strategy. It is therefore important to allow for the possibility that foreign-owned firms are more capable than purely domestic ones of accessing broader knowledge bases and more diverse sources of information through building inter- and intra-company linkages. Finally, sectoral and regional heterogeneity are controlled for by their dummies. Appendix Table 2.B1 summarises the variable definitions.

2.4.3 Empirical specification

To identify the key determinants of firms' IoT patenting activities, we adopt a multiple choice modelling approach to estimate the likelihood of a firm's engagement in patenting in three types of domains, j, described above: IoT technologies (j=1), ICT technologies more broadly (j=2), and other non-ICT technologies (j=3). It is worth noting that our dependent variable has three distinct and separable choice alternatives, these choice alternatives in question are not nested, and there are no alternative-specific independent variables. In the present context, our choice narrows down to a multinomial logit or multinomial probit model. The former model's validity is contingent on the IIA assumption not being violated, while the latter model relaxes this assumption (Long, 1997; Long and Freese, 2014). Our results of Hausman-McFadden test show that the IIA assumption is not violated. Since the multinomial probit model is much more computationally demanding and produces qualitatively similar results as the multinomial logit model (Thrane, 2015), a multinomial logit model is specified with an underlying assumption of firms' maximising utility by making such a choice:

$$Pr(y_{it} = j \mid X_{1it}) = \frac{exp\left(X_{1it-2} * \alpha_j\right) exp\left(Z_{1it-1} * \beta_j\right)}{\left[1 + \sum_{h=1}^{J} exp(X_{1it-2} * \alpha_h)\, exp(Z_{1it-1} * \beta_h)\right]} \quad (j = 1, 2, 3) \quad (1)$$

where y indicates the choice of patenting strategy of firm i at time t. X is a vector of explanatory variables that are hypothesised to determine patenting choices, including the firm's core-technology competence ($coretec_{it-2}$), related technological diversification (rv_{it-2}), and unrelated technological diversification (uv_{it-2}), all lagged by two years to mitigate potential endogeneity problems. The estimates of X will test the hypotheses *H1*, *H2a*, and *H2b*. Z is a vector of control variables hypothesised to influence firm's patenting choices. These variables include innovation persistence: $persistence_{it}$, innovation intensity: $intensity_{it}$, and firm's experience in innovation since its first patent: $experience_{it}$, which capture the patterns of a firm's innovation pathway. Firm characteristics are captured by age, size, productivity, cash holding, intangible assets ratio, average wage, and foreign ownership. $Region_{it}$ controls for regional fixed effects, $Industry_{it}$ controls for the effects at the NACE section level, and $Year_t$ stands for year dummies.

As noted earlier, the key assumption of a multinomial logit model is the IIA, which requires that the relative probability of any given choice over another is independent of considering an alternative option. The Hausman-McFadden test is used for testing, and the results suggest no violation of the IIA assumption.

To test *H3*, we add two interaction terms to account for the moderating effects of innovation persistence on the effect of technological related and unrelated technological diversification on different types of innovation activities.

2.5 Empirical results

2.5.1 Summary Statistics

Table 2.1 reports summary statistics of the variables in our final sample. The statistics are available for the overall sample and for each group of firms according to their patenting type. Overall, firms turn out to be highly heterogeneous. With an average age of 33 years and 152 employees in company size ($e^{5.03}$), sampled firms have a wide range of productivity. Half of the firms are owned by foreign owners. They show a strong tendency to innovate persistently (*persistence*) and have a relatively high level of innovation intensity (*intensity*).

Interesting findings emerge for firms in the different groups. Firms with IoT patents have the lowest core-technology competence and the largest related and unrelated technological diversification across all the groups. In contrast, firms without any ICT patents enjoy the highest core-technology competence and the lowest related and unrelated technological diversification, while firms with other ICT patents fall somewhere in the middle.

In respect of innovation trajectory, firms innovating in the IoT domain seem to have the highest innovation persistence, but they do not necessarily have higher innovation intensity than the group that innovates in other ICT domains.

Interestingly, firms patenting in IoT are younger (although not actually young), bigger, and more productive. More such firms are foreign owned. However, firms in this group are possess fewer intangible assets than those patenting in other ICT.

<Table 2.1 inserts here>

Table 2.2 summarises the correlation coefficients for the key variables in the sample. Core-technology competence is weakly positively correlated with related technological diversification. As well as being positively correlated with each other to some extent, both related and unrelated technological diversification are moderately positively correlated with innovation persistence. As expected, innovation persistence and experience since the first patent are moderately positively correlated, but not excessively so.

<Table 2.2 inserts here>

2.5.2 Regression results

To estimate the determinants of firm’s patenting choice, a multinomial logit model is specified, shown in Equation (1), with standard errors clustered at the industry level. Three types of patenting choice are categorised: (I) patenting in IoT field, (II) patenting in non-IoT ICT field, and (III) patenting in non-ICT field, with the last being the reference group. In order to compare the likelihood of IoT patenting relative to two other choices, we compute the relative-risk ratios of (I) and (II) relative to (III), and the relative-risk ratio of (I) relative to (II) (see Table 2.3). A relative-risk ratio of less than one indicates less likelihood, while a value higher than one shows more likelihood, with the value suggesting how many times more likely. Estimates of marginal effects are reported in Appendix Table 2.C1. Here, two specifications of the baseline regression are reported. Model (1) focuses on the direct effects of the explanatory variables, and model (2) incorporates additional interactions to examine the moderating effects of innovation persistence.

<Table 2.3 inserts here>

Across all model specifications, core-technology competence is statistically significant in explaining patenting choices. A higher level of core-technology competence reduces the likelihood of patenting in both the IoT and non-IoT ICT domains (with respective estimated relative-risk ratios of 0.728 and 0.861 in Model 1), relative to the non-ICT domains. This suggests that core-technology competence is something of a catalyst for non-ICT patenting, but plays a less important role in ICT patenting. When comparing IoT and other ICT patenting (I versus II), we discover that firms with a higher level of core-technology competence are less likely to have IoT patents, further suggesting that core-competence may hamper success in innovating IoT technologies. Results in Model 2 are similar. This supports our hypothesis *H1*.

The variables of technological diversification are statistically significant and highly positively related to IoT patenting. Related technological diversification seems to be a typical feature of IoT patentees, in that firms with a one unit increase in their related diversification index are three times more likely to have IoT patents than any other types of patents (Model 1). It is interesting that scoring higher in related technological diversification does not seem to differentiate patenting choices between the ICT and non-ICT domains (II versus III). Thus, while expanding firm's knowledge base within related subdomains is instrumental to innovating in IoT, it has no effect on firms' patenting in traditional ICT or non-ICT fields. This then suggests that for such firms it is more beneficial to specialise within a knowledge domain that is relatively narrowly defined. In Model 2 with additional interaction terms, we find the estimate of related technological diversification to be qualitatively the same and quantitatively magnified. Firms with a one unit increase in related technological diversification index are now at least 4.8 times more likely to have IoT patents compared to any other types of patents, and 6 times more likely to have IoT patents than traditional ICT ones.

Unrelated technological diversification also predicts IoT patenting. A one unit increase in unrelated technological diversification makes a firm 13 times more likely to produce IoT patents than non-ICT patents and nearly 5 times more likely to produce IoT patents than ICT ones. This suggests that compared with innovation in other traditional ICT subdomains, ground-breaking innovation in IoT tends to rely on larger varieties of prior capabilities within the same technological field as well as across a wider range of technological domains. This is consistent with the preceding postulation that the boundary-spanning nature of IoT technologies goes beyond the relatively narrow fields of information and communication, and is able to extend to other fields such as logistics, architecture, healthcare, and human behaviour. Thus, hypotheses *H2a* and *H2b* are confirmed.

The contrasts in how core-technology competence and diversity drive IoT and more traditional ICT technologies may rest on the differences in the nature of such technologies. IoT technologies are generally composed of a complex architecture building on different layers of specific technologies, with each layer consisting of various components, and dealing with distinctive functions to support the whole information network. These components may be objects, platforms, gateways, processes, and algorithms of different sizes and capacities, some of which expand beyond the traditional ICT domains. To incorporate these components into IoT technologies requires knowledge and capacities from a set of fields that are much wider than the traditional or more homogenous technological domains. Issues such as device accessibility and compatibility mean that IoT innovation requires innovators to possess an open mind if they are to adapt such technologies to the changing demands posed by real life scenarios.

Next, we turn to innovation persistence. Model 1 suggests that innovation persistence is important for ICT patenting but has no effect on IoT patenting (an insignificant relative-risk ratio of 0.87). It is expected that the path dependence of innovation is particularly observable in the ICT fields, given the well-documented evidence not only in terms of firms' patenting activities (Alfranca, Rama and von Tunzelmann, 2002; Cefis, 2003; Cefis and Orsenigo, 2001; Geroski *et al*., 1997; Malerba *et al*., 1997) but also generally in product and process innovation (Peters, 2009; Raymond *et al*., 2010). Considering that the traditional ICT innovation often features incremental and developmental innovative activities by, say, widening the applications within relatively established technologies, firms are expected to exhibit persistent innovation by building on continuous learning and knowledge accumulation (Leten *et al*., 2007). In contrast, what is interesting is the lack of predictability of IoT patenting based on firms' innovation persistence. This shows that IoT technological innovation is typically pathbreaking, which suggests that the prior persistence of knowledge creation may be insufficient for, or even irrelevant to, creating new technologies in the IoT domains.

Does this mean that innovation persistence is of no use to IoT innovation? We investigate this further through Model 2 which incorporates interactions of innovation persistence and related and unrelated technological diversification. The first thing to note is that interacting innovation persistence with related diversification does not make IoT innovation more likely, but it does enhance ICT innovation by a factor of 1.7. This suggests that persistent ICT innovators can benefit further by diversifying into fields within the technological domain of their knowledge bases.

However, interacting innovation persistence with unrelated diversification does make IoT and ICT innovation much more likely. The relative-risk ratio estimates suggest that persistent innovators who technologically diversify more widely across different technological domains are 4 times more likely to produce IoT patents than non-ICT patents, and 3 times more likely to produce IoT patents than traditional ICT patents. These findings show that while innovation persistence does not directly drive ground-breaking IoT innovation itself—i.e., adding interactions seems to make IoT innovation less likely—it can strengthen the benefits of unrelated technological diversification on IoT innovation. This offers clear support for hypothesis *H3* with respect to unrelated technological diversification.

The results regarding control variables are consistent with our expectations. Higher innovation intensity and longer experience in innovation are accompanied by a higher likelihood of traditional ICT innovation across the two models, but these results do not hold in the case of IoT innovation. When considered with discoveries on innovation persistence, these findings indicate that a firm's intensive and long history of innovation activities is not sufficient to spur discoveries in ground-breaking and boundary-spanning technologies such as IoT. They further show that the estimates of innovation persistence remain robust even after controlling for the intensity of existing innovation and length of innovation history.

It is worth noting that firm characteristics that historically relate to firm innovation have limited explanatory power in IoT patenting. Firm size, age, and foreign ownership are the only characteristics that matter to this patenting choice. Younger firms are more likely to innovate in IoT compared to other ICT fields, although the two relative-risk ratios are statistically insignificant in baseline models. There is evidence that larger firms seem to be more likely to produce IoT, but firm size loses its statistical significance when interaction terms are added. Unsurprisingly, among the UK businesses, foreign-owned firms are more likely to engage in IoT than other ICT and non-ICT innovation. This may be explained by multinationals' strong dynamic capabilities to access a wide range of knowledge bases through internationalisation and intra-company linkages, favouring extensive knowledge searching and novel knowledge recombinations.

Firms innovating in the IoT areas are not necessarily more productive or more cash rich, as estimates of those two variables are not statistically significant. Similarly, intangible assets and wage level, a proxy for labour quality, do not increase the likelihood of IoT innovation.

2.6 Robustness tests and additional analysis

Although the baseline models offer clear support to the hypotheses, several measurement issues and an identification question may exist and affect the robustness of the findings. In this section, we report and discuss the robustness test procedures and findings.

2.6.1 Measurement issues

Time dimensions of core-technology competence and technological diversification

In the baseline models, core-technology competence and related and unrelated technological diversification are lagged two years behind the dependent variable in order to control for the potential endogeneity. To test the sensitivity of results to the chosen time dimension, lagged values by one and three years of the three main predictors are employed for additional analysis, and the main results remain valid[18].

Alternative definition of innovation persistence

As an important variable, persistence in innovation needs to be carefully defined. Besides adopting the concept of 'innovation spell' and relying on firms' patenting states for the last consecutive five years, a more restricted criterion of the last seven consecutive years is used for testing, with the alternative variable taking the value of 1 for a firm in a given year if at least one patent has been published in the last seven consecutive years. Again, key results remain unchanged in this analysis[19].

2.6.2 Potential endogeneity

In the baseline model, related and unrelated technological diversification are lagged two periods to counteract potential endogeneity with the dependent variable. However, one cannot dismiss the possibility that endogeneity may still occur. For example, omitted variables such as firm leadership and strategic vision may drive firms' innovation outcomes as well as potentially correlating with their technological strength or knowledge stock. This would result in biased estimates. In this case, adopting an instrumental variable strategy for the variation in technological diversification becomes necessary. To this end, we instrument related and unrelated technological diversification with more aggregate variables that are, by construction, exogenous to firms' strategic innovation choices, such as an impulse in the firm's industry or economic environment (e.g., Lachenmaier and Wößmann, 2006). In influencing all the firms within the same region or sector in similar ways, such variables are unlikely to determine individual firms' innovation choices. In the meantime, variations in the innovation eco-system between regions and industries can be expected to have explanatory power in the variations of firms' innovation choices.

[18] Results are available on request.
[19] Results are available on request.

As the first step, a region-specific variable is constructed, which is the current level of total public R&D related to the IoT and Big Data technology in a region, defined by log-transformed R&D grant value (£) ($fund\_ib_t$). Conceptually, offering public support for private R&D stimulates firms to increase private sector R&D activities, generating enhanced innovation capabilities and better organisation performance in the long run (Vanino, Roper and Becker, 2019). Extant literature has identified several mechanisms through which public R&D support induces innovation activities. Such mechanisms include raising financial slack (Zona, 2012) and creating new knowledge and capabilities by enabling access to new or pre-existing knowledge stocks (Vanino *et al*., 2019). The rationale behind the impacts of public R&D grants on innovation output is the assumption that public funds can potentially enlarge firms' resources and knowledge bases, which further build up companies' capabilities. For instance, Marlin and Geiger (2015), focusing on US manufacturing firms, show that companies are able to improve innovation outcomes through internal slack (where they integrate sets of their own resources) or external slack (i.e., resources potentially available to them, such as public R&D support). This suggests that the two potential endogenous variables seem to offer channels for public R&D grants to exert effects on a given firm's innovation outcome.

The generated variable at regional (NUTS-1) level captures the related R&D grants funded by UK research councils (UKRCs)[20] and the other three funding organisations[21] from the Gateway to Research (GtR) portal over the funding period of 1973 to 2050[22]. This measure of public R&D funding and support to some extent captures companies' local innovation context, which offers a potential exogenous source of variation to the varieties of company's innovation activities. To identify the relevant funded research projects, we conduct text searching on the key words within the title of each project. After eliminating unrelated projects and those without an end date or region information (and those outside the UK), 1,415 projects remain from a total of 88,144. The subsample contains projects related to the IoT and Big Data technologies (by reference to the list of key words summarised in Appendix Table 2.A3), which are worth nearly £620 million. The regional breakdown (by number and value) of those research projects at the NUTS-1 level is shown in Table 2.4. By allocating the awarded value of each project to its corresponding region across the duration of the support period, we transform the project-level public R&D data into a region-level panel data set. The right-hand panel of Table 2.4 presents value statistics of projects within the sampled period from 2008 to 2017.

<Table 2.4 inserts here>

[20] The seven are the Arts and Humanities Research Council (AHRC), the Biotechnology and Biological Sciences Research Council (BBSRC), the Economic and Social Research Council (ESRC), the Engineering and Physical Sciences Research Council (EPSRC), the Medical Research Council (MRC), the Natural Environment Research Council (NERC), and the Science and Technology Facilities Council (STFC).
[21] They are Innovate UK, the National Centre for the Replacement, Refinement and Reduction of Animals in Research (NC3Rs), and UK Research and Innovation (UKRI).
[22] The data for this study was extracted in January 2020 from the Gateway to Research (GtR) website available at: https://gtr.ukri.org/search/project?term=*. It covers the time period from the start to end date of all projects.

Further, another two **industry/region-specific** variables are constructed as additional instruments. The first variable is total number of patentees for the patents registered within a sector ($patentee\_s_t$), while the second is total number of patentees for the patents registered within in a region ($patentee\_r_t$). Both are rescaled by taking their natural logarithm. According to Roper and Love (2018), there are three elements of a firm's knowledge environment that play important roles in driving its innovation activities: spatial, sectoral, and network. The local context in terms of cooperative networks and the innovative atmosphere in the 'air' or in the 'buzz' exerts impacts on innovation output through facilitating resources and knowledge accumulation. The $fund\_ib_t$ variable may capture some of the 'air' from the supply side in the form of innovation inputs, but we are also interested in capturing some of the 'buzz' through innovation outputs. To do so, we further exploit information from the linked firm-level data, and calculate the total number of co-patentees of companies within a given NACE 4-digit level industry or in a NUTS-3 level region. These two variables are designed to proxy an industry or a region's participation in innovation networks that encompass knowledge subsets stemming from different collaborative partners. A higher number of patentees within a sector or region for the same number of patents is expected to imply a higher level of collaboration for knowledge creation, and the broader local innovation networks that incorporate diverse intellectual domains. This characteristic of regional and sectoral knowledge creation and exploitation, without necessarily determining an individual firm's innovation output directly, is expected to shape how firms explore and exploit external knowledge in order to branch out their own networks of knowledge generation. This would help forge companies' patterns in related and unrelated technological diversification.

In a nonlinear panel-data model, an appropriate strategy to deal with endogeneity is to use an instrumental variable approach in the control function, specifying equations for all the endogenous variables within the system (Wooldridge, 2010). Here, we adopt a generalised structural equation model (GSEM) to construct a generalised regression-adjustment estimator for nonlinear panel data (e.g., Rabe-Hesketh and Skerondal, 2008). This offers a solution that handles endogeneity by incorporating common, unobserved components into system equations with different endogenous variables (e.g., Bartus, 2017; Drukker, 2016). In this case, residuals from the first-stage equations on related and unrelated technological diversification are allowed to be correlated with the residuals derived from the second-stage multinomial logit regression, following the procedure of Bartus (2017). The GSEM model specifies simultaneous estimations of the baseline multinomial logit model and two linear regressions of related and unrelated technological diversification on chosen instruments and controls. They are jointly estimated using the full information maximum likelihood method (Loaba, 2022). Table 2.5 presents the estimates.

<Table 2.5 inserts here>

The results first show that the instruments included are individually and jointly statistically significant in the technological diversification equations, indicating the presence of likely endogeneity in the baseline model (Wooldridge, 2010). Interestingly, controlling for heterogeneity between different regions and sectors, regional R&D grants on the IoT and Big Data technology fields lead to decreased related diversification or, to put it differently enhance specialisation. A greater number of collaborative innovators in a sector and region (captured by numbers of patentees) are significantly and positively associated with both related and unrelated technological diversification, consistent with our expectation.

The relative-risk ratios of key variables are similar to those displayed in the baseline Table 2.3. For the focused group, IoT patenting, core-technology competence, related and unrelated technological diversification, and the interaction between persistence and unrelated technological diversification all show the same signs at a 1% significance level. To sum up, the results produced after dealing with potential endogeneity lend further support for our hypotheses, and GSEM performs better in correctly estimating standard errors.

2.6.3 Quantity of IoT patents

We extend the analysis by considering not simply whether a firm patents IoT technologies, but also the extent of that innovative activities. Here, the number of IoT patents owned by each firm is used as the dependent variable for testing whether the above hypotheses are still valid. The average marginal effects of two negative binomial estimators are presented in Table 2.6. In line with the main results, the effect of core-technology competence is still significantly negative, and both related and unrelated technological diversification are positively related to creating more IoT-related innovations. The positive sign and significance of the interaction between persistence and unrelated technological diversification still exist, suggesting that innovation persistence can strengthen the positive influence of unrelated diversification in increasing the extent of firms' involvement in IoT innovation.

< Table 2.6 inserts here >

2.7 Discussion and implications

2.7.1 Discussion

The primary aim of this chapter is to examine the factors that facilitate the generation of ground-breaking technologies in Industry 4.0. Specifically, it focuses on the effects of firms' competence in their core area of technology, technological diversification, and innovation persistence on ground-breaking innovation, as measured by IoT technology patenting. Until now, little attention has been paid to the nature of the players in the IoT domain and there is scant empirical evidence of their technology trajectory. It is also rare to find research that identifies the factors contributing to firms' involvement in IoT innovation. Thus, this work shows an advance in understanding the route towards innovation in specific pathbreaking fields within Industry 4.0. By exploring innovation patterns and firm characteristics, one can get a sense of what kind of prerequisites enable a business to create related knowledge within these emerging technological fields and which types of firms tend to be more ready for this iteration of technology revolution. Answers to the above questions are of critical importance in that they offer valuable insights for management and decision makers tasked with planning and stimulating related innovative activities in such a rapidly emerging field.

One crucial finding is that firm-specific core-technology competence is statistically significant and negatively related to innovation in IoT. Core-technology competence not only represents a firm's competitive advantage in a specific technological field, but also identifies the firm's level of specialisation in that area. Its characteristics in terms of cognitive proximity and technological interdependence tend to give rise to knowledge inertia, making firms persist in their existing technological trajectory, which attenuates their potential to connect with external technological bases and explore novel knowledge combinations. A possible reason for this might lie in the typical characteristics of IoT. Its sheer scale and high levels of heterogeneity and interconnectivity, braced by a highly complex architecture, require organisations to think beyond the scope of their proximate technological competences and to build diversified capabilities by exploring broader knowledge domains. Stated otherwise, technological specialisation in the forms of firm-specific competence in the core technological fields tends to attenuate firms' propensity to generate pathbreaking innovation.

With respect to technological diversification, a diversified technology portfolio significantly and positively enhances the likelihood of engaging in ground-breaking innovative activities. Having a diversified knowledge base facilitates searching for novel solutions and technological complementarities, which increases the propensity to create innovation breakthroughs and reduces the effects of knowledge inertia. The positive associations between different forms of technological diversification and IoT innovation accord with previous work on diversification's positive effects on innovation exploration (Quintana-Garcia and Benavides-Velasco, 2008). The positive effects of both related and unrelated technological diversification can also be explained by the features of IoT technologies. The underlying idea here is that cultivating this sort of knowledge demands exposure to new technical disciplines and the incorporation of various capabilities in order to connect new streams of knowhow and create new combinations. This conclusion aligns with the claim that the winners in this new and revolutionary world will be those who are able to link seemingly unrelated streams of information to discover unexpected connections, and those who realise that disruptions lie ahead for their industries and that they would do well to join the flow rather than cling doggedly to the old ways (Schwab, 2018).

As mentioned in the hypotheses development, innovation is considered as a process of persistence, where organisations rely on their previous innovation pathway. What is notable here is that innovation persistence fails to predict firms' innovation propensity in IoT technologies. This result does not offer support for the premise that continuity of innovation and previous innovation performance in terms of innovation intensity and experience will help to generate creative accumulation and creative destruction (Malerba *et al*., 1997). The fact that previous innovation patterns and experience are not prerequisites for cultivating the ground-breaking technologies in Industry 4.0 sheds light on the strategic management of innovation. This appears to be good news for new entrants who intend to keep pace with the technological revolution despite lacking outstanding innovation performance and experience. Rather than being a game only for the technological giants or advanced innovative incumbents, innovation in these emerging fields opens up opportunities for newcomers to get in on the act and equip themselves with the technological preparations for a new industrial revolution. However, while persistence in innovation seems to have no direct positive impacts on the innovation related to Industry 4.0, it has significant positive indirect impacts on emerging innovation, especially through unrelated technological diversification. If a firm continuously and persistently innovates by exploiting existing knowhow and absorbing external resources, the level of unrelated diversification within its knowledge base tends to accumulate over time, strengthening its dynamic capabilities. This process of knowledge accumulation and capabilities development in turn supports enterprises in taking advantage of cross-fertilisation or synergy effects (Suzuki and Kodama, 2004).

2.7.2 Managerial and policy implications

The above results provide insights not only for new entrants who desire to take part in this new area but also for pioneering innovators who wish to strengthen their technological positions within Industry 4.0. First, persistence in innovation does not enable pathbreaking innovation within the IoT technologies, and the firms involved in IoT patenting tend to be somewhat younger than those in non-ICT technology areas. This implies that new, agile, and young entrants, who might appear to be lagging behind, have a role to play in this wave of technological revolution. Second, managers would do well to be cautious about relying on firms' core-technology competence, which is likely to impede the emergence of IoT innovation. This is consistent with the argument that careful consideration should be paid to 'focus and back to basics' strategies in R&D activities (Granstrand *et al*., 1997). In order to be ready for the next generation of advanced manufacturing, companies should keep an eye on reducing the likelihood of experiencing core rigidities and the knowledge inertia induced by excessive core-technology focus. The management of firms seeking a way into IoT must distribute organisational capabilities and sustain a broader set of technological competences rather than largely focusing on firms' core-technology competence. Third, organisations should recognise the importance of establishing broad technological disciplines to assimilate or incorporate streams of varieties and to yield novel combinations. Given the velocity at which innovations and disruptions are taking place in this technological wave, new forms of comprehensive collaborations and partnerships connecting offline and online worlds, both for established incumbents and young firms, are becoming essential. Last though not least, since innovation persistence does play an indirect role in promoting innovation in this emerging field through strengthening unrelated knowledge diversification, companies need to recognise the importance of persistent knowledge accumulation so as to further benefit from cross-fertilisation.

The findings also have potentially important policy implications. In the new wave of Industry 4.0 technological innovation, the likelihood of predicting innovators becomes even weaker. For instance, the usual champions of innovation with persistent records may not be the pioneering innovators of IoT technologies. In fact, results suggest that public R&D funding seems to do little to encourage firms' technological diversification, which is instrumental for stimulating IoT technologies. Thus, the policy approach of cherry-picking potentially innovative firms to support is unlikely to bear much fruit. What is likely to be more effective is to build a breeding ground for creating new technologies with the right nutrients. In order to achieve this, our results suggest that policy makers should understand the benefits of firms' technological diversification and further facilitate its formation. Place-based industrial strategies (e.g., McCann, 2019) should encourage firms to diversify their own technological competences with the aim of accelerating unrelated diversity among firms within the regions.

Second, as has already been the case in several major economies, governments must take a more hands-on and top-down approach to promote businesses' readiness for Industry 4.0 (Yang and Gu, 2021). Given that knowledge depth and scope economies are prerequisites for ground-breaking innovations, fostering technological coordination and helping firms expose themselves to diverse knowledge connections might be a cheaper and more effective way of building on the existing large scale of direct investments in these technological fields.

Finally, policy makers expecting to advance technologies in Industry 4.0 should realise the effect of efficient and long-lasting policies to stimulate innovation (with the ultimate goal of catalysing growth), as innovation persistence exerts indirect effects on technological advancement through unrelated technological diversification.

2.7.3 Limitations and future research

The generalisability of the above results is subject to certain limitations. For instance, only IoT technologies are taken into consideration, and therefore caution must be applied as the conclusions might not be transferable to other technologies within Industry 4.0. Second, as the current analysis is restricted to firms operating within the UK, findings regarding the roles played by core-technology competence and related and unrelated technological diversification may not be applicable to countries with different institutional and regulatory regimes. Third, while defining different types of technologies with a search strategy based on classified IPC symbols is an efficient way of capturing innovation in the respective domains, it is at risk of missing technological classes that are not mentioned in previous publications but are nevertheless part of the target fields.

This chapter has also thrown up questions in need of further investigation. It would be interesting to extend this work to other technologies within Industry 4.0 and to verify the contributing factors of firm-level innovation in wider domains. These findings would be of greater importance to firms' strategy formulation and policy makers' decision-making. Previous studies (Daim, Rueda, Martin and Gerdsri, 2006; Dernis *et al*., 2019; Trappey *et al*., 2017) imply that emerging technologies can be properly described and captured through different types of approaches and data sources. More precisely, textual and content analysis using keywords from the ontology that corresponds to certain technology are driving the methodological trend for defining emerging technologies. Thus, it is rewarding to leverage bibliographic information of patent records for searching key words which correspond to certain technologies. Scientific documents and other forms of intellectual property rights, namely, trademarks and design rights, can be used as various sources of data that embody technological development from different dimensions. Lastly, more research is therefore needed to fully understand what kind of factors actually drive this type of pathbreaking innovation.

Table 2.1. Descriptive statistics by patenting groups

Variables		All firms				IoT patenting firms				Non-IoT ICT patenting firms				Non-ICT Patenting firms			
		Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Core-technology competence	***coretec***	6.5	1.5	2.25	11.2	6.06	1.61	2.92	9.8	6.21	1.5	2.92	10.53	6.62	1.48	2.25	11.2
Related technological diversification	***rv***	0.39	0.41	0	2.67	0.57	0.4	0	2.04	0.46	0.4	0	2.28	0.36	0.41	0	2.67
Unrelated technological diversification	***uv***	0.51	0.64	0	3.48	1.39	0.93	0	3.48	0.79	0.73	0	3.42	0.36	0.5	0	2.99
Innovation Persistence	***persistence***	0.45	0.5	0	1	0.67	0.47	0	1	0.56	0.5	0	1	0.4	0.49	0	1
Innovation intensity	***intensity***	0.46	2.48	0	92	0.65	1.8	0	28.36	0.81	4.24	0	92	0.33	1.45	0	47.33
Experience since first patent	***experience***	2.78	0.97	0.69	5	2.87	0.91	0.69	4.65	2.87	0.9	0.69	4.97	2.75	0.99	0.69	5
Firm age	***age***	33.43	24.4	2	147	27.46	18.12	3	92	30.35	22	2	125	34.83	25.33	2	147
Firm size	***size***	5.03	1.34	0.69	8.89	5.76	1.67	1.39	8.89	5.19	1.45	0.69	8.89	4.94	1.26	0.69	8.89
Total Factor Productivity	***productivity***	1.08	1.04	0.31	11.69	1.33	1.7	0.31	11.69	1.23	1.25	0.31	11.69	1.01	0.89	0.31	11.69
Cash	***cash***	3.26	2.05	0	9.87	4.1	2.33	0.01	9.87	3.51	2.03	0	9.87	3.13	2.02	0	9.87
Intangible asset ratio	***intangible***	0.05	0.51	0.00	47.67	0.05	0.10	0.00	0.74	0.06	0.13	0.00	0.88	0.05	0.60	0.00	47.67
Average wage	***ave_wage***	4.46	22.67	0	1418	6.22	21.44	0.25	138.86	4.47	34.07	0.09	1418	4.36	16.98	0	214.49
Foreign ownership	***foreign***	0.5	0.5	0	1	0.68	0.47	0	1	0.59	0.49	0	1	0.46	0.5	0	1
Observations		**9175**				**344**				**2304**				**6527**			

Note: The detailed variable definitions are provided in Appendix Table 2.B1.

Table 2.2. Correlation coefficient for the key variables

Variables	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*
1. Core-technology competence	1.00												
2. Related Technological diversification	0.29	1.00											
3. Unrelated technological diversification	0.19	0.32	1.00										
4. Innovation Persistence	0.18	0.40	0.45	1.00									
5. Innovation intensity	0.04	0.12	0.16	0.14	1.00								
6. Experience since first patent	0.15	0.21	0.26	0.35	0.03	1.00							
7. Firm age	0.11	0.02	0.04	0.07	-0.05	0.43	1.00						
8. Firm size	0.09	0.15	0.27	0.17	-0.21	0.26	0.25	1.00					
9. Total Factor Productivity	-0.10	0.03	0.00	0.01	0.09	-0.07	-0.10	-0.14	1.00				
10. Cash	0.00	0.07	0.14	0.06	-0.05	0.09	0.07	0.38	0.07	1.00			
11. Intangible asset ratio	-0.01	0.00	0.01	0.02	0.00	0.00	-0.01	0.02	0.02	0.00	1.00		
12. Average wage	-0.05	-0.03	-0.04	-0.04	0.00	-0.07	-0.06	-0.02	0.15	0.33	0.00	1.00	
13. Foreign ownership	-0.02	0.08	0.12	0.10	0.01	0.13	-0.03	0.14	-0.02	0.08	0.02	0.01	1.00

Table 2.3. IoT patents, core-technology competence and diversification: relative-risk ratios

	Model 1			Model 2		
	I vs III	**II vs III**	**I vs II**	**I vs III**	**II vs III**	**I vs II**
	IoT vs non-ICT	**Non-IoT ICT vs non-ICT**	**IoT vs non-IoT ICT**	**IoT vs non-ICT**	**Non-IoT ICT vs non-ICT**	**IoT vs non-IoT ICT**
$coretec_{it-2}$	0.728***	0.861***	0.846***	0.747***	0.873***	0.855***
	(0.048)	(0.025)	(0.051)	(0.043)	(0.025)	(0.046)
rv_{it-2}	3.589***	1.076	3.336***	4.790***	0.791*	6.056***
	(1.176)	(0.112)	(0.985)	(1.908)	(0.111)	(2.475)
uv_{it-2}	12.979***	2.716***	4.778***	5.177***	2.304***	2.247***
	(3.240)	(0.263)	(1.104)	(0.858)	(0.240)	(0.286)
$persistence_{it} * rv_{it-2}$				1.128	1.771***	0.637
				(0.494)	(0.338)	(0.259)
$persistence_{it} * uv_{it-2}$				4.171***	1.395**	2.989***
				(1.280)	(0.222)	(0.656)
$persistence_{it}$	0.866	1.167**	0.742	0.215**	0.718***	0.300*
	(0.234)	(0.091)	(0.203)	(0.156)	(0.091)	(0.199)
$intensity_{it}$	0.986	1.045**	0.944**	0.961	1.037*	0.926**
	(0.030)	(0.019)	(0.025)	(0.037)	(0.020)	(0.030)
$experience_{it}$	1.036	1.190***	0.871	1.091	1.200***	0.909
	(0.157)	(0.076)	(0.123)	(0.168)	(0.076)	(0.133)
age_{it}	0.985**	0.992***	0.992	0.983**	0.992***	0.991
	(0.006)	(0.002)	(0.006)	(0.007)	(0.002)	(0.007)
$size_{it-1}$	1.183**	1.107	1.069	1.110	1.093	1.015
	(0.081)	(0.077)	(0.078)	(0.073)	(0.077)	(0.061)
$productivity_{it-1}$	1.080	1.028	1.051	1.079	1.027	1.050
	(0.080)	(0.044)	(0.037)	(0.079)	(0.044)	(0.035)
$cash_{it-1}$	1.041	1.036	1.005	1.036	1.037	0.999
	(0.078)	(0.030)	(0.060)	(0.083)	(0.029)	(0.065)
$intangible_{it-1}$	0.290	1.030	0.281	0.310	1.032	0.301
	(0.242)	(0.026)	(0.234)	(0.280)	(0.027)	(0.270)
ave_wage_{it-1}	1.002	1.000	1.002	1.002	1.000	1.002
	(0.004)	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)
$foreign_{it}$	1.744**	1.360**	1.282*	1.675**	1.367**	1.225
	(0.392)	(0.196)	(0.174)	(0.383)	(0.197)	(0.169)
Constant	0.000***	0.017***	0.000***	0.000***	0.020***	0.000***
	(0.000)	(0.006)	(0.000)	(0.000)	(0.008)	(0.000)
Hausman-McFadden test of IIA assumption: Chi^2; df; $P>Chi^2$	-6.657; 46;	0.000; 2; 1.000		-1.410; 48;	3.097; 12; 0.995	
Industry (NACE section)	Y	Y	Y	Y	Y	Y
Region (NUTS 1)	Y	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y	Y
Observations	9,175	9,175	9,175	9,175	9,175	9,175

Notes: Relative-risk ratios from multinomial logit model estimation of Equation (1) are reported. The reference group of the 1st column of each model is the firms with a patent only in other non-ICT technological domains. The reference group of the 3rd column in each model is the firms with a patent only in non-IoT ICT domains. Robust standard errors in exponentiated form reported in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 2.4. Regional breakdown of number and value of research projects related to IoT and Big Data technologies

Region	Research projects related to IoT and Big Data				Project value statistics of the sampled firms	
	Number	Share	Total value (Thousand £)	Share	Mean (Thousand £)	Mean (log-transformed)
East Midlands	58	4.1%	27,226.3	4.4%	2,307.6	14.31
East of England	106	7.5%	38,236.5	6.2%	1,811.7	14.31
London	207	14.6%	133,265.1	21.5%	6,530.8	15.44
North East	43	3.0%	10,172.4	1.6%	656.1	13.10
North West	98	6.9%	30,171.3	4.9%	1,456.5	14.14
Northern Ireland	15	1.1%	2,394.4	0.4%	90.8	11.27
Scotland	464	32.8%	247,116.7	39.9%	15,600.0	16.48
South East	186	13.1%	67,911.4	11.0%	5,260.6	15.37
South West	61	4.3%	15,334.1	2.5%	609.5	13.27
Wales	37	2.6%	10,643.2	1.7%	321.9	12.09
West Midlands	59	4.2%	13,191.4	2.1%	846.2	13.55
Yorkshire and The Humber	81	5.7%	24,028.2	3.9%	1,293.7	13.94
Total	**1415**	**100.0%**	**619,690.9**	**100.0%**	**3,066.3**	

Notes: Data extracted from Gateway to Research (GtR) portal which include all the projects funded by UK research councils (UKRCs) and the other three funding organisations over the funding period of 1987-2027. Project number is calculated based on the number of projects in progress in each year. In order to build the panel data structure, project value is evenly distributed across the whole funding period based on project start and end date. Number and value of individual projects are aggregated based on project's region information at the NUTS1 level. Value statistics are calculated based on those projects within the sampled period from 2008 to 2017.

Table 2.5. IoT patents, core-technology competence, and instruments for related and unrelated technological diversification: relative-risk ratios of Model 2 and regression coefficients of related and unrelated technological diversification

	Model 2			
	I vs III	**II vs III**	**(1)**	**(2)**
	IoT vs non-ICT	**Non-IoT ICT vs non-ICT**	**Related diversification**	**Unrelated diversification**
$coretec_{it-2}$	0.747***	0.873***		
	(0.035)	(0.014)		
rv_{it-2}	4.790***	0.791*		
	(1.565)	(0.107)		
uv_{it-2}	5.177***	2.304***		
	(1.115)	(0.209)		
$persistence_{it} * rv_{it-2}$	1.128	1.771***		
	(0.456)	(0.299)		
$persistence_{it} * uv_{it-2}$	4.171***	1.395***		
	(1.084)	(0.156)		
$persistence_{it}$	0.215***	0.718***	0.278***	0.439***
	(0.091)	(0.090)	(0.008)	(0.012)
$intensity_{it}$	0.961	1.037***	0.010***	0.032***
	(0.034)	(0.014)	(0.002)	(0.002)
$experience_{it}$	1.091	1.200***	0.066***	0.088***
	(0.120)	(0.050)	(0.005)	(0.007)
age_{it}	0.983***	0.992***	-0.001***	-0.002***
	(0.004)	(0.001)	(0.000)	(0.000)
$size_{it-1}$	1.110*	1.093***	0.016***	0.093***
	(0.070)	(0.028)	(0.003)	(0.005)
$productivity_{it-1}$	1.079*	1.027	0.005	-0.001
	(0.043)	(0.024)	(0.003)	(0.005)
$cash_{it-1}$	1.036	1.037**	0.002	0.010***
	(0.039)	(0.017)	(0.002)	(0.003)
$intangible_{it-1}$	0.310**	1.032	-0.001	0.000
	(0.172)	(0.047)	(0.007)	(0.011)
ave_wage_{it-1}	1.002	1.000	-0.001**	-0.000
	(0.004)	(0.002)	(0.000)	(0.000)
$foreign_{it}$	1.675***	1.367***	0.023***	0.035***
	(0.246)	(0.079)	(0.008)	(0.012)
$\boldsymbol{fund\_ib_t}$			-0.018*	-0.001
			(0.010)	(0.015)
$\boldsymbol{patentee\_s_t}$			0.011***	0.026***
			(0.002)	(0.004)
$\boldsymbol{patentee\_r_t}$			0.011***	0.011**
			(0.003)	(0.005)
var(e.related diversification)			0.130***	
			(0.002)	
var(e.unrelated diversification)				0.281***
				(0.004)
Constant	0.000	0.020***	0.127	-0.723***
	(0.000)	(0.009)	(0.138)	(0.203)
IVs' joint significance			Chi^2=36.86, p-value=0.000	Chi^2=60.97, p-value=0.000
Industry (NACE section)	Y	Y	Y	Y
Region (NUTS 1)	Y	Y	Y	Y
Year	Y	Y	Y	Y
Observations	9,175	9,175	9,175	9,175

Notes: Relative-risk ratios of Generalised Structural Equations Model (GSEM) estimation are reported in the left panel. Coefficients of two linear regressions (OLS) of related and unrelated technological diversification are presented in the right panel. Model 2 has the same specification as the right-side panel of Table 3, in which two interaction terms are added. The reference group is firms that only have a patent in other non-ICT technological domains. *fund_ib*, *patentee_s,* and *patentee_r* are instruments included to account for potential endogeneity stemming from technological diversification. Region, industry, and year dummies are included in both steps of GSEM. Explanatory variables are lagged. In the left panel, standard errors in exponentiated form reported in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 2.6. Count of IoT patents, core-technology competence, and diversification: average marginal effects

	Model 1	Model 2
$coretec_{it-2}$	-0.035**	-0.030**
	(0.016)	(0.014)
rv_{it-2}	0.317**	0.301**
	(0.124)	(0.127)
uv_{it-2}	0.352**	0.205**
	(0.143)	(0.096)
$persistence_{it} * rv_{it-2}$		0.082
		(0.054)
$persistence_{it} * uv_{it-2}$		0.212**
		(0.086)
$persistence_{it}$	-0.071	-0.309**
	(0.067)	(0.152)
$intensity_{it}$	-0.005	-0.010
	(0.006)	(0.007)
$experience_{it}$	-0.060	-0.040
	(0.039)	(0.027)
age_{it}	-0.002*	-0.002**
	(0.001)	(0.001)
$size_{it-1}$	0.047	0.034*
	(0.029)	(0.019)
$productivity_{it-1}$	0.010	0.009
	(0.011)	(0.010)
$cash_{it-1}$	0.006	0.004
	(0.014)	(0.014)
$intangible_{it-1}$	-0.171	-0.156
	(0.161)	(0.167)
ave_wage_{it-1}	-0.001	-0.001
	(0.001)	(0.001)
$foreign_{it}$	0.065	0.049
	(0.042)	(0.035)
Industry (NACE section)	Y	Y
Region (NUTS 1)	Y	Y
Year	Y	Y
Observations	**9,175**	**9,175**

Notes: Average marginal effects from negative binomial estimation are reported. Here, the dependent variable of Equation (1) has been replaced with the number of IoT patents, with the explanatory variables being the same. Region, industry and year dummies are included. Explanatory variables are lagged. Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 2.A1. List of IPC symbols of the IoT and Big Data

Technology type	IPC code	Descriptions from IPC system	Source
IoT	H04L12/24	Data switching networks -> Details -> Arrangements for maintenance or administration	Trappey *et al.* (2017)
	H04L29/10	Arrangements, apparatus, circuits or systems, not covered by a single one of groups H04L 1/00-H04L 27/00 -> Communication control; Communication processing -> Characterised by an interface, e.g. the interface between the data link level and the physical level	Trappey *et al.* (2017)
	H04L29/06	Arrangements, apparatus, circuits or systems, not covered by a single one of groups H04L 1/00-H04L 27/00 -> Communication control; Communication processing -> Characterised by a protocol	Trappey *et al.* (2017)
	H04L29/08	Arrangements, apparatus, circuits or systems, not covered by a single one of groups H04L 1/00-H04L 27/00 -> Communication control; Communication processing -> Characterised by a protocol -> Transmission control procedure, e.g. data link level control procedure	Trappey *et al.* (2017)
	H04L12/28	Data switching networks -> Characterised by path configuration, e.g. LAN [Local Area Networks] or WAN [Wide Area Networks]	Trappey *et al.* (2017)
	H04L29/12	Arrangements, apparatus, circuits or systems, not covered by a single one of groups H04L 1/00-H04L 27/00 - > Characterised by the data terminal	Trappey *et al.* (2017)
	H04L12/56	Data switching networks -> Store-and-forward switching systems -> Packet switching systems	Trappey *et al.* (2017)
	H04L29/02	Arrangements, apparatus, circuits or systems, not covered by a single one of groups -> Communication control; Communication processing	Trappey *et al.* (2017)
	H04L12/66	Data switching networks (interconnection of, or transfer of information or other signals between, memories, input/output devices or central processing units G06F 13/00) -> Arrangements for connecting between networks having differing types of switching systems, e.g. gateways	Trappey *et al.* (2017)
	G06F15/173	Digital computers in general; Data processing equipment in general -> Combinations of two or more digital computers each having at least an arithmetic unit, a program unit and a register, e.g. for a simultaneous processing of several programs -> Interprocessor communication -> Using an interconnection network, e.g. matrix, shuffle, pyramid, star or snowflake	Trappey *et al.* (2017)
	H04L12/70	Data switching networks (interconnection of, or transfer of information or other signals between, memories, input/output devices or central processing units G06F 13/00) -> Packet switching systems	Trappey *et al.* (2017)
	H04L12/46	Data switching networks (interconnection of, or transfer of information or other signals between, memories, input/output devices or central processing units G06F 13/00) -> characterised by path configuration, e.g. LAN [Local Area Networks] or WAN [Wide Area Networks] (wireless communication networks H04W) -> Interconnection of networks	Trappey *et al.* (2017)
	H04W84/18	Network topologies -> Self-organising networks, e.g. ad hoc networks or sensor networks	UK IP Office (2014b)
	H04W4/00	Services specially adapted for wireless communication networks; Facilities therefor	UK IP Office (2014b)
	G08C17/02	Arrangements for transmitting signals characterised by the use of a wireless electrical link -> using a radio link	UK IP Office (2014b)
	H04B7/26	Radio transmission systems, i.e. using radiation field -> for communication between two or more posts -> at least one of which is mobile	UK IP Office (2014b)
	G06F15/16	Digital computers in general; Data processing equipment in general -> Combinations of two or more digital computers each having at least an arithmetic unit, a program unit and a register, e.g. for a simultaneous processing of several programs	Trappey *et al.* (2017)

	G06F13/00	Interconnection of, or transfer of information or other signals between, memories, input/output devices or central processing units	Trappey *et al.* (2017)
	H04L12/26	Data switching networks (interconnection of, or transfer of information or other signals between, memories, input/output devices or central processing units G06F 13/00) -> Details -> Monitoring arrangements; Testing arrangements	Trappey *et al.* (2017)
	H04L9/32	Arrangements for secret or secure communication -> including means for verifying the identity or authority of a user of the system	Trappey *et al.* (2017)
	H04L29/14	Arrangements, apparatus, circuits or systems, not covered by a single one of groups H04L 1/00-H04L 27/00 -> counter-measures to a fault	Trappey *et al.* (2017)
	G06F17/30	Digital computing or data processing equipment or methods, specially adapted for specific functions-> Information retrieval; Database structures therefor	Trappey *et al.* (2017)
	H04L1/00	Arrangements for detecting or preventing errors in the information received	Trappey *et al.* (2017)
	G05B19/418	Programme-control systems -> Electric -> Total factory control, i.e. centrally controlling a plurality of machines, e.g. direct or distributed numerical control (DNC), flexible manufacturing systems (FMS), integrated manufacturing systems (IMS), computer integrated manufacturing (CIM)	Trappey *et al.* (2017)
	H04W72/04	Local resource management, e.g. selection or allocation of wireless resources or wireless traffic scheduling -> Wireless resource allocation	UK IP Office (2014b)
The Big Data	G06F17/30	Digital computing or data processing equipment or methods, specially adapted for specific functions -> Information retrieval; Database structures therefor	UK IP Office (2014a)
	G06F7/00	Methods or arrangements for processing data by operating upon the order or content of the data handled	UK IP Office (2014a)
	G06F15/16	Digital computers in general; Data processing equipment in general -> Combinations of two or more digital computers each having at least an arithmetic unit, a programme unit and a register, e.g. for a simultaneous processing of several programmes	UK IP Office (2014a)
	G06F17/00	Digital computing or data processing equipment or methods, specially adapted for specific functions	UK IP Office (2014a)
	H04L29/08	Arrangements, apparatus, circuits or systems, not covered by a single one of groups H04L01/00-H04L27/00 -> Communication control; Communication processing -> characterised by a protocol -> Transmission control procedure, e.g. data link level control procedure	UK IP Office (2014a)
	G06Q10/00	Administration, e.g. office automation or reservations; Management, e.g. resource or project management	UK IP Office (2014a)
	G06F17/50	Digital computing or data processing equipment or methods, specially adapted for specific functions -> Computer-aided design	UK IP Office (2014a)
	G06F12/00	Accessing, addressing or allocating within memory systems or architectures	UK IP Office (2014a)
	G06F19/00	Digital computing or data processing equipment or methods, specially adapted for specific applications	UK IP Office (2014a)
	G06F15/173	Digital computers in general; Data processing equipment in general -> Combinations of two or more digital computers each having at least an arithmetic unit, a programme unit and a register, e.g. for a simultaneous processing of several programmes -> Interprocessor communication -> using an interconnection network, e.g. matrix, shuffle, pyramid, star, snowflake	UK IP Office (2014a)
	G06F19/10	Digital computing or data processing equipment or methods, specially adapted for specific applications -> Bioinformatics, i.e. methods or systems for genetic or protein-related data processing in computational molecular biology	Martinelli *et al.* (2021)

	G06F19/12	Digital computing or data processing equipment or methods, specially adapted for specific applications -> Bioinformatics, i.e. methods or systems for genetic or protein-related data processing in computational molecular biology -> For modelling or simulation in systems biology, e.g. probabilistic or dynamic models, gene-regulatory networks, protein interaction networks or metabolic networks	Martinelli *et al.* (2021)
	G06F19/14	Digital computing or data processing equipment or methods, specially adapted for specific applications -> Bioinformatics, i.e. methods or systems for genetic or protein-related data processing in computational molecular biology -> For phylogeny or evolution, e.g. evolutionarily conserved regions determination or phylogenetic tree construction	Martinelli *et al.* (2021)
	G06F19/16	Digital computing or data processing equipment or methods, specially adapted for specific applications -> Bioinformatics, i.e. methods or systems for genetic or protein-related data processing in computational molecular biology -> For molecular structure, e.g. structure alignment, structural or functional relations, protein folding, domain topologies, drug targeting using structure data, involving two-dimensional or three-dimensional structures	Martinelli *et al.* (2021)
	G06F19/18	Digital computing or data processing equipment or methods, specially adapted for specific applications -> Bioinformatics, i.e. methods or systems for genetic or protein-related data processing in computational molecular biology -> For functional genomics or proteomics, e.g. genotype-phenotype associations, linkage disequilibrium, population genetics, binding site identification, mutagenesis, genotyping or genome annotation, protein-protein interactions or protein-nucleic acid interactions	Martinelli *et al.* (2021)
	G06F19/20	Digital computing or data processing equipment or methods, specially adapted for specific applications -> Bioinformatics, i.e. methods or systems for genetic or protein-related data processing in computational molecular biology -> For hybridisation or gene expression, e.g. microarrays, sequencing by hybridisation, normalisation, profiling, noise correction models, expression ratio estimation, probe design or probe optimisation	Martinelli *et al.* (2021)
	G06F19/22	Digital computing or data processing equipment or methods, specially adapted for specific applications -> Bioinformatics, i.e. methods or systems for genetic or protein-related data processing in computational molecular biology -> For sequence comparison involving nucleotides or amino acids, e.g. homology search, motif or Single-Nucleotide Polymorphism [SNP] discovery or sequence alignment	Martinelli *et al.* (2021)
	G06F19/24	Digital computing or data processing equipment or methods, specially adapted for specific applications -> Bioinformatics, i.e. methods or systems for genetic or protein-related data processing in computational molecular biology -> For machine learning, data mining or biostatistics, e.g. pattern finding, knowledge discovery, rule extraction, correlation, clustering or classification	Martinelli *et al.* (2021)
	G06F19/26	Digital computing or data processing equipment or methods, specially adapted for specific applications -> Bioinformatics, i.e. methods or systems for genetic or protein-related data processing in computational molecular biology -> For data visualisation, e.g. graphics generation, display of maps or networks or other visual representations	Martinelli *et al.* (2021)
	G06F19/28	Digital computing or data processing equipment or methods, specially adapted for specific applications -> Bioinformatics, i.e. methods or systems for genetic or protein-related data processing in computational molecular biology -> For programming tools or database systems, e.g. ontologies, heterogeneous data integration, data warehousing or computing architectures	Martinelli *et al.* (2021)
	G06Q30/02	Commerce, e.g. shopping or e-commerce -> Marketing, e.g. market research and analysis, surveying, promotions, advertising, buyer profiling, customer management or rewards; Price estimation or determination	Martinelli *et al.* (2021)
	G06N	Computer systems based on specific computational models	Martinelli *et al.* (2021)

Appendix Table 2.A2. List of IPC symbols of the ICT technology

Source: OECD (2011). *OECD Guide to Measuring the Information Society 2011*.

IPC symbols	Details
Telecommunications	
G01S	Radio navigation
G08C	Transmission systems for measured values
G09C	Ciphering apparatus
H01P, H01Q	Waveguides, resonators, aerials
H01S003-025, H01S003-043, H01S003-06, H01S003-085, H01S003-0915, H01S003-0941, H01S003-103, H01S003-133, H01S003-18, H01S003-19, H01S003-25, H01S005	Semiconductor lasers
H03B-D	Generation of oscillations, modulation, demodulation
H03H	Impedance networks, resonators
H03M	Coding, decoding
H04B	Transmission
H04J	Multiplex communication
H04K	Secret communication
H04L	Transmission of digital information
H04M	Telephonic communication
H04Q	Selecting, public switching
Consumer electronics	
G11B	Information storage with relative movement between record carrier and transducer
H03F, H03G	Amplifiers, control of amplification
H03J	Tuning resonant circuits
H04H	Broadcast communication
H04N	Pictorial communication, television
H04R	Electromechanical transducers
H04S	Stereophonic systems
Computers, office machinery	
B07C	Postal sorting
B41J	Typewriters
B41K	Stamping apparatus
G02F	Control of light parameters
G03G	Electrography
G05F	Electric regulation
G06	Computing
G07	Checking devices
G09G	Control of variable information devices
G10L	Speech analysis and synthesis
G11C	Static stores
H03K, H03L	Pulse technique, control of electronic oscillations or pulses
Other ICT	
G01B, G01C, G01D, G01F, G01G, G01H, G01J, G01K, G01L, G01M, G01N, G01P, G01R, G01V, G01W	Measuring, testing
G02B006	Light guides
G05B	Control and regulating systems
G08G	Traffic control systems
G09B	Educational or demonstration appliances
H01B011	Communication cables
H01J011, H01J013, H01J015, H01J017, H01J019, H01J021, H01J023, H01J025, H01J027, H01J029, H01J031, H01J033, H01J040, H01J041, H01J043, H01J045	Electric discharge tubes
H01L	Semiconductor devices

Appendix Table 2.A3. List of key words for defining research projects related to the IoT and Big Data technologies

Data source: Gateway to Research (GtR) portal which includes all the projects funded by UK research councils (UKRCs) and the other three funding organisations

Technology type	Key words	Source
Internet of Things (IoT)	Internet of things, Ubicomp, Industrial Internet, Pervasive Computing, Ambient Intelligence, Smarter Planet, Smart Dust, Smart Device, Digital Life, Web of Things, M2M, Machine to Machine, Smart Home, Smart Meter, Smart Grid, Cloud of Things (CoT), Internet of Everything, data transmission and data storage, home automation, vehicle remote control, IoT security (e.g. authentication devices) and wireless network arrangements	UK IP Office (2014b). Eight Great Technologies: The Internet of Things
	Industrial Internet of Things, life augmented, CPS, IoT	Web Semantics: some synonyms for the Internet of Things (available at: https://www.wired.com/2014/02/web-semantics-synonyms-internet-things/)
	Actuators, Controllers, RFID technology, Printed Circuit Board (PCB), Camera, Computational Component, Session/Communication Protocols, Data Aggregation/Processing Protocols, Data Storage/Retrieval Protocols, Business Model Protocols, Business application Protocols, Circuits, Sensors, Link Layer Protocols, Transport Protocols, Multiplexing Methods, Topology Management, Baseband Processing, Radio Frequency Protocols, Internet Protocol (IP), Network Protocol, Medium Access Control Protocol, Wireless Sensor, Network, Connectivity Protocols, Cyber-Physical System, Embedded System, Automated IoT Based Access Control System, Software, Algorithms, Cloud Platform, Encryption, IoT Control System	Trappey *et al*. (2017). A review of essential standards and patent landscapes for the Internet of Things: A key enabler for Industry 4.0.
Big Data	Big Data, Hadoop®, Yarn, Aster®, Datameer®, FICO® Blaze, Vertica®, Platfora®, Splunk®, MapReduce, open data, data warehous*, informatic*, data mine, data mining, simulate*, model*, analy*, artificial intelligence, neural network*, distributed *, croudsourc*, crowd sourc*, massively parallel process*, massively parallel software, massively parallel database, distributed process*, distributed server, distributed quer*, distributed database, massive data	UK IP Office (2014a). Eight Great Technologies: Big Data

Appendix Table 2.B1. Variable definitions

	Variable name	Name in the model	Definition
Core-technology competence	Core-technology competence	*coretec*	Calculated based on **revealed technology advantage** (RTA) index (Kim *et al*., 2016); $coretec_{it} = ln\left[max\left(RTA_{iqt} \times P_{iqt}\right)\right]$ Where RTA is to derive the relative importance of firm's different kinds of patenting to each field of technology after taking account of firm's share of total patenting in all the fields and P_{iqt} is firm *i*'s number of publications in technological field *q* at time *t*.
Technological diversification	Related technological diversification	*rv*	Technology diversification based on IPC codes at the **Subgroup level** within the **Subclass** level using entropy method (Kim *et al*., 2016)
	Unrelated technological diversification	*uv*	Technology diversification based on IPC codes at the **Subclass** level using entropy method (Kim *et al*., 2016)
Interaction terms	Interaction of persistence and related diversification	*persistence*rv*	The interaction term of innovation persistence and related technological diversification
	Interaction of persistence and unrelated diversification	*persistence*uv*	The interaction term of innovation persistence and unrelated technological diversification
Control variables	Innovation Persistence	*persistence*	A dummy equal to 1 in a given year if a firm published at least one patent during each of the last five years consecutively, otherwise 0. *(The criterion of last seven consecutive years is tested in robustness analysis.)*
	Innovation intensity	*intensity*	The ratio of accumulative number of patent publications for the last five years to number of employees at time *t*
	Experience since the first patent	*experience*	Natural log of years since patenting for the first time (report here the number)
	Firm age	*age*	Firm age since establishment
	Firm size	*size*	Natural log of number of employees (report here the number)
	Total factor productivity	*productivity*	Total factor productivity estimated based on OLS method using sales revenue
	Cash	*cash*	Natural log of cash and cash equivalent (report here the number)
	Intangible asset ratio	*intangible*	The ratio of intangible fixed assets over total assets
	Average wage	*ave_wage*	The ratio of cost of employees over firm size
	Foreign ownership	*foreign*	A dummy taking value of 1 for a firm owned by a parent located in other foreign countries, otherwise 0

Appendix Table 2.C1. IoT patents, core-technology competence, and diversification: average marginal effects

	Model 1			Model 2		
	IoT patenting	**Non-IoT ICT patenting**	**Non-ICT Patenting**	**IoT patenting**	**Non-IoT ICT patenting**	**Non-ICT Patenting**
$coretec_{it-2}$	-0.006***	-0.017***	0.023***	-0.005***	-0.016***	0.021***
	(0.002)	(0.004)	(0.004)	(0.001)	(0.004)	(0.004)
rv_{it-2}	0.033***	-0.011	-0.023	0.045***	-0.062***	0.016
	(0.008)	(0.014)	(0.015)	(0.010)	(0.022)	(0.019)
uv_{it-2}	0.052***	0.108***	-0.160***	0.030***	0.098***	-0.128***
	(0.005)	(0.011)	(0.010)	(0.003)	(0.014)	(0.015)
$persistence_{it} * rv_{it-2}$				-0.006	0.084***	-0.078***
				(0.011)	(0.028)	(0.028)
$persistence_{it} * uv_{it-2}$				0.032***	0.026	-0.058***
				(0.006)	(0.020)	(0.022)
$persistence_{it}$	-0.007	0.026**	-0.019*	-0.035**	-0.024	0.059***
	(0.007)	(0.012)	(0.011)	(0.017)	(0.016)	(0.021)
$intensity_{it}$	-0.001	0.007***	-0.006**	-0.002*	0.006**	-0.005
	(0.001)	(0.002)	(0.003)	(0.001)	(0.003)	(0.003)
$experience_{it}$	-0.002	0.026***	-0.024**	-0.001	0.026***	-0.025***
	(0.004)	(0.009)	(0.009)	(0.004)	(0.009)	(0.009)
age_{it}	-0.000*	-0.001***	0.001***	-0.000*	-0.001**	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$size_{it-1}$	0.003*	0.013	-0.015	0.001	0.012	-0.013
	(0.002)	(0.010)	(0.009)	(0.001)	(0.010)	(0.010)
$productivity_{it-1}$	0.002	0.003	-0.004	0.002	0.003	-0.004
	(0.001)	(0.005)	(0.006)	(0.001)	(0.005)	(0.006)
$cash_{it-1}$	0.000	0.005	-0.005	0.000	0.005	-0.005
	(0.002)	(0.004)	(0.004)	(0.002)	(0.004)	(0.004)
$intangible_{it-1}$	-0.034	0.026*	0.008	-0.032	0.024*	0.007
	(0.022)	(0.014)	(0.010)	(0.024)	(0.015)	(0.010)
ave_wage_{it-1}	0.000	-0.000	0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$foreign_{it}$	0.010**	0.037**	-0.047**	0.008**	0.039**	-0.047**
	(0.004)	(0.018)	(0.020)	(0.004)	(0.018)	(0.020)
Industry (NACE section)	Y	Y	Y	Y	Y	Y
Region (NUTS 1)	Y	Y	Y	Y	Y	Y
Year	Y	Y	Y	Y	Y	Y
Observations	**9,175**	**9,175**	**9,175**	**9,175**	**9,175**	**9,175**

Notes: Average marginal effects from multinomial logit model estimation of Equation (1) are reported. The reference group is firms with only a patent in other non-ICT technological domains. Marginal effects of a predictor for all choices add up to zero. Explanatory variables are lagged. Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

CHAPTER 3: CONNECTIVITY AND ENVIRONMENTAL INNOVATION: A DEVELOPED COUNTRY MNE PERSPECTIVE

3.1 Introduction

The existential threat faced by businesses and the responses of societies and governments in recent decade have led to the net zero emission goal by mid-century (IPCC, 2021). Revolutionary changes in technology are needed to achieve such objectives (Hoffert *et al*., 2002). The recent fast-growing literature on eco-innovation and environmental innovation[23] has painted an emerging picture that environmental innovation is an important way of pursuing competitiveness while helping to create environmentally sustainable societies (Carrillo-Hermosilla, del Río and Könnölä, 2010; De Marchi, 2012; del Río, Peñasco and Romero-Jordán, 2015). Clearly, this challenges the way MNEs have always strategized and operated.

MNEs, especially those from the developed economies, present an important context for studying sustainability related issues (e.g., environmental innovation) because they possess the resources and abilities to promote social and environmental values, making them major players in global economic and environmental development (Marin and Zanfei, 2019). The sustainability imperative is prompting MNEs to cultivate their capabilities for making environmental and sustainable innovations (Amendolagine, Lema and Rabellotti, 2021). They have a crucial role in developing and disseminating environmental innovations through their global R&D facilities (Noailly and Ryfisch, 2015), and MNEs that develop a socially responsible attitude and innovative green practices can also influence and put pressure on other organizations through their GVCs and production networks (Aguilera‐Caracuel, Aragón‐Correa and Hurtado‐Torres, 2011; Chang and Gotcher, 2020).

Conceptually, the existing research attempts to link sustainability with firm-specific advantages by connecting the characteristics and drivers of MNEs to environmental innovation (Rugman and Verbeke, 1998; 2003). Prior research is relatively silent about what production networks and innovation networks mean for MNEs in terms of their strategy and capacity for achieving environmental innovation, except for one study of Dugoua and Dumas (2021) focusing on industrial networks. The factors that affect how eco-innovations are developed are also under-researched, especially those related to cooperative arrangements (De Marchi, 2012). To the best of our knowledge, no existing study has examined how an MNE's different types of international and inter-organisational networks contribute to its capacity to

[23] The key contributions of this literature include analyses of eco-innovation (e.g., Colombelli, Krafft and Quatraro, 2021; Costantini *et al*., 2017) and environmental innovation (e.g., Cainelli and Mazzanti, 2013; Cainelli, Mazzanti and Montresor, 2012; Chiarvesio, De Marchi and Di Maria, 2015; Ghisetti and Rennings, 2014; Horbach, 2008; Horbach and Rennings, 2013; Konadu, Owusu-Agyei, Lartey, Danso, Adomako and Amankwah-Amoah, 2020; Konara, Lopez and Shirodkar, 2021; Liao and Liu, 2021; Marin and Zanfei, 2019; Rennings and Rammer, 2011; Rexhäuser and Rammer, 2014), among many others.

generate environmental innovation. This knowledge gap is echoed by Gomez-Trujillo and Gonzalez-Perez (2020), who contend that internationalisation is an important factor in firms' pursuit of sustainability initiatives (Perez-batres, Miller and Pisani, 2010). Furthermore, there is limited empirical evidence concerning the specificities of environmental innovation and how it is conceived and realised. Most existing studies are heavily qualitative, building on case studies or restricted geographic areas; this results in a lack of empirical setting (De Marchi, 2012).

Hence, this chapter aims to provide insights into the interplay between the global connectedness of MNEs and their capacity for environmental innovation capacity. Our investigation enriches the IB literature by understanding MNEs' internationalisation strategies and cross-border innovation management in the light of the contemporary challenges and opportunities presented by the need to respond to the climate emergency. Specifically, we draw on the knowledge-based view (Grant, 1996; 1997) to explain why some MNEs can be more environmentally innovative than others. We therefore analyse antecedents related to their internationally networked relationships for production and innovation, as well as their firm characteristics. We draw on theoretical arguments about the global connectedness of MNEs and their cross-border innovation connectivity to develop and test hypotheses around the antecedents of environmental innovation. The lessons drawn can help guide the actions of practitioners and policymakers in home and host countries.

As such, we contribute to an important intersection between IB literature and the environmental innovation field in the following ways. First and foremost, we bring the topic of environmental innovation into the IB and management research arena and explain its determinants from a novel IB and management perspective. Second, we contribute to the literature on the drivers of environmental innovation by focusing on how the cooperative arrangements of MNEs contribute to their eco-innovation R&D. We explore multiple facets of MNEs' global linkages: organisational, production, and more importantly, cross-border innovation networks. To the best of our knowledge, this is the first study to reveal diverse antecedents of environmental innovation from the perspective of MNE connectivity. Third, our incorporation of cross-border intra- and inter-organisational networks into environmental innovation research extends the existing theoretical framework for analysing the determinants of environmental innovation at the level of the MNE parent firm. This idea aligns with Kolk and van Tulder's (2010) proposal that a consideration of the drivers related to institutional, industry and organisational aspects is appropriate for understanding the MNE's approach to gaining sustainable competitive advantage and its role in advancing sustainable development. Finally, we provide concrete evidence and practical implications based on a large-scale secondary dataset, which supplements the limited empirical evidence about the specificities of environmental innovation and how it is conceived and realised.

Our work also offers valuable managerial and policy implications. We advance understanding of what kind of prerequisites will allow firms to effectively cultivate their environmental innovation capacity and put them in a better position to create new green knowledge. We identify the types of MNE that tend to be more ready for this green transformation. These insights can inform practitioners on how to foster environmental innovation capacity by promoting and facilitating diversity in their firms' internationally-integrated production networks and their internal and external innovation networks. Such capacity is conducive to firms' financial performance and long-term competitiveness. Additionally, we offer valuable insights for policymakers on how to plan initiatives in response to the 'sustainability imperative' (Zhan, 2021).

Our empirical work utilises the Thomson Reuters ASSET4 database and Bureau van Dijk's Orbis main database. We link firms in the two databases by employing a string-matching approach that takes company names and the country code of the company's location into consideration. The final sample is an unbalanced panel of 4,510 firm-year observations from 622 unique DMNEs across France, Germany, the United Kingdom, Netherlands, and Sweden over the period 2009-2017. By employing a pooled Tobit model of firms' environmental innovation capacity as the empirical approach, we find consistent support for the majority of our hypotheses and the results are robust to sensitivity testing.

We find that wider global linkages built on production networks, and intra- and inter-MNE innovation co-production linkages contribute to a MNE's capability to produce environmental innovation. However, intra-organisational linkages motivated by traditional control and coordination mechanisms do not play an important role in environmental innovation capacity. This emphasises that specific types of ties related to knowledge connectivity and innovation collaboration matter more for environmental innovation than general control and coordination linkages.

The current chapter is organised as follows. The next section introduces the literature review, followed by a description of the theoretical foundations and our hypotheses. The fourth section describes the data sources and research method. The next section reports our baseline model results, followed by a further discussion of the robustness test. The last section discusses and concludes.

3.2 Literature review

Several terms can be found in the literature to refer to environmental innovation, including 'green innovation', 'environmental innovation', 'ecological innovation' and 'sustainable innovation' (e.g., Ben Arfi *et al*., 2018; Boons and Lüdeke-Freund, 2013; Carrillo-Hermosilla *et al*., 2010; Konara *et al*., 2021). Researchers seem to use these terms interchangeably and, to a certain degree, they share the same content (Schiederig, Tietze and Herstatt, 2012). However, the first three emphasise ecological and environmental dimensions while the last is a broader concept that encompasses an extra social dimension (Schiederig *et al*., 2012). As a subset of eco-innovation (Konara *et al*., 2021), environmental innovation underlines the environmentally-motivated intentions of innovators (Carrillo-Hermosilla *et al*., 2010). The term environmental innovation, like green innovation, expresses an innovation that is designed to improve environmental and economic performance (Ekins, 2010). In this chapter, we use environmental innovation to refer to products, processes, or management practices designed to reduce and prevent harm to the environment, in which we follow Beise and Rennings (2005), Dias Angelo, Chiappetta Jabbour and Galina (2012), Rennings and Zwick (2002), and Triguero, Moreno-Mondéjar and Davia (2013).

Environmental innovation is a subset of general innovation (Wagner, 2008) and thus shares commonalities with other innovations. However, it has the peculiarity that policy intervention is one of its key drivers (De Marchi, 2012). It is also characterised by 'double externality' (Rennings and Zwick, 2002), producing both a positive externality of knowledge and external environmental spillover effects (Ben Arfi *et al.*, 2018; De Marchi, 2012). The environmental dimension causes environmental innovation to be deemed more complex than other types of innovations (Ben Arfi *et al.*, 2018; De Marchi, 2012). Typically, environmental innovation is at a technological frontier, with a range of market and technological uncertainties and without widely accepted standards of technological solutions and measures for performance evaluation (Ben Arfi *et al.*, 2018; Pinkse and Kolk, 2010). Organisations are still somewhat inexperienced in creating products or processes that lower environmental impacts, because it involves rather complex tasks that often require knowledge and skills that are outside of industry's conventional knowledge base (Ben Arfi *et al.*, 2018). This explains why empirical studies find that environmental innovations are systemic and require R&D cooperation (De Marchi, 2012). Such collaborations call for higher cooperative efforts and greater complementarities in the activities carried out by network partners (Andersen, 2002; Nygren and Andersen, 2002), particularly in relation to the external knowledge sourced from business suppliers and customers (Seuring and Müller, 2008).

Existing empirical studies have attempted to examine the antecedents of the firm's environmental sustainability strategies and environmental innovation. According to del Río (2009), environmental innovation is driven by internal firm-level resources (e.g., Horbach, 2008; Ramus, 2002), such as technological and financial strengths. A set of external institutional factors has also been identified, which includes institutional pressures, environmental regulation stringency (e.g., Chen, Yi, Zhang and Li, 2018; Horbach, 2008; Kesidou and Wu, 2020), and consumer demand (e.g., Horbach, Rammer and Rennings, 2012). In addition, researchers have noted the importance of the growing environmental pressure from various stakeholders (Ben Arfi *et al.*, 2018), to which firms must react by coming up with new ways of implementing sustainable development (Mariadoss, Tansuhaj and Mouri, 2011).

Nevertheless, the existing literature concerning the drivers of environmental innovation is incomplete in the following respects. First, in spite of MNEs' competitive advantages and their crucial role in advancing sustainable development, few studies explore the intersection between a firm's internationalisation strategy and its environmental innovation (examples include Duque-Grisales, Aguilera-Caracuel, Guerrero-Villegas, and García-Sánchez, 2020; Kawai, Strange, and Zucchella, 2018; Kim, Pantzalis, and Zhang; 2021; Konara *et al.*, 2021). This indicates that we still know little about what the resources and capabilities, and global production and innovation networks of MNEs mean in terms of their strategy and capability for environmental innovation. To date, there is only one paper (De Marchi, Cainelli and Grandinetti, 2022) that touches on how intra-MNE and inter-MNE cooperation contribute to the introduction of green innovation among multinational subsidiaries. How those organisational linkages and networks affect the environmental innovation capacity of the parent company remains largely unexplored. A second issue is the lack of empirical evidence concerning the specificities of environmental innovation and how it is conceived and realised. Most of the existing works are mainly qualitative, relying on case studies or restricted geographic areas (De Marchi, 2012). The present chapter aims to fill these gaps by investigating how the different types and characteristics of international intra- and inter-organisational networks affect MNEs' environmental innovation.

3.3 Conceptual framework and hypotheses

In the current competitive business environment, the innovation activities of companies tend to be organisationally and geographically dispersed (Castellani *et al*., 2022), resulting in interconnected networks of organisations and individuals (Castellani and Zanfei, 2006; Scalera *et al*., 2018). The traditional model where a single inventor or R&D lab makes isolated efforts to innovate has been transformed into a collective team-based activity that, by incorporating and recombining knowledge, better meets the increasing need for accelerated innovation outcomes. Such collectives involve a wide range of actors, including partner companies, suppliers, and the MNE's foreign subsidiaries (Choudhury and Kim, 2019; Marino *et al*., 2020; Papanastassiou *et al*., 2020). Moreover, a recent review of cross-border innovation by Castellani and colleagues (2022) reveals that innovation activities are increasingly distributed across a variety of new geographical locations with R&D centres of excellence. This increased connectivity has important implications for knowledge combination in terms of more dispersed innovation activities and higher knowledge complexity across both technological scope and geographical space (Cantwell and Marra, 2022).

MNEs govern and nurture the flow of knowledge within their dispersed and interconnected internal and external networks that traverse both organisational and geographical spaces (Castellani *et al*., 2022). The organisational space is populated by intra- and inter-organisational networks composed of MNEs' foreign subsidiaries, partner companies, suppliers, and customers. The geographical dimension denotes the various locations across the globe where knowledge and competences are generated as inputs for cross-border innovation (Castellani *et al*., 2022). Based on the perspective of place and organisational space, our key theoretical argument centres on the idea that MNEs are able to enhance their ability to innovate by leveraging heterogenous external environments (Almeida and Phene, 2004) and by utilising and recombining knowledge obtained from within and without the organisation's boundaries.

Compared with domestic players, MNEs engage in international business activities by organising and arranging their productions globally. Their global production networks allow them to organise and orchestrate operation activities to optimise the different location-specific advantages as a means of acquiring competitive advantage. This type of enterprise opts for various governance modes to obtain technological knowledge and inputs from overseas (Contractor *et al*., 2010). MNEs can arrange and organise internationally integrated production networks and value chains as well as participate in international networks for technological accumulation (Cantwell and Marra, 2022). Specifically, their knowledge search can take the shape of GPNs, GVCs (Gereffi *et al*., 2005; Pietrobelli and Rabellotti, 2011), and R&D collaborations that feature a high degree of connectivity (Cantwell and Marra, 2022).

In our analysis, we focus on two broad types of network identified by Cantwell (2017) and Cantwell and Marra (2022). The first type is the intra-MNE network. These are networks of international production, including international research and R&D facilities, that are owned by the MNEs themselves. The second is the inter-organisational network. These result from MNEs joining strategic alliances with external partners (Cantwell and Marra, 2022). Intra- and inter-organisational networks lay the foundation for the internal and external networks for innovation, through which MNEs can access diverse knowledge bases that are distinct from those in their home countries. They thus enrich their own knowledge bases and foster knowledge diffusion across actors and countries, which ultimately leads to the increased potential for knowledge recombination (Cantwell and Marra, 2022). The key to this strand of research is that MNEs strive to connect and orchestrate international networks, thereby increasing their potential for knowledge recombination and development, from which they can create solutions for complex problems (Cantwell and Marra, 2022). The emphasis that Cantwell and Marra (2022) place on resource accumulation and technological capability in MNEs builds upon the literature of dynamic capabilities (Athreye, 2022). Focusing on environmental innovation, Orsato (2006) proposes that firms' capabilities can be deployed and arranged so as to create competitive advantages in environmental innovation.

Building on the above discussion, we employ a theoretical framework that integrates both strands of thinking. That is, we explore MNEs' sustainable competitive advantages by focusing on the global connectedness of multinationals and their cross-border innovation networks. The following section discusses the hypothesis development, which draws on arguments related to global connectivity and the internationalisation of innovative activities.

3.3.1 Intra-organisational production network - International diversification

MNEs engage in international business activities by organising and arranging their production activities globally. They can thus arrange and orchestrate their operations to derive different location-specific advantages. The international diversification of production networks is considered to be an important aspect of global connectedness (Maksimov, Wang and Yan, 2019). The literature on international diversification defines it as the degree to which a firm diversifies across geographic locations globally (Kim, Hwang and Burgers, 1989). By interacting with both local firms (Turkina and Van Assche, 2018) and various individual stakeholders in the host markets (Kolk and Fortanier, 2013), MNEs' foreign subsidiaries are able to form locally embedded networks. As MNEs expand their internationalisation breadth, multiple embeddedness can be formed (Meyer, Mudambi and Narula, 2011), facilitating the acquisition of various tangible or intangible resources (Riviere, Bass and Andersson, 2021) and diverse knowledge content (Phene, Fladmoe-Lindquist and Marsh, 2006). This has been regarded as a mechanism for expanding multinationals' existing technological competences (Scalera *et al*., 2018).

More precisely, internationalisation breadth allows MNEs not only to mitigate risks through diversifying their activities across different geographic locations but also to access and incorporate complementary knowledge from those places through resource and capability coordination (Kafouros, Buckley and Clegg, 2012; Lessard, Teece and Leih, 2016). Subsidiaries can therefore be thought of as instruments for strategically tapping into local pockets of knowledge within host markets (Cantwell and Santangelo, 1999; Christmann, 2000; Turkina and Van Assche, 2018). By building networks and relationships with various stakeholders globally through foreign subsidiaries, MNEs can obtain relevant knowledge about a wide range of environmental sustainability issues and absorb the complementary knowledge that is necessary for improving their practices for better sustainable solutions (Van Zanten and Van Tulder, 2018).

In our context, MNEs are exposed to diverse knowhow and best management practices that might not exist in their home countries (Kostova, Roth and Dacin, 2008) via their global networks of environmentally-certified participants and the various stakeholders in the host markets (Van Zanten and Van Tulder, 2018). The complementary resources and knowledge inputs from foreign stakeholders enable MNEs to improve their existing environmental knowledge stocks, and the resulting local embeddedness facilitates the acquisition and integration of complementary and distinctive knowhow. More specifically, these knowledge inputs not only promote the internalisation of complementary resources, but also facilitate the firm's learning routines in terms of knowledge dissemination, sharing, and integrating, which are necessary for fostering green competences and effectively sensing green opportunities and threats (Maksimov *et al*., 2019). In such a context, these knowledge advantages equip firms with competences to deal effectively with environmental issues, such as reduction in environmental costs, the alleviation of burdens for customers, and advancements in environmentally-related products and practices. These strengths may also help firms identify opportunities that offer them global competitiveness, and consequently fostering their potential to improve their future business prospects by via offering a global vision (Riviere *et al*., 2021).

Existing research has recognised the importance to environmental innovation creation of accessing and using both internal (Ben Arfi *et al*., 2018) and external knowledge sources (Ghisetti, Marzucchi and Montresor, 2013). In a recent study on the antecedents of eco-innovation, Chiarvesio *et al*. (2015) indicate that a firm's geographic scale of economic operations is positively related to the flows of knowledge required for eco-innovation activities. This is because sharing knowledge rooted in diverse locations and pooling resources heightens firms' awareness of green opportunities or threats, making them willing to invest in green practices and competent to surmount environmental obstacles. Relatedly, Aguilera-Caracuel, Hurtado-Torres and Aragón-Correa (2012) find that export diversification helps firms replicate and exploit knowledge and experience regarding environmental practices across markets, thus affecting their adoption of environmental strategies. Furthermore, using an enterprise-level sensing-seizing-reconfiguring framework (Teece, 2007), Maksimov *et al*. (2019) elaborate two channels through which an MNE's international spread of sales facilitates the cultivation of their dynamic green capabilities; such capabilities are regarded as a prerequisite for pursuing environmental innovation. More recently, when exploring the determining factors of environmental innovation, Biscione, Caruso and de Felice (2021) emphasise the critical role played by the geographic dimension of markets. Following this line of reasoning, we can expect that the MNE's wider global production networks or global connections derived from larger geographical coverage across different countries (i.e., international diversification) will generate greater knowledge advantages and more dynamic green capabilities for making green improvements (Chen and Chang, 2013) in products, technologies, and production processes.

When firms establish connections with locations, they can obtain locally generated specialised knowledge (Cano-Kollmann, Cantwell, Hannigan, Mudambi, and Song, 2016). Furthermore, creating internal and external linkages for accessing and sharing knowledge inputs across locations increases the firm's embeddedness within the host markets. In the case of MNEs, increased local embeddedness improves knowledge flows between the host economy and the companies (Yang, Martins and Driffield, 2013) and contributes to MNEs' learning routines for new knowledge integration (Cantwell and Santangelo, 1999; Scalera *et al*., 2018). In practical terms, MNE connectivity results in the development of production networks across both space and the organisational subunits, which facilitates resource coordination and tacit knowledge integration across geographical and technological space (Cano-Kollmann *et al*., 2016). This organisational learning (Barkema and Vermeulen, 1998) tends to foster firms' knowledge base, skills, competencies, and thus competitiveness (Zahra, Ireland and Hitt, 2000).

In line with this reasoning, it appears that MNEs are in a better position to invent new environmental products, processes, and novel technologies, given their higher availability of green knowledge stocks and stronger knowledge learning and integration routines by way of their internal intra-organisational linkages. Such knowledge advantages are prone to substituting the sensing of global trends and complementing the seizing of green opportunities, consequently fostering MNE's dynamic green capability (Maksimov *et al*., 2019). This specific type of dynamic capability equips them with competences to deal with environmentally-related issues effectively and to pursue environmental innovation. Environmental innovations are characterised by high levels of complexity, novelty, uncertainty, and variety compared with traditional technological or market domains (Cainelli, De Marchi and Grandinetti, 2015); hence, connectivity via geographically diversified production networks is required if firms are to obtain the necessary atypical knowledge and skills for producing environmental innovation. Taken together, we propose that MNEs with greater international diversification of production networks possess a higher capability of creating environmental innovation to react to the sustainability imperative.

H1. International diversification of production networks increases MNEs' capacity to undertake environmental innovation.

3.3.2 Intra-organisational networks - Ownership of foreign subsidiaries

Host countries may suffer from 'institutional voids' where the ecosystem of the market is not fully functioning (Khanna, Koss, Jones and Ervin, 2007). Accordingly, MNEs must fill such institutional voids in other ways (e.g., Tatoglu, Bayraktar, Sahadev, Demirbag and Glaister, 2014). The extent of their ownership of subsidiaries can be an effective mechanism for mitigating institutional deficiency. Empirical evidence shows that parent firms typically retain controlling equity stakes in foreign affiliates when they face weak institutional environments (Mani, Antia and Rindfleisch 2007), which suggests that uncertain environments amplify the need for protection.

The need to retain ownership and control of firm-specific assets is at the core of internationalisation theory and is a backbone of the dominant paradigms in IB literature (Driffield, Mickiewicz and Temouri, 2016). Given that FDI is characterised by a high extent of commitment and by the exercise of control via equity (Aguilera and Jackson, 2003), it is crucial that parent firms establish an ownership structure that allows them optimal control over the organisation's physical and knowledge capital (Carr, Markusen and Maskus, 2001; Driffield, Mickiewicz and Temouri, 2014). Hence, the ownership structure of foreign affiliates is considered to be a vital channel for retaining control of strategic assets and alleviating the risks presented by the different and uneven institutional environments of host nations (e.g., Brouthers, 2002; Meyer, Estrin, Bhaumik and Peng, 2009).

An MNE's organisational structure offers it opportunities to direct resources and activities to its foreign affiliates (Uhlenbruck, 2004) and move productions globally. Prior research has assumed that the parent company is the decision maker, and generally takes the initiative on ownership structure (e.g., Dikova and van Witteloostuijn, 2007; Driffield *et al*., 2014). Research on the parent-subsidiary relationship has therefore primarily concentrated on the parent's control and coordination mechanisms

(Paterson and Brock, 2002). Control is the use of power or authority by headquarters (HQ) to ensure that the subsidiary's behaviours comply with corporate goals (Child, 1973), while coordination refers to the enabling process that offers a suitable link between the organisation's separate tasks (Tuggle, 1978). These two mechanisms, as the embodiments of HQ management, allow HQ to monitor subsidiaries' activities and curtail their opportunistic actions (Liou and Rao-Nicholson, 2021; O'Donnell, 2000). We can thus infer that HQ functions to direct the efforts of subsidiaries to jointly work towards the MNE's common good (Liou and Rao-Nicholson, 2021).

An investor who holds a large ownership stake in an investment enterprise in a host nation is signalling that they consider the investment relationship to be relatively long-term. Such an investor has both a long-lasting interest in the investment and a substantial level of governance influence (Wacker, 2016). Indeed, the controlling shareholder's large ownership share triggers stronger monitoring incentives (Goergen, 2018) and creates two types of control benefits (Grossman and Hart, 1988): security benefits and private benefits of control. It is plausible that a higher equity holding allows MNEs to efficiently and completely reconfigure subsidiaries that are under their effective control, transferring processes and tacit knowhow to them to meet the organisation's needs and emerging global trends.

As already noted, MNEs build organisationally motivated linkages to acquire and develop knowledge related to their existing knowledge base (Cano-Kollmann, Hannigan and Mudambi, 2018). These linkages are a key component of the global innovation networks, being the principal form of cross-border knowledge connectivity (Perri, Scalera, and Mudambi, 2017), As such, we contend that the intra-MNE networks that are built on organisational ownership linkages between the parent company and its foreign subsidiaries encourage coordination of capital and resources, as well as knowledge exchange across organisational spaces. Relatedly, it has been observed that that stronger ties between actors make it easier to exchange information and thus learn from each other (Hansen, 1999). By applying the same reasoning to the strength of a parent firm's intra-MNE linkages, we suggest that the mechanism of the MNE's ownership stake improves knowledge flows and enhances firm's learning routines for knowledge integration and creation. Indeed, equity control not only creates the conditions for knowledge connectivity and offers motivations for capital coordination and knowledge exchange between HQ and its subunits, but also tends to make those processes more efficient and effective. This theoretical approach suggests that the higher the MNE's ownership stake in its subsidiaries, the greater chance it has to reconfigure its capital and resources and acquire knowledge and skills in accordance with its needs. As a result, knowledge advantages and capabilities can be expected. These put the parent company in a better position to create competitive advantages and foster the capacity to respond to changing global demands, such as the sustainability imperative. The ownership intra-MNE network therefore enables MNEs to deal with the environmental innovation characteristics of novelty, uncertainty, and variety.

To sum up, we infer that the intra-organisational linkage in the form of ownership stake promotes knowledge flows and learning routines, which in turn foster improvements in MNEs' knowledge bases, skills, and competences. These create favourable conditions for MNEs to cultivate the capacity and capability to undertake environmental innovation. In light of the above arguments and *H1*, we postulate that:

H2. Intra-organisational network in terms of ownership stake of foreign subsidiaries enhances MNEs' capacity to undertake environmental innovation.

3.3.3 Intra-organisational innovation co-production networks - Parent firm and foreign subsidiaries

A large body of the extant research on global innovation networks focuses on HQ-subsidiary relationships and tackles issues such as dual embeddedness and multiple embeddedness (e.g., Andersson, Forsgren, and Holm, 2002; Cano-Kollmann *et al*., 2018). Drawing on the seminal work of Kogut and Zander (1993), existing studies adopt the knowledge-based view of organisations (Grant, 1996; 1997) and hold that the subsidiary is embedded in diverse knowledge flows, including knowledge inflows from the parent (Gupta and Govindarajan, 2000) and other MNE subsidiaries (Tsai, 2001), and knowledge outflow from its domestic environment (De Marchi *et al*., 2022).

Another type of international R&D network possessed by MNEs is the internal innovation network within organisational boundaries. This is associated with intra-MNE technological collaboration and exchanges. The literature on internal MNE networks focuses on the role of foreign subsidiaries in the cross-border organisation of MNE innovation and technological advancement. A recent study by Athreye (2022) suggests that MNEs, especially mature ones, have become a unique network within which subsidiaries serve as nodes that facilitate knowledge flows from local locations to HQ and the MNE's other units. Foreign subsidiaries thus play a vital role in enabling external knowledge sourcing and knowledge exploitation within the boundaries of the organisation (Gupta and Govindarajan, 2000; Phene and Almeida, 2008). Subsidiaries tend to have more expertise in marketing, which can be combined with the technological knowhow of the parent company (Santos, Doz, and Williamson, 2004). This explains the continued focus of the current research on subsidiaries' capabilities and their role in MNE innovation (e.g., Kostova, Marano, and Tallman, 2016; Meyer, Li, and Schotter, 2020; Papanastassiou *et al*., 2020).

The ability to cooperate with an international network of firms within the same ownership boundaries is exclusive to MNEs (De Marchi *et al*., 2022). Relying on its organisational networks (Cantwell, 2019), the parent company is able to internally coordinate learning processes by collaborating with its foreign subsidiaries for knowledge production. As such, intra-MNE networks hold significant potential for collaboration aimed at innovation (De Marchi *et al*., 2022), through which parent companies are able to complement their own R&D efforts. Co-production of innovation between HQ and its subsidiaries is a way of collaborating in which subsidiaries are empowered to make contributions to the innovation capability of the organisation as a whole (Phene and Almeida, 2008). Indeed, HQ allocates ownership rights over technological assets to foreign subsidiaries through this co-production mechanism, while at the same time keeping hold of the monitoring, direction, and control of the cooperative innovation. From the perspective of the parent firm, this internal innovation network (Cantwell and Marra, 2022) enables it to coordinate the learning process to meet its requirements and needs. These can include sourcing local information via its global subsidiaries (Kuemmerle, 1999), adapting existing knowledge to the needs of the local market, and recombining its own knowledge with localised knowhow (Cantwell and Marra, 2022). MNEs can thereby adopt a transnational approach to knowledge learning and innovation generation (Phene and Santangelo, 2022).

Although related evidence on intra-MNE international connectivity has been empirically tested in the context of general innovations (e.g., Lo, 2016; Yamin and Otto, 2004), only one work (as far as we know) has investigated how subsidiaries' external partnerships and intra-MNE collaboration affect their introduction of environmental innovation. De Marchi *et al*., (2022) find that intra-MNE resources contribute to the introduction of environmental innovation by subsidiaries, and that intra-MNE and extra-MNE cooperation for innovation enhances the likelihood of subsidiaries' introducing environmental innovation. As yet, no extant work has thoroughly investigated these factors for environmental innovation at the MNE level, and this is what we seek to explore in this work.

MNEs can create a comparative advantage related to the scope of integration by utilising and exploiting different pieces of subsidiaries' knowledge (Grant, 1996). We therefore build on Cantwell and Piscitello (2014) to posit that linkages associated with innovation activities between HQ and the foreign sub-units further enhance this advantage by facilitating interactions and promoting international knowledge flows. The increased connectivity generated by this form of innovation collaboration encourages the creation of a more innovative technological portfolio.

As far as the subsidiary is concerned, explicit cooperation on innovation with external players highlights the diversity and complementarity of knowledge that can be accessed by the subsidiary from both sides (Albis, Álvarez and García, 2021; Ciabuschi, Holm, and Martin, 2014; Figueiredo and Brito, 2011). In this way, the knowledge that is created locally and accumulated by different subsidiaries can be fed into the MNE's knowledge flows and processes so that the different knowledge pieces are integrated and combined with those of HQ. This tends to be conducive to producing new knowhow that is useful for environmental innovation creation. Indeed, this has been found to be a typical way of dealing with environmental innovation's complexity and novelty (De Marchi, 2012; De Marchi *et al*., 2022). We therefore suggest that the same reasoning can be applied to the context of the parent company, so that cooperating with an intra-MNE network to co-produce innovation enables HQ to deal with the complexity of environmental innovation. Furthermore, a greater extent of intra-MNE co-production of innovation contributes to larger advantages in terms of the organisational capacity for environmental innovation. Our argument is in line with De Marchi *et al*. (2022), who advise that the intrinsically complex nature of environmental innovation implies that companies that wish to produce environmental innovation should utilise their network of external and internal inter-organisational relationships to a larger extent than is required for undertaking other types of innovations.

Hence, we hypothesise that:

H3. Intra-organisational innovation co-production networks between the parent firm and its foreign subsidiaries enhances MNEs' capacity to undertake environmental innovation.

3.3.4 Inter-organisational innovation co-production networks - Geographical diversification

Now we turn to another external mode of inter-organisational network: international R&D collaboration. This refers to developing R&D activities cooperatively and fostering inter-firm networks of relations with foreign partners. This is an attractive strategy for obtaining international external knowledge (Nieto and Rodríguez, 2022) because it allows companies to cooperatively 'learn from partners' and 'learn from country' and thus to exploit the heterogeneity of existing knowledge between firms (Kogut, 1991) and even across countries (Furman, Porter, and Stern, 2002).

Extant literature has summarised and categorised the potential benefits of an international R&D sourcing strategy into two groups: access to superior resources and capabilities, and the potential for efficiency and competitiveness gains (Nieto and Rodríguez, 2022). R&D collaboration allows companies to access not only country-specific knowledge but also the specialised expertise and technology of their partners (Kafouros and Forsans, 2012). It supplies a variety of knowhow and thus enhances knowledge diversity within the organisations (van Beers and Zand, 2014), and mitigates the liabilities of foreignness to some extent (Lu and Beamish, 2006). It can equip companies with the two-fold experience of working abroad and managing an international collaboration (Kafouros, Love, Ganotakis, and Konara, 2020). Moreover, it can generate efficiency and competitiveness gains in terms of spreading risks and costs through R&D collaborative agreements (Sampson, 2005).

However, these many advantages come with some risks. For example, the high degree of organisational complexity that results from cross-border R&D alliances may impose governance and managerial costs, and also require an investment of resources to maintain communication and control (Narula and Martínez-Noya, 2015). It can also be difficult to achieve knowledge transfer and integration across long distances (Driffield, Love, and Yang, 2016).

Most firm-level empirical studies of international R&D collaboration have discovered its positive effects on innovation capacity and various innovation results. According to Kafouros *et al*. (2020), technological alliances with foreign partners tend to be more beneficial for firm innovation performance than national alliances. International collaboration on R&D initiatives can also exert positive effects that can go beyond firms' enhanced innovation capacity (Nieto and Rodríguez, 2022). Indeed, as suggested by Elango and Pattanik (2007), collaboration with foreign partners facilitates companies' connection with new sources of information abroad, their networking with international contacts, and their subsequent international expansion.

The diversity of technological knowledge sources is critical in this context (Almeida and Phene 2004) and is indeed seen a key factor in technological collaboration (Nieto and Santamaría, 2007). Diversity offers firms the opportunity to access different, and possibly complementary, knowledge (Rodríguez, Nieto and Santamaría, 2018). This external knowhow can be combined with the firm's own knowledge to create a heterogeneity of knowledge that improves the possibility of generating novel ideas and innovations (Rodríguez *et al*., 2018). Based on Lavie and Miller (2008), van Beers and Zand (2014) argue that geographical diversity in their overseas R&D collaborative partners is of particular benefit to firms' incremental innovation performance because it allows organisations to adapt their products to local requirements. This implies that increased diversity in partners' national backgrounds (i.e., their geographical diversification) leads to greater benefits regarding resources and learning (Rodríguez *et al*., 2018). More recently, Rodríguez *et al*. (2018) focus on firms in technological knowledge-intensive business services and reveal that sharing knowledge diversity by collaborating with diverse partners tends to be highly beneficial to innovation performance because firms can benefit from the remarkable variety of innovativeness across different countries (Furman *et al*., 2002).

Thus, we suggest that MNEs that collaborate for innovation with international partners from a range of different countries can gain access to heterogenous multidisciplinary and complementary technological capabilities, and possibly also designated skills, knowhow, or knowledge. Drawing on their geographically dispersed networks of connected knowledge units and specialised innovators, MNEs are better able to search for knowledge in different technological domains (Castellani and Zanfei, 2006; Frenz and Ietto-Gillies, 2009). They can thus develop new knowledge, which is accelerated by cross-fertilisation across different knowledge domains. These lead to high synergies and encourage the creation of innovative products.

As advised by Chesbrough (2003) and Laursen and Salter (2006), a wide array of knowledge intake is derived from diverse knowledge sources. This allows individuals within the organisation to come up with novel linkages and associations (Cohen and Levinthal, 1990), which in turn promote the organisation's innovativeness. It can particularly promote radical innovation (such as is required for environmental innovation) because this is usually associated with greater technological complexity and uncertainty, and more financial risk (Belderbos, Carree and Lokshin, 2006).

Empirical evidence regarding the driving of environmental innovation by networking activities (e.g., Andersen, 2002; Mazzanti and Zoboli, 2006) is scant. According to Andersen (1999), the greening of industry is an innovation process with four distinct characteristics: radical, highly systemic, politically influenced, and associated with substantial information problems. Industry greening therefore needs a high degree of inter-firm coordination (Andersen, 2002), including cooperation with supply chain partners because developing environmental innovations, even more so than other innovations, requires knowledge and skills that fall outside the firm's usual domain (De Marchi, 2012).

In short, collaboration on innovations must be highly active, committed, and explicit. Building on the argument of Un and Rodríguez (2018), we expect that inter-firm innovation co-production networks create incentives, abilities, and the mindset to support knowledge transfer and combination, and thus help firms absorb complementary tacit information and knowledge. As a result, higher innovation propensity can be expected. Given the benefits of knowledge diversity, which is supplied by innovation networks with geographically diversified international collaborators, and the prerequisites of environmental innovation, we hypothesise that:

H4. Geographical diversification of inter-organisational innovation co-production networks increases MNEs' capacity to undertake environmental innovation.

3.4 Methods

3.4.1 Data sources and sample

The empirical analysis partially draws on data of ESG practices for the period 2009 to 2020 from Thomson Reuters ASSET4 database. This database compiles publicly available information, including annual and sustainability reports as well as proxy filings, for firms subjected to integrated ESG monitoring (Thomson Reuters, 2011). With a database of more than 7,000 firms, ASSET4 is mainly employed for studying corporate social responsibility (e.g., Stellner, Klein and Zwergel, 2015) and operational performance (e.g., Chopra and Wu, 2016).

We also draw on Bureau van Dijk's Orbis main database of MNE information, in which subsidiaries from over the world (collected by the database) are linked with their parent firms. Here, an MNE is defined as a shareholder with at least one foreign subsidiary during the observation period. This implies that corporate and financial information at the parent and subsidiary level can be extracted. Our analysis scope includes MNEs whose headquarters are located in five developed countries: France, Germany, the United Kingdom, Netherlands, and Sweden over the period 2009 to 2019.

We obtain information on MNEs' patents from the Bureau van Dijk's Orbis IP database of patent records from 1808 to 2019. Orbis IP provides detailed patent records by publication date, current direct owner(s), country of current direct owner(s), and a complete symbol of IPC administered by the WIPO. A unique advantage of this data is that patent records can be matched to their current direct owners' detailed corporate and financial information using the unique firm identifier. This means that patents owned by the parent company or its foreign subsidiaries can be identified from the unique identifier of direct owner(s), from which one can tell whether the patent is co-produced by the parent and any of its affiliates, or by the parent and its foreign partners.

Finally, we obtain information on the stringency and enforcement level of environmental regulation from the Executive Opinion Survey managed by World Economic Forum. This survey has indices scaled from 1 (very lax) to 7 (most stringent/most rigorous) and they are provided for every two years from 2007 until 2018. The values originate from answers about a country's environmental policy given by its businesses, business associations, and universities. The survey covers over 100 countries (Noailly and Ryfisch, 2015). Its wide coverage and time-variant data makes it ideal for analysis of the impacts of environmental regulations (e.g., Noailly and Ryfisch, 2015; Peñasco, del Río and Romero-Jordán, 2017).

To link firms in the ASSET4 database with those in the Orbis main database, we employ a string-matching approach, in which the strings of company names and the country code for the company's location are taken into account. Authorial judgement is required when no or multiple object(s) is(are) deemed to be matched between one data source and the other. In order to aggregate patent information to the firm level, the publication date of each record is employed to capture the time when the technological knowledge was created because this variable has fewer missing values compared with the application date. Individual patent data is then organised in a panel setting using its current direct owner(s)' identifier and publication year, which can be matched with Bureau van Dijk's Orbis firm database. A range of company characteristics, including firm age, size, type of corporation, environmental sustainability practices, sector, location, and various financial indicators are obtained and taken into account. After a standard data cleaning procedure to deal with infeasible values and missing observations, we construct a sample of an unbalanced panel of 4,510 firm-year observations from 622 unique firms across 5 developed countries from 2009-2017.

3.4.2 Variables and Measures

3.4.2.1 Dependent variable

Our dependent variable, the environmental innovation score, is directly extracted from Thomson Reuters ASSET4 database, stored as an index ranging from 0 to 100. We rescale the score by dividing it by 100. In line with the definition provided by Thomson Reuters, this score reflects an organisation's capacity to introduce new environmental technologies and processes, or eco-designed products with the aim of reducing environmental costs and burdens for its customers and thereby creating new market opportunities. Recent studies on environmental innovation employ similar measurement include Albitar, Borgi, Khan and Zahra (2023) and Phung, Trinh, Nguyen and Trinh (2023). The larger the score, the higher the firm's capability for reducing environmental burdens and creating environmental innovations.

3.4.2.2 Independent variables

We adopt a similar method to that suggested by Maksimov *et al*. (2019) to measure international diversification of MNEs' global production networks, which derives from the diversity of total assets' distribution across different foreign countries. A Herfindahl index of subsidiaries' total assets, ranging from 0 to 1, measures the concentration of MNEs' production assets overseas. Following the diversification literature (Berry, 1971; Garcia-Vega, 2006), we reverse the way of coding by computing 1 minus the Herfindahl index of total assets across different foreign markets. The variable is thus constructed as follows:

$$diver\_intra\_GPN_{it} = 1 - \sum_{j=1}^{n} (\frac{TA_{ijt}}{TA_{it}})$$

Where TA_{ijt} is the total assets of MNE i in the j^{th} market at time t, and TA_{it} stands for the total assets of MNE i across n foreign markets at time t.

We next consider how to account for an MNE's intra-organisational linkages as a result of internationalisation. The concept of inter-organisational relationships proposed by Grant and Tan (2013) refers to a situation where various types of organisations, including at least one business organisation, are linked by formal relations for socio-economic objectives (Siemieniako, Kubacki and Mitręga, 2021). Applying this to the intra-organisational relationship, we consider ownership stake to be a type of formal relationship between HQ and its affiliates. Additionally, governance is connected with structure, power, and the authority to make decisions on collective activities (Abdul-Rasheed, Li, Abdul-Fatawu, Boamah and Bediako, 2017); as such, it largely determines how different actors are connected and linked with each other. Thus, to measure the strength of an MNE's intra-organisational linkages, we depict its ownership structure through its control and coordination over both physical and knowledge capital, which is believed to be a channel through which MNEs maintain intra-relationships with their foreign affiliates and exert influence on them. Hence, we first collect the share of an MNE's total participation in each of its foreign subsidiaries. Each share is then weighted by the proportion of that subsidiary's total assets to the total amount of all the foreign subsidiaries in a given year, from which the mean value is calculated. The resulting average weighted ownership stake of foreign subsidiaries captures how strongly an MNE and its affiliates are, on average, linked and associated with each other.

In the previous studies on MNE innovation, co-invented patents are regarded as a measure of internal and external collaboration (Athreye, 2022). The main idea here is that cooperation within the intra-MNE and across the inter-MNE networks boosts knowledge flows among the partners and thus increases the diversity and complementarity of knowledge that can be accessed by both parties to the partnership. Due to information constraints on patent inventors in our data, we capture organisational innovation networks by exploiting information on the direct owner(s). We contend that a patent is co-produced by different partners if multiple owners are listed as its direct owners, based on which the intra- and inter-organisational innovation co-production networks are established. Indeed, to capture the strength of intra-organisational innovation co-production between the parent firm and its foreign subsidiaries, we compute the extent to which an MNE's patents are co-produced with its foreign subsidiaries. This is the ratio of co-owned patent publications between HQ and the affiliates to the total number of the parent company's patents.

In similar vein, we gauge an MNE's inter-organisational innovation co-production network from its patent co-ownership with foreign collaborators. Following the method of constructing international diversification, we again employ 1 minus the Herfindahl index to measure the geographical diversification of an MNE's inter-organisational innovation co-production network. This is derived from the geographical distribution of its patents co-owned with other foreign companies across different foreign countries. The Herfindahl index, ranging from 0 to 1, captures the concentration of the patents co-produced with cross-border foreign partners across different foreign markets. The variable is computed as follows:

$$diver\_inter\_co-patent_{it} = 1 - \sum_{k=1}^{m} \left(\frac{PA_{ijt}}{PA_{it}}\right)$$

where PA_{ijt} is the number of patents of MNE i in the k^{th} country at time t, and PA_{it} represents the total number of patents of MNE i across m foreign countries at time t.

3.4.2.3 Control variables

Our choice of control variables is guided by theoretical considerations and existing empirical evidence on the determinants of environmental innovation and limited by data availability.

Prior research emphasises the particularity of environmental innovation in terms of its externalities and the drivers of its introduction (De Marchi, 2012), highlighting the crucial contributory role of regulation (e.g., Jaffe *et al*., 2002; Marin and Zanfei, 2019). Empirically, Kawai *et al*. (2018) present explanations of how stakeholder pressures in host countries stimulate subsidiaries to engage in green product and process innovations. Noailly and Ryfisch (2015) further claim that the probability of undertaking green R&D abroad is enhanced by the stringency level of environmental regulation in the host country. Here, we consider environmental policy in the context of both host and home countries. Taking the stringency and enforcement aspects of policy into account, we compute the average value of the indices of stringency and enforcement level of environmental regulation for each home and host country. The value of the MNE's host country is then weighted by the proportion of total assets within that country to the total amount of all the foreign subsidiaries in a given year; the average value is then taken across the host markets. The resulting value becomes the weighted average of overall environmental policy stringency that an MNE experiences within its host countries.

Firm age and size by employees (both in logarithm form) are included as controls to account for the resources and capacity of the enterprise. As summarised by Liao and Liu (2021), organisational factors, mainly organisational size, have been used as controlling variables in many environmental innovation studies (e.g., Jové-Llopis and Segarra-Blasco, 2018; Martinez-Ros and Kunapatarawong, 2019).

Labour productivity (revenue per employee) is taken into account to reflect the efficiency of the workforce, given the literature's acknowledgement that productivity plays a positive role in the innovativeness of organisations (Chiarvesio *et al*., 2015).

In the innovation literature, R&D activities are expected to be crucial inputs for a firm's knowledge production and innovation process. Patents are generally regarded as an alternative measure of innovation capacity (e.g., Costantini *et al*., 2015), but they play a different role in the knowledge creation process because not all R&D commitments or research successes will lead to patents (Popp *et al*., 2011). Here, we use the natural logarithm value of the number of green patent publications to account for existing knowledge stocks and the outputs related to environmental innovation. Our green patents are identified by a set of designated IPC codes related to environmentally sound technologies (ESTs) in numerous technical fields listed in the IPC Green Inventory. For the sake of data aggregation, the individual patent record is organised in a panel setting using its current direct owner's firm identifier and patent publication year, enabling it to be linked with the MNE's other dynamic information.

Finally, heterogeneity at the levels of sector (one-digit section level) and country are controlled for by their respective dummies. Table 3.1 summarises the variable definitions.

3.4.3 Empirical specification

This section describes the empirical approach employed to identify the antecedents of MNEs' environmental innovation capacity in terms of role played by the different types of international intra- and inter-organisational linkages and networks. Accordingly, we formulate a pooled Tobit model of environmental innovation capacity estimated by maximum likelihood:

$$Environmental\ innovation_{ijt} = max\big(0, \gamma_0 + \gamma_1 diver\_intra\_GPN_{ijt} + \gamma_2 intra\_ownership_{ijt} + \gamma_3 intra\_co - patent_{ijt} + \gamma_4 diver\_inter\_co - patent_{ijt} + \gamma_5 home\ policy_{ijt} + \gamma_6 host\ policy_{ijt} + \gamma_7 X_{ijt} + \gamma_8 D_{ijt} + \varepsilon_{ijt}\big), \varepsilon \sim N(0, \sigma^2) \quad (1)$$

where $Environmental\ innovation_{ijt}$ indicates the environmental innovation score of firm i in industry *j* at time *t*. The vector of explanatory variables hypothesised to affect green innovation capacity are as follows: geographical diversification of global production networks ($diver\_intra\_GPN_{ijt}$) tests hypothesis *H1*, intra-organisational linkages in terms of ownership stake ($intra\_ownership_{ijt}$) tests *H2*, the extent of the intra-organisational innovation co-production network ($intra\_co-patent_{ijt}$) tests *H3*, and the geographical diversification of inter-organisational innovation co-production linkages ($diver\_inter\_co-patent_{ijt}$) tests *H4*. The vector of control variables comprises the indices environmental policy stringency within the home country ($home\ policy_{ijt}$) and the host markets ($host\ policy_{ijt}$), and *X*, which is a vector of firm characteristics including firm age, size, labour productivity, and natural logarithm form of green patents number. Finally, D is a full set of industry (NACE section one-digit), time, and country dummies and ε is a random error term.

3.5 Results

3.5.1 Summary statistics

Table 3.2 reports the descriptive statistics of variables in our analysed sample. The statistics are available for the overall sample and for each country. Overall, firms appear to be highly heterogeneous. With an average age of 39 ($e^{3.69}$) years and 6,310 ($e^{8.75}$) employees in company size, sampled firms have a wide range of labour productivity and profitability. On average, sampled firms have published 1.57 ($e^{0.45}$) green patents.

<Table 3.2 inserts here>

The level of environmental innovation score varies across the five countries, with firms in the United Kingdom being at the top and those in Sweden at the bottom. Companies in France occupy first place in terms of international diversification of GPNs. On average, German and Swedish companies have relatively stronger intra-organisational ownership linkages with their foreign subsidiaries than MNEs from the other countries. The strength of intra-organisational co-patenting network tends to be strongest in Sweden, with German and France at the bottom of the list. Regarding the degree of geographical diversification of cross-border innovation co-production network, German companies take the lead, surpassing by far those in France (2nd place) and Netherlands (3rd place).

In terms of environmental regulations, Germany and Sweden exert more stringent environmental requirements on firms operating within their jurisdictions. As for the environmental policy in host countries, firms in Sweden have, on average, the most stringent environmental policies in their overseas markets, while those in Germany have the lowest.

Table 3.3 summarises the correlation coefficients for the key variables in the sample. Firm environmental innovation capacity shows a moderate positive correlation with the international diversification of the intra-organisational production network and a weak positive correlation with both intra- and inter-organisational innovation co-patenting networks. Environmental innovation appears to be weakly negatively related to intra-organisational ownership linkage. International diversification of GPNs is weakly positively correlated with the other three variables in respect of organisational linkages, including intra-organisational ownership linkage, intra-organisational co-patenting network, and geographical diversification of inter-organisational co-patenting network. Additionally, intra-organisational co-patenting network and geographical diversity of cross-border innovation co-production are weakly positively correlated with each other.

<Table 3.3 inserts here>

3.5.2 Regression results

To estimate the determinants of MNE environmental innovation capacity, we employ the Pooled Tobit modelling specified in Equation (1). The dependent variable is environmental innovation score ranging from 0 to 1. The estimates of coefficients and average marginal effects are reported in Table 3.4 and Table 3.5, respectively.

<Table 3.5 inserts here>

As shown in Table 3.5, across all the model specifications, we find international diversification of production networks in terms of geographical diversity to be statistically significant in explaining MNE environmental innovation capacity. A one unit increase in the international diversification index lifts the expected value of the environmental innovation score by 0.14. This supports our *H1* that through their wider global linkages built on GPNs across diverse countries, MNEs are expected to possess more resources and knowledge advantages as well as stronger knowledge learning and integration routines. Theoretical arguments of global connectedness and firm-specific advantages suggest that these give rise to higher green capabilities to innovate environmentally.

However, we are unable to find support for the effect of intra-organisational ownership linkage on environmental innovation capacity across Models B, C, and D. Intra-organisational linkages, motivated by traditional control and coordination mechanisms, turn out not to play an important part in environmental innovation capacity. MNEs can exploit their ownership advantages through retaining ownership and control of physical and knowledge capital (Carr *et al*., 2001). Their ownership structure of foreign affiliates (their production assets overseas) offers them motivations and opportunities to optimise resources and productions globally. Such control and coordination over physical and intangible capital can be beneficial for knowledge exchanges and the learning routines for knowledge integration, but they may not have significant direct impacts on the MNE's capacity to innovate green technologies, processes, and eco-designed products.

Two other measures of the innovation co-production network are added to Models C and D in turn. As expected, the extent of the intra-MNE co-patenting network is statistically significant and highly positively related to MNE's capacity to engage in environmental innovation in Models C and D, with the environmental innovation score going up by nearly 0.3 when the intra-organisational co-patenting network variable experiences a one percentage point increase. This suggests that firms that explicitly cooperate on innovation with foreign affiliates are able to integrate and combine locally accumulated knowledge with their own internal knowledge, thus giving rise to advantages in producing new knowledge conducive to environmental innovation creation. This lends support to our *H3*. Turning to Model D, we find that the international diversification of the inter-MNE innovation co-production network is also statistically significant and directly advantageous to the capacity to innovate environmentally, with the coefficients of the other three key variables remaining fairly consistent. This suggests that knowledge diversity attained through innovation connections with geographically diversified collaborators puts MNEs in a better position to come up with novel knowledge recombination, consequently fostering their innovation capacity in response to changing global demands, most notably environmental innovation. Thus, *H4* is confirmed. Turning to the magnitude of average marginal effects, it is worth mentioning that intra-organisational linkages for innovation co-production have higher predictability than the inter-organisational innovation co-production network. This underlines the significant role that intra-MNE cooperation on innovation plays in feeding locally created knowledge into the flows and processes of the parent firm for environmental innovation creation.

In the light of the above results, it is also plausible to infer that specific types of ties related to knowledge connectivity and innovation collaboration are more significant to environmental innovation. A plausible reason for this finding is that active and explicit collaboration on innovation is likely to entail high-level involvement and commitment, which creates the necessary incentive and mindset for transferring, combining, and absorbing complementary knowledge. The resulting knowledge advantages lead to higher innovation propensity. Another possible reason may be that environmental innovation's intrinsically complex, novel, and uncertain nature renders R&D cooperation and innovation collaboration essential.

Turning to environmental policy stringency, we can only detect the expected positive relationship (which is only marginally significant) between environmental policy stringency in the home country and our dependent variable in Model D. This adds to existing evidence on the contributory role that policy stringency plays in stimulating the ability to innovate environmentally. Results for other control variables are broadly consistent with expectations. There is evidence to suggest that older, larger, and more productive MNEs are likely to have higher capacity to create such innovations. Unsurprisingly, we show that organisations with larger green knowledge stocks and outputs in the form of patents show higher capacity for environmental innovation.

3.6 Robustness test

In our baseline model, we report the results of the pooled Tobit estimation of Equation (1). As a robustness check, we employ panel Tobit random effects estimation to re-estimate the model, with results presented in Table 3.6. The coefficients of our key variables are similar to those displayed in the baseline Table 3.4, with all of them showing the same sign at a 5% significance level. These results lend further support to our main hypotheses.

<Table 3.6 inserts here>

3.7 Discussion and implications

3.7.1 Discussion

The primary aim of this work is to examine the factors that facilitate the firm's environmental innovation capacity. It indicates that developed country MNEs are in an advantageous position to develop such innovation capability and sheds light on their potential contribution to achieving the SDGs. Specifically, we focus on the effects of different types of intra- and inter-organisational production and innovation networks, and show that wider global linkages built on production networks, and intra- and inter-MNE innovation co-production linkages contribute to a MNE's capability to produce environmental innovation. However, intra-organisational linkages motivated by traditional control and coordination mechanisms do not play an important role in environmental innovation capacity. This emphasises that specific types of ties related to knowledge connectivity and innovation collaboration matter important for environmental innovation than general control and coordination linkages. MNEs' arrangements for international production and innovation activities are grounded in their cross-border organisational linkages. These appear to be important channels for facilitating knowledge transfer and recombination, which cultivates high levels of knowledge development and environmental innovation capacity.

Thus, this work is grounded in the knowledge-based view and MNEs' global connectedness in terms of both their production and innovation activities. The knowledge-based view has a long tradition, which considers knowledge as a strategic resource of the firm. In our study, we combine it with the more recent literature on MNEs' global connectedness, which allows us to develop and test the global connectedness arguments in the context of environmental innovation. Our results demonstrate that the existing theories within the IB field are well placed to explain the strength of MNEs (particularly DMNEs) for pursuing environmental innovation endeavours. At a higher level, we bring the topic of environmental innovation into the IB and management research arena, laying the foundation for further exploration of interdisciplinary research on IB and sustainability.

The related literature on MNEs' global connectedness is rich, but it has not been fully developed and tested in the context of environmental innovation. Considering that MNEs have advantages in undertaking innovation and R&D based on their firm-specific advantages, we still know little about if this is also the case with the creation of environmental innovation under the emerging sustainability context. In the intersection of the knowledge-based view of MNEs and the environmental innovation literature, prior literature neglected to consider whether the MNEs' knowledge advantages (derived from global connectedness) could provide them with competitive advantage in terms of environmental innovation, particularly from the perspective of the parent company. Indeed, the existing conceptual framework of environmental innovation's determinants did not incorporate the global connectedness derived from production networks and innovation networks. Answers to the aforementioned questions are of vital importance not only in terms of advancing the existing conceptual framework of environmental innovation's determinants by analysing such innovation from the global connectedness lens, but also guiding actions of practitioners and policymakers who strive to engage in and drive the green transformation.

The current chapter addresses such gaps by explaining the determinants of environmental innovation through an IB and management research lens. We explore the multifacets of MNEs' global linkages, including organisational linkages, production linkages, and, most importantly, cross-border innovation networks. In addition, we extend the existing theoretical framework of determinants of environmental innovation at the level of the parent firm by our incorporation of intra- and inter-MNE linkages of different kinds, and geographically diversified organisational spaces. Lastly, based on a large-scale secondary dataset, our work provides concrete empirical evidence and practical implications for the specificities of environmental innovation and how it is conceived and realised.

3.7.2 Managerial and policy implications

In practical terms, our results provide valuable insights for management and policymakers on how to plan and stimulate related innovative activities within the sustainable development domain. In order to be ready for the future trend of environmental innovation, MNEs, as large leading firms in the global value chains, are able to take advantage of their cross-border organisational linkages of production and innovation activities, putting them in a good position to invest in and invent new environmental products, processes, and novel technologies. Policymakers need to take a differentiated approach when interacting with MNEs, and developed country MNEs in particular, because their vital role in contributing to sustainable development makes them good targets for policymakers. Attention should be directed to creating and fostering mechanisms that can stimulate the formation and diversity of internationally integrated production networks, and internal and external innovation networks, in order to cultivate organisational capacity to innovate environmentally.

3.7.3 Limitations and future research

However, we need to admit that this research is not without its limitations, and it points out the directions for future research.

The study touches the concept of dynamic green capability, but it fails to explicitly measure this construct. The concept of dynamic green capability seems to provide a promising approach in explaining businesses' involvement in environmental sustainability. Therefore, it is worthwhile delving into different aspects of dynamic green capabilities, in terms of sensing, seizing, and reconfiguring functions, and exploring how these different dimensions affect firms' green innovation capacity.

With the GVCs going through green transformations, we are not yet sure how MNEs will change their strategies to adapt to the associated challenges and how they strike a balance between maintaining the economic goals and pursuing the SDGs.

Corporate governance research provides a vital approach for understanding the link between the corporate governance practices and the performance outcomes of MNEs. It would be of great value to probe into specific mechanisms and processes of MNEs' corporate governance, and to investigate how companies are directed and controlled facilitate organisations' green transformation.

Table 3.1. Variable definitions

	Variable name	Name in the model	Definition
Dependent variable	**Environmental innovation score**	*Environmental innovation*	Firm's capacity to reduce environmental costs for its customers and thereby create new market opportunities via new environmental technologies as well as processes or eco-designed products, ranging from 0 to 1
Independent variables	**International diversification of intra-organisational production network**	*diver_intra_GPN*	1 minus the Herfindahl index of total assets across different foreign markets, ranging from 0 to 1 (Berry, 1971; Garcia-Vega, 2006)
	Intra-organisational ownership linkage	*intra_ownership*	Weighted share of an MNE's total participation in each of its foreign subsidiary by the proportion of that subsidiary's total assets to the total amount of all the foreign subsidiaries, after which the mean value is calculated
	Intra-organisational innovation co-production network	*intra_co-patent*	The ratio of co-owned patent publications between headquarter and its affiliates to the total patent number of the parent company
	Diversification of inter-organisational innovation co-production network	*diver_inter_co-patent*	1 minus the Herfindahl index of patent publications which are co-owned with other foreign companies across different foreign markets, ranging from 0 to 1
Control variables	**Environmental policy stringency in home country**	*home policy*	Average value of environmental policy stringency and enforcement indices for a country
	Environmental policy stringency in host countries	*host policy*	Average index of environmental policy stringency and enforcement indices for a host country, weighted by the proportion of total assets within that country to the total amount of all foreign subsidiaries, after which the mean value is calculated
	Firm age	*age*	Natural logarithm value since establishment (report here the number)
	Firm size	*size*	Natural logarithm of number of employees (report here the number)
	Labour productivity	*productivity*	Turnover per employee (USD in thousands)
	Green patent	*green patent*	Natural logarithm value of number of green patent publications (report here the number)

Table 3.2. Descriptive statistics by countries

Variables	Total				DE				FR				GB				NL				SE			
	Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Environmental innovation	0.40	0.36	0	1.00	0.35	0.37	0	1.00	0.44	0.40	0	1.00	0.45	0.31	0	0.99	0.38	0.35	0	1.00	0.32	0.37	0	0.99
diver_intra_GPN	0.48	0.31	0	1	0.53	0.30	0	0.93	0.59	0.27	0	0.92	0.39	0.32	0	1	0.51	0.27	0	0.90	0.47	0.29	0	0.92
intra_ownership	84.00	26.58	0	100	87.56	21.86	0.37	100	81.89	24.63	0.01	100	83.01	30.06	0	100	76.84	29.32	0.47	100	87.16	24.90	0.31	100
intra_co-patent	0.005	0.05	0	1	0.003	0.02	0	0.36	0.003	0.03	0	0.5	0.005	0.04	0	0.52	0.007	0.03	0	0.33	0.011	0.10	0	1
diver_inter_co-patent	0.05	0.17	0	0.88	0.11	0.22	0	0.85	0.07	0.18	0	0.81	0.02	0.11	0	0.88	0.06	0.18	0	0.85	0.02	0.11	0	0.83
home policy	5.59	0.47	4.95	6.5	6.09	0.29	5.59	6.5	5.06	0.10	4.95	5.26	5.32	0.12	5.04	5.45	5.79	0.17	5.45	6	6.08	0.20	5.82	6.45
host policy	5.17	0.61	0	6.5	5.04	0.53	3.50	6.35	5.07	0.51	3.23	6.38	5.17	0.72	0	6.5	5.28	0.49	3.05	6.5	5.42	0.58	3.01	6.40
age	3.69	0.91	0.69	6.02	3.89	0.90	0.69	5.31	3.83	0.74	1.79	5.87	3.42	0.93	0.69	5.80	3.75	0.96	0.69	5.21	3.79	0.90	1.79	6.02
size	8.75	2.01	1.39	12.97	8.80	2.06	1.61	12.97	9.48	1.81	4.37	12.97	8.55	2.01	1.39	12.97	8.71	2.29	1.79	12.82	8.12	1.79	1.79	12.55
productivity	5.79	0.97	0.12	13.67	5.93	0.91	2.66	12.08	5.69	0.94	0.12	9.58	5.72	0.98	0.47	11.82	6.17	1.39	3.29	13.67	5.72	0.77	1.38	8.30
green patent	0.45	1.16	0	7.69	0.97	1.68	0	7.69	0.58	1.18	0	5.95	0.15	0.64	0	5.59	0.47	1.36	0	7.21	0.15	0.50	0	3.14
Observations	**4510**				**1031**				**957**				**1527**				**320**				**675**			

Table 3.3 Correlation coefficient for the key variables

Variables	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***	***11***
1. Environmental innovation	1.00										
2. diver_intra_GPN	0.25	1.00									
3. intra_ownership	-0.18	0.05	1.00								
4. intra_co-patent	0.08	0.01	-0.01	1.00							
5. diver_inter_co-patent	0.19	0.19	0.02	0.12	1.00						
6. home policy	-0.14	-0.02	0.07	0.02	0.05	1.00					
7. host policy	-0.02	-0.13	0.12	0.00	-0.02	0.06	1.00				
8. age	0.16	0.26	-0.10	0.02	0.10	0.10	-0.03	1.00			
9. size	0.46	0.37	-0.05	0.05	0.20	-0.11	-0.05	0.23	1.00		
10. productivity	0.05	-0.09	-0.15	0.03	0.05	0.08	-0.01	0.00	-0.38	1.00	
11. green patent	0.21	0.24	0.00	0.10	0.66	0.09	-0.05	0.13	0.26	0.05	1.00

Table 3.4. MNEs' intra- and inter-organisational networks and environmental innovation capacity: coefficients

	(1)			
	Model A	Model B	Model C	Model D
$diver\_intra\_GPN_{ijt}$	0.215***	0.220***	0.223***	0.222***
	(0.056)	(0.055)	(0.055)	(0.055)
$intra\_ownership_{ijt}$		-0.001	-0.001	-0.001
		(0.001)	(0.001)	(0.001)
$intra\_co-patent_{ijt}$			0.456**	0.414**
			(0.187)	(0.193)
$diver\_inter\_co-patent_{ijt}$				0.221*
				(0.113)
$home\ policy_{ijt}$	0.060	0.057	0.059	0.067*
	(0.040)	(0.040)	(0.040)	(0.039)
$host\ policy_{ijt}$	0.014	0.019	0.019	0.018
	(0.023)	(0.023)	(0.023)	(0.023)
age_{ijt}	0.030*	0.028	0.028	0.029
	(0.018)	(0.018)	(0.018)	(0.018)
$size_{ijt}$	0.141***	0.139***	0.138***	0.137***
	(0.012)	(0.012)	(0.012)	(0.012)
$productivity_{ijt}$	0.128***	0.125***	0.124***	0.122***
	(0.020)	(0.020)	(0.020)	(0.020)
$green\ patent_{ijt}$	0.030**	0.030**	0.028*	0.008
	(0.015)	(0.015)	(0.015)	(0.017)
var(e.Environmental innovation)	0.150***	0.150***	0.149***	0.149***
	(0.009)	(0.009)	(0.009)	(0.009)
Constant	-4.855***	-4.745***	-4.751***	-4.792***
	(0.339)	(0.352)	(0.352)	(0.345)
Industry (NACE 1 digit)	Y	Y	Y	Y
Country	Y	Y	Y	Y
Year	Y	Y	Y	Y
Observations	4,510	4,510	4,510	4,510

Notes: (1). Coefficients of Pooled Tobit estimation of Equation (1) are reported. (2). Region, industry, and year dummies are included. (3). Robust standard errors (clustered at the firm level) in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 3.5. MNEs' intra- and inter-organisational networks and environmental innovation capacity: average marginal effects

	(1)			
	Model A	Model B	Model C	Model D
$diver\_intra\_GPN_{ijt}$	0.136***	0.140***	0.142***	0.141***
	(0.035)	(0.035)	(0.035)	(0.035)
$intra\_ownership_{ijt}$		-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)
$intra\_co-patent_{ijt}$			0.289**	0.262**
			(0.118)	(0.122)
$diver\_inter\_co-patent_{ijt}$				0.140**
				(0.071)
$home\ policy_{ijt}$	0.038	0.036	0.038	0.042*
	(0.025)	(0.025)	(0.025)	(0.025)
$host\ policy_{ijt}$	0.009	0.012	0.012	0.012
	(0.015)	(0.015)	(0.015)	(0.014)
age_{ijt}	0.019*	0.018	0.017	0.018
	(0.011)	(0.011)	(0.011)	(0.011)
$size_{ijt}$	0.089***	0.088***	0.088***	0.087***
	(0.007)	(0.007)	(0.007)	(0.007)
$productivity_{ijt}$	0.081***	0.079***	0.079***	0.077***
	(0.012)	(0.012)	(0.012)	(0.012)
$green\ patent_{ijt}$	0.019**	0.019**	0.017*	0.005
	(0.009)	(0.009)	(0.009)	(0.011)
Industry (NACE 1 digit)	Y	Y	Y	Y
Country	Y	Y	Y	Y
Year	Y	Y	Y	Y
Observations	4,510	4,510	4,510	4,510

Notes: (1). Average marginal effects of Pooled Tobit estimation of Equation (1) are reported. (2). Region, industry, and year dummies are included. (3). Robust standard errors in exponentiated form reported in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 3.6. MNEs' intra- and inter-organisational networks and environmental innovation capacity: coefficients of Panel Tobit random effects estimation

	(1)			
	Model A	Model B	Model C	Model D
$diver\_intra\_GPN_{ijt}$	0.161***	0.161***	0.164***	0.162***
	(0.025)	(0.025)	(0.025)	(0.025)
$intra\_ownership_{ijt}$		-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)
$intra\_co-patent_{ijt}$			0.262**	0.227**
			(0.106)	(0.107)
$diver\_inter\_co-patent_{ijt}$				0.100***
				(0.035)
$home\ policy_{ijt}$	0.037	0.036	0.038*	0.041*
	(0.022)	(0.022)	(0.022)	(0.022)
$host\ policy_{ijt}$	0.001	0.001	0.002	0.001
	(0.011)	(0.011)	(0.011)	(0.011)
age_{ijt}	0.072***	0.071***	0.070***	0.070***
	(0.018)	(0.018)	(0.018)	(0.018)
$size_{ijt}$	0.115***	0.115***	0.114***	0.113***
	(0.007)	(0.007)	(0.007)	(0.007)
$productivity_{ijt}$	0.058***	0.058***	0.058***	0.058***
	(0.009)	(0.009)	(0.009)	(0.009)
$green\ patent_{ijt}$	0.007	0.007	0.007	0.005
	(0.008)	(0.008)	(0.008)	(0.008)
sigma_u	0.401***	0.401***	0.400***	0.397***
	(0.015)	(0.015)	(0.015)	(0.015)
sigma_e	0.175***	0.175***	0.175***	0.175***
	(0.002)	(0.002)	(0.002)	(0.002)
Constant	-4.883	-4.938	-4.807	-4.832
	(1,562.209)	(3,003.245)	(974.524)	(1,006.270)
Industry (NACE 1 digit)	Y	Y	Y	Y
Country	Y	Y	Y	Y
Year	Y	Y	Y	Y
Number of firms	622	622	622	622
Observations	4,510	4,510	4,510	4,510

Notes: (1). Coefficients of Panel Tobit random effects estimation of Equation (1) are reported. (2). Region, industry and year dummies are included. (3). Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

CHAPTER 4: AGGLOMERATION EXTERNALITIES OF GREEN INNOVATION

4.1 Introduction

The analysis of eco-innovation (e.g., Colombelli, Krafft and Quatraro, 2021; Costantini *et al.*, 2017), green innovation (e.g., Karimi Takalo, Sayyadi Tooranloo and Shahabaldini parizi, 2021), and their impacts has gained momentum in the last few years, primarily because governments are striving to meet net zero targets while still maintaining economic growth. For example, by the end of 2021, the UK Government had promised over £116 million in new funding for green innovation and related technologies that can lead to a reduction in carbon emissions, with another £22.8 million promised to SMEs involved in the creation and commercialisation of green innovation (GOV UK, 2021).

The environmental innovation is expected to drive positive employment outcomes (e.g., Horbach, 2010; Rennings, Ziegler and Zwick, 2004) as well as economic performance in terms of productivity over the medium to long term (e.g., Marin, 2014). Studies have identified some of the reasons behind the more prominent effects of green innovation on firms and the economy. Those include its being in the early phase of its technology life cycle (Colombelli *et al.*, 2021), its potential to create opportunities in new and growing markets (Gagliardi, Marin and Miriello, 2016), and its ability to generate considerable knowledge spillovers (Dechezleprêtre, Martin and Mohnen, 2017). Likewise, according to Rennings and Zwick (2002), green innovation is characterised by a ‘double externality’, which is the supposition that it can generate both positive knowledge externality effects and environmental spillover effects (Ben Arfi *et al.*, 2018). Continuing this line of reasoning, unpacking the dynamics of the external impacts of green innovation appears to be a crucial research question given that green innovation has the potential to generate a variety of considerable knowledge spillovers compared with other emerging technological fields such as robotics and 3D printing (Dechezleprêtre *et al.*, 2017).

The recent environmental economics literature has shed light on the importance of the diffusion of green technologies through vertical linkages, leading to improved environmental performance in related sectors (e.g., Costantini *et al.*, 2017; Ghisetti and Quatraro, 2017). However, that literature has overlooked the economic geography arguments about agglomeration externalities, and it may be the case that technological dissemination is being diluted over wide geographical ranges.

The extant literature concerning green innovation has focused almost exclusively on the relationship between having a green business strategy and firm performance (e.g., Lin *et al.*, 2021), the determinants of green innovation development (e.g., Perruchas, Consoli and Barbieri, 2020; Ren, Sun and Zhang, 2021), its internal impacts on the focal firm performance (e.g., Horbach, 2010; Marin, 2014; Rennings *et al.*, 2004), and its external impacts on sectoral environmental performance (e.g., Costantini, *et al.*, 2017). What is missing is how green innovation interacts with the local economy to affect other firms' economic performance via both horizontal and inter-sectoral linkages. This is something that cannot be well explained by small-scale surveys. Although there is one study that touches on the idea that green innovation spills over to economic growth in terms of company market values, we still have no clear answer about the economic relevance of green innovation spillovers on firm performance in terms of productivity and growth. Still more importantly, we lack understanding about the channels through which such impacts of green innovation externalities may take place. Consequently, in this study, we explore how variations in such agglomeration externalities affect other firms' economic performance via horizontal and vertical linkages, and we reveal the conditions under which this can happen.

This study is intended to bridge the literatures on environmental innovation and agglomeration externalities, filling a knowledge gap by examining the external impacts of green innovation on the wider local economy; specifically, on the economic performance of other industrially related and geographically adjacent non-green-tech companies. Moreover, we explore how a firm's absorptive capacity affects its ability to absorb such spillovers. We propose that a firm's intangible assets intensity and technological competence (in other words, its core-technology competence and technological diversification) tend to determine the extent to which it can leverage green innovation externalities. These indicators do so by helping firms develop an awareness of the value of external green technology, and by enabling them to connect to, assimilate, and exploit related knowledge. This may eventually lead to better firm performance. To the best of our knowledge, this is the first study to investigate the spillover effects of green innovation via both horizontal and vertical linkages, and to show how they drive economic performance at the firm level.

Accordingly, we contribute to the existing literature in the following ways. First, our firm-level analysis of green innovation diffusion is much finer grained than the usual national, regional, or sectoral level analysis. This idea responds to the call of Dechezleprêtre and his co-authors (2017) for the use of micro data to evaluate the impacts of knowledge spillovers from clean technologies on firms' productivity and growth. Second, this chapter augments the currently limited empirical evidence of green innovation's effects on economic performance through inter-sectoral linkages by studying its influences on firm productivity and employment growth. Third, instead of focusing on the internal impacts of green innovation on the focal firm, we propose to extend the state of the art by analysing green innovation's externalities and its wider economic values. In particular, we assert that an empirical investigation of this issue is crucial, given the current policy focus on environmental innovation, and the considerable resources and efforts that are being devoted to stimulating environmental sustainability endeavours.

We draw on Bureau van Dijk's Orbis IP database for UK manufacturers over the period 2008 to 2017. We identify the channels through which externalities of green innovation occur and show how they can influence the productivity and employment growth of other firms within a given locality. We find that the sign and strength of such impacts vary across the value chains and depend on firm characteristics and sectors.

In short, our results show that overall, non-green-tech manufacturers in downstream sectors can benefit from their green-tech suppliers in terms of both productivity and employment growth. SMEs present the potential for benefiting from the externalities of upstream green innovators in both productivity and employment growth. For large enterprises, only those with core-technology and diversified technological competence can obtain positive productivity spillovers from upstream suppliers. Meanwhile, technological diversification allows SMEs and low-tech businesses to exploit the upstream productivity gains. We also observe positive backward spillovers on the employment growth of high-tech firms, while those positive signs become negative when it comes to large firms.

The positive impacts of overall horizontal productivity spillovers are mainly captured by the businesses with technological core competence. Typically, core-technology and diversified technological competence within both SMEs and low-tech firms allow them to gain efficiency improvements led by the fierce intra-industry competition, which is potentially triggered by the agglomeration of green innovators. However, large firms that are intangible-intensive tend to experience negative horizontal productivity spillovers, which can be regarded as a sign of competition led crowding-out effects.

Referring to forward linkages, we observe market disruption effects on the productivity and operational efficiency of large-sized and high-tech upstream suppliers. These adverse effects potentially derive from green innovators' creative destruction in terms of their changing demands and requirements. Turning to employment growth, although there is an overall negative forward spillover effect from green-tech consumers, non-green-tech firms with core-technology and diversified technological competence can more easily manage innovation investments and react to related technological risks and challenges, mitigating the induced demand shocks. We also find interesting heterogenous effects of green externalities across firm characteristics and different sectors, which we detail in the regression results and findings section of this chapter.

The rest of the chapter is structured as follows. The next section reviews three streams of literature: impacts of green innovation, agglomeration externalities, and absorptive capacity. Section 3 describes the data, the construction of the variables, and the empirical specifications. The results and findings are presented in Section 4, followed by a discussion and conclusion.

4.2 Theory and literature review

4.2.1 Green innovation as a shaper of performance and its diffusion

The study mainly draws on three broad literatures, the first of which regards green innovation as a shaper of firm performance. We also take green innovation's external impacts into account here, which are mainly environmental, through inter-sectoral knowledge diffusion.

Researchers studying sustainability development seem to use several terms interchangeably; for example, 'green innovation', 'environmental innovation', 'ecological innovation', and 'sustainable innovation' (e.g., Ben Arfi *et al*., 2018; Boons and Lüdeke-Freund, 2013; Carrillo-Hermosilla *et al*., 2010; Konara *et al*., 2021), with the last term being a broader concept encompassing an extra social dimension (Schiederig *et al*., 2012). As a subset of eco-innovation (Konara *et al*., 2021), environmental innovation underlines the environmentally motivated intentions of innovators (Carrillo-Hermosilla *et al*., 2010). This chapter focuses on green innovation which, like environmental innovation, refers to products, processes, or management practices designed to reduce and prevent harm to the environment. As such, we follow Beise and Rennings (2005), Dias Angelo *et al*. (2012), Rennings and Zwick (2002), and Triguero *et al*. (2013).

Green innovation shares commonalities with general innovations, yet its distinctive characteristic lies in its 'double externality' (Rennings and Zwick, 2002), a term that recognises that green innovation can produce not only a positive externality of knowledge and but also external environmental spillover effects (Ben Arfi *et al.*, 2018). Its environmental dimension means that green innovation is regarded as more complex than other types of innovations (Ben Arfi *et al.*, 2018; De Marchi, 2012). Typically, it stands for a technological frontier, characterised by a range of market and technological uncertainties and where there are no widely accepted standards of technological solutions (Ben Arfi *et al*., 2018). In other words, companies are still inexperienced in producing green products or processes, which tend to be complex and generally require knowledge and skills that differ from those of the industries' conventional knowledge base (Ben Arfi *et al*., 2018).

There is a growing body of literature exploring the relationship between eco-innovation and the economic performance of the firm. When the advantages gleaned from eco-innovation efforts surpass their costs, they are considered to contribute to both the environmental and economic performance of organisations (Jaffe and Palmer, 1997).

Within this literature, one strand of research mainly relies on indicators related to productivity (e.g., Marin, 2014) or profitability (e.g., Ghisetti and Rennings, 2014; Rennings and Rammer, 2011; Rexhäuser and Rammer, 2014). However, the firm-level productivity effects of environmental innovations are not straightforward (Marin, 2014). For example, Marin (2014) finds that in the short run, green innovations generate a return that is lower than that of the non-green innovations, implying that green innovations have crowding-out effects on non-green innovations due to financial resource constraints on R&D investments. He also claims that green innovations' potential positive effects on competitiveness and, ultimately, on measured productivity, are prone to come to light only over the medium to long term.

The relationship between environmental innovation and employment represents another recent strand of literature, with the relationship varying with the type of innovation activity (e.g., Horbach and Rennings, 2013; Licht and Peters, 2013; Pfeiffer and Rennings, 2001). Rennings *et al*. (2004) posit that environmentally related innovation in products and services drive positive employment outcomes, an argument that has been confirmed by Horbach (2010). Licht and Peters (2013) further demonstrate that product innovations, when compared with process innovations, have a positive and significant effect on employment growth. More recently, Gagliardi *et al*. (2016) find that green innovation, measured by environmentally related patents, creates a positive effect on firm-level job creation in the long run, with such impact being considerably larger than that of other non-green innovation. Leoncini, Marzucchi, Montresor, Rentocchini, and Rizzo (2019) reach a similar conclusion for Italian manufacturing firms that green technologies exercise greater positive effects than non-green ones on employment growth. They further examine such relationship across the distribution of growth rates and explore how age moderates the benefits of green technologies on growth. However, Cainelli, Mazzanti and Zoboli (2011) draw on the Italian Community Innovation Survey (CIS) and find a negative association between environmental innovation and both employment and turnover growth. That being said, in studies based on innovation surveys, discretional definitions of environmental innovation and response bias may cause them to suffer from measurement problems (Gagliardi *et al*., 2016). Another issue for these surveys is that researchers may find it struggling to capture green innovation's influences in the medium to long run (Gagliardi *et al*., 2016).

The literature has posited several mechanisms for explaining the benefits of eco-innovation. First, this type of innovation is within the early phase of the technology life cycle (Colombelli *et al*., 2021). As such, there are expected to be more technological opportunities to invest in (Gagliardi *et al*., 2016) and a larger impact on the firms and the economy. Second, eco-innovation has the potential to create opportunities in a new and growing market (Gagliardi *et al*., 2016). For example, a more focused consumer attention on the environmental sustainability aspect of products and services has opened up a new path to commerce, and it is a path that has significant market prospects. Third, eco-innovations are able to generate 'extra returns' and thus offer additional chances and returns for reinvestment, leading to better growth performance despite the heavier innovation costs (Colombelli *et al*., 2021). Specifically, this type of innovation can improve firms' competitiveness and create competitive advantages by utilising resources more efficiently and responsibly (Gagliardi *et al*., 2016). Most importantly, in contrast with non-green technologies and other emerging technological fields such as robotics and 3D printing, green technologies are characterised by considerable knowledge spillovers (Dechezleprêtre *et al*., 2017), suggesting that a variety of potential positive spillovers may be associated with investing in green innovations. For instance, Dechezleprêtre *et al*. (2017), using patent citation data in the automobile and electricity production sectors, show that, overall, clean patented inventions receive over 40% more citations than their dirty counterparts, probably because these green inventions are relatively new and radical, and thus have wider range of general applications.

More recently, Colombelli and Quatraro (2019) offer evidence that spillovers from local knowledge stocks, especially those resulting from clean technologies, can be expected to exert larger impacts on the formation of green innovative start-ups compared with dirty ones. The above evidence suggests that green technologies tend to generate larger knowledge spillovers, which aligns with the argument of Gagliardi *et al*. (2016) that green technologies make it feasible to create complementary innovations of many sorts, given that they appear to be more general than other technologies.

Particularly, the environmental economics literature has emphasised the importance of the diffusion of green technologies along the supply value chain (Costantini *et al*., 2017). The interplay between suppliers and consumers is believed to influence environmental, social, and economic performance, given their close links from sharing environment responsibility and adopting social behaviours (Sarkis, 2006). Costantini *et al*. (2017) also claim that it is not just the technological sphere that benefits from inter-sectoral linkages; the environmental performance also benefits, as identified by the literature on sustainable supply chains. This explains firms' increasing attention to their governance choices with respect to sustainable supply chains in order to reach environmental objectives. For instance, findings have been made on the importance of the connections between sustainability issues and supply chains, which introduces a new set of concepts to the literature, such as the green supply chain (e.g., Khan, Idrees, Rauf, Sami and Ansari, 2022; Lee, Ooi, Chong and Seow, 2014) and green innovation value chains (e.g., Lee and Kim, 2011; Olson, 2013).

Empirically, Corradini, Costantini, Mancinelli, and Mazzanti (2014) show that innovation efforts positively correlate with various spillover effects, in which R&D innovation expenses help to abate other sectors' emissions. Focusing on interregional technological spillovers across 20 Italian regions, Costantini, Mazzanti, and Montini (2013) find that such spillover effects play a larger role than sectoral internal innovation in improving environmental performance, and that the environmental performance of neighbouring regions affects regional internal environmental performance through agglomerative effects. Likewise, using NAMEA data for the Italian regions, Ghisetti and Quatraro (2017) reach a similar conclusion that environmental innovations, proxied by patents in green technologies, directly contribute to sectoral environmental productivity within the same sector, and that those generated by vertically integrated sectors make an indirect contribution, usually through a demand-pull mechanism. In addition, Costantini *et al*. (2017) emphasise the importance of inter-sectoral linkages in facilitating the impact of eco-innovations on sectoral environmental performance among EU countries. In short, these empirical results highlight the roles played by inter-sectoral transactions in enabling the diffusion of green products and process in the markets and the transmission of green innovation and its environmental impacts along the value chains (Costantini *et al*., 2017).

Given the nature of vertical interactions between organisations, there are two channels through which spillovers may take place: improvements related to the machinery and inputs purchased from suppliers (Los and Verspagen, 2002), and those contained in the user-producer relationships (Isaksson, Simeth and Seifert, 2016). This is because such inter-sectoral linkages across companies and sectors favour technology diffusion and knowledge spillovers in terms of product-embodied knowledge via customer-supplier relationships (Geffen and Rothenberg, 2000; Hauknes and Knell, 2009). Building collaborations with suppliers can help prompt the development of new products and technological integration (Lee and Kim, 2011); when suppliers sell intermediate inputs with product-embodied knowledge, this is known as the push effect (Cainelli and Mazzanti, 2013). A closeness to the downstream sectors enables suppliers to sharply perceive the opportunities for new inventions and meet the demand for new intermediate goods; this is called the pull effect (Antonelli, 1998).

To put the above demand-pull dynamics (Schmookler, 1957) in our context, upstream firms produce green innovation, possibly because companies in the downstream count on these firms for introducing new and more eco-friendly technologies into the production process (Ghisetti and Quatraro, 2013; 2017). The upstream sectors, being specialised suppliers of technologies and knowledge, help downstream industries achieve higher environmental performance and environmental productivity (Franco and Marin, 2017). In such a case, the relationship is assumed to foster the adoption and diffusion of environmental innovation (Costantini *et al*., 2017) in the supplying and purchasing sectors via spillover effects, thus promoting positive effects on environmental and economic performance (Luzzini, Brandon-Jones, Brandon-Jones and Spina, 2015; Vachon and Klassen, 2006) along the value chain. More explicitly, Ghisetti and Quatraro (2017) argue that this interplay between users and producers is likely to shape the ultimate effects of green technologies. Their perspective, with which we concur, implies the need to go beyond corporate boundaries and account for inter-sectoral linkages when examining the impact of green innovation on companies' economic performance.

To sum up, it is plausible to expect that green innovations are conducive to firm performance with respect to productivity and employment growth. More importantly, this type of innovation is recognised as creating more prominent knowledge spillover effects. Our hypotheses are mainly grounded in this recognition.

Nevertheless, the existing literature is incomplete in the following respects. First, the majority of the existing empirical studies on green innovation diffusion are carried out at an insufficiently granular level (i.e., national, regional, or sectoral). This is mainly due to the difficulty of gaining emissions information at the firm level (Ghisetti and Quatraro, 2017). This means that the external impacts of green-tech companies through their interplay with the local economy have been rarely touched on at the micro level. So far, only one article (Dechezleprêtre *et al*., 2017) has examined the economic value of the knowledge externalities of relevant clean technologies using firm-level financial data. However, their study primarily focuses on the effect of knowledge spillovers on company market value rather than on the more usual economic performance indicators, such as productivity and employment growth. Second, most research attention has been devoted to how the positive externalities derived from inter-sectoral linkages affect sectoral environmental performance in terms of, say, production sustainability (e.g., Corradini *et al*., 2014; Tarancón and del Río, 2007) or environmental productivity (e.g., Ghisetti and Quatraro, 2017). Evidence of their impacts on economic performance is rather limited. In particular, the majority of the empirical works investigating how green innovation shapes firms' environmental or economic performance ignore the external impact of the green-tech firm's activities and its interactions with the local economy. Specifically, it is not clear how green innovators interact with other firms that do not have green technology through both horizontal and inter-sectoral linkages and thus how the economic performance of the latter can be potentially shaped by the former. As policy making and resources become ever more focused on green innovation, it becomes crucial to evaluate the wider economic impact of green-tech companies within the local economy. The present chapter aims at filling these gaps in the literature on green innovation as a shaper of performance.

4.2.2 Agglomeration externalities of green innovation

The second stream of literature is based on the main economic geography theory about agglomeration externalities, which introduce different mechanisms for the spillovers (Iammarino and McCann, 2013). To investigate the spillovers arising from the co-location of green-tech firms and other companies in agglomerated regions and industries, we connect the green innovation literature to arguments concerning agglomeration externalities. This is where we propose that regional agglomeration externalities arising from the co-location of green-tech firms and other firms can shape the economic performance of the latter.

The concept of agglomeration economies denotes location-specific economies of scale, essentially experienced by a group of spatially clustered organisations and people (Iammarino and McCan, 2013). Typically, three different types of externalities are mentioned in the literature, namely, Marshall-Arrow-Romer (MAR), Jacobs' externalities (local diversity), and urbanisation externalities (Neffke, Henning, Boschma, Lundquist and Olander, 2011).

The Marshallian tradition (1920) advances analysis of the nature and advantages of agglomeration economies for localities and explains three mechanisms through which economies of scale may come into being: access to skilled labour, input-output linkages, and intra-industry knowledge spillovers (Marshall, 1920; Arrow,1962; Romer, 1986). Duranton and Puga (2004) note that the three underlying mechanisms of the Marshallian tradition reflect the processes of matching, sharing, and learning. By applying these mechanisms to our green innovation context, we suggest that the agglomeration of green-tech firms within a given region and industry may create both positive and negative externalities for other spatially proximate and industrially related non-green-tech companies.

4.2.2.1 Labour pooling and matching

The first Marshallian mechanism is known as labour pooling and matching. The established traditions in certain sectors can, over time, lead to the development of a local labour force with the appropriate technical and organisational skills within a clustered location (Iammarino and McCan, 2013). By locating themselves close to other firms within the sector, firms can benefit from the availability of a specialised local pool of workers, which allows for efficient job searches and hiring-matching processes within the labour market (Iammarino and McCan, 2013). This will lead to a reduction in the search costs of employment and the matching costs between employers and employees (Duranton and Puga, 2004).

When applying this mechanism to our analysis context, we can infer that both green and non-green-tech firms, which are geographically adjacent within the same industry, can benefit from a large pool of skilled labour in that they have access to suitable and highly productive employees (Combes and Duranton, 2006). In addition, the clustering of green innovators facilitates the flow of skilled labour between green innovators and other firms within the same industry, leading to a better match between employees and employers (Helsley and Strange, 1990). The reduced search costs of employment and matching costs between employers and employees, derived from efficient job searches and hiring-matching processes, can help firms achieve higher productivity. However, the rising agglomeration of green innovators might also lead to negative externalities from labour poaching (Boschma, Eriksson and Lindgren, 2014). This happens when the disadvantages of competing for skilled and specialised labour outweigh the benefits of labour pooling (Grillitsch and Nilsson, 2017) in that the pool of workers is no longer large enough to meet the demand, meaning that workers become concentrated in the most successful companies within the locality (Combes and Duranton, 2006). Job hopping may cause non-green-tech companies to lose key personnel to their green competitors, which is distinctly the case when workers are offered green jobs with higher wages (Christie-Miller and Luke, 2021).

4.2.2.2 Input-output linkages

The second Marshallian mechanism is input-output linkages (Neffke *et al*., 2011), otherwise known as the presence of specialist local inputs (Iammarino and McCan, 2013). The key idea here is that the local market's provision of inputs or services give rise to economies of scale on the grounds of the size of local market (Iammarino and McCan, 2013). Typically, a large local market, featuring a high number of consumers, allows suppliers to lower the unit production costs of transportation and inventory (Neffke *et al*., 2011), reducing the risks of making large capital investments. Meanwhile, a pool of locally available specialised services, infrastructure, and intermediate inputs, provide benefits to consumer firms by reducing the purchasing and sourcing costs.

Sharing specialised input providers allows both green innovators and other firms to reduce the production costs of acquiring inputs and shipping goods (Neffke *et al*., 2011). More importantly, as suggested above, green innovative firms also generate knowledge spillovers to others in the vertically integrated supply chains by exposing others to their green-tech knowhow through interactions. Suppliers and consumers without green technologies can internalise the positive externalities in terms of increased demand, efficiency gains, and introducing new improved inputs, which are induced by green innovators in vertically related sectors (Ghisetti and Quatraro, 2013; 2017). These can be perceived as the channels through which productivity and growth may benefit from the aforementioned positive externalities. However, firms may also experience negative externalities arising from exceedingly high agglomeration. These negative spillovers include increased production costs, such as rental and transportation, as well as crowding-out effects from the fierce competition (Du and Vanino, 2021) presented by upstream and downstream green innovators. Moreover, as already discussed, downstream firms may require more eco-friendly intermediate inputs from suppliers. Hence, negative externalities may occur when the inputs providers cannot meet the demand from, say, green-tech consumers. This can happen when suppliers try to produce inputs for which they are not yet equipped, or when they are locked into producing specialised inputs for which the production lines are not easily changed due to their high sunk costs. This is distinctly the case when the downstream green innovators have stronger bargaining power than their suppliers in the negotiation of input contracts (e.g., Newman, Rand, Talbot and Tarp, 2015). In a similar vein, such negative externalities can also exert influence over firm productivity and employment growth.

4.2.2.3 Localised knowledge spillovers

The third Marshallian mechanism, as advised by Iammarino and McCan (2013), concerns localised knowledge spillovers (e.g., Neffke *et al.*, 2011; Du and Vanino, 2021). This generally happens when firms' access to knowledge, intentionally or unintentionally, freely spills over from other co-located players (Iammarino and McCan, 2013). Existing research has proved that firms located in regions and sectors with higher levels of agglomeration tend to enjoy higher growth rates, thanks to the indirect effect of tacit externalities established by the better performing players (Raspe and Van Oort, 2007). Thus, we posit that the increasing clustering of green innovators can, through their dynamism, innovation, and productivity growth, create relevant knowledge externalities for other spatially proximate non-green-tech firms within the same industry. The performance of the nearby companies tends to be affected by idea sharing, movement of workers, and other types of informal interactions facilitated by face-to-face contacts (Storper and Venables, 2004). In addition, cooperation, competition, and imitation among the green-tech and other companies bring about horizontal externalities. These, however, may be positive or negative, as we will now discuss.

Positive horizontal externalities on productivity may be seen when agglomerative green-tech firms within an industry demonstrate the utilisation of green technologies (Han, Xie and Fang, 2018). This allows other actors, typically competitors, to observe, imitate, and adopt such technologies in their own production processes; these effects are known as the demonstration effects (Iammarino and McCan, 2013). Non-green-tech firms can also experience competition led efficiency improvement, a consequence suggested by Porter (1990). Another related mechanism acting on productivity worth mentioning here is labour mobility, which can also induce a localised learning process (Malmberg, 2003). This is because the mobility of skilled workers (human capital) acts as a crucial mechanism through which knowledge and skills can be transferred between firms and regions (Boschma *et al*., 2014). Empirically, Breschi and Lissoni (2009) demonstrate that labour mobility generates social connections between firms. These support post-mobility knowledge flows between local companies via organisations' connections with former employees (Dahl and Pedersen, 2004). Thus, we can deduce that labour flows from green-tech firms to other firms within the same industry may allow the knowledge related to green technologies to be spread and diffused to other geographically adjacent non-green-tech companies. However, negative externalities may arise due to crowding-out effects, which appear as the result of fierce intra-industry competition between green-tech firms and other firms for production factors and common resources (Glaeser, Kallal, Scheinkman and Schleifer, 1992).

The processes through which green-tech firms create agglomeration externalities appear to be complex, and the benefits and disadvantages of different types of mechanism are influenced by a number of factors. Those include the level of agglomeration, concentration of local industry, and intensity of vertical linkages (Du and Vanino, 2021). Therefore, it is reasonable to infer that the overall effects of green-tech agglomeration externalities are context-based (e.g., Neffke *et al*., 2011), affecting co-located firms within the same industry or across related industries very differently. In the meantime, it is worth noting that the foregoing three mechanisms through which agglomeration externalities of green innovation act on other non-green-tech enterprises are prone to be different for productivity and employment growth.

4.2.3 Heterogeneity in absorptive capacity

This last extensive stream of literature is concerned with firms' absorptive capacity which, we conjecture, determines the extent to which companies are able to gain from the externalities of green innovation.

The fact that not every company is capable of first learning and then gathering and fully utilising information coming from the external environment contributes to the heterogeneity among firms. How much an organisation can benefit from externalities depends on its absorptive capacity, defined as the firm's ability to learn and improve performance by internalising and assimilating knowledge generated outside itself (Cohen and Levinthal, 1989). According to Todorova and Durisin (2007), the concept has different dimensions. At the individual level, this includes recognition of the value of external knowledge and knowledge acquisition. At the organisational level, it includes the assimilation, transformation, and exploitation of knowledge. We incorporate this notion in our theorising as it connects the knowledge sets generated outside of the organisation to those created inside it (Gluch *et al*., 2009), showing that external, complex, and cross-disciplinary environmental knowledge can be transformed and integrated into organisational capabilities (Dzhengiz and Niesten, 2020) that further enable the development of competences and capabilities. In sum, it allows us to explain the learning of individuals and organisations through both intra- and inter-organisational processes, given the agglomeration externalities.

It has been long recognised that firms' absorptive capacity determines the extent to which they can benefit from external knowledge (e.g., Falvey, Foster and Greenaway, 2007; Nieto and Quevedo, 2005). As suggested by Cohen and Levinthal (1990), the capacity to evaluate and utilise external knowhow mainly depends on prior related knowledge. Nieto and Quevedo (2005) point out that such prior knowledge includes shared languages and the awareness of emerging technological advances within a certain domain, and such knowledge tends to arise when a company conducts internal R&D activities (Cohen and Levinthal, 1989). Hence, one might expect that the extent to which a company can take advantage of technological opportunities largely relies on the available knowledge and capabilities generated within the organisation (Nieto and Quevedo, 2005). This means that only those who have accumulated a large amount of knowledge and possess a certain capacity for assimilation are able to utilise the emerging technological opportunities (Klevorick, Levin, Nelson and Winter, 1995) by understanding, assessing, and integrating what is on offer externally.

Absorptive capacity is formulated cumulatively via a long process of research and knowledge accumulation (Jiménez-Barrionuevo, García-Morales, and Molina, 2011). According to Cohen and Levinthal (1990), two primary sources of absorptive capacity come from the way in which companies organise communications with the outside environment and, more importantly, the nature of the knowhow and experience within the organisation. Harris and Yan (2019) claim that only firms with certain types of business characteristics possess that higher level of absorptive capacity. Organisations that have a good knowledge base in specific fields tend to possess higher absorptive capacity, which enables them to act on new ideas developed in these knowledge fields (Zahra and George, 2002) and adapt to the changes in their environment (Escribano, Fosfuri and Tribó, 2009). As such, in this work, we take into account intangible assets intensity (a proxy for knowledge capital) and two important dimensions of firm's existing technological knowledge, namely, the degree of its core-technology competence and technological diversification.

According to Jiménez-Barrionuevo *et al*. (2011), absorptive capacity is deemed as one of the intangible assets, and the intangible nature of this construct makes it difficult to conceptualise and evaluate. Intangibles provide a compelling proxy for the knowhow and knowledge assets possessed by the organisation (Denicolai, Ramirez and Tidd, 2016). Based on the resource-based view (e.g., Barney, 1991), intangible assets possess a great potential to contribute to organisations' competitive success and sustainable competitive advantages over time (Jiménez-Barrionuevo *et al*., 2011). Relying on the internal knowledge capital reflected by intangible assets, firms will be capable of acquiring, assimilating, and transforming new ideas and exploiting opportunities outside the organisations' limits (Sun and Anderson, 2010). This makes intangibles an important instrument in leveraging firm performance.

Core-technology competence reflects a firm's accumulated R&D resources, consisting of tacit knowledge and knowhow as well as R&D architectural competence in the core technology (Henderson and Clark, 1990; Henderson and Cockburn, 1994). Similarly, Kim *et al*. (2016) describe core-technology competence as the level of competence in the field of core technology and in architectural knowledge related to R&D and innovation management, implying that this concept has dual roles or characteristics. Kim *et al*. (2016) further argue that this competence acts as a centripetal force when firms attempt to manage R&D resources across various technological fields, reducing coordination and integration costs and enabling organisations to effectively exploit opportunities created through, say, technological diversification. Strong core-technology competence, in the form of architectural knowledge of R&D and innovation management, allows firms to better identify technological opportunities and efficiently distribute R&D resources across diverse technological fields (Choi and Lee, 2021). It is reasonable to infer that companies with a high level of core-technology competence can formulate a competitive advantage through knowledge assimilation, exerting positive effects on organisational performance (Xie, Zhan, and Wang, 2014).

Technological diversification refers to a firm's extension of its technological capability into a wider variety of technical fields (Granstrand and Oskarsson, 1994). It is plausible to infer that companies with more diverse technological competences are more likely to be capable of evaluating, connecting to, and integrating exterior knowhow based on what they possess. This is because knowledge spills over effectively only if complementarities in terms of shared competences or capabilities exist. Further, some degree of cognitive proximity is needed to permit effective information and knowledge communication as well as interactive learning (Iammarino and McCann, 2013; Nooteboom, 2000). Accordingly, we can speculate that higher technological diversification offers a greater likelihood of complementing and sharing knowledge with external knowhow, which tends to enhance firm-specific technological competences and thus further foster absorptive capacity.

The underlying assumption here is that intangible intensity and the above two characteristics of technological knowledge within the organisation reflect the knowledge resources and capabilities available to the firm. Therefore, they can be viewed as the proxies for organisational absorptive capacity, which are projected to exercise moderating effects when knowledge spillovers are present.

In the context of sustainability, Dzhengiz and Niesten (2020) integrate studies on absorptive capacity with those on organisational learning to argue that the first two dimensions of absorptive capacity—the recognition and acquisition of external knowledge—are beneficial for developing managers' and employees' environmental competences, which include an eco-centric mindset and collaboration competences. Environmental awareness, concern for environmental issues, and openness to new perspectives enable firms to sense the technological opportunities related to ecological sustainability and, by collaborating with external partners, to identify complementary knowhow through a 'green lens' (Borland, Ambrosini, Lindgreen and Vanhamme, 2016). As such, we have reason to believe that these environmental competences, essentially derived from absorptive capacity, will enhance companies' ability to leverage and benefit from the externalities of green innovation. Dzhengiz and Niesten (2020) further point out that the three organisational level dimensions—knowledge assimilation, transformation, and exploitation—contribute to the development of environmental capabilities. This notion refers to an organisation's ability to manage the tension between the bottom line of environmental performance and economic performance (Dzhengiz and Niesten, 2020). Specific examples include environmental manufacturing, environmental supply chain, and collaboration capabilities. Through building those environmental capabilities, companies are able to redesign products to meet ecological requirements, reconfigure their supply chains to be eco-friendly, and find new channels from which they can reap financial gains by leveraging environmental knowledge and practices (Borland *et al*., 2016). Similar reasoning may be applied here, in that firms with absorptive capacity, operating as a source of organisational environmental capabilities (Delmas, Hoffmann and Kuss, 2011; Pinkse, Kuss and Hoffmann, 2010), tend to gain more returns from environmental externalities compared with other companies.

We thus propose that absorptive capacity will determine the extent to which the agglomeration externalities of environmental innovation can be leveraged. Absorptive capacity, which in our case takes the form of intangible intensity, core-technology competence, and technological diversification, contributes to individuals' environmental competences and organisations' environmental capabilities, and thus increases the likelihood that firms can benefit from relevant knowledge and complementary resources when they are exposed to externalities of green innovation. We further contend that this will give rise to improvements in both innovation and economic performances.

4.3 Data, variables, and empirical specifications

4.3.1 Green innovation

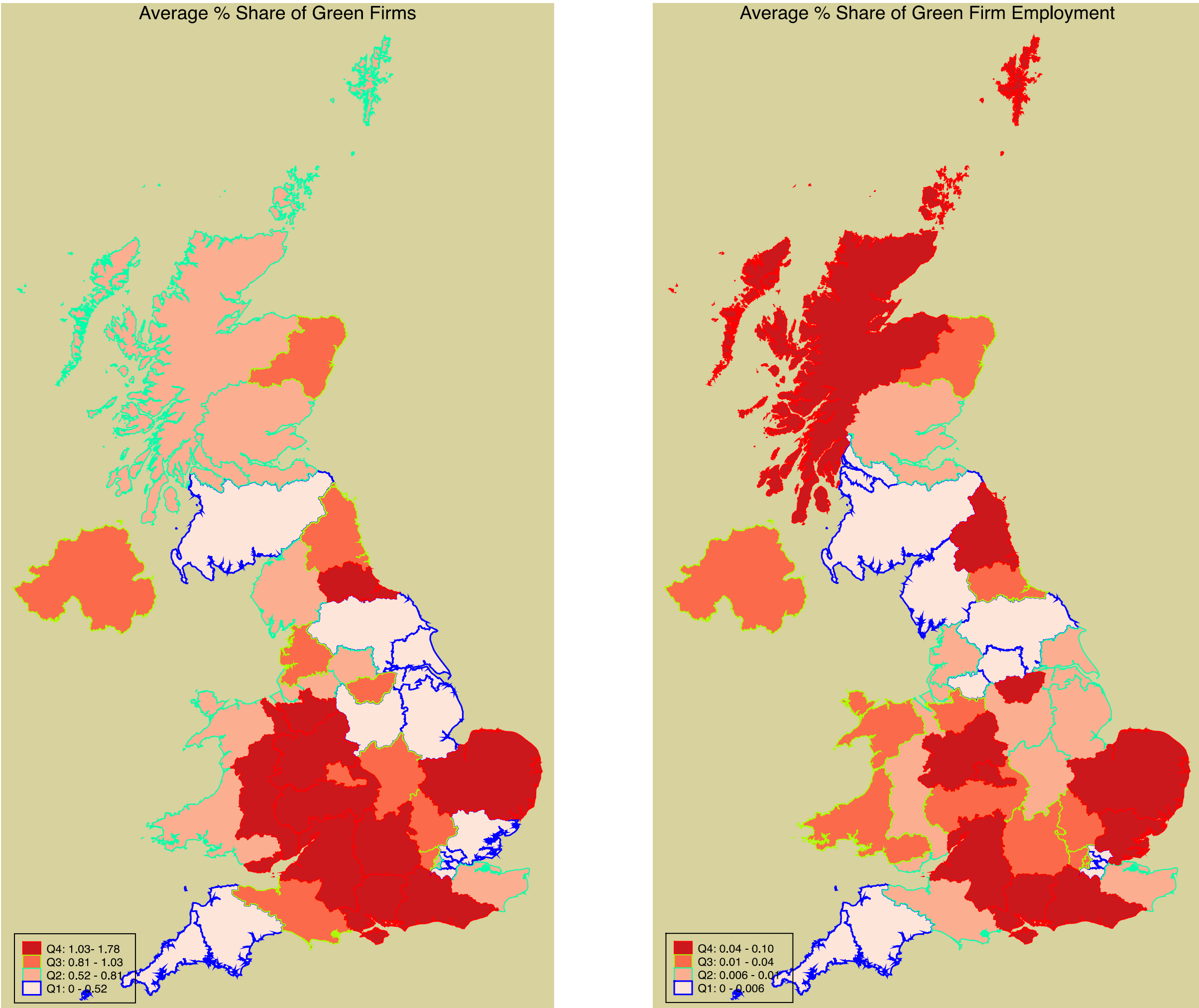
We use patent data to capture green technologies, which we refer to as green innovation. The limitations inherent in using patent information as a proxy for innovation have been discussed in both academic and practitioner-oriented literature. To summarise, not all of firms' innovations can meet the patentability criteria (Choi *et al*., 2007) and the propensity to use patents as the means of protecting technologies varies across different organisations or industries (Hasan and Tucci, 2010). In particular, there are types of green innovation that might not be effectively measured by patents, such as process innovations (e.g., energy efficient machinery) or organisational innovations (Franco and Marin, 2017). That being said, patent data is still regarded as the most diffused source of information for constructing continuous firm-level innovation variables (e.g., Gagliardi *et al*., 2016). Patents are regarded as one of the most standardised and reliable indicators of trends of technological innovation, given their statistical consistency, high comparability, and strong association with technology development (Sheikh and Sheikh, 2016). Generally, patent application in a specific technology field implies an advancement in the corresponding knowledge space and an accumulation of relevant knowhow (Suzuki and Kodama, 2004).

Following Gagliardi *et al*. (2016), Leoncini *et al*. (2019) and Marin and Lotti (2017), we draw on two sources for identifying green technologies using patent information. The first is the IPC Green Inventory provided by WIPO, which covers nearly 200 topics directly relevant to environmentally sound technologies within the IPC system (Marin and Lotti, 2017). The other source is the OECD's schedule of search strategies for selected environmental-related technologies (ENV-TECH) (OECD, 2016)[24]. Both sources provide a list of technological classes that correspond to environmental or green technologies. Green patents, reflecting green innovation, are described as the records with their technological class covered by either the WIPO or OECD list. In our setting, a green-tech company or green innovator is defined as a firm that has at least one green patent across our observation period.

Figure 4.1 presents the geographical distribution of the average share of green innovators among all the firms in our sample, and the average share of green-tech firms' employment over total employment for each NUTS-2 UK region from 2008 to 2017. Overall, the two maps depict some differences in the geographical distribution of different green innovation indicators. Regions with an especially high incidence rate of green innovators are mainly in England, particularly Tees Valley and Durham, Cheshire, West Midlands (England), East Anglia, South East (England), Gloucestershire, Wiltshire and Bristol/Bath area, and East Wales. Yet, the employment share of green innovators follows a slightly different pattern, being considerably high in Northumberland and Tyne and Wear, South Yorkshire, Shropshire and Staffordshire, West Midlands, East of England, South East (England)[25], Gloucestershire, Wiltshire and Bristol/Bath area, and Scotland's Highlands and Islands. It is worth noting that green innovators tend to be distributed in both urban (more agglomerated) and rural areas rather than concentrated in large cities, suggesting that green innovation can take place everywhere.

[24] Available at: https://www.oecd.org/environment/consumption-innovation/ENV-tech%20search%20strategies,%20version%20for%20OECDstat%20(2016).pdf [Accessed 30 September 2022]
[25] South East (England) except for Kent.

Figure 4.1. Share of green-tech firms over total firms and their employment over total employment per region (NUTS-2 level)



Notes: (1). Statistics are based on Orbis IP and Orbis databases between 2008 – 2017. (2). A green-tech company or green innovator is defined as a firm that has at least one green patent across the observation period.

4.3.2 Data sources

Our empirical analysis draws on different data sources at the firm and industry level. We extract the green patents of UK firms from the Bureau van Dijk's Orbis IP database. It offers detailed records of patents including their publication date, current direct owner(s), and complete symbol of the primary IPC. A distinctive advantage of Orbis IP is that patent records can be linked to their current direct owner's financial information using a unique identifier. It is worth noting that the empirical work draws on the patent records owned by the UK firms; these include not only the UK IPO records but also those registered under other patent authorities.

For purposes of data aggregation, the publication date of each patent record is employed to capture the time when the technological knowledge was created. Individual record is structured in a panel setting to match with the UK firms from Orbis database, using its current direct owner's company identifier and publication year. The linked data gives us in total 18,106 green patents published by 5,964 firms over the period of 2008-2017.

Our strategy for assigning green patents to their relevant sectors relies on matching green patents to their owners, based upon which we can extract information about firms' sectors. By exploiting and aggregating firm-level linked green patents to the division level (2-digit) of UK Standard Industrial Classification (SIC 2007) and the NUTS-2 region level, we can construct sectoral and regional green innovation indicators as exogenous explanatory variables, which will be further discussed in the next section. The vertical backward and forward linkages are computed using the ONS input-output tables, estimating the supply and demand relationships across all the sectors (at the 2-digit level of SIC) in the UK.

A set of firm characteristics, including firm age, size, sector, location, and various financial indicators, are also collected and taken into account, totalling 58,102 firm-year observations for 10,733 UK manufacturing firms between 2008 and 2017.

4.3.3 Variable definitions

4.3.3.1 Dependent variables

Various indicators of firm performance can be found in the literature. These attempt to describe it from different perspectives such as return on assets, productivity, employment, sales, innovation or R&D, as well as wage level (Beņkovskis, Tkačevs and Yashiro, 2019; Borin and Mancini, 2016; Oh, Lee, Heshmati and Choi, 2009; Sharma, 2018; Sharma, Cheng, and Leung, 2020). We examine company performance from two of the most commonly used aspects: total factor productivity (TFP) and employment growth.

In the literature concerning production function estimation, the control function approach tends to have wider use than the approaches that adopt instrumental variables and fixed-effects (Rovigatti and Mollisi, 2018). For example, Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg, Caves, and Frazer (2015) have contributed to literature related to the control function approach by developing two-step estimation procedures that are widely used. Wooldridge (2009), however, demonstrates a way of implementing the control function within a single step generalised method of moments framework. This approach can overcome the potential identification issue (see Ackerberg *et al*., 2015) in the first stage of the two-step estimation routine. The Wooldridge approach also makes it relatively easy to obtain robust standard errors (Rovigatti and Mollisi, 2018). Thus, we employ the

Wooldridge estimator implemented in Stata's *prodest* command (Rovigatti and Mollisi, 2018) to estimate TFP within each industrial sector. This measure is based on a revenue-based Cobb-Douglas production function with production factors of labour, capital, and materials. As such, it refers to the efficiency of all the inputs to production (Sharma *et al*., 2020). The second dependent variable, employment growth, is defined as the annual rate of growth of employee numbers (e.g., Jung and Lim, 2020) and is generated by taking the difference of the natural logarithm value of number of employees between t and t-1.

4.3.3.2 Independent variables

4.3.3.2.1 Green innovation externalities

Following the above theoretical predictions and the established empirical literature developed since Javorcik (2004) on identifying agglomeration externalities, we generate three proxies for spillovers from green-tech companies.

First, green innovation industrial externalities at the horizontal level ($Horizontal_{jrt}$) captures the spillovers arising from the green-tech companies operating in the same SIC 2-digit industry j and NUTS-2 region r at time t, following the MAR theory. This is measured by the summation of each green-tech firm i's share of green patents (i.e., number of green patents over total number of patents) weighted by its share of employment over total employment of each industry j and region r at year t. This value increases with green-tech firms' share of green patents and their employment shares. Our measure of green innovation agglomeration based on the weighted green patent intensity is backed up the most recent related literature. For instance, Pan, Wei, Han, and Shahbaz (2021) empirically investigate the effects of interregional green technology spillover on energy intensity using a panel data of 30 provinces in China from 2000 to 2016. Their work measures interregional green technology spillover using economic distance-weighted sum of green technology stock in all other regions, with the green technology stock captured by effective green technology amount based on patent data calculated by perpetual inventory method.

$$Horizontal_{jrt} = \sum_{i\ for\ all\ i \in j} \left[\frac{Green\ patent_{irt}}{Total\ patent_{irt}} * \left(Employee_{irt} \Big/ \sum_{i\ for\ all\ i \in j} Employee_{irt} \right) \right]$$

Second, we measure inter-sectoral agglomeration externalities along the same value chain of production, on the basis that green innovation spillovers occur via vertically integrated industries. For each sector j, we construct two measures of the vertical externalities of green innovation: one capturing backward linkages with the upstream supply sectors (*s*) and the other capturing forward linkages with the downstream customer sectors (*k*). To put it simply, the first measure estimates backward linkages with green-tech suppliers, while the latter captures forward linkages with green-tech customers.

Following Du and Vanino (2021), we adopt the average intermediate supply linkages between each pair of SIC 2-digit industries to compute industrial integration for all the sector pairs in the UK (α_{js}), using time-variant UK input-output analytical tables released by ONS. We weight the extent of green-tech companies' green innovation presence ($Horizontal_{jrt}$) in each upstream and downstream sector of industry *j* within the same NUTS-2 region *r*, by the relative importance of vertical linkages between each pair of sectors (*js*) and (*jk*). We then take the average of the values of all the backward (*s*) and forward (*k*) sectors[26]. $Backward_{jrt}$ captures the presence of green technology within *j*'s upstream sectors, while α_{js} denotes the share of sector *j*'s inputs purchased from sector *s* over the total inputs sourced by sector *j*. $Forward_{jrt}$ is a proxy for the green innovation presence in the sectors that are being supplied by sector *j*, where α_{jk} is the share of sector *j*'s output supplied to sector *s* as taken from the input-output matrix.

In this way, we consider the externalities of green innovation not only from the green innovators operating in the same sector and region, but also from vertically integrated sectors within the same region.

$$Backward_{jrt} = \frac{1}{n1} \sum_{s\ if\ s \neq j,\ \ s=1}^{n1} (\alpha_{js} * Horizontal_{srt})$$

$$Forward_{jrt} = \frac{1}{n2} \sum_{k\ if\ k \neq j,\ \ k=1}^{n2} (\alpha_{jk} * Horizontal_{krt})$$

4.3.3.2.2 Absorptive capacity measurements

In the literature, there is no standard measurement for absorptive capacity. Nieto and Quevedo (2005) review related studies and note that the majority have adopted proxies that are relevant to the outcomes of innovation efforts. Specific measures include the number of patents or a company's scientific publications (Cockburn and Henderson, 1998), the ratio of R&D expenditures to sales (Stock, Greis and Fischer, 2001), and an indication that a firm has a formally established R&D department (Cassiman and Veugelers, 2002; Veugelers, 1997). As we assume that firms' ability to exploit and internalise external technological opportunities rests on the knowledge and capabilities held within the organisations, we employ intangible assets intensity and two important characteristics of firms'

[26] n1 and n2 denote the number of backward supplying sectors and forward buying sectors for the focal sector *s*, respectively.

technological knowledge, core-technology competence and technological diversification, as proxies for absorptive capacity.

Intangible fixed assets cover goodwill, brand recognition, and possibly various forms of intellectual property. Thus, they become a proxy for organisational creativity and innovation strength. The increasingly important role of intangible assets in driving firm competitiveness and productivity has been proved in the extant literature (e.g., Bobillo, Rodriguez Sanz and Tejerina Gaite, 2006; Du and Temouri, 2015; Marrocu *et al*., 2011). Intangibles offer a compelling proxy for internal knowhow and knowledge assets, based on which organisations will be able to assimilate, transform, and exploit new information and ideas outside their limits. Tangible fixed assets commonly include land, buildings, plant, machinery, and equipment (Aboody, Barth and Kasznik, 1999). Investments in tangible capital tend to have positive effects on firm profitability and productivity (e.g., Bobillo *et al*., 2006). In view of these two factors and following Marrocu *et al*. (2011), we compute the ratio of intangible to tangible fixed assets ($Intangible\_intensity_{it}$) to account for the effects of knowledge capital on the spillovers to firms' economic performance.

Our index of core-technology competence, $Coretec_{it}$, is measured following Kim *et al*. (2016), based on the RTA (Patel and Pavitt, 1997). This reflects a firm's patent share in technological field q when taking into account the share of its patent publications over the entire patent sample across all the fields. In effect, it is intended to assess the extent of firm i's specialisation in a specific domain q, giving us an index:

$$RTA_{iqt} = \frac{P_{iqt} \;/\; \sum_i P_{iqt}}{\sum_q P_{iqt} \;/\; \sum_i \sum_q P_{iqt}}$$

where P_{iqt} stands for the number of patent publications of firm i in technological field q defined at the four-digit Subclass of the IPC symbol at year t. Then, core-technology competence is the maximum value of the product of RTA index and the number of patent publications in the corresponding technological domain:

$$Coretec_{it} = ln[max(RTA_{iqt} * P_{iqt})]$$

Following the strategic management literature on using the entropy index to quantify technological relatedness or unrelatedness (e.g., Chen and Chang, 2012; Zander, 1997), our index of technological diversification TD_{it} is constructed based on the method introduced by Kim *et al*. (2016), as follows:

$$TD_{it} = \sum \left[PS_{ipt} * \; ln(\frac{1}{PS_{ipt}}) \right]$$

where PS_{ipt} is firm i's patent share of IPC p at year t (i.e., $PS_{ipt} = P_{ipt}/P_{it}$)[27]. This measure evaluates the firm's patent shares across the full IPC symbol.

4.3.3.3 Control variables

Our selection of control variables is directed by the extant literature on the determinants of firm performance, albeit somewhat limited by data availability.

Patents have economically and statistically significant influences on firm-level productivity and market value (Bloom and Van Reenen, 2002). Patent stock captures firms' knowledge accumulation over time, which is expected to drive growth based on innovation (Leoncini *et al.*, 2019). Hence, we take account of this factor and introduce a patent stock variable, which is constructed using the perpetual inventory method (e.g., Berlemann and Wesselhöft, 2014) following Guellec and van Pottelsberghe de la Potterie (2004):

$$PSTOCK_{it} = PFLOW_{it} + (1 - \delta) * PSTOCK_{it-1}$$

where $PSTOCK_{it}$ stands for the patent stock of firm i at time t, and $PFLOW_{it}$ is the number of new patents published by firm i at time t. The rate of obsolescence is presumed to be annually constant at 15% following the recent literature (Colombelli and Quatraro, 2019). We then rescale this variable by taking its natural logarithm.

Average wage ($Average\_wage_{it}$) is calculated as the natural logarithm value of cost of employees per employee. This variable is considered as a proxy for overall labour quality, with higher labour quality generally associated with a stronger capability to absorb external knowhow, create new knowledge, and thus drive companies' growth.

As shown in Coad, Segarra, and Teruel (2013), firms improve with age. Aging firms are expected to have steadily increasingly levels of productivity, size, and profits. Hence, firm age (Age_{it}), computed as the number of years since establishment, and size ($Size_{it}$), which is the natural logarithm value of number of employees, are included to account for the experience and resources owned by the company.

[27] P_{ipt} is the number of patent publications of firm i in IPC p at time t, whereas P_{it} counts the total number of patents published by firm i at time t.

Finally, heterogeneity at the aggregated sector level[28] is controlled by their respective dummies following Jones and Temouri (2016). The definitions of the variables are summarised in Table 4.1.

<Table 4.1 inserts here>

4.3.4 Empirical specification

Given that the mechanisms through which agglomeration externalities of green innovation act on other non-green-tech enterprises are prone to be different for productivity and employment growth, we specify different models to test the impacts of green innovation externalities on these two performance indicators of other non-green-tech firms separately, controlling for both firm and industry heterogeneity, as follows:

$$Performance_{ijrt} = \beta_0 + \beta_1 Horizontal_{jrt} + \beta_2 Backward_{jrt} + \beta_3 Forward_{jrt} + \beta_4 Controls_{it} + Sector_j + Year_t + c_i + \varepsilon_{it}$$

(1)

$$Performance_{ijrt} = \beta_0 + \beta_1 Horizontal_{jrt} + \beta_2 Backward_{jrt} + \beta_3 Forward_{jrt} + (\beta_4 Horizontal_{jrt} + \beta_5 Backward_{jrt} + \beta_6 Forward_{jrt}) * Intangible\_intensity_{it} + \beta_7 Controls_{it} + Sector_j + Year_t + c_i + \varepsilon_{it}$$

(2)

$$Performance_{ijrt} = \beta_0 + \beta_1 Horizontal_{jrt} + \beta_2 Backward_{jrt} + \beta_3 Forward_{jrt} + (\beta_4 Horizontal_{jrt} + \beta_5 Backward_{jrt} + \beta_6 Forward_{jrt}) * Coretec_{it} + \beta_7 Controls_{it} + Sector_j + Year_t + c_i + \varepsilon_{it}$$

(3)

$$Performance_{ijrt} = \beta_0 + \beta_1 Horizontal_{jrt} + \beta_2 Backward_{jrt} + \beta_3 Forward_{jrt} + (\beta_4 Horizontal_{jrt} + \beta_5 Backward_{jrt} + \beta_6 Forward_{jrt}) * TD_{it} + \beta_7 Controls_{it} + Sector_j + Year_t + c_i + \varepsilon_{it}$$

[28] We employ broad categories of different sectors defined by Eurostat, which are high technology manufacturing, medium-high technology manufacturing, medium-low technology manufacturing and low technology manufacturing. Available at: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:High-tech_classification_of_manufacturing_industries

(4)

where the dependent variable $Performance_{ijrt}$ is measured by the TFP and employment growth of firm i (with no green technologies) in sector j and region r at time t. In the equations, the key explanatory variable $Horizontal_{jrt}$ represents horizontal green innovation externalities derived from green-tech companies that have the same SIC 2-digit industry j and NUTS-2 region r as firm i. The regional vertical externalities linked to the backward industries $Backward_{jrt}$ and forward industries $Forward_{jrt}$ respectively account for the spillovers of green-tech companies in the upstream s and downstream k sectors in region r.

Our baseline model is specified in equation (1) to test the direct effects of green externalities on dependent variables of firm performance. Firm i's intangible intensity $Intangible\_intensity_{it}$, core-technology competence index $Coretec_{it}$, and technological diversification index TD_{it} are added respectively and interacted with each metric of green innovation externalities in equation (2), (3), and (4). The idea here is that intangible intensity and characteristics of technological knowledge within the organisations, which capture internally available knowledge capital and capabilities, are considered as the proxies for organisational absorptive capacity. As already noted, heterogeneity in organisational knowledge assets and technological capabilities affects firms' capacity to internalise external knowhow and benefit from green innovation externalities. In view of the resource-based theory, absorptive capacity can be recognised as one type of the intangible assets (Jiménez-Barrionuevo *et al.*, 2011), which contribute to companies' capacity to acquire, assimilate, and exploit external information and knowledge. When new technological opportunities arise, strong core-technology competence will allow firms to better identify such opportunities and efficiently manage R&D investments across different technological domains (Choi and Lee, 2021) to serve the financial objectives of businesses. Firms with diversified technological knowledge are better placed to exploit the economies of scope in knowledge, and to adapt to a fast-changing technological environment. This factor also makes it more achievable for firms to connect to and leverage external knowledge through internal diverse knowledge nodes or domains. Considering that different dimensions of absorptive capacity are beneficial for developing both individual environmental competences and organisational environmental capabilities (Dzhengiz and Niesten, 2020), we presume that intangible knowledge resources, core-technology competence and diversified technological competence, as proxies for absorptive capacity, will give rise to environmental competences and capabilities, and thus assist firms to benefit more from green technology externalities.

The equations include a set of control variables. The vector $Controls_{it}$ stands for several firm-level characteristics: the level of patent stock, average wage, firm age, and size.

To examine the related spillovers of green-tech companies, we estimate the above equations using panel fixed-effects with standard errors clustered at the firm level. The explanatory variable may be affected by unobservable components that systematically vary across firms, resulting in biased coefficients for any variable that is correlated with the variation (Wooldridge, 2003). Adopting a fixed-effects model here allows us to remove unobserved heterogeneity between the different firms in the data. Moreover, clustered standard errors are considered when there is some unexplained variation in the dependent variable that is correlated across time. Thus, our estimation method assumes temporal serial correlation in the error terms within the firm. Besides firm-level control variables, we also introduce aggregated industry dummies $Sector_j$ and year dummies $Year_t$, to control for industry and year specific effects.

4.4 Empirical results and findings

4.4.1 Summary statistics

Table 4.2 summarises the statistics of variables employed in our sample. To explore the heterogenous distribution of green innovation externalities across firm and industries characteristics, we provide descriptive statistics for the overall manufacturing sample and for each group of firms according to the size and characteristics of their sectors. Overall, heterogeneity in firm characteristics is present across different groups. With an average age of 29 years and size of 69 employees ($e^{4.23}$), the sampled manufacturing firms have a wide-ranging level of TFP and on average enjoy 1% employment growth across the observation period.

Interesting findings emerge between firms in the different groups. Compared with small and SMEs, large firms appear to have larger intangible intensity ratio, higher levels of core-technology competence, technological diversification, and patent stock, and slightly higher employment growth rate, but they are not necessarily more productive and paying higher wages. Both groups of firms enjoy similar levels of externalities of green innovation, including horizontal, backward, and forward green externalities.

Drawing upon the above classification of manufacturing industries based on their technological intensity, we classify companies' economic activities as medium-high and high-tech (hereafter, high-tech) or medium-low and low-tech (hereafter, low-tech). As expected, companies in high-tech industries are likely to be more productive, more knowledge-intensive in terms of patent stock, and they have higher intangible intensity, core-technology competence, and technological diversification than low-tech firms. Rather more surprisingly, we discover that while high-tech businesses experience much higher horizontal green externalities than their low-tech counterparts, their employment growth rate and average wage are lower.

<Table 4.2 inserts here>

Table 4.3 reports the correlation coefficients for the key variables in the final sample. Three variables measuring green innovation externalities are weakly positively correlated with each other. In

line with expectation, the indicators that are constructed based on patents information (i.e., core-technology competence, technological diversification, and patent stock) are highly positively correlated with each other. However, they are not excessively so.

<Table 4.3 inserts here>

4.4.2 Regression results and findings

To estimate the economic relevance of green innovation spillovers on other firms' TFP and employment growth, we employ the panel fixed-effects modelling specified in equation (1) to (4). To unpack the heterogenous effects of green externalities across firm characteristics and sectors, we split the whole manufacturing sample into large firms or SMEs; this categorisation supplements the high-tech/low-tech industry subsamples. Recent literature has found that small firms are more prone to depend on spillover effects, given their limited capacity and resources for investing in internal capabilities (Abubakar and Mitra, 2017). Moreover, we examine whether the strength of these spillovers varies for different levels of industrial technological intensity. Green externalities might be stronger in high-tech industries, which appear to be ideal candidates for benefiting from spillovers (De Silva and McComb, 2012), or in low-tech industries that are far from the technology frontier and thus have greater scope for catching up (Du and Vanino, 2021).

4.4.2.1 Productivity

Table 4.4 reports the estimates of the direct impacts of green innovation externalities on the level of TFP and the moderating effects of absorptive capacity on the spillovers to TFP for the whole manufacturing sample.

<Table 4.4 inserts here>

The first column in Table 4.4 tests the direct effects of horizontal and vertical externalities on the TFP of non-green-tech companies, and three moderators in terms of intangible intensity, core-technology competence, and technological diversification are added respectively and interacted with each metric of green externalities in column (2), (3), and (4).

In column (1), we cannot find an overall statistically significant impact from horizontal green technology externalities. Turning to vertical linkages, upstream green innovators generate an overall positive spillover effect on the TFP of non-green-tech downstream firms operating within the same region. There is, overall, no statistically significant result linked to forward green innovation externalities for all manufacturers. Unsurprisingly, intangible intensity is statistically significantly and positively associated with the level of productivity. Yet, it seems that there is no direct impact of core-technology competence and technological diversification on firms' productivity.

In column (2), even though intangible intensity remains positive and statistically significant, we cannot detect any of its statistically significant moderating effects on the relationship between green innovation externalities and firm productivity. We will explain the possible reasons when reaching the results of employment growth in the next section.

Turning to column (3), businesses that possess core-technology competence are likely to enjoy the productivity gains from the horizontal spillovers of agglomerated green-tech companies. Such positive productivity externalities from the same industry may be motivated by competition led improvements in efficiency (Du and Vanino, 2021; Schmitz, 2005). Selection processes and heightened competition due to agglomerated green innovators give rise to aggregate productivity gains (Syverson, 2011), which can happen through various efficiency improvements within organisations (Schmitz, 2005). This result suggests that technological core competence equips businesses with architectural knowledge related to innovation management, which allows firms to gain efficiency improvements through localised knowledge spillovers in terms of cooperation and demonstration effects, or via fierce intra-industry competition within the same region.

Results in column (4) show that only those with diversified technological competence are benefiting from the positive impacts of backward green externalities. Meanwhile, technologically diversified companies may suffer from a market destruction effect resulting from forward spillovers of green-tech consumers, where a single unit increase in downstream green externalities prompts a 0.018 decrease in the average productivity of other technologically diversified manufacturers in the same area. This result may be explained by the attempts made by technologically diversified suppliers to supply intermediate inputs for green-tech consumers which turn out to be not yet ready to be manufactured, causing the negative impacts on firm productivity. We will come across the negative productivity spillovers linked to forward green externalities for high-tech firms in Table 4.7, which are potentially attributable to similar reasons.

We then unpack the heterogenous effects of green externalities by splitting our sample into large firms and SMEs, with the results presented in Table 4.6.

<Table 4.6 inserts here>

The first two columns in Table 4.6 show that the direct gains in productivity from green-tech suppliers are typically pushed by SMEs, presumably due to their greater need for knowledge spillovers (Abubakar and Mitra, 2017) resulting from their limited internal resources (Du and Vanino, 2021) and their scope for productivity catch up. This positive spillover effect on SMEs also echoes recent evidence in Du and Vanino (2021) that the marginal effects of fast-growth spillovers from backward suppliers appear to be larger for the productivity growth of SMEs than that of large firms. We observe strong negative spillover effects linked to forward green externalities on the TFP of large companies, though we cannot find similar effects for all manufacturers in Table 4.4. This result may be explained by market disruption and destructive efforts, primarily exerted by the demands and requirements of green innovators, on the overall operational efficiency and profitability of upstream suppliers. In particular, this might occur when upstream suppliers who are inexperienced at creating green products or processes fail to meet the demand by downstream green innovators for more eco-friendly intermediate inputs (Ben Arfi *et al*., 2018). The emphasis of green innovation on reducing the environmental impacts of business activities can disrupt the market for others by, for example, affecting industries in the upstream supply chain. This argument is related to Schumpeter's idea of creative destruction (Schumpeter, 1943): the initiation by creative individuals of new solutions, usually enabled by new technologies, often disrupts the existing market (Li-Ying and Nell, 2020). In this regard, the more established firms, for example, large-sized, may find themselves locked into producing established and specialised inputs, such that they find it difficult to promptly change their production lines and routines, especially given the relatively high sunk costs of these.

From columns (3) to (8), we take into account the moderating effects of the variables related to absorptive capacity. As already stated, intangible intensity predicts firm productivity. Surprisingly, large firms that are intangible-intensive tend to experience a negative horizontal productivity spillovers. This can be regarded as a sign of competition led crowding-out effects on intangible-intensive large enterprises. When clustering with green innovators in thick local markets, other companies may face intense intra-industry competition for production factors and common resources (Glaeser *et al*., 1992). This implies that large companies with intensive knowhow and knowledge resources are more likely to share the common production factors, say, skilled and specialised labour, with green-tech firms, which explains the fact that they are the ones subjected to the cost of competition.

In column (6), we find that the productivity gains from horizontal green-tech spillovers, which are likely to be obtained by firms with core-technology competence, mainly go to SMEs. Noteworthily, core-technology competence appears to reinforce the above noted negative direct impacts of forward green externalities for large firms. Companies with established competence in the core technological field tend to be specialised in specific technological domains, which keeps firms moving path-dependently based on related knowledge and past experience (Liu, Chen and Chen, 2003) and gives rise to knowledge inertia and lock-in mechanisms (Boschma, 2005). This effect reflects our conjecture that technological core competence may further lock large firms into manufacturing established and specialised inputs and thus make it more difficult to rapidly adapt to the emerging demands of downstream green-tech customers.

Column (8) shows that those technologically diversified SMEs can take the advantage of productivity spillovers at the horizontal level. These two characteristics of technological knowledge within the organisations equip SMEs with the competences to experience localised knowledge spillovers and competition led improvements in efficiency, potentially through efficiently and effectively assimilating and exploiting external knowledge and information. Along the vertical supply chain, both large firms and SMEs are capable of obtaining positive productivity gains from backward green externalities, with technological diversification further strengthening the positive direct impacts of backward spillovers for SMEs.

Table 4.7 displays the results of the subsamples with respect to high-tech and low-tech industry.

<Table 4.7 inserts here>

By comparing the results of firms from different sectors, we discover strong direct negative spillover effects associated with forward green externalities on the TFP of high-tech businesses. This result reflects that high-tech sector is likely to be influenced by the market disruptions driven by the demand of green-tech consumers. The reasons behind this can be that technology-intensive input providers may attempt to adapt to such requirements and restructure production processes in order to supply products for which they are not yet equipped, resulting in their lower productivity.

Remarkably, the overall positive results of intangible intensity on firm productivity are primarily driven by companies in the high-tech sector, while intangible capital allows low-tech businesses to acquire efficiency gains from the horizontal spillovers, as shown in column (4). Among the organisations with core-technology or diversified technological competence, those in the low-tech sector are prone to benefit from the horizontal productivity spillovers. Different from the findings of large firms and SMEs in column (7) and (8) of Table 4.6, only low-tech companies that possess diversified technological competence turn out to be the beneficiaries of backward green externalities. The statistically insignificant coefficients for the high-tech sector in column (3), (5) and (7) further indicate that there seems to be less scope for productivity improvement for the high-tech sector, given their relatively high level of TFP. Notably, the overall market destruction effect on technologically diversified businesses, resulting from forward spillovers of green-tech consumers (column (4) of Table 4.4), mainly affects low-tech firms. One plausible interpretation is that for low-tech firms, their existing diversified technological competence may have already taken up the limited technological resources and organisational capacity within the organisations, limiting their ability to change established productions and operational routines in response to consumers' sustainability requirements. This may explain why the technologically diversified low-tech companies in our sample seem to experience the market disruptions, leading to negative impacts on productivity.

Turning to the control variables, firm size and age can also predict firm productivity throughout all the models considered, in that age is statistically significantly and positively associated with the level of productivity.

By comparing the marginal effects of interaction terms, we observe that the moderating effects of core-technology competence and technological diversification are strongest through the channel of backward green externalities, highlighting the crucial role played by backward linkages in creating green-tech knowledge externalities that spill over to the productivity of downstream companies.

4.4.2.2 Employment growth

Table 4.5 summarises the regression results of green innovation spillovers on employment growth for the total manufacturing sample, taking into account the moderators of absorptive capacity in column (2), (3) and (4).

<Table 4.5 inserts here>

As was the case for productivity, in column (1), we cannot identify a statistically significant direct impact of horizontal green externalities on the employment growth of other non-green-tech firms. On the whole, green innovators in the upstream (supplying sectors) spill employment growth to other non-green-tech firms in the downstream. Meanwhile, we find an overall strong negative spillover effect linked to forward green innovation externalities. We can deduce that the market demand by green-tech consumers for green products or processes may lead to market disruptions to and destructive efforts on upstream suppliers' operational efficiency and outputs, curbing their capacity to expand and grow. Organisational technological diversification is positively and statistically significantly associated with firm employment growth, with a single unit increase in the level of this index resulting in a 0.010% increase in the average employment growth.

After taking into account the moderating effects of different variables of absorptive capacity, we find similar direct impacts of vertical green externalities as shown in column (1) across three different model specifications. As we have seen in the productivity results, we still cannot detect any of the statistically significant effect of intangible intensity on the relationship between green spillovers and employment growth. Therefore, it is reasonable to infer that intangible assets in general might not be specific enough to capture the absorptive capacity (Denicolai *et al*., 2016) required in the context of green-tech spillovers. More specific indicators of codified technological knowledge in the forms of core-technology competence and technological diversification appear to play better roles.

In contrast to the overall negative forward spillovers of green-tech consumers, we discover a positive and statistically significant moderating effect of both core-technology competence and technological diversification on the relationship between forward green externalities and non-green-tech suppliers' employment growth in column (3) and (4). This reveals that firms' core-technology competence and diversified technological competence can mitigate the overall negative demand shock on businesses' growth employment, which is induced by green-tech consumers. When demand shocks triggered by new solutions are present, core-technology competence will enable firms to better manage R&D investments across different technological domains including those with emerging technological opportunities, consequently alleviating the negative impacts on company growth. Diversified technological knowledge allows organisations to connect to the emerging green technologies and react more easily to the related technological risks and challenges, thereby weakening the destructive effects of consumers' sustainability needs.

To disclose the heterogenous spillover effects on employment growth, results of the subsamples regarding large firms and SMEs are shown in Table 4.8.

<Table 4.8 inserts here>

Interesting patterns emerge along the vertical supply chains across all the models specified. Although we discover the overall positive growth spillovers to non-green-tech customers in Table 4.5, interestingly, these positive signs become negative, albeit marginally significant, when it comes to large firms. This reveals that firms that are already big may not give priority to maintain employment growth when they are exposed to positive externalities linked to backward linkages. There is good chance that different organisational objectives can substitute one for another, which in our case decelerates the employment growth rate of large enterprises. Our result also echoes previous evidence concerning backward fast-growth externalities, which is that large firms seem not to profit from the positive spillovers of upstream fast-growth firms in terms of employment growth (Du and Vanino, 2021).

SMEs in our sample largely drive the overall strong negative spillovers of forward green innovation externalities. We can deduce that compared with large businesses, SMEs are more likely to find it difficult to meet the market demand by green-tech consumers potentially due to resource constraints, resulting in market disruptions to SMEs' outputs and thus restraining their capacity to expand and grow.

However, contrasting results are detected when absorptive capacity is considered. As opposed to the overall negative forward spillovers on the growth of SMEs, their core-technology and diversified technological competence positively and statistically significantly moderate such effects in that these two factors abate the negative demand shocks imposed on them. This outcome highlights the important role played by technological diversification in not only predicting SMEs' employment growth but alleviating the negative impact of market disruptions on their growth as well.

As was the case for productivity, we split our manufacturing sample into high-tech and low-tech industries, with the results of employment growth summarised in Table 4.9.

<Table 4.9 inserts here>

Firms in the high-tech industry appear to be the beneficiaries of backward green spillovers in terms of employment growth, implying their capability to seize and grow from the green opportunities offered by upstream suppliers. However, high-tech companies are also the group suffering from the negative forward green spillovers described in column (1) of Table 4.5. As we have seen in the evidence of productivity, this echoes our previous explanation that high-tech businesses may make attempts to change routines and transform production processes, with the aim of satisfying the needs of downstream green innovators. However, these technology-intensive providers might be not yet equipped for producing the eco-friendly intermediate inputs or products in demand, given that green innovation represents a technological frontier with a variety of market and technological uncertainties. Businesses will need to employ their limited capacity for the outputs that they are unskilled in producing, resulting in lower productivity than previous level and thus limiting their capacity to grow. This explains the job destruction effect among establishments owing to the disruptions brought by downstream green innovators.

Intangible-intensive companies in the high-tech industries are subjected to negative horizontal spillovers on employment growth, whereas their counterparts in low-tech sector reveal contrasting results. This can be interpreted as the evidence of competition led crowding-out effects, especially for intangible-intensive businesses in the high-tech sector, when businesses are clustering with green innovators in thick local markets. In this regard, we can deduce that establishments with intensive human capital will tend to face fierce competition and thus suffer from the cost of labour competition and poaching (Combes and Duranton, 2006) due to the presence of green innovators.

In column (4) and (8), absorptive capacity variables in terms of intangible intensity and technological diversification seem to exert the moderating effects on forward green spillovers to low-tech firms' employment growth, such that firms' existing knowledge assets and technological competence can weaken the above noted market destruction effects on the employment growth.

Interestingly, for low-tech downstream consumers, having core-technology competence or technological diversification seems not to help them benefit from upstream green externalities in terms of employment growth. Instead, these two factors tend to slow down low-tech businesses' employment growth rate. This also echoes our previous evidence that technologically diversified low-tech enterprises tend to prioritise productivity rather than employment growth when they are subjected to positive upstream spillovers of green-tech suppliers. We can also infer from here that organisational objectives of increased productivity and employment growth might not always be complementary; this is particularly the case for low-tech firms with limited level of technological resources and intensity.

Turning to the control variables, we also find average wage to be statistically significant in explaining companies' employment growth.

To summarise, our results underline the various externality channels through which green innovators influence other firms' productivity and growth in related sectors. Productivity spillovers are largely pushed by localised knowledge spillovers at the horizontal level and backward linkages with green-tech suppliers. Employment growth externalities are mainly connected to improved intermediate inputs or efficiency gains from upstream green innovators, as well as increased demand driven by green-tech consumers in the downstream sectors. Our green spillover effects are largely dependent on firm absorptive capacity, suggesting the moderating roles of intangible assets intensity, core-technology competence and technological diversification in the relationship between green innovation externalities and productivity and employment growth.

4.5 Robustness test and additional analysis

We believe that the results of the baseline specifications are reliable, given that the fixed-effects estimator is reasonably robust in estimating the population-average slope coefficients in a panel data setting with individual-specific slopes (Wooldridge, 2003). This estimator controls for all the time-invariant differences between companies and eliminates the influences of time-invariant characteristics, allowing the study of the net effects of explanatory variables on dependent variables (Kohler and Kreuter, 2009). This is because it was designed to analyse the reasons and causes of changes within an individual or an entity (Kohler and Kreuter, 2009).

To test the robustness of the baseline results, we relax our stringent restriction of regional boundary from the NUTS-2 to NUTS-1 level within the UK and recalculate the three green innovation externalities variables. After putting the three newly generated externalities variables into equation (1) – (4), we find that our main results in Table 4.4 and 4.5 remain valid[29]. This shows that our regression results are robust and consistent when we loosen the regional boundaries. We can further infer that green innovation spillovers and related knowledge dissemination seem to remain present over wider geographical ranges.

[29] Results are available on request.

4.6 Conclusions and discussions

4.6.1 Conclusions

By connecting the extant environmental innovation literature with economic geography theory on agglomeration externalities, this work explores the external impacts of green innovation on the economic performance of other industrially related non-green-tech firms within the same locality. As far as we know, this is the first study to evaluate the extent to which spillovers of green innovation via both horizontal and vertical linkages drive productivity and employment growth at the firm level. Considering that the amount of knowledge resources and the nature of technological knowledge within the organisation form the important sources of absorptive capacity, we view companies' intangible assets and technological competence as proxies for organisational absorptive capacity. In doing so, we can explore the moderating effects of intangible intensity, core-technology competence, and technological diversification on firms' ability to benefit from spillovers by assisting them to sense the value of external green technologies and also to acquire, assimilate and exploit such knowledge. Additionally, we identify the heterogenous effects of agglomerated green innovation by splitting the whole manufacturing sample based on firm size and level of industrial technological intensity.

Overall, our results suggest that downstream non-green-tech manufacturers benefit from their green-tech suppliers in terms of both productivity and employment growth, while the positive productivity effects are only pronounced for the technologically diversified downstream firms. SMEs show the potential for benefiting from the externalities of upstream green innovators in both productivity and employment growth. Positive upstream productivity spillovers are acquired only by those large enterprises with core-technology and diversified technological competence, while large companies experience direct negative spillovers on employment growth when they link to agglomerated upstream green innovators. This reveals that different organisational objectives may not always be complementary. Noteworthily, technological diversification makes SMEs and low-tech businesses capable of exploiting the positive productivity gains from upstream supplying sectors, but such technological competence is not helpful in maintaining the employment growth rate of low-tech businesses against the upstream green innovation spillovers. Furthermore, while we cannot detect any statistically significant results on the productivity of downstream high-tech firms, we observe strong positive employment spillovers from agglomerated green-tech suppliers on their growth.

It appears that the statistically significant and positive impacts of overall horizontal productivity spillovers are mainly captured by the businesses with technological core competence. In particular, core-technology competence and diversified technological competence within both SMEs and low-tech firms allow them to gain efficiency improvements led by intra-industry competition within the same region. Typically, all of our three indicators of absorptive capacity positively moderate the horizontal green spillovers to low-tech businesses' productivity. However, large firms that are intangible-intensive tend to experience a negative productivity spillover effect from green-tech companies within the same sector and region, which can be regarded as a sign of competition led crowding-out effects on intangible-intensive large enterprise. Similarly, intangible-intensive companies in the high-tech industries are subjected to negative horizontal spillovers on growth potentially due to the cost of labour competition and poaching, whereas their counterparts in low-tech sector reveal contrasting results.

Turning now to forward linkages, we observe market disruption effects on the productivity of large-sized and high-tech upstream suppliers. In particular, both technologically diversified companies in the low-tech sector and large enterprises with core-technology competence may suffer from similar market destruction effects resulting from forward spillovers of green-tech consumers. With regard to employment growth, green-tech consumers exert an overall negative forward spillover effect on our manufacturing sample, with the result mainly driven by SMEs and high-tech firms. Core-technology competence and diversified technological competence allow manufacturers, mainly SMEs and low-tech companies, to efficiently manage investments and respond more easily and quickly to related technological risks and challenges, thus alleviating the induced demand-driven shocks.

To summarise, our results underline the various externality channels through which green innovators influence other firms' productivity and growth in related sectors. Productivity spillovers are largely pushed by localised knowledge spillovers in the forms of demonstration effects and competition led efficiency improvements at the horizontal level, and by backward linkages with green-tech suppliers through efficiency gains and the introduction of new improved inputs. Employment growth externalities are mainly connected to improved intermediate inputs or efficiency gains from upstream green innovators, which may then give rise to firm growth. Moreover, employment growth is also derived from the increased demand driven by green-tech consumers in the downstream sectors, leading to job creation.

The above results hint that more established firms (i.e., large-sized enterprises) tend to profit less than SMEs from backward linkages with green innovators in terms of both productivity and growth. Moreover, low-tech sector appears to the beneficiary of productivity through all the examined channels of green externalities.

Our results also indicate that absorptive capacity, which in our case equates to intangible intensity, core-technology competence, or technological diversification, enables organisations to boost productivity through competition led improvements in efficiency, or through localised knowledge spillovers via ideas sharing, movement of workers, and other types of informal interactions. In addition, these three indicators make organisations capable of mitigating the induced demand-driven market disruptions to employment growth, whereas only core-technology competence and technological diversification facilitate the exploitation of positive productivity spillovers from upstream supplying sectors. By contrasting the results of different moderators, we infer that compared with specific indicators of codified technological knowledge, intangible assets in general might not be specific enough to capture the absorptive capacity required in the context of green innovation spillovers.

Relatedly, we can also conclude that, given their resistance and reluctance to make changes, the established companies specialised in specific technological domains tend to experience larger disruptions to their existing production processes and routines. This may come from the creative destruction triggered by green technologies. Furthermore, chances are that technology-intensive providers may try to satisfy consumers' green needs even when they are not yet ready to produce such eco-friendly outputs, resulting in lower productivity and thus limiting their capacity to grow. These arguments, taken in conjunction with our earlier findings and inferences, highlight several policy implications.

4.6.2 Managerial and policy implications

First, our results provide empirical grounds for policies aimed at promoting green technology by showing that green-tech companies are able to generate overall welfare effects on the wider economy through their green innovations.

Second, our conclusion that SMEs and low-tech firms are the main beneficiaries, in terms of productivity, of exposure to green externalities hints at the potential of the less established companies and the disadvantaged group for learning and growing in this environmental endeavour. This has meaningful implications for the formulation of policies intended to promote long-term and balanced growth, or to use the current buzzwords, economic growth in terms of levelling up.

Third, even though all of our three indicators of absorptive capacity reveal, at least to some extent, the moderating effects on green spillovers to economic performance of other industrially related non-green-tech firms, not all of the aspects are of equal importance. Specific measures of codified technological knowledge, instead of general knowledge resources, turn out to be more crucial under the condition of green spillovers absorption. This inference may rest on the nature of green technology, which stands for a technological frontier, appears to be more complex, and is thus more in need of knowledge and skills unlike industries' conventional knowledge stock. As a result, businesses who wish to take advantage of this green transformation should focus on building their strong technological competence, so that they can maximise the benefits of knowledge spillovers related to green innovation and mitigate the induced demand-driven market disruptions.

Fourth, just as the organisational objectives of increased productivity and employment growth might not always be complementary, this is also the case for policy goals (Du and Vanino, 2021). The national government may wish to implement policies that promote green technology and an environmentally sustainable society, but the indirect impacts of green innovation may not always be favourable. Hence, it is important to realise the implications of green technology on the productivity and employment growth of other industrially related and geographically adjacent non-green-tech companies.

More importantly, spillover effects of externalities of agglomerated green innovation are heterogeneous across different positions in the value chains, firm characteristics, and technological intensity within industries. This reveals the necessity to design targeted policy instruments that specifically consider such variations so as to maximise the rewards from green innovation.

4.6.3 Limitations and future research

This study is subject to the following limitations and raises further questions that are worthy of further research. For instance, with only the manufacturing sectors having been taken into account, the results should be interpreted with caution, particularly with regard to transferring the conclusions to the services sectors. This also throws up questions that are worthy of further research. For instance, Cainelli and Mazzanti (2013) focus on the integration of services and manufacturing sectors through push and pull effects and examine whether such integration will exert any impact on environmental innovation diffusion. It would be interesting to extend our work and verify the impacts of green innovation externalities on the performance of services industry companies. Such findings will be of great importance to policy makers' decision making given the dominant role that services play in the UK economy[30].

Second, our way of defining green technology (i.e., using a search strategy based on classified IPC symbols) appears to be efficient at following the existing green innovation literature, but it risks omitting the environmental process innovations or organisational innovations that might not meet the patentability criteria. Thus, future research needs to go beyond the current reliance on patent information and employ other methodologies.

Third, it would be valuable to explore how the agglomerated externalities of green technology exert impacts upon other firm performance indicators such as average wage bill and profitability, which will provide a broader view of the external impacts of this type of innovation.

Given the increasing relevance of green innovation to society and the economy, it is worthwhile delving into the specific mechanisms and channels through which green technology can be adopted and diffused.

[30] Available at: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/695969/services-blackett-report.pdf [Accessed 30 September 2022]

Lastly, it is not clear what kind of role the public policy plays in promoting the diffusion of green technology. How policy making maintains the balance between promoting such technology diffusion and at the same time encouraging businesses to keep investing in and inventing green technology appears to be a very important issue.

Table 4.1. Definition of variables

	Variable name	Name in the model	Definition
Dependent variables	**Total factor productivity (TFP)**	$Performance_{ijrt}$	Based on a revenue-based Cobb-Douglas production function with production factors of labour, capital, and materials, this work employs the Wooldridge estimator implemented via *prodest* command in Stata to estimate TFP within each industrial sector.
	Employment growth	$Performance_{ijrt}$	The difference of the natural logarithm value of number of employees between t and $t-1$
Independent variables	**Horizontal green externalities**	$Horizontal_{jrt}$	Measured by the summation of each green-tech firm i's share of green patents weighted by its share of employment (firm i's employment over the total employment of its industry j and region r at time t).
	Backward green externalities	$Backward_{jrt}$	The average extent of green innovation presence in the upstream sectors (s) of industry j within the same NUTS-2 region r, computed based on the vertical linkages between each pair of sectors (js) in the UK input-output matrix.
	Forward green externalities	$Forward_{jrt}$	The average extent of green innovation presence in the downstream sectors (k) of industry j within the same NUTS-2 region r, computed based on the vertical linkages between each pair of sectors (jk) in the UK input-output matrix.
	Intangible intensity	$Intangible\_intensity_{it}$	Calculated by dividing the intangible fixed assets by tangible fixed assets
	Core-technology competence	$Coretec_{it}$	Measured by the maximum value of number of patents in a technological domain multiplied by the RTA index for the subclass of the IPC symbol (Kim *et al.*, 2016): $Coretec_{it} = ln\left[max\left(RTA_{iqt} \times P_{iqt}\right)\right]$ Where RTA[31] derives the relative importance of a firm's different kinds of patenting to each field of technology after taking account of the firm's share of total patenting in all the fields.
	Technological diversification	TD_{it}	Overall technology diversification measured by entropy index of patents across the full IPC symbol[32] (Kim *et al.*, 2016)
Control variables	**Patent stock**	$PSTOCK_{it}$	Constructed using the perpetual inventory method following Guellec and van Pottelsberghe de la Potterie (2004): $PSTOCK_{it} = PFLOW_{it} + (1 - \delta) * PSTOCK_{it-1}$
	Average wage	$Average\_wage_{it}$	Natural logarithm value of cost of employees per employee (report here the number)
	Firm size	$Size_{it}$	Natural logarithm value of number of employees (report here the number)
	Firm age	Age_{it}	Number of years since establishment (report here the number)

[31] Formula to calculate RTA can be found in 4.3.3.2.2 Absorptive capacity measurements.
[32] Formula can be found in 4.3.3.2.2 Absorptive capacity measurements.

Table 4.2. Descriptive statistics by different groups of firms

Variables	Total Manufacturing			Large			SMEs			Medium high and high-tech			Medium low and Low-tech		
	Mean	SD	N	Mean	SD	N	Mean	SD	N	Mean	SD	N	Mean	SD	N
Total factor productivity (TFP)	0.60	0.40	58102	0.51	0.37	7097	0.61	0.40	51005	0.65	0.41	17877	0.58	0.39	40225
Employment growth	0.01	0.15	47386	0.03	0.14	6225	0.01	0.15	41161	0.01	0.15	14858	0.02	0.15	32528
Horizontal green externalities	1.39	4.91	58102	1.39	5.49	7097	1.39	4.82	51005	2.84	6.82	17877	0.75	3.58	40225
Backward green externalities	0.04	0.10	58102	0.03	0.09	7097	0.04	0.11	51005	0.03	0.09	17877	0.04	0.11	40225
Forward green externalities	0.03	0.16	58102	0.03	0.18	7097	0.03	0.15	51005	0.03	0.10	17877	0.03	0.18	40225
Intangible intensity	0.59	3.15	58102	0.62	2.78	7097	0.58	3.20	51005	0.97	4.09	17877	0.41	2.61	40225
Core-technology competence	0.57	1.89	58102	1.07	2.51	7097	0.50	1.77	51005	0.78	2.15	17877	0.48	1.75	40225
Technological diversification	0.06	0.27	58102	0.14	0.46	7097	0.04	0.23	51005	0.08	0.32	17877	0.04	0.25	40225
Patent stock	0.43	0.92	58102	0.85	1.30	7097	0.37	0.83	51005	0.62	1.04	17877	0.35	0.84	40225
Average wage	0.57	0.75	55478	0.50	0.54	7090	0.58	0.78	48388	0.48	0.30	17272	0.61	0.88	38206
Firm size	4.23	1.27	58102	6.29	0.73	7097	3.94	1.05	51005	4.25	1.22	17877	4.22	1.29	40225
Firm age	28.98	21.32	58102	36.54	25.96	7097	27.93	20.37	51005	28.59	20.23	17877	29.16	21.78	40225

Table 4.3. Correlation coefficients of the key variables

Variables	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*
1. Total factor productivity (TFP)	1.00											
2. Employment growth	-0.01	1.00										
3. Horizontal green externalities	0.01	-0.01	1.00									
4. Backward green externalities	0.03	0.01	0.01	1.00								
5. Forward green externalities	-0.04	-0.01	0.02	0.04	1.00							
6. Intangible intensity	0.14	-0.01	0.01	0.00	0.00	1.00						
7. Core-technology competence	0.04	-0.01	0.05	0.01	0.02	0.04	1.00					
8. Technological diversification	0.04	-0.01	0.04	0.00	0.01	0.03	0.68	1.00				
9. Patent stock	0.05	-0.04	0.06	0.00	0.01	0.05	0.72	0.64	1.00			
10. Average wage	0.28	-0.02	-0.05	0.03	-0.02	0.01	-0.04	-0.03	-0.05	1.00		
11. Firm size	-0.16	0.09	0.00	-0.01	0.02	-0.03	0.13	0.12	0.21	-0.14	1.00	
12. Firm age	-0.01	-0.06	0.01	0.01	0.00	-0.09	0.05	0.04	0.13	0.00	0.19	1.00

Table 4.4. Region-industry spillover effects of green-tech firms on the productivity of non-green-tech companies in the manufacturing sectors

	(1) **Total manufacturing**	(2) **Total manufacturing**	(3) **Total manufacturing**	(4) **Total manufacturing**	(5) **Total manufacturing**	(6) **Total manufacturing**	(7) **Total manufacturing**	(8) **Total manufacturing**
Horizontal$_{jrt}$	0.0000	0.0000	-0.0001	-0.0000	0.0013***	0.0011***	0.0013***	0.0012***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Backward$_{jrt}$	0.0142**	0.0121*	0.0112*	0.0104	0.0802***	0.0801***	0.0858***	0.0820***
	(0.0068)	(0.0064)	(0.0067)	(0.0066)	(0.0184)	(0.0192)	(0.0188)	(0.0185)
Forward$_{jrt}$	-0.0014	-0.0015	-0.0020	0.0002	-0.0306**	-0.0302**	-0.0330**	-0.0311**
	(0.0035)	(0.0035)	(0.0041)	(0.0037)	(0.0132)	(0.0133)	(0.0159)	(0.0144)
Intangible intensity$_{it}$	0.0041***	0.0040***	0.0041***	0.0041***	0.0116***	0.0113***	0.0116***	0.0116***
	(0.0009)	(0.0010)	(0.0009)	(0.0009)	(0.0011)	(0.0012)	(0.0011)	(0.0011)
Coretec$_{it}$	-0.0005	-0.0005	-0.0011	-0.0005	0.0005	0.0005	0.0011	0.0006
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0017)	(0.0017)	(0.0018)	(0.0017)
TD$_{it}$	0.0014	0.0014	0.0013	-0.0031	0.0257*	0.0259*	0.0258*	0.0250*
	(0.0058)	(0.0058)	(0.0058)	(0.0062)	(0.0135)	(0.0135)	(0.0134)	(0.0141)
Horizontal$_{jrt}$ * Intangible intensity$_{it}$		-0.0000				0.0003*		
		(0.0001)				(0.0001)		
Backward$_{jrt}$ * Intangible intensity$_{it}$		0.0035				0.0003		
		(0.0038)				(0.0060)		
Forward$_{jrt}$ * Intangible intensity$_{it}$		0.0001				-0.0015		
		(0.0018)				(0.0029)		
Horizontal$_{jrt}$ * Coretec$_{it}$			0.0001**				-0.0000	
			(0.0000)				(0.0001)	
Backward$_{jrt}$ * Coretec$_{it}$			0.0088				-0.0154	
			(0.0061)				(0.0124)	
Forward$_{jrt}$ * Coretec$_{it}$			0.0003				0.0021	
			(0.0011)				(0.0029)	
Horizontal$_{jrt}$ * TD$_{it}$				0.0005				0.0008
				(0.0003)				(0.0012)
Backward$_{jrt}$ * TD$_{it}$				0.1071***				-0.0496
				(0.0320)				(0.0751)
Forward$_{jrt}$ * TD$_{it}$				-0.0176**				0.0078
				(0.0086)				(0.0239)
PSTOCK$_{it}$	-0.0066	-0.0066	-0.0062	-0.0062	0.0251***	0.0251***	0.0251***	0.0251***
	(0.0059)	(0.0059)	(0.0059)	(0.0059)	(0.0050)	(0.0050)	(0.0050)	(0.0050)
Firm size	-0.0496***	-0.0497***	-0.0496***	-0.0496***	-0.0567***	-0.0567***	-0.0567***	-0.0567***
	(0.0064)	(0.0064)	(0.0064)	(0.0064)	(0.0031)	(0.0031)	(0.0031)	(0.0031)
Firm age	0.0030*	0.0030*	0.0029*	0.0029*	0.0006***	0.0006***	0.0006***	0.0006***
	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Constant	1.8596***	1.8560***	1.8616***	1.8606***	1.2500***	1.2503***	1.2497***	1.2501***
	(0.0489)	(0.0497)	(0.0490)	(0.0490)	(0.0205)	(0.0205)	(0.0205)	(0.0205)
Hausman test (fixed vs random effects): Prob>Chi^2	0.0000; Chi^2=170.18	0.0000; Chi^2=166.70	0.0000; Chi^2=177.71	0.0000; Chi^2=179.02				
Sector	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
Year	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
Firm	**Y**	**Y**	**Y**	**Y**				
Observations	58,102	58,102	58,102	58,102	58,102	58,102	58,102	58,102
Number of firms	10,733	10,733	10,733	10,733				
R-squared	0.0172	0.0172	0.0174	0.0176	0.2404	0.2405	0.2404	0.2404

Notes: Coefficients from panel fixed-effects model estimation of equation (1) – (4) are reported in column (1) – (4) respectively. Coefficients from pooled ordinary least squares model estimation of equation (1) – (4) are reported in column (5) – (8) respectively as benchmarks. Robust standard errors clustered at the firm level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Sector and year dummies are included.

Table 4.5. Region-industry spillover effects of green-tech firms on the employment growth of non-green-tech companies in the manufacturing sectors

	(1) **Total manufacturing**	(2) **Total manufacturing**	(3) **Total manufacturing**	(4) **Total manufacturing**	(5) **Total manufacturing**	(6) **Total manufacturing**	(7) **Total manufacturing**	(8) **Total manufacturing**
$Horizontal_{jrt}$	-0.0000	0.0000	-0.0001	-0.0001	-0.0000	-0.0000	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0002)
$Backward_{jrt}$	0.0117*	0.0104*	0.0124*	0.0125**	0.0136**	0.0154***	0.0127**	0.0132**
	(0.0063)	(0.0062)	(0.0065)	(0.0064)	(0.0055)	(0.0057)	(0.0057)	(0.0055)
$Forward_{jrt}$	-0.0100***	-0.0103***	-0.0132***	-0.0117***	-0.0077*	-0.0104**	-0.0090*	-0.0076
	(0.0035)	(0.0035)	(0.0045)	(0.0039)	(0.0042)	(0.0041)	(0.0054)	(0.0047)
Intangible $intensity_{it}$	-0.0007	-0.0006	-0.0007	-0.0007	-0.0005	-0.0005	-0.0005	-0.0005
	(0.0008)	(0.0009)	(0.0008)	(0.0008)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
$Coretec_{it}$	0.0008	0.0008	0.0007	0.0008	0.0013**	0.0014**	0.0012*	0.0013**
	(0.0006)	(0.0006)	(0.0007)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
TD_{it}	0.0099**	0.0099**	0.0099**	0.0094*	0.0072*	0.0070*	0.0072*	0.0062
	(0.0046)	(0.0046)	(0.0046)	(0.0049)	(0.0041)	(0.0041)	(0.0041)	(0.0045)
$Horizontal_{jrt}$ * Intangible $intensity_{it}$		-0.0001				-0.0000		
		(0.0001)				(0.0001)		
$Backward_{jrt}$ * Intangible $intensity_{it}$		0.0018				-0.0036*		
		(0.0028)				(0.0022)		
$Forward_{jrt}$ * Intangible $intensity_{it}$		0.0017				0.0080***		
		(0.0040)				(0.0018)		
$Horizontal_{jrt}$ * $Coretec_{it}$			0.0001				0.0000	
			(0.0000)				(0.0000)	
$Backward_{jrt}$ * $Coretec_{it}$			-0.0023				0.0028	
			(0.0037)				(0.0036)	
$Forward_{jrt}$ * $Coretec_{it}$			0.0017**				0.0008	
			(0.0008)				(0.0009)	
$Horizontal_{jrt}$ * TD_{it}				0.0007				0.0002
				(0.0005)				(0.0004)
$Backward_{jrt}$ * TD_{it}				-0.0402				0.0187
				(0.0360)				(0.0371)
$Forward_{jrt}$ * TD_{it}				0.0172*				-0.0018
				(0.0101)				(0.0102)
$PSTOCK_{it}$	-0.0114**	-0.0113**	-0.0113**	-0.0114**	-0.0081***	-0.0081***	-0.0081***	-0.0081***
	(0.0044)	(0.0044)	(0.0044)	(0.0044)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Average $wage_{it}$	-0.2072***	-0.2072***	-0.2072***	-0.2072***	-0.0061***	-0.0061***	-0.0062***	-0.0061***
	(0.0195)	(0.0195)	(0.0195)	(0.0195)	(0.0012)	(0.0012)	(0.0012)	(0.0012)
Firm age	-0.0017	-0.0017	-0.0017	-0.0017	-0.0005***	-0.0005***	-0.0005***	-0.0005***
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	0.0684	0.0715	0.0703	0.0705	0.0142***	0.0142***	0.0144***	0.0143***
	(0.0761)	(0.0763)	(0.0766)	(0.0764)	(0.0032)	(0.0032)	(0.0032)	(0.0032)
Hausman test (fixed vs random effects): Prob>Chi^2	0.0000; Chi^2= 1511.35	0.0000; Chi^2= 1519.14	0.0000; Chi^2= 1514.16	0.0000; Chi^2= 1518.76				
Sector	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
Year	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
Firm	**Y**	**Y**	**Y**	**Y**				
Observations	53,246	53,246	53,246	53,246	53,246	53,246	53,246	53,246
Number of firms	9,390	9,390	9,390	9,390				
R-squared	0.0324	0.0325	0.0325	0.0325	0.0103	0.0106	0.0103	0.0103

Notes: Coefficients from panel fixed-effects model estimation of equation (1) – (4) are reported in column (1) – (4) respectively. Coefficients from pooled ordinary least squares model estimation of equation (1) – (4) are reported in column (5) – (8) respectively as benchmarks. Robust standard errors clustered at the firm level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Sector and year dummies are included.

Table 4.6. Region-industry spillover effects of green-tech firms on the productivity of non-green-tech companies – Large-sized and SMEs

	(1) Large	(2) SMEs	(3) Large	(4) SMEs	(5) Large	(6) SMEs	(7) Large	(8) SMEs
$Horizontal_{jrt}$	0.0001	0.0000	0.0002	0.0000	0.0000	-0.0001	0.0001	-0.0000
	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0002)
$Backward_{jrt}$	0.0296	0.0134*	0.0278	0.0112*	0.0073	0.0122*	0.0113	0.0112*
	(0.0272)	(0.0069)	(0.0281)	(0.0063)	(0.0282)	(0.0069)	(0.0260)	(0.0068)
$Forward_{jrt}$	-0.0198***	0.0009	-0.0193***	0.0010	-0.0165**	0.0002	-0.0176**	0.0023
	(0.0061)	(0.0034)	(0.0062)	(0.0034)	(0.0072)	(0.0041)	(0.0069)	(0.0036)
Intangible $intensity_{it}$	0.0049***	0.0042***	0.0049***	0.0041***	0.0049***	0.0042***	0.0049***	0.0042***
	(0.0015)	(0.0010)	(0.0015)	(0.0011)	(0.0015)	(0.0010)	(0.0015)	(0.0010)
$Coretec_{it}$	0.0015	-0.0007	0.0014	-0.0007	0.0008	-0.0012	0.0014	-0.0007
	(0.0020)	(0.0008)	(0.0020)	(0.0008)	(0.0019)	(0.0009)	(0.0020)	(0.0008)
TD_{it}	-0.0024	0.0032	-0.0025	0.0032	-0.0027	0.0033	-0.0065	-0.0030
	(0.0086)	(0.0074)	(0.0086)	(0.0073)	(0.0087)	(0.0074)	(0.0086)	(0.0086)
$Horizontal_{jrt}$ * Intangible $intensity_{it}$			-0.0002**	-0.0000				
			(0.0001)	(0.0001)				
$Backward_{jrt}$ * Intangible $intensity_{it}$			0.0049	0.0036				
			(0.0073)	(0.0041)				
$Forward_{jrt}$ * Intangible $intensity_{it}$			-0.0030	-0.0005				
			(0.0019)	(0.0019)				
$Horizontal_{jrt}$ * $Coretec_{it}$					0.0000	0.0001**		
					(0.0001)	(0.0001)		
$Backward_{jrt}$ * $Coretec_{it}$					0.0178*	0.0047		
					(0.0096)	(0.0077)		
$Forward_{jrt}$ * $Coretec_{it}$					-0.0053*	0.0004		
					(0.0029)	(0.0011)		
$Horizontal_{jrt}$ * TD_{it}							0.0001	0.0016*
							(0.0005)	(0.0008)
$Backward_{jrt}$ * TD_{it}							0.1142***	0.1022*
							(0.0299)	(0.0579)
$Forward_{jrt}$ * TD_{it}							-0.0180	-0.0161
							(0.0143)	(0.0105)
$PSTOCK_{it}$	-0.0146*	-0.0073	-0.0145*	-0.0072	-0.0138*	-0.0070	-0.0135*	-0.0070
	(0.0084)	(0.0074)	(0.0084)	(0.0074)	(0.0081)	(0.0074)	(0.0081)	(0.0074)
Firm size	-0.0351**	-0.0490***	-0.0346**	-0.0490***	-0.0353**	-0.0490***	-0.0357**	-0.0489***
	(0.0147)	(0.0073)	(0.0147)	(0.0072)	(0.0146)	(0.0073)	(0.0146)	(0.0072)
Firm age	0.0061**	0.0020	0.0061**	0.0020	0.0060**	0.0019	0.0061**	0.0019
	(0.0028)	(0.0021)	(0.0028)	(0.0021)	(0.0028)	(0.0021)	(0.0028)	(0.0021)
Constant	0.5494***	1.8841***	0.5452***	1.8803***	0.5535***	1.8854***	0.5540***	1.8837***
	(0.1220)	(0.0566)	(0.1221)	(0.0575)	(0.1223)	(0.0567)	(0.1221)	(0.0567)
Sector	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
Year	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
Firm	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
Observations	7,097	51,005	7,097	51,005	7,097	51,005	7,097	51,005
Number of firms	1,217	9,998	1,217	9,998	1,217	9,998	1,217	9,998
R-squared	0.0149	0.0163	0.0152	0.0164	0.0168	0.0164	0.0178	0.0166

Notes: Coefficients from panel fixed-effects model estimation of equation (1) – (4) are reported. Robust standard errors clustered at the firm level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Sector and year dummies are included.

Table 4.7. Region-industry spillover effects of green-tech firms on the productivity of non-green-tech companies – High-tech and low-tech sectors

	(1) **High-tech**	(2) **Low-tech**	(3) **High-tech**	(4) **Low-tech**	(5) **High-tech**	(6) **Low-tech**	(7) **High-tech**	(8) **Low-tech**
Horizontal$_{jrt}$	0.0000	-0.0000	0.0001	-0.0001	-0.0000	-0.0002	-0.0000	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Backward$_{jrt}$	0.0292	0.0088	0.0190	0.0087	0.0206	0.0075	0.0230	0.0057
	(0.0178)	(0.0068)	(0.0162)	(0.0069)	(0.0187)	(0.0066)	(0.0179)	(0.0065)
Forward$_{jrt}$	-0.0320***	0.0006	-0.0335***	0.0005	-0.0348***	0.0009	-0.0283**	0.0023
	(0.0117)	(0.0036)	(0.0123)	(0.0037)	(0.0123)	(0.0043)	(0.0120)	(0.0039)
Intangible intensity$_{it}$	0.0059***	0.0017	0.0061***	0.0015	0.0059***	0.0017	0.0059***	0.0017
	(0.0012)	(0.0011)	(0.0014)	(0.0012)	(0.0012)	(0.0011)	(0.0012)	(0.0011)
Coretec$_{it}$	-0.0010	-0.0002	-0.0010	-0.0002	-0.0019	-0.0007	-0.0011	-0.0002
	(0.0012)	(0.0010)	(0.0012)	(0.0010)	(0.0012)	(0.0010)	(0.0012)	(0.0010)
TD$_{it}$	-0.0079	0.0082	-0.0079	0.0083	-0.0079	0.0087	-0.0121	0.0038
	(0.0079)	(0.0082)	(0.0079)	(0.0082)	(0.0080)	(0.0082)	(0.0090)	(0.0084)
Horizontal$_{jrt}$ * Intangible intensity$_{it}$			-0.0002	0.0002**				
			(0.0001)	(0.0001)				
Backward$_{jrt}$ * Intangible intensity$_{it}$			0.0052	0.0006				
			(0.0047)	(0.0041)				
Forward$_{jrt}$ * Intangible intensity$_{it}$			0.0013	0.0014				
			(0.0017)	(0.0070)				
Horizontal$_{jrt}$ * Coretec$_{it}$					0.0000	0.0002**		
					(0.0001)	(0.0001)		
Backward$_{jrt}$ * Coretec$_{it}$					0.0165	0.0044		
					(0.0128)	(0.0069)		
Forward$_{jrt}$ * Coretec$_{it}$					0.0025	-0.0001		
					(0.0043)	(0.0011)		
Horizontal$_{jrt}$ * TD$_{it}$							0.0005	0.0017***
							(0.0004)	(0.0005)
Backward$_{jrt}$ * TD$_{it}$							0.1294	0.0993***
							(0.0823)	(0.0355)
Forward$_{jrt}$ * TD$_{it}$							-0.0723	-0.0162**
							(0.0615)	(0.0081)
PSTOCK$_{it}$	-0.0055	-0.0056	-0.0053	-0.0057	-0.0051	-0.0053	-0.0049	-0.0052
	(0.0092)	(0.0076)	(0.0092)	(0.0076)	(0.0092)	(0.0075)	(0.0091)	(0.0075)
Firm size	-0.0614***	-0.0439***	-0.0617***	-0.0439***	-0.0613***	-0.0438***	-0.0614***	-0.0438***
	(0.0134)	(0.0068)	(0.0134)	(0.0068)	(0.0134)	(0.0068)	(0.0134)	(0.0068)
Firm age	-0.0034	0.0050***	-0.0034	0.0050***	-0.0037	0.0050***	-0.0037	0.0050***
	(0.0035)	(0.0019)	(0.0035)	(0.0019)	(0.0035)	(0.0019)	(0.0035)	(0.0019)
Constant	0.9832***	0.6405***	0.9838***	0.6408***	0.9913***	0.6397***	0.9897***	0.6396***
	(0.1003)	(0.0538)	(0.1002)	(0.0538)	(0.1006)	(0.0538)	(0.1003)	(0.0538)
Sector	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
Year	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
Firm	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
Observations	17,877	40,225	17,877	40,225	17,877	40,225	17,877	40,225
Number of firms	3,059	7,678	3,059	7,678	3,059	7,678	3,059	7,678
R-squared	0.0283	0.0106	0.0287	0.0107	0.0287	0.0108	0.0288	0.0112

Notes: Coefficients from panel fixed-effects model estimation of equation (1) – (4) are reported. Robust standard errors clustered at the firm level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Sector and year dummies are included.

Table 4.8. Region-industry spillover effects of green-tech firms on the employment growth of non-green-tech companies – Large-sized and SMEs

	(1) **Large**	(2) **SMEs**	(3) **Large**	(4) **SMEs**	(5) **Large**	(6) **SMEs**	(7) **Large**	(8) **SMEs**
$Horizontal_{jrt}$	-0.0001	0.0000	-0.0002	0.0001	-0.0002	0.0000	-0.0001	-0.0000
	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0002)
$Backward_{jrt}$	-0.0305*	0.0171**	-0.0295*	0.0153**	-0.0319*	0.0181***	-0.0283*	0.0178***
	(0.0159)	(0.0066)	(0.0162)	(0.0066)	(0.0171)	(0.0068)	(0.0161)	(0.0067)
$Forward_{jrt}$	-0.0118	-0.0092***	-0.0138	-0.0093***	-0.0098	-0.0124***	-0.0128	-0.0106***
	(0.0160)	(0.0034)	(0.0162)	(0.0034)	(0.0169)	(0.0047)	(0.0167)	(0.0040)
Intangible $intensity_{it}$	-0.0003	-0.0006	-0.0004	-0.0004	-0.0003	-0.0006	-0.0003	-0.0006
	(0.0019)	(0.0008)	(0.0020)	(0.0009)	(0.0019)	(0.0008)	(0.0019)	(0.0008)
$Coretec_{it}$	0.0022*	0.0006	0.0022*	0.0006	0.0020	0.0007	0.0022*	0.0006
	(0.0012)	(0.0007)	(0.0012)	(0.0007)	(0.0013)	(0.0008)	(0.0012)	(0.0007)
TD_{it}	0.0047	0.0138**	0.0048	0.0138**	0.0044	0.0138**	0.0054	0.0130**
	(0.0076)	(0.0058)	(0.0076)	(0.0058)	(0.0076)	(0.0058)	(0.0079)	(0.0062)
$Horizontal_{jrt}$ * Intangible $intensity_{it}$			0.0001	-0.0001				
			(0.0001)	(0.0001)				
$Backward_{jrt}$ * Intangible $intensity_{it}$			-0.0032	0.0026				
			(0.0097)	(0.0024)				
$Forward_{jrt}$ * Intangible $intensity_{it}$			0.0057*	0.0006				
			(0.0030)	(0.0050)				
$Horizontal_{jrt}$ * $Coretec_{it}$					0.0001	0.0000		
					(0.0001)	(0.0001)		
$Backward_{jrt}$ * $Coretec_{it}$					0.0012	-0.0037		
					(0.0062)	(0.0048)		
$Forward_{jrt}$ * $Coretec_{it}$					-0.0014	0.0016**		
					(0.0068)	(0.0007)		
$Horizontal_{jrt}$ * TD_{it}							0.0002	0.0011
							(0.0004)	(0.0007)
$Backward_{jrt}$ * TD_{it}							-0.0404	-0.0446
							(0.0491)	(0.0481)
$Forward_{jrt}$ * TD_{it}							0.0073	0.0148*
							(0.0302)	(0.0083)
$PSTOCK_{it}$	-0.0149**	-0.0136**	-0.0148**	-0.0135**	-0.0147*	-0.0137**	-0.0149**	-0.0137**
	(0.0074)	(0.0053)	(0.0075)	(0.0053)	(0.0075)	(0.0053)	(0.0075)	(0.0053)
Average $wage_{it}$	-0.2441***	-0.2050***	-0.2442***	-0.2050***	-0.2442***	-0.2050***	-0.2441***	-0.2050***
	(0.0601)	(0.0222)	(0.0602)	(0.0222)	(0.0601)	(0.0222)	(0.0601)	(0.0222)
Firm age	-0.0024	-0.0031	-0.0024	-0.0031	-0.0025	-0.0031	-0.0024	-0.0031
	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)
Constant	0.3728***	0.1683***	0.3747***	0.1722***	0.3762***	0.1700***	0.3735***	0.1695***
	(0.0824)	(0.0560)	(0.0826)	(0.0566)	(0.0827)	(0.0560)	(0.0828)	(0.0560)
Sector	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
Year	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
Firm	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
Observations	7,527	45,719	7,527	45,719	7,527	45,719	7,527	45,719
Number of firms	1,362	8,567	1,362	8,567	1,362	8,567	1,362	8,567
R-squared	0.0287	0.0317	0.0289	0.0319	0.0288	0.0318	0.0287	0.0318

Notes: Coefficients from panel fixed-effects model estimation of equation (1) – (4) are reported. Robust standard errors clustered at the firm level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Sector and year dummies are included.

Table 4.9. Region-industry spillover effects of green-tech firms on the employment growth of non-green-tech companies – High-tech and low-tech sectors

	(1) **High-tech**	(2) **Low-tech**	(3) **High-tech**	(4) **Low-tech**	(5) **High-tech**	(6) **Low-tech**	(7) **High-tech**	(8) **Low-tech**
$Horizontal_{jrt}$	-0.0000	0.0000	0.0001	-0.0000	-0.0001	-0.0000	-0.0001	0.0000
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$Backward_{jrt}$	0.0341**	0.0072	0.0262	0.0081	0.0312**	0.0092	0.0340**	0.0084
	(0.0143)	(0.0066)	(0.0166)	(0.0066)	(0.0156)	(0.0068)	(0.0147)	(0.0066)
$Forward_{jrt}$	-0.0576***	-0.0035	-0.0568***	-0.0044	-0.0582***	-0.0056	-0.0566***	-0.0054*
	(0.0140)	(0.0028)	(0.0147)	(0.0028)	(0.0149)	(0.0038)	(0.0145)	(0.0032)
Intangible $intensity_{it}$	-0.0014	0.0001	-0.0010	-0.0001	-0.0014	0.0001	-0.0014	0.0001
	(0.0012)	(0.0009)	(0.0013)	(0.0010)	(0.0012)	(0.0009)	(0.0012)	(0.0009)
$Coretec_{it}$	0.0002	0.0012	0.0002	0.0011	-0.0001	0.0013	0.0002	0.0012
	(0.0010)	(0.0008)	(0.0010)	(0.0008)	(0.0011)	(0.0009)	(0.0010)	(0.0008)
TD_{it}	0.0212***	0.0008	0.0211***	0.0011	0.0211***	0.0010	0.0195**	0.0038
	(0.0075)	(0.0056)	(0.0075)	(0.0056)	(0.0075)	(0.0056)	(0.0080)	(0.0061)
$Horizontal_{jrt}$ * Intangible $intensity_{it}$			-0.0002*	0.0002*				
			(0.0001)	(0.0001)				
$Backward_{jrt}$ * Intangible $intensity_{it}$			0.0033	-0.0048				
			(0.0025)	(0.0058)				
$Forward_{jrt}$ * Intangible $intensity_{it}$			-0.0005	0.0108***				
			(0.0059)	(0.0039)				
$Horizontal_{jrt}$ * $Coretec_{it}$					0.0000	0.0001		
					(0.0001)	(0.0001)		
$Backward_{jrt}$ * $Coretec_{it}$					0.0047	-0.0078*		
					(0.0067)	(0.0046)		
$Forward_{jrt}$ * $Coretec_{it}$					0.0008	0.0011		
					(0.0040)	(0.0007)		
$Horizontal_{jrt}$ * TD_{it}							0.0006	0.0003
							(0.0006)	(0.0009)
$Backward_{jrt}$ * TD_{it}							0.0003	-0.0974**
							(0.0537)	(0.0448)
$Forward_{jrt}$ * TD_{it}							-0.0209	0.0173*
							(0.0645)	(0.0097)
$PSTOCK_{it}$	-0.0169**	-0.0062	-0.0168**	-0.0064	-0.0168**	-0.0064	-0.0166**	-0.0065
	(0.0068)	(0.0058)	(0.0068)	(0.0058)	(0.0068)	(0.0058)	(0.0067)	(0.0058)
Average $wage_{it}$	-0.1917***	-0.2137***	-0.1920***	-0.2138***	-0.1917***	-0.2137***	-0.1917***	-0.2137***
	(0.0402)	(0.0216)	(0.0402)	(0.0216)	(0.0402)	(0.0216)	(0.0402)	(0.0216)
Firm age	0.0006	-0.0026*	0.0007	-0.0026*	0.0005	-0.0026*	0.0005	-0.0026*
	(0.0038)	(0.0015)	(0.0037)	(0.0015)	(0.0038)	(0.0015)	(0.0038)	(0.0015)
Constant	0.0983	0.2273***	0.0958	0.2279***	0.1010	0.2278***	0.1017	0.2275***
	(0.1028)	(0.0421)	(0.1027)	(0.0421)	(0.1030)	(0.0421)	(0.1032)	(0.0421)
Sector	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
Year	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
Firm	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**	**Y**
Observations	16,572	36,674	16,572	36,674	16,572	36,674	16,572	36,674
Number of firms	2,775	6,619	2,775	6,619	2,775	6,619	2,775	6,619
R-squared	0.0322	0.0341	0.0328	0.0343	0.0323	0.0342	0.0323	0.0342

Notes: Coefficients from panel fixed-effects model estimation of equation (1) – (4) are reported. Robust standard errors clustered at the firm level in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Sector and year dummies are included.

CHAPTER 5: CONCLUSION

The last decade has seen an accelerating pace of important transformations of business environment in which businesses operate. More than ever, businesses face the need for strategising to respond to these transitions: the fourth generation of digital revolution known as Industry 4.0, transitioning to a more sustainable world, to name a few. These two driving forces of the transformation of GVCs, known as the digital and green transitions, are largely driven forward by technological advancements and innovation, and they are prone to create long-term social and economic opportunities and challenges. However, it is less clear how market players should respond to these technological transformations with the aim of maximising benefits and mitigating risks, and what kind of impacts the big trends will bring to the wider economy. Understanding what these big trends mean for businesses has critical implications for both practitioners and public policy makers.

Against such a backdrop, this thesis was developed to investigate how companies react to the ongoing economic and societal challenges within their business environment during such two transitions. In particular, we intend to understand how businesses develop their technological competence or capacity for creating ground-breaking innovation within Industry 4.0 and environmental innovation under the current global endeavour to achieve SDGs. We also propose to analyse how the wave of green technology influences businesses in the wider economy through the diffusion of green innovation.

For each of our empirical studies, the last chapter provides a summary of the key points that have been made and reviews the implications for both management and policy makers.

5.1 Discussion and conclusion of Chapter 2 – Innovation of IoT technologies

5.1.1 Summary

Chapter 2 advances our understanding of the route towards pathbreaking innovation activities. Firms often face a tension between innovation persistence in their technological core competence and technological diversification that typically expands the boundary of knowledge. This tension is especially acute in the case of pathbreaking technologies such as the IoT, a core infrastructure element of Industry 4.0.

Focusing on the factors that drive firms' creation of ground-breaking IoT technologies, we investigate how companies' technology trajectory in terms of their core-technology competence, technology diversification, and innovation persistence affects pathbreaking innovation, as measured by IoT technology patenting. We develop theory suggesting that technological core competence is inimical to engagement in IoT patenting, whereas possessing a technological related and unrelated knowledge base is strongly positively linked to IoT innovation.

We employ a multiple choice modelling approach to test the hypotheses, and confirm empirically that the determinants of innovation in IoT differ substantially from those of more established technologies. Technological specialisation in the form of firm-specific competence in their core technological fields tends to attenuate firms' propensity to generate pathbreaking innovation relative to other traditional ICT areas. By contrast, having a diversified knowledge base facilitates searching for novel solutions and technological complementarities, which increases the tendency to create ground-breaking innovations and reduces the effects of knowledge inertia. The typical characteristics of IoT require organisations to think beyond the scope of their proximate technological competences and to build diversified capabilities by exploring broader knowledge domains. The fact that previous innovation patterns and experience are not prerequisites for cultivating the ground-breaking IoT technologies appears to be good news for new entrants who wish to keep pace with the technological revolution despite lacking outstanding innovation performance and experience. If firms continuously and persistently innovate by exploiting existing knowhow and absorbing external resources, the level of unrelated diversification within their knowledge base tends to accumulate over time, strengthening organisations' dynamic capabilities, which in turn support enterprises in taking advantage of cross-fertilisation (Suzuki and Kodama, 2004).

5.1.2 Managerial and policy implications

Our results in Chapter 2 provide insights not only for new entrants who desire to take part in this new area but also for pioneering innovators who wish to strengthen their technological positions within Industry 4.0. First, new, agile, and young entrants, who might appear to be lagging behind, turn out to have a role to play in this wave of technological revolution. Second, managers should keep an eye on reducing the likelihood of experiencing core rigidities and the knowledge inertia induced by excessive focus of core technology, in order to be ready for the next generation of advanced manufacturing. Third, organisations ought to recognise the importance of establishing broad technological disciplines to absorb or incorporate streams of varieties and to produce novel knowledge combinations. Last but not least, given that innovation persistence does play an indirect role in promoting innovation in this emerging field through enhancing the effects of unrelated knowledge diversification, businesses need to recognise the importance of persistent knowledge accumulation so as to further gain from cross-fertilisation.

In respect of the policy implications, the likelihood of predicting innovators tends to become even weaker in the new wave of technological evolution. Therefore, governments' approach of cherry-picking potentially innovative firms to support is likely to bear little fruit. It seems to be more effective to build a breeding ground for facilitating the formation of firms' technological diversification and creating new technologies with the right nutrients. Second, fostering technological coordination and setting up new forms of comprehensive collaborations and partnerships between established incumbents and young firms might be more cost-effective ways of promoting firms' readiness for industry 4.0. Finally, decision makers aiming to advance technologies in Industry 4.0 should recognise the stimulating effects of efficient and long-lasting policies, with their ultimate goal of catalysing growth.

5.2 Discussion and conclusion of Chapter 3 – Connectivity and environmental innovation of developed county MNEs

5.2.1 Summary

The related literature on MNEs' global connectedness is rich, but it has not been fully developed and tested in the context of environmental innovation. Considering that MNEs have advantages in undertaking innovation and R&D based on their firm-specific advantages, we still know little about if this is also the case with the creation of environmental innovation under the emerging sustainability context. In the intersection of the knowledge-based view of MNEs and the environmental innovation literature, prior literature neglected to consider whether the MNEs' knowledge advantages (derived from global connectedness) could provide them with competitive advantage in terms of environmental innovation, particularly from the perspective of the parent company. Indeed, the existing conceptual framework of environmental innovation's determinants did not incorporate the global connectedness derived from production networks and innovation networks. Answers to the aforementioned questions are of vital importance not only in terms of advancing the existing conceptual framework of environmental innovation's determinants by analysing such innovation from the global connectedness lens, but also guiding actions of practitioners and policymakers who strive to engage in and drive the green transformation.

We address the abovementioned gaps by explaining the determinants of environmental innovation through an IB and management research lens. We explore the multifacets of MNEs' global linkages, including organisational linkages, production linkages, and, most importantly, cross-border innovation networks. In addition, we extend the existing theoretical framework of determinants of environmental innovation at the level of the parent firm by our incorporation of intra- and inter-MNE linkages of different kinds, and geographically diversified organisational spaces. Lastly, based on a large-scale secondary dataset, our work provides concrete empirical evidence and practical implications for the specificities of environmental innovation and how it is conceived and realised.

Thus, this chapter is grounded in the knowledge-based view and MNEs' global connectedness in terms of both their production and innovation activities. The knowledge-based view has a long tradition, which considers knowledge as a strategic resource of the firm. In this research, we combine it with the more recent literature on MNEs' global connectedness, which allows us to develop and test the global connectedness arguments in the context of environmental innovation. Our results demonstrate that the existing theories within the IB field are well placed to explain the strength of MNEs (particularly DMNEs) for pursuing environmental innovation endeavours. At a higher level, we bring the topic of environmental innovation into the IB and management research arena, laying the foundation for further exploration of interdisciplinary research on IB and sustainability.

The primary aim of this chapter is to examine the factors that facilitate the firm's environmental innovation capacity. To be more precise, we focus on the effects of different types of intra- and inter-organisational production and innovation networks. By adopting a pooled Tobit modelling approach, we confirm empirically that wider global linkages built on production networks, and intra- and inter-MNE innovation co-production linkages contribute to a MNE's capability to produce environmental innovation. We find consistent support for the majority of our hypotheses and the results are robust to sensitivity testing. It indicates that developed country MNEs are in an advantageous position to develop such innovation capability and sheds light on their potential contribution to achieving the SDGs. Nevertheless, intra-organisational linkages motivated by traditional control and coordination mechanisms do not play an important role in environmental innovation capacity. This emphasises that specific types of ties related to knowledge connectivity and innovation collaboration matter important for environmental innovation than general control and coordination linkages. MNEs' arrangements for international production and innovation activities are grounded in their cross-border organisational linkages. These appear to be important channels for facilitating knowledge transfer and recombination, which cultivates high levels of knowledge development and environmental innovation capacity.

5.2.2 Managerial and policy implications

In practical terms, our findings in Chapter 3 provide valuable insights for management and policymakers on how to plan and stimulate related innovative activities within the sustainable development domain.

In order to be ready for the future trend of environmental innovation, MNEs, as large leading firms in the global value chains, are able to take advantage of their cross-border organisational linkages of production and innovation activities, putting them in a good position to invest in and invent new environmental products, processes, and novel technologies. Given the stimulating role of international connectedness, MNE managers pursuing greater environmental sustainability should find ways to further build connections related to innovative activities and improve organisational connectedness with diverse stakeholders globally.

Policymakers need to take a differentiated approach when interacting with MNEs, and developed country MNEs in particular, because their vital role in contributing to sustainable development makes them good targets for policymakers. Attention should be directed to creating and fostering mechanisms that can stimulate the formation and diversity of internationally integrated production networks, and internal and external innovation networks, in order to cultivate organisational capacity to innovate environmentally.

5.3 Discussion and conclusion of Chapter 4 – Agglomeration externalities of green innovation

5.3.1 Summary

Given the increasingly crucial roles of sustainable thinking and environmental concerns, research on environmental innovations or green innovations, and their impacts have attracted considerable attention of academics and practitioners in recent years. This stream of literature has largely focused on the determinants of green innovation development, its internal impacts on the focal firm, and external impacts on the sectoral environmental performance. Despite this, we still lack understanding of how green technology interacts with the local economy and thus affects other firms' economic performance.

By connecting the environmental innovation literature with economic geography arguments on agglomeration externalities, we fill the knowledge gap by investigating the economic relevance of green innovation spillovers on the performance of other related businesses within the same locality and revealing the conditions under which the spillovers can happen. Moreover, we consider how different dimensions of absorptive capacity affect firms' ability to leverage green innovation externalities and absorb such spillovers. As far as we are aware, this is the first study to investigate the spillover effects of green innovation via both horizontal and vertical linkages in driving firm-level economic performance, which tends to offer important implications for both practitioners and policy makers.

Drawing on Orbis IP and Orbis databases for the UK manufacturers, we adopt the fixed-effects panel data modelling to examine the spillover effects of green-tech firms. We find that the signs and strength of such impacts vary across the positions of value chains and depend on firms' characteristics and sectors. Overall, green technology appears to have positive spillovers on other businesses' productivity and growth through the backward linkages, but it can also trigger disruptions to upstream suppliers' existing production processes and routines attributable to creative destructions via the forward linkages. By contrasting the results of different measures of absorptive capacity, we discover that compared with the indicators of codified technological knowledge, intangible resources in general might not be specific enough to capture the capability required in the context of green innovation spillovers. Our result that the less established firms and the disadvantaged group reveal as the main beneficiaries in terms of productivity offers meaningful implications for the policy making designed to strive for long-term and balanced growth.

5.3.2 Managerial and policy implications

Our results in Chapter 4 offer empirical grounds for managers and policy makers aiming at promoting green technology by showing that green-tech companies are able to generate overall welfare effects on the wider economy.

First, not all the aspects of absorptive capacity are of equal importance. Measures of codified technological knowledge, instead of general knowledge assets, turn out to be more crucial under the condition of green spillovers absorption. Hence, businesses who wish to take advantage of this green transformation should focus on building their strong technological competence so as to maximise the benefits of knowledge spillovers and mitigate the induced demand-driven market disruptions.

Second, the organisational objectives of increased productivity and employment growth might not always be complementary. The national government may plan to formulate policies that promote green technology and an environmentally sustainable society, but the impacts of green innovation are not always favourable. Therefore, it is important for decision makers to recognise the implications of how green technology influences the productivity and growth in the wider economy when implementing policy goals.

More importantly, heterogeneity in the impacts of green innovation externalities across firm characteristics and industrial technological intensity highlights the necessity to design targeted policy instruments that specifically consider the variations in order to maximise the gains.

Our conclusion that the less established firms and the disadvantaged group are the main beneficiaries in terms of firm productivity has meaningful implications for the policy formulation intended to promote long-term and balanced growth.

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