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Harnessing Green Knowledge in Small and Medium Enterprises

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Harnessing Green Knowledge in Small and Medium Enterprises

Abstract

Green technologies play a crucial role in fostering regional comparative advantages during the sustainability transition. Despite their importance, the extent to which knowledge spillovers from these technologies impact a broad spectrum of firms remains underexplored. This study provides pioneering evidence on the independent and combined effects of green knowledge relatedness and green knowledge complexity on SMEs' firm-level productivity. Utilising data from Orbis Intellectual Property and Orbis Balance Sheet, encompassing 17,736 UK manufacturing firms from 2013 to 2020, we employ multilevel modeling estimations. Finer-grain analyses are conducted by splitting the regions into different groups, comparing the effects between regions with high and low levels of green knowledge relatedness and complexity. Our findings underscore the importance of both green knowledge relatedness and complexity, as well as their interaction, in enhancing SMEs' productivity. The paper concludes by providing a practical framework for SMEs in the green transition for the UK.

Plain English Summary

This study estimates the independent and combined effects of green knowledge relatedness and green knowledge complexity on firm-level productivity of small and medium-sized enterprises (SMEs). Utilising data from Orbis Intellectual Property and Orbis Balance Sheet, encompassing 17,736 UK manufacturing firms from 2013 to 2020, we employ multilevel modeling estimations with regional breakdowns. Both green knowledge relatedness and complexity, as well as their interaction, are significant in enhancing SMEs' productivity. The paper provides a practical framework for SMEs in the green transition for the UK.

Keywords: green knowledge spillovers; green knowledge relatedness; green knowledge complexity; productivity; SMEs

JEL classifications: L10; L20; O12; O33; Q55; R11

1. Introduction

Green innovation refers to the development of products, services, or processes that minimize environmental harm, impact, and deterioration while optimising resource use (Schiederig *et al.,* 2012). Regional and national policies have increasingly focused on supporting the creation and adoption of green technologies to achieve sustainable growth. Existing literature predominantly focuses on green innovation production (Becchetti *et al.,* 2022), green entrepreneurship (Colombelli and Quatraro, 2019; Corradini, 2019; DiVito and Ingen-Housz, 2021), the impacts of green innovation on firms' economic performance (Colombelli *et al.,* 2021), and environmental performance (Costantini *et al.,* 2017; Cojoianu *et al.,* 2024). Despite investigations into green knowledge spillovers from regional green knowledge investment and stock (Colombelli and Quatraro, 2019), it remains unclear how the composition of regional green knowledge (*e.g.,* similarities between green technological domains; the difficulty of producing and transferring green technologies across regions) influences the extent to which local firms benefit from green knowledge spillovers.

This paper addresses this gap by investigating how green innovation can generate knowledge spillovers that affect the economic performance of external firms using SME firm-level evidence. We adopt the concepts of knowledge relatedness and knowledge complexity from economic geography (Balland *et al.,* 2019). Knowledge relatedness indicates regions' technological capabilities and learning processes that share roots in similar knowledge domains (Balland *et al.,* 2022). Knowledge complexity represents regions' technological capabilities to produce non-ubiquitous knowledge, creating barriers to imitation for other regions (Yayavaram and Chen, 2015). We apply these concepts to green technologies and examine how SMEs can utilise green knowledge spillovers from regional green related and complex knowledge to boost productivity. The importance of addressing this question lies in evaluating the economic impacts of green technologies on SMEs that may not directly engage in creating green technologies in-house, but are exposed to knowledge spillovers from external green technologies.

Our empirical analysis is based on 17,736 UK manufacturing SMEs over the period 2013-2020 using Orbis balance sheet and Orbis Intellectual Property data from Bureau van Dijk. We hypothesise that regional related green knowledge can facilitate inter-firm learning by leveraging similar knowledge backgrounds, including scientific backgrounds and analytical skills (Aarstad and Kvitastein, 2020). Complex green knowledge could provide local firms with rare bundles of green knowledge elements, enabling them to extract economic benefits (Balland and Rigby, 2017). SMEs in regions can also benefit from the combined effect from related and complex green knowledge to enhance productivity.

This paper makes three contributions. First, our analysis provides a comprehensive understanding of how SMEs can leverage green knowledge spillovers from external related and complex green knowledge to autonomously enhance economic performance. Existing studies have predominantly focused on top-down and bottom-up approaches in promoting green technologies (Ball and Kittler, 2019; Cecere *et al.,* 2020; Colombelli *et al.,* 2021). While emphasising the significance of public funding and policies, key factors identified include firms' accumulated technological capacity, the ability to conduct mergers and acquisitions, build international connections, or establish overseas research centres for technological advancement (Hansen and Hansen, 2020; Schäfer *et al.,* 2024). However, these strategies are often challenging for SMEs to implement. Despite the high novelty and broad applicability of green technologies across various industries (Pearson and Foxon, 2012), its substantial potential to generate knowledge spillovers that enhance productivity has been largely overlooked (Dechezleprêtre, *et al*., 2014). Our paper addresses this gap by highlighting the necessity to complement existing research with an examination of how SMEs can autonomously identify and utilise green knowledge spillovers to boost economic performance in the green transition, supported by large-scale micro-level evidence.

Second, it offers a micro-level analytical framework and provides evidence of how regional green knowledge relatedness, green knowledge complexity, as well as their joint effect can shape local SMEs' economic performance. Although prior studies have typically examined these two dimensions separately (Davies and Maré, 2021; Pintar and Scherngell, 2021; Moreno and Ocampo-Corrales 2022), we still have limited understanding of how they come about when they are strategically combined (Balland *et al.,* 2019). The overarching reasoning for combining them is that without green related knowledge, knowledge spillovers may be difficult to realise because complex knowledge is more difficult to diffuse than simple knowledge (Balland and Rigby, 2017). On the other hand, despite the presence of a related green knowledge in the region, it is unlikely to generate economic benefits for local SMEs if the composition of knowledge is rather simple, easy to move across space, and can be easily copied by firms in other regions (Balland *et al.,* 2019).

Third, this paper contributes to the discussion about sub-national policies to boost SMEs' productivity. The existing literature predominantly explores how regions develop new green technologies (Montresor and Quatraro, 2020; Perruchas *et al.,* 2020; Santoalha *et al.,* 2021; Moreno and Ocampo-Corrales, 2022). It is equally crucial to examine the economic benefits derived from the exploitation of green technologies. There have been only a few attempts, not specially focusing on green technologies, to discover how knowledge relatedness and complexity affect regional economic performance (*e.g.,* employment or GDP) in Europe (Antonelli *et al.,* 2020; Mewes and Broekel, 2020; Davies and Maré, 2021; Pintar and Scherngell, 2021) and in China (Chatzistamoulou *et al.,* 2022). Addressing this gap at the firm level is essential for identifying targets of place-based development policies that support SMEs in the green transition. This paper also provides a practical application of the framework in the UK at the NUTS-2 regional level, offering valuable insights for sub-national policy-making.

2. Literature Review and Research Hypotheses

2.1 Knowledge relatedness and complexity

Regional knowledge relatedness and complexity are two building blocks of the smart specialisation literature on regional economic development (Balland *et al.,* 2019). A high degree of knowledge relatedness facilitates inter-firm learning through interactions. Firms tend to search new knowledge around their core knowledge domains. Inter-firm learning requires sharing and exchanging knowledge that is similar, but not identical, to facilitate knowledge spillovers without bringing in direct competition that can hinder mutual learning opportunities (Nooteboom *et al.,* 2007). A high degree of knowledge relatedness indicates that businesses in a region have similar "combinations of inputs, knowledge and routines" (Hidalgo, 2021), and this in turn allows knowledge spillovers between local firms to enhance productivity. Related knowledge shares similar cognitive capabilities, physical factors, infrastructure, institutions and routines (Balland *et al.,* 2019). Regional knowledge relatedness reflects the degree of complementary set of knowledge, skills and technological classes at regional level.

Complex knowledge is more difficult to generate, diffuse and imitate than simple knowledge. Knowledge complexity captures whether the knowledge produced in a region can be easily imitated by many other regions, and if the knowledge is complex that only a few regions have the capabilities to produce it. Not every region is capable of producing complex knowledge (Balland and Rigby, 2017). Regions that manage to develop complex knowledge create barriers for other regions to compete, and can enjoy long-run economic benefits (Balland *et al.,* 2019). As for empirical evidence, Mewes and Broekel (2020) and Pintar and Scherngell (2021) found that knowledge complexity drove regional GDP growth in Europe. However, Antonelli *et al.* (2020) suggested that knowledge complexity reduced labour productivity because complex knowledge could be difficult to apply and exploit benefits from.

Although knowledge relatedness and complexity are key drivers for regional economic development, they are typically examined separately (Balland *et al.,* 2022). A few exceptions include Balland *et al.* (2019) who suggested that regions could fix a growth path by developing more complex knowledge, and regions needed to develop more complex knowledge in knowledge domains where they have already developed related knowledge to minimise investment and risks. Pintar and Scherngell (2021) found that both knowledge relatedness and complexity drove regional economic growth in Europe. Even considering both knowledge relatedness and complexity (Balland and Rigby, 2017; Balland *et al.,* 2019; Rigby *et al.,* 2019; Perruchas *et al.,* 2020; Davies and Maré, 2021; Hane-Weijman *et al.,* 2022), little has been done to appreciate their potential joint effect at the micro (*i.e.,* firm) level.

2.2 Features of green technologies and their spillover potential

2.2.1 Cognitive and contextual specificity of green technologies

The development of green technologies typically involves integrating knowledge from distant and heterogeneous domains—such as environmental science, engineering, and public policy—which demands interdisciplinary collaboration and increases the need for interdisciplinary collaboration (Barbieri *et al.,* 2020). This broad knowledge base makes green technologies more sensitive to local contexts, in contrast to the standardised and technically specialised nature of non-green technologies (De Marchi, 2012).

In terms of transferability, green knowledge encompasses both codified elements (*e.g.,* patents, standards, manuals) and tacit components, including experiential know-how and collaborative routines. The tacit dimension is particularly significant, as green technologies often require adaptation to local environmental conditions and integration into existing production systems. Consequently, their diffusion relies more heavily on relational and experiential mechanisms than on formal, codified channels.

These characteristics make green knowledge more prone to spillovers than non-green knowledge. Its context-dependent and tacit nature means that effective transfer often depends on proximity, trust, and interactive learning—such as through partnerships and collaborative routines. This aligns with theories of localised learning and innovation, which emphasise the importance of relational networks in facilitating knowledge exchange.

2.2.2 Cross-sectoral applicability and structural diversity

Green technologies are characterised by broad applicability and cross-sectoral relevance. They are more frequently cited and deployed across diverse technological domains, reflecting their potential for recombination and diffusion beyond their original context (Colombelli and Quatraro, 2019). This wide-ranging relevance stems from their foundation in diverse knowledge bases, which span multiple disciplines and industries.

These structural features make green knowledge more prone to spillovers than non-green knowledge. The cross-sectoral nature of green technologies facilitates knowledge transfer across industries, especially in regions with dense innovation networks. Their diversified foundations increase the likelihood that insights developed in one domain can be adapted and applied elsewhere, enhancing inter-industry diffusion.

2.2.3 Institutional support and policy-driven diffusion

Third, green technologies are frequently embedded in policy and institutional frameworks—including environmental regulations, subsidies, and mission-oriented R&D programmes—that actively promote their production and adoption (Porter and van der Linde, 1995). These institutional supports reduce barriers to knowledge access and amplify spillover effects, particularly for resource-constrained firms.

2.3 Importance of green knowledge spillovers for SMEs

The tacit dimension of green knowledge is particularly important for SMEs, as successful adoption often requires hands-on learning, adaptation to local conditions, and interaction with external partners. SMEs typically face financial and human resource limitations that restrict their ability to develop green technologies in-house. (Hervas-Oliver *et al.,* 2020). External green knowledge can create spillover effects, enabling SMEs to access and assimilate various subsets of green knowledge. This process helps them overcome internal technological limitations to enhance efficiency.

For SMEs with limited in-house managerial expertise, external green technologies provide access to innovative ideas and green practices from other firms and industries. They can benefit from collaborative routines, peer learning, and informal exchanges with other firms and institutions. It can help them integrate new knowledge into their operations, enabling them to internalise new green technologies and boost efficiency (Cecere *et al.,* 2020).

The cross-sectoral nature of green technologies means that spillovers are not confined to specific industries. SMEs across various sectors can benefit from green innovations developed in other industries, especially in regions with a rich and diverse green technology bases (Colombelli and Quatraro, 2019).

Prior studies have highlighted that knowledge spillovers are mediated by firm-level absorptive capacity — the ability to identify, assimilate, and apply external knowledge (Cohen and Levinthal, 1990). This capacity is shaped by prior knowledge, managerial experience, and organisational routines, which influence how effectively firms can internalise externally sourced knowledge. This paper proposes that even SMEs with limited internal capabilities can benefit from green knowledge spillovers to improve performance, provided that such knowledge is deeply embedded in local knowledge networks. The following sections outline the channels through which green knowledge relatedness and green knowledge complexity generate spillovers that enhance SMEs' productivity.

2.4 The impact of green knowledge relatedness on SMEs' productivity

There are at least three reasons to expect that firm productivity could be determined by regional green knowledge relatedness. First, related green knowledge facilitates inter-firm learning by reducing cognitive distance between firms and external green knowledge sources (Hidalgo, 2021). SMEs, often lacking internal capacity to adapt green technologies, benefit from proximity to green knowledge producers—such as suppliers, customers, and business networks—which enables the transfer of tacit knowledge and best practices. This could also occur via buyer-supplier linkages where suitable knowledge producers allow continuous interactions for SMEs to grasp new green knowledge and improve productivity. Even when SMEs operate in cognitively distant technological domains, exposure to related knowledge can help them adopt greener inputs, production methods, and problem-solving approaches (Ghisetti *et al.,* 2015).

Second, co-location with related green knowledge producers enhances SMEs' access to specialised expertise, research infrastructure, and support services, and helps them identify green technology opportunities and improve production efficiency (Pintar and Scherngell, 2021). Co-location with green knowledge producers increases SMEs' likelihood to identify emerging green technologies and market trends, such as new green raw materials, cleaner methods of production, and technologies to re-use products at the end of product life-cycles. This enables cost reductions and efficiency gains (Kveton *et al.,* 2022).

Third, regions rich in related green knowledge offer access to human capital with relevant green skills. These skills are particularly important for applying green technologies, which often require higher analytical capabilities than conventional ones (Horbach *et al.,* 2013). Workers' experience in related knowledge fields could help SMEs better evaluate the feasibility and applicability of new green technologies for cost saving and productivity improvements (Jara-Figueroa *et al.,* 2018). Labour mobility further facilitates the diffusion of tacit knowledge and conforms green knowledge to different practices across industries (Östbring *et al.,* 2018). We therefore propose:

Hypothesis 1: Green knowledge relatedness is positively associated with SMEs' productivity.

2.5 The impact of green knowledge complexity on SMEs' productivity

Regional green knowledge complexity—defined by the sophistication and rarity of technological capabilities—can significantly enhance SME productivity. Such knowledge typically emerges in regions with dense networks of specialised firms, skilled labour, and supportive institutions (Maskell and Malmberg, 1999). These regions often possess robust interpersonal connections and well-established local innovation networks (Antonelli *et al.,* 2017). SMEs embedded in these environments benefit from access to advanced green skills, including understanding customer needs, adopting cleaner production approaches, and developing sustainable supply chain strategies (Vona *et al.,* 2015). Proximity to complex knowledge enables learning through collaboration, labour mobility, and informal spillovers.

Moreover, complex green technologies also offer higher economic returns and stronger spillover potential due to their novelty and broad applicability (Ardito *et al.,* 2016). SMEs engaging with such technologies can improve productivity by entering higher-value markets and leveraging strategic partnerships, imitation, or reverse engineering (Roper *et al.,* 2017).

Importantly, local access to complex knowledge reduces the need to source expertise from distant regions, minimising knowledge transmission and interpretation errors, and facilitating timely problem-solving (Tubiana *et al.,* 2022). Continuous interaction with local green knowledge producers supports the effective adoption of green technologies, particularly in adapting raw materials, production processes, product designs and technical integration with external partners (De Marchi, 2012). Therefore, minimising communication errors with local green knowledge providers can enable SMEs to effectively leverage complex external green knowledge, thereby enhancing productivity. We therefore propose:

Hypothesis 2: Green knowledge complexity is positively associated with SMEs' productivity.

While complex knowledge may pose internalisation challenges—such as higher cognitive demands and integration costs (Antonelli *et al.,* 2020)—SMEs in regions with strong knowledge creation and diffusion networks are better positioned to overcome these barriers. Mechanisms such as labour turnover and peer learning help SMEs access and absorb complex green knowledge (Aboelmaged and Hashem, 2019). These channels reduce the costs and risks of adoption, enabling SMEs to benefit from complex green knowledge without needing to develop them entirely in-house.

2.6 Joint effect of green knowledge relatedness and complexity on SMEs' productivity

The motivation to interact green knowledge relatedness and complexity is that regions with high relatedness possess a coherent technological structure that facilitates recombination for innovation, while regions with high complexity host rare and diverse knowledge domains that offer substantial potential for innovation and economic development. When these two dimensions co-exist, novel yet cognitively proximate knowledge combinations are possible. Theoretical perspectives from evolutionary economics and economic geography (*e.g.,* Balland *et al.,* 2019) suggest that such environments foster innovation and economic growth, making the joint presence of relatedness and complexity particularly conducive to productivity gains.

There are at least two reasons to expect that knowledge relatedness and complexity jointly contribute to SMEs' productivity. First, relatedness indicates the degree of connection between knowledge domains, enabling regions to build on existing capabilities to develop new technologies (Balland *et al.,* 2022). Knowledge complexity captures the rarity and difficulty of replicating knowledge, offering SMEs access to diverse non-ubiquitous knowledge that fuels productivity (Glaeser *et al.,* 1992). While expanding into related knowledge domains may risk a "lock-in" effect, where regional capabilities do not extend to unfamiliar domains, knowledge complexity broadens the scope for valuable technological advancements that drive productivity gains (Balland *et al.,* 2019).

Second, regions rich in both related and complex knowledge support more efficient resource (re-)allocation and resilience to economic shocks. Jobs requiring complex knowledge yield stronger growth multipliers (Hane-Weijman *et al.,* 2022), and shared competencies allow faster adaptation during downturns (Davies and Maré, 2021).

Exposure to related green knowledge locally facilitates interactive learning among firms, promoting green knowledge spillovers and enhancing SMEs' productivity. Improving production efficiency often involves adopting cleaner production technologies, supported by novel changes in industrial design and engineering mechanisms (Marzucchi and Montresor, 2017). The broad scope of green knowledge suggests that it is challenging for SMEs to source such knowledge from a single external provider (Ghisetti *et al.,* 2015). The presence of multiple green knowledge providers with related knowledge makes it easier for SMEs to identify, acquire, and internalise external green knowledge to improve productivity. SMEs can either jointly develop green knowledge with external knowledge providers or learn to acquire green knowledge spillovers to reduce production costs. Due to the complexity of knowledge, localised individuals, networks and routines create barriers for firms in other regions to imitate. Consequently, SMEs in regions with complex green knowledge can leverage access to rare bundles of green knowledge to enhance efficiency.

In summary, related green knowledge facilitates green knowledge dissemination and spillovers, while complex green knowledge offers significant opportunities for economic benefits. Furthermore, more complex knowledge can be challenging for firms to internalise, exploit, and benefit from spillovers to boost productivity (Antonelli *et al.,* 2020). These challenges can be mitigated by a robust green knowledge base. The cognitive proximity between green knowledge domains makes it easier for local SMEs to absorb even complex green knowledge compared to more distant domains (Hidalgo, 2021). Therefore, green knowledge relatedness and complexity are expected to jointly contribute to firm productivity. We therefore propose:

Hypothesis 3: Green knowledge relatedness and complexity are jointly positively associated with SMEs' productivity.

3 Data and Model

3.1 Data

This paper follows the mainstream literature to measure green technologies by patents that have their International Patent Classification (IPC) codes listed in the World Intellectual Property Organisation (WIPO) IPC Green Inventory, or their Cooperative Patent Classification (CPC) codes listed as "Greenly Sound Technologies" (ENV-TECH) technology domains by the OECD (2016) (Perruchas *et al.,* 2020; Moreno and Ocampo-Corrales, 2022).

The data to construct the green knowledge relatedness and complexity variables are obtained from the Orbis Intellectual Property database. The most relevant information to this study includes patent application date, International Patent Classification (IPC) code and Cooperative Patent Classification (CPC) code which show technological classes, and patent owners' NUTS-2 location. The other variables are based on balance sheet data from the Bureau van Dijk Orbis. A total of 82,668 observations for 17,736 manufacturing firms in the UK during 2013-2020 were included in this analysis.

3.2 Key explanatory variables

The first key variable is green knowledge relatedness density, which proxies the degree of proximity between a green technology and the green technological portfolio of a region. This is generated by two steps. First, we calculate the degree of relatedness between green technologies, following the knowledge space framework applied by Boschma *et al.* (2015) and Balland and Boschma (2021). It captures technology relatedness through the frequency of co-occurrence of two technology classes in patents. The co-occurrences are normalised using the cosine similarity index (Balland and Boschma, 2021). In this $n \times n$ network, each node a (a = 1, ..., n) represents a specific green technological class. There are 118 four-digit green IPC classes present in 41 NUTS-2 regions in the UK. The relatedness ϕ_{abt} between each pair of technologies a and b is generated by taking the minimum of the pair-wise conditional probabilities of regions patenting in the technological class a given that they patent in the technological class b during the same period:

$$\phi_{abt} = min\{P(RTAx_{at}|RTAx_{bt}), P(RTAx_{bt}|RTAx_{at})\}$$

where a region r has a revealed technological advantage (RTA) in green technology a in time t if the share of this technology a in the region's green technological portfolio is higher than the share of this technology a in the entire green patent portfolio in the UK. More specifically, if:

$$\frac{green\,patents^t_{r,a} / \sum_a green\ \ patents^t_{r,a}}{\sum_r green\ \ patents^t_{r,a} / \sum_r \sum_a green\ \ patents^t_{r,a}} > 1, RTA^t_{r,a} = 1, and\ \ 0\ \ otherwise$$

In the second step, the density of related green knowledge around a specific green technology a in region r at time t is derived from the sum of relatedness ϕ_{abt} of the focal green technology a to all the other green technologies b in which the region has an RTA, divided by the sum of relatedness of this green technology a to all the other green technologies b in all the regions (*i.e.*, UK as a whole) at time t.

Knowledge relatedness density has a minimum value of 0 when no other green technologies are related to the focal green technology a present in region r at time t, and it takes the maximum value of 100 when all the other green technologies related to the green technology a are present in the region r at time t:

$$Green\ \ knowledge\ \ relatedness\ \ density_{art} = \frac{\sum_{b\in r, b\neq a} \phi_{abt}}{\sum_{b\neq a} \phi_{abt}} * 100$$

Another key variable is green knowledge complexity index. Based on Hidalgo and Hausmann (2009), a binary-valued network is constructed which links regions to green patent IPC where they have an RTA. It is an $n \times k$ two-mode binary matrix $M_{r,z}$ which has dimension n = 41 NUTS-2 regions by z = 118 green technological domains. Green knowledge complexity index is an iteration between two variables: the diversity of region r and the ubiquity of green technology z. The degree of diversity of a region is given by the number of green technologies where the region has RTA:

$$k_{r,o} = \sum_{z} M_{r,z}$$

The degree of ubiquity of a green technology is given by the number of regions with an RTA in this green technology:

$$k_{z,o} = \sum_{r} M_{r,z}$$

Green knowledge complexity index (green KCI) is the iteration of diversity and ubiquity, following Balland and Rigby (2017):

$$Green\ \ KCI_{r,n} = \frac{1}{k_{r,0}} \sum_{z} M_{r,z} k_{z,n-1}$$

$$Green\ \ KCI_{z,n} = \frac{1}{k_{z,0}} \sum_{z} M_{r,z} k_{y,n-1}$$

For $n = 1$, $Green\ \ KCI_{r1}$ represents the average ubiquity of the green technologies where region y has RTA. For $n = 2$, $Green\ \ KCI_{r2}$ represents the average diversity of regions that have green technologies similar to region r. The matrix $M_{r,z}$ and its transpose $(M_{r,z}^{T})$ are row standardised. The product matrix $(B = \ M_{r,z} \times M_{r,z}^{T})$ is a square matrix with dimensions equal to the number of NUTS-2 regions. The green knowledge complexity index for each region r is provided by the second highest eigenvalue of the projected region-region matrix B:

$$\overrightarrow{Green\ \ KCI_r} = \frac{\vec{K} - average(\vec{K})}{stdev(\vec{K})}$$

3.3 Control variables

Firm-level controls include the share of green patent stock in total patent stock, capturing firms' accumulated green technological capabilities that can boost productivity (Leoncini *et al.,* 2019). Patent data from the Orbis Intellectual Property database are used to construct patent stock and total patent stock following the perpetual inventory method (Guellec and Potterie, 2004). In addition, intangible assets are included as a control variable to account for SMEs' internal knowledge and innovation capacity. According to Orbis, intangible assets encompass research and development expenses, goodwill, and knowledge development costs. These components reflect a firm's investment in non-physical resources that contribute to innovation, learning, and competitive advantage, which are found to be positively associated with firm-level productivity (Higon *et al.,* 2017). Firm size and age are measured by the number of employees and years since establishment, respectively. As for the regional control, a regional diversification index is included by counting the number of green technologies in which a region has RTA based on the region-green technologies matrix $M_{r,z}$ (Pintar and Scherngell, 2021). Industry-level controls include market concentration (Herfindahl-Hirschman index), industry size (total number of employees), and industry sales growth at the NACE2 level (Cainelli *et al.,* 2019; Howell, 2020). NACE2 industry dummies and year dummies are included to control for the aggregate industry and year-specific fixed effects, respectively. Table 1 presents the summary statistics. Figure 1a and Figure 1b demonstrate the regional heterogenous distribution of green knowledge relatedness and green KCI.

3.4 Model

The model for the empirical estimations can be expressed as:

$$\begin{aligned} Productivity_{isrt} = {} & \beta_0 + \beta_1 Green\ \ knowledge\ \ relatedness_{rt-1} + \beta_2 Green\ \ KCI_{rt-1} + \\ & \beta_3 Green\ \ knowledge\ \ relatedness_{rt-1} \times Green\ \ KCI_{rt-1} + \ Firm\ \ controls_{it-1} + \\ & Regional\ \ control_{rt-1} + Industry\ \ controls_{st-1} + Industry\ \ dummies_s + \\ & Year\ \ dummies_t + c_i + u_{it} \quad \textit{Eq. (1)} \end{aligned}$$

where $Productivity_{isrt}$ is the productivity of a manufacturing SME i in NACE2 industry s in region r in year t. c_i in the error term is the unobserved individual heterogeneity, and u_{it} is the idiosyncratic errors. Productivity is measured by Total Factor Productivity (TFP) following Levinsohn and Petrin (2003). It addresses simultaneity bias in production function estimation by using intermediate inputs (*e.g.,* materials) as proxies for unobserved productivity shocks. This method assumes that firms choose input levels based on their productivity, and that intermediate inputs respond more flexibly to productivity than capital. The estimation is performed using a semi-parametric procedure that recovers productivity as the residual from a production function, controlling for input choices (see Appendix A for more details). All the explanatory variables are lagged one year to address the potential endogeneity concern (Moreno and Ocampo-Corrales, 2022).

3.5 Estimation method

We use multilevel modelling as the key estimator to address the concern that parameters vary at more than one level (Antonakis *et al.,* 2021). More specifically, the dependent variable is at the firm level nested in a higher level NUTS-2 region. As for robustness checks, we used the linear panel fixed effects estimation because the continuous nature of the dependent variable makes this estimator the most appropriate. The approach also has the advantage of allowing for any correlations between the explanatory variables and the individual unobserved heterogeneity (c_i) in the error term, thus controlling for bias due to unobserved heterogeneity and omitted variables (Wooldridge, 2010). The explanatory variables are assumed to be exogenous with respect to the idiosyncratic error terms (u_{it}).

Multilevel modeling is preferred because it explicitly accounts for the hierarchical structure of SMEs nested within NUTS-2 regions. It allows the inclusion of both firm-level and region-level predictors while modeling the dependency among SMEs within the same region. Unlike fixed effects models, which discard between-group variation and assume independence across units, multilevel modeling provides a coherent framework that respects the nested data structure and improves inference. Appendix B provides details comparing both estimation methods.

To explore whether the relationship between the explanatory variables and the outcome varies across different regional contexts, we split the sample based on the median value of green knowledge relatedness and complexity. This helps uncover whether the effect of key variables is stronger or weaker in different regional environments. If results differ across subsamples, it suggests that the effect of certain variables may be conditional on the regional context, which is important for policy and theoretical implications.

4 Findings

4.1 Main results

Table 2 Column (1) shows suggestive evidence that green knowledge relatedness is positively related to SMEs' productivity ($\beta_{\text{Green knowledge relatedness}} = 0.004$, $p < 0.10$). It provides tentative support for Hypothesis 1 at the 10% level. This finding indicates that SMEs in regions that have more related green technologies are more likely to capture new technological benefits to boost productivity.

Moreover, column (1) also shows that regional green knowledge complexity is significantly and positively related to SMEs' productivity ($\beta_{\text{Green knowledge complexity}} = 0.039$, $p < 0.01$), supporting Hypothesis 2.

Column (2) shows that the interaction term between green knowledge relatedness and green knowledge complexity is significantly positive ($\beta_{\text{Green knowledge relatedness * Green knowledge complexity}} = 0.004$, $p < 0.01$). It indicates that SMEs in regions with highly related green knowledge tend to enjoy extra benefits from complex green knowledge to drive up productivity, supporting Hypothesis 3.

Figure 2 is marginal effects graph presents three lines representing the predicted impact of green knowledge complexity on SMEs' productivity at different levels of green knowledge relatedness. These levels are defined using the 25th, 50th (median), and 75th percentiles of the green knowledge relatedness variable across UK regions. The orange dashed line corresponds to low relatedness (25th percentile), the blue solid line represents medium relatedness (median), and the green solid line reflects high relatedness (75th percentile). As complexity increases, TFP rises across all levels of green knowledge relatedness. However, the slope of the increase is steeper in regions with higher relatedness (*i.e.,* 75th percentile). This indicates that the productivity-enhancing effect of green knowledge complexity is stronger in regions where green technologies are more related, reinforcing the idea that relatedness amplifies the benefits of complexity.

As for other control variables, SMEs that have higher share of green patent stock and those with more intangible assets have higher productivity. Larger and older SMEs have higher productivity. SMEs in larger-sized industries and industries that experienced higher growth rate tend to have higher productivity. However, regions with more diversified technological domains are negatively associated with SMEs' productivity.

4.2 A fine-grained analysis

Next, a fine-grained analysis is conducted by splitting the regions into high versus low relatedness by the median value of green knowledge relatedness density across the UK, similar to Balland *et al.* (2019). High green knowledge relatedness regions are the NUTS-2 regions that have higher than the median value of green knowledge relatedness across the NUTS-2 regions in the UK, whereas low green knowledge relatedness regions have less than the median value of green knowledge relatedness across the UK.

Column (3) includes only regions with high green knowledge relatedness as a sub-sample for estimation. The interaction term stays significantly positive with a larger magnitude ($\beta_{\text{Green knowledge relatedness * Green knowledge complexity}} = 0.021$, $p < 0.01$) than that in column (2), suggesting that SMEs benefit more from complex green knowledge in regions with highly related green knowledge. Green knowledge complexity is still significantly positive ($\beta_{\text{Green knowledge complexity}} = 0.045$, $p < 0.10$), but only at 10% level. Also, green relatedness becomes insignificant in the sub-sample of regions all of which have high green knowledge relatedness. In contrast, column (4) includes only regions with low green knowledge relatedness as an estimation sub-sample. Green knowledge complexity becomes significantly negative at 10% level ($\beta_{\text{Green knowledge complexity}} = -0.044$, $p < 0.10$) and also the interaction term becomes negative at 10% level ($\beta_{\text{Green knowledge relatedness * Green knowledge complexity}} = -0.007$, $p < 0.10$).

Furthermore, regions are divided into high versus low green knowledge complexity by the median value of green knowledge complexity across the UK. High green knowledge complexity regions are the NUTS-2 regions that have higher than the median value of green knowledge complexity across the NUTS-2 regions in the UK, whereas low green knowledge complexity regions have less than the median value of green knowledge relatedness across the UK. Column (5) only includes the regions with high green knowledge complexity. Notably, green knowledge relatedness ($\beta_{\text{Green knowledge relatedness}} = 0.009$, $p < 0.05$), green knowledge complexity ($\beta_{\text{Green knowledge complexity}} = 0.058$, $p < 0.05$) and their interaction ($\beta_{\text{Green knowledge relatedness * Green knowledge complexity}} = 0.009$, $p < 0.01$) remain significantly positive, and the magnitude of their marginal effects double compared with that in column (2). By comparison, in column (6), green knowledge complexity ($\beta_{\text{Green knowledge complexity}} = -0.132$, $p < 0.10$) is significantly negative at 10% level. Its interaction with green knowledge relatedness ($\beta_{\text{Green knowledge relatedness * Green knowledge complexity}} = -0.011$, $p < 0.05$) becomes significantly negative at 5% level.

4.3 Additional robustness checks[1]

First, we use linear fixed effects estimation in Table 3 columns (1) and (2), with clustered standard errors by firms to allow account for firm-level clustering. This estimation method does not explicitly consider that SMEs are nested within a higher (*i.e.,* regional) level. As the multilevel modeling estimation already allows for correlations between different levels, it is not surprising that the linear fixed effects estimation reports consistent results, as it equivalently allows for any correlations between the explanatory variables and the error term. The results for green knowledge relatedness and complexity, as well as their interaction effects, are consistent with those in Table 2.

Second, we adopt the Mundlak approach by adding level-1 and level-2 mean values of all the explanatory variables, as shown in columns (3) and (4). These additional mean values of explanatory variables are also known as contextual effects in multilevel modeling. Consistent results are observed.

Third, we also add potential confounding factors at the regional level (*i.e.,* transport infrastructure length, and share of high-tech sector employment) to account for broader structural factors that may influence SMEs' productivity. Appendix F show that they have expected signs but are insignificant. Results are similar to that in Table 2.

Forth, to allow for heterogeneity in SMEs' absorptive capacity and innovation intensity, we add interaction terms between green knowledge variables and firm-level indicators (*i.e.,* share of green patent stock and intangible assets) in Appendix

[1] The results presented reflect statistical associations rather than causal effects. While the robustness checks support the consistency of these relationships, further research is needed to establish causal mechanisms.

G and Appendix H, respectively. These additional interaction terms are insignificant and the results are consistent with that in Table 2.

Fifth, rather than median splits, we conduct subsample analysis using top and bottom 25th percentiles of green knowledge relatedness and complexity in Appendix G and Appendix H[2]. These more extreme values still show that more related and complex green knowledge benefits SMEs' productivity.

Sixth, we use labour productivity as an alternative dependent variable in Appendix I and J. Results are weaker when splitting the sample using median values. This is not unexpected and the difference likely reflects the conceptual distinction between labour productivity and total factor productivity. Labour productivity measures output per unit of labour input and captures only one dimension of firm performance. In contrast, total factor productivity accounts for the efficiency with which all inputs — including labour, capital, and intermediate goods — are used in production. and suggests that the regional knowledge environment influences firm performance through broader mechanisms than labour efficiency alone.

5 Discussion

5.1 Research implications

Green knowledge meets the VRIO criteria—valuable, rare, inimitable, and difficult to organise—making it a strategic resource for enhancing firm productivity (Barney, 1991). From an open innovation perspective (Chesbrough, 2003), SMEs can leverage external networks to access and exploit regional green knowledge spillovers. Regions with high levels of related or complex green knowledge often host coherent technological structures that generate economies of scope (Rocchetta *et al.,* 2022). SMEs could maximise the learning outcome to boost productivity as they learn and internalise externally-sourced green technologies to boost efficiency. On the contrary, SMEs in regions with cognitively distant green domains may struggle to absorb and benefit from such knowledge, as we find that they do not appear to benefit from regional green knowledge to improve productivity. Prior research highlights the role of knowledge relatedness in regional technological diversification (Balland and Boschma, 2022), with growing

[2] Interpretations are added in the Notes under Appendix H.

attention to its importance in developing green specialisations (Montresor and Quatraro, 2020; Perruchas *et al.,* 2020; Santoalha *et al.,* 2021). Some studies focusing on the occupational relatedness find contradictory results (Davies and Maré, 2021; Hane-Weijman *et al.,* 2022) regarding whether such relatedness supports regional economic growth. This study contributes to the literature by providing the first evidence on how regional green knowledge relatedness can shape SMEs' firm-level economic performance.

Regarding the knowledge complexity theory, which was originally developed to explain country-level economic performance (Hidalgo and Hausmann, 2009), has recently been applied to regional and industry contexts with mixed findings (Rigby *et al.,* 2019; Mewes and Broekel, 2020; Chatzistamoulou *et al.,* 2022). Some studies suggest that complexity may hinder productivity due to the difficulty of applying diverse and specialised knowledge (Antonelli *et al.,* 2020; Bucci *et al.,* 2021). In contrast, our findings support the theory, showing that regional green knowledge complexity enhances SME efficiency, probably via providing multi-purpose technologies that enhance production efficiency and product quality while meeting environmental standards (Barbieri *et al.,* 2020). This paper contributes to the literature by offering the first micro-level evidence that regional green knowledge complexity positively influences SME productivity, possibly due to the broad applicability of green technologies across industries (Colombelli and Quatraro, 2019).

Moreover, the joint effects from knowledge relatedness and complexity is rarely studied. One exception is Davies and Maré (2021) who observed positive joint impact from occupational relatedness and complexity on employment growth in a few large cities in New Zealand. In contrast, our findings reveal broader green knowledge spillovers that enhance SME productivity. Locating in regions with existing green related knowledge can help SMEs gain extra efficiency from complex green knowledge. One possible reason is that green related knowledge can enhance regional abilities to develop new green knowledge that can further enhance productivity, meanwhile green complex knowledge has low substitutability and can establish barriers for SMEs in other regions to imitate and reduce competition. Despite the challenges to implement complex green knowledge, having a robust green knowledge base makes firms more likely to absorb external green complex knowledge (Hidalgo, 2021). Conversely, the absence of either dimension limits SMEs' ability to benefit from green knowledge spillovers. In short, green knowledge relatedness conditions the extent to which SMEs can benefit from complex green knowledge.

Our findings on the joint effects of green knowledge relatedness and complexity can also be interpreted through the lens of dynamic capabilities (Teece *et al.,* 1997) - a firm's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments. The observed threshold effects—where SMEs in regions with both high relatedness and high complexity experience greater productivity gains—suggest that these firms may be leveraging external green knowledge in combination with internal capabilities. This interplay reflects dynamic capabilities, which enable firms to adapt, innovate, and sustain competitive advantage in evolving technological landscapes. While we do not directly measure dynamic capabilities, our results imply that such capabilities may underpin SMEs' ability to benefit from complex and related green knowledge.

While prior green innovation studies have focused on the performance of green technology producers (Leoncini *et al.,* 2019), less attention has been paid to productivity gains via green knowledge spillovers. Given the characteristics of green technologies and the economic importance of SMEs in the UK, this paper suggests that SMEs can benefit from locally embedded related and complex green knowledge to enhance their productivity. This extends existing studies that either emphasises top-down policy interventions (*i.e.,* via public funding and policies) or bottom-up approaches (*i.e.,* significant investment in internal R&D efforts) to develop and utilise green technologies (Ball and Kittler, 2019; Schäfer *et al.,* 2024). By examining the composition of regional green knowledge—specifically its relatedness and non-ubiquity—this study moves beyond the notion of green knowledge stock to explore its spillover effects (Colombelli and Quatraro, 2019; Corradini, 2019). The findings suggest that SMEs can enhance productivity by autonomously accessing and exploiting local green knowledge.

5.2 Policy implications

This study contributes to the policy debate on regional attractiveness for green investments. First, policymakers can use patent-based indicators of green knowledge relatedness and complexity to inform place-based strategies, such as identifying which green technological domains have developed revealed technological advantage, which are related to a region's existing green knowledge base, and which are complex to yield economic benefits. Policymakers can prioritise green technological domains that are both feasible and economically promising. Complexity measures help highlight non-ubiquitous green technologies that may yield higher returns but require targeted support. Effective policies would entail the evaluation and identification of the strengths of existing green technological capabilities, and investments in domains that can yield the highest economic benefits. These indicators can be integrated into regional innovation dashboards, making green knowledge spillovers both measurable and targetable.

Second, our categorisation of UK NUTS-2 regions provides a practical framework for applying these insights. Some regions may maximise benefits by expanding into related green technological domains to better extract economic benefits from complex green knowledge. Conversely, other regions may benefit more by deepening efforts in more complex strategic areas.

5.3 Managerial implications

To illustrate the practical relevance of green knowledge spillovers, consider two UK regions. The Humber region leveraged its existing industrial base in maritime engineering and logistics to diversify into offshore wind technologies, with firms like Siemens Gamesa benefiting from local skills and supply chains. This reflects how green knowledge relatedness can lower barriers to innovation (HullCCNews, 2019). In addition, the Orkney Islands developed leadership in tidal stream energy—a highly complex technology—by coordinating across diverse domains such as marine engineering and environmental science (Anthony, 2017). These cases demonstrate how regional capabilities can support firms in absorbing and adapting complex green knowledge, highlighting the importance of dynamic capabilities in translating spillovers into economic performance.

Based on these examples, SMEs' managers should invest in business and social networks, and collaborations with firms that produce green knowledge to introduce new ideas for process innovation, product design, distribution channels for green products, risk management associated with adopting green technologies in production, and cost-savings to enhance production efficiency. Linking internal know-how with external, especially complex and hard-to-imitate, green knowledge can enhance productivity. This requires strengthening absorptive capacity to evaluate and assimilate external knowledge (Cohen and Levinthal, 1990), and developing internal learning routines and cross-functional capabilities to adapt and reconfigure resources—core elements of dynamic capabilities essential for navigating evolving green innovation landscapes.

5.4 Limitations

First, the effect of green knowledge relatedness is only marginally significant (10% level) across UK regions and should be tested in other contexts. Although we lag independent variables by one year to reduce reverse causality, potential endogeneity from omitted variables or simultaneity remains. Thus, findings should be interpreted as correlational, not causal.

Second, while our robustness checks do not confirm a significant role for SMEs' absorptive capacity (Cohen and Levinthal, 1990), this does not imply it is unimportant. It may suggest that external green knowledge benefits a broad range of SMEs, not only those with high absorptive capacity. Future research should explore this with richer measures of firm-level heterogeneity.

Third, although dynamic capabilities are conceptually relevant, we do not directly measure them. Future studies should develop empirical strategies to capture firms' ability to reconfigure internal and external knowledge, especially in green innovation contexts.

Forth, the knowledge relatedness and complexity measures are based on RTA. While other metrics exist, they rely on different foundations and are not directly applicable within our framework. We acknowledge this as a limitation and suggest future work could explore suitable alternatives.

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Table 1: Summary statistics

	Mean	Std. Dev.	Min	Max
Dependent variable				
Total factor productivity	3.623	2.637	-3.348	9.417
Labour productivity	2.459	2.178	-2.580	11.601
Green Knowledge Spillovers				
Green knowledge relatedness	16.257	6.804	0.902	34.765
Green knowledge complexity index (green KCI)	0.006	0.177	-1.890	1.010
Firm Characteristics				
Green patent stock share	1.439	9.540	0	100
Intangible assets (logarithm)	0.466	1.313	0	9.170455
Firm size (logarithm)	3.704	1.269	0.693	5.521
Firm age	26.120	19.998	1.000	88.000
Region and Industry Control Variables				
Regional technological diversification index	18.590	8.551	1.000	41.000
Herfindahl index	0.085	0.113	0.006	1.000
Industry size	11.393	0.824	6.172	12.727
Industry sales growth	0.024	0.215	-1.588	1.919
Transport (motorways and roads) length (logarithm)	10.403	0.416	9.607	10.993
Share of high-technology manufacturing employment in total employment	0.971	0.369	0.380	1.710
Observations	82,668			

Figure 1a

Figure 1b

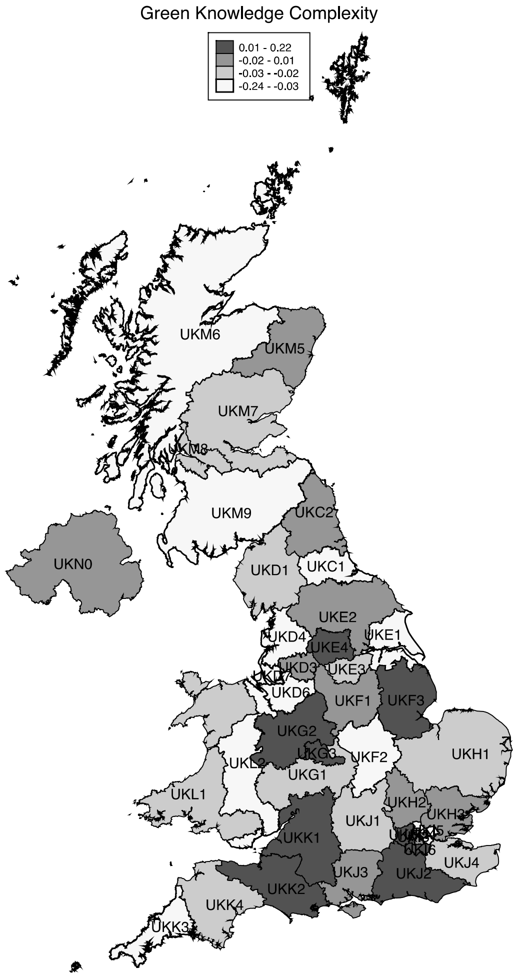
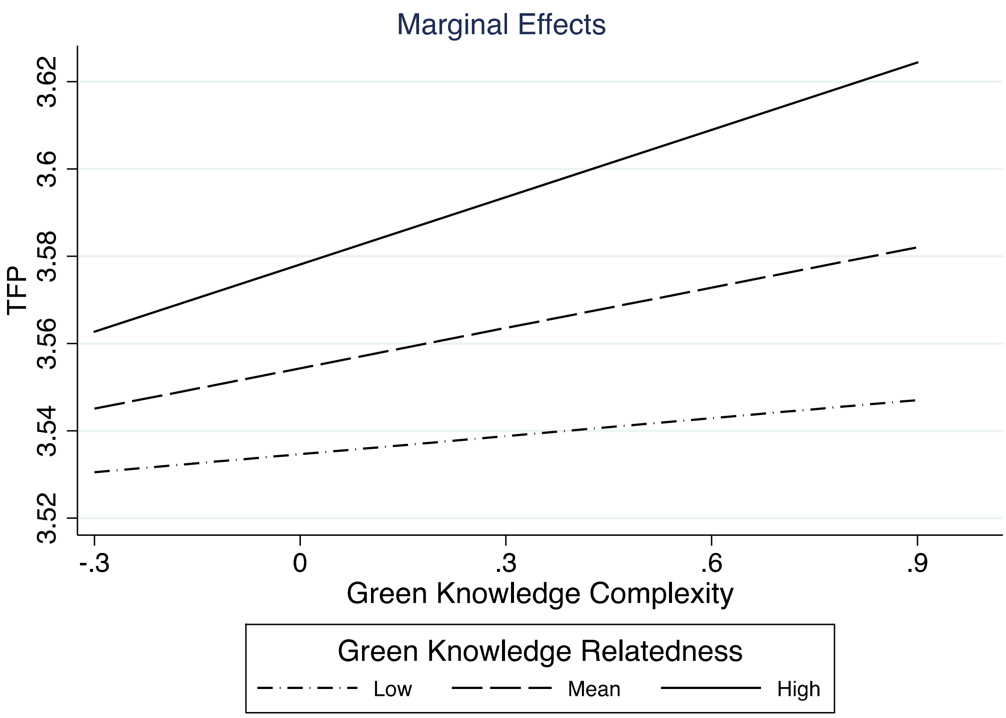


Table 2: Impacts of green knowledge relatedness and complexity on SMEs' productivity

	(1)	(2)	(3)	(4)	(5)	(6)
	All regions	All regions	High green knowledge relatedness regions	Low green knowledge relatedness regions	High green knowledge complexity regions	Low green knowledge complexity regions
Green Knowledge Spillovers						
Green knowledge relatedness	0.004*	0.005**	-0.005	0.004	0.009**	0.004
	(0.002)	(0.002)	(0.005)	(0.003)	(0.004)	(0.004)
Green knowledge complexity	0.039***	0.040***	0.045*	-0.044*	0.058**	-0.132*
	(0.011)	(0.011)	(0.023)	(0.022)	(0.029)	(0.074)
Green knowledge relatedness * Green knowledge complexity		0.004***	0.021***	-0.007*	0.009***	-0.011**
		(0.001)	(0.008)	(0.004)	(0.003)	(0.005)
Firm Characteristics						
Share of green patent stock	0.002***	0.002***	0.002**	0.002***	0.003***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Intangible Assets (logarithm)	0.032***	0.032***	0.023***	0.041***	0.033***	0.040***
	(0.003)	(0.003)	(0.005)	(0.004)	(0.004)	(0.004)
Firm size (logarithm)	0.360***	0.360***	0.403***	0.383***	0.410***	0.441***
	(0.006)	(0.006)	(0.010)	(0.007)	(0.008)	(0.008)
Firm age	0.008***	0.008***	0.008***	0.004***	0.005***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Region and Industry Control Variables						
Regional technological diversification index	-0.007***	-0.007***	-0.001	-0.004	-0.007*	-0.009***
	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)	(0.003)
Herfindahl-Hirschman index	-0.017	-0.016	0.005	0.008	0.025	0.013
	(0.029)	(0.029)	(0.055)	(0.034)	(0.044)	(0.045)
Industry size	0.169***	0.168***	0.177***	0.140***	0.123***	0.161***
	(0.020)	(0.020)	(0.036)	(0.024)	(0.031)	(0.029)
Industry sales growth	0.021**	0.021**	0.044***	0.003	0.014	0.011
	(0.009)	(0.009)	(0.017)	(0.011)	(0.013)	(0.015)
Constant	-1.545***	-1.451***	-1.734***	-1.273***	-1.011**	-1.606***
	(0.258)	(0.260)	(0.474)	(0.305)	(0.398)	(0.379)
Observations	82,668	82,668	35,719	46,949	38,713	43,955
Number of groups	41	41	19	37	41	41

Notes: (1) The dependent variable is firm-level total factor productivity. (2) Multilevel modelling estimation is used. (3) Year dummies and NACE2 industry dummies are included in all estimations. (4) *** p<0.01, ** p<0.05, * p<0.10.

Figure 2: Green knowledge relatedness and complexity interaction effect



Note: To interpret the interaction effects, we categorise green knowledge relatedness into three levels based on its distribution across regions: low (25th percentile), medium (50th percentile or median), and high (75th percentile). These cut-off values allow us to examine how the marginal effect of green knowledge complexity on productivity varies across regions with differing degrees of technological coherence.

Table 3: Robustness checks

	(1)	(2)	(3)	(4)
	Fixed Effects	Fixed Effects	Multilevel modelling with contextual-effects	Multilevel modelling with contextual-effects
Green Knowledge Spillovers				
Green knowledge relatedness	0.004*	0.004**	0.004*	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)
Green knowledge complexity	0.034**	0.031**	0.031***	0.033***
	(0.014)	(0.013)	(0.011)	(0.011)
Green knowledge relatedness * Green knowledge complexity		0.004***		0.004***
Firm Characteristics		(0.001)		(0.001)
Share of green patent stock	0.002**	0.002**	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Intangible Assets (logarithm)	0.030***	0.018***	0.030***	0.030***
	(0.006)	(0.005)	(0.003)	(0.003)
Firm size (logarithm)	0.168***	0.151***	0.172***	0.172***
	(0.019)	(0.017)	(0.008)	(0.008)
Firm age	0.007	0.009	0.030***	0.030***
	(0.010)	(0.007)	(0.004)	(0.004)
Region and Industry Control Variables				
Regional technological diversification index	-0.008***	-0.008***	-0.007***	-0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
Herfindahl-Hirschman index	-0.055	-0.029	-0.054*	-0.054*
	(0.034)	(0.033)	(0.030)	(0.030)
Industry size	0.185***	0.166***	0.182***	0.181***
	(0.025)	(0.022)	(0.020)	(0.020)
Industry sales growth	0.026***	0.023***	0.023**	0.023**
	(0.008)	(0.008)	(0.009)	(0.009)
Mundlak Firm-level Means				
Green knowledge relatedness			0.076***	0.077***
			(0.023)	(0.023)
Green knowledge complexity			0.635***	0.643***
			(0.121)	(0.121)
Share of green patent stock			-0.003**	-0.003**
			(0.001)	(0.001)
Intangible Assets (logarithm)			0.036***	0.036***
			(0.010)	(0.010)
Firm size (logarithm)			0.470***	0.469***
			(0.012)	(0.012)
Firm age			-0.028***	-0.028***
			(0.004)	(0.004)

Regional technological diversification index			0.026	0.025
			(0.020)	(0.020)
Herfindahl-Hirschman index			1.279***	1.278***
			(0.158)	(0.158)
Industry size			-0.225***	-0.224***
			(0.047)	(0.047)
Industry sales growth			-0.374***	-0.374***
			(0.128)	(0.128)
Mundlak Region-level Means				
Green knowledge relatedness			0.150**	0.152**
			(0.072)	(0.073)
Green knowledge complexity			-3.316***	-3.296***
			(0.684)	(0.688)
Share of green patent stock			0.116	0.120
			(0.178)	(0.179)
Intangible Assets (logarithm)			1.104**	1.108**
			(0.454)	(0.457)
Firm size (logarithm)			-0.819***	-0.819***
			(0.303)	(0.305)
Firm age			0.084**	0.084**
			(0.035)	(0.035)
Regional technological diversification index			-0.206***	-0.208***
			(0.059)	(0.060)
Herfindahl-Hirschman index			18.139***	18.236***
			(7.030)	(7.069)
Industry size			0.215	0.211
			(0.462)	(0.465)
Industry sales growth			-0.146	-0.111
			(5.985)	(6.019)
Observations	82,668	82,668	82,668	82,668
R-squared	0.022	0.020		
Number of region groups			41	41
Number of firm ID	17,736	17,736		

Notes: (1) Standard errors are clustered by firms to allow for firm-level clustering. (2) The dependent variable is firm-level total factor productivity. (3) Year dummies and NACE2 industry dummies are included in all estimations. (4) *** p<0.01, ** p<0.05, * p<0.10.

Appendices

Appendix A: Estimation of total factor productivity

The estimation of total factor productivity (TFP) is estimated following the widely adopted approach proposed by Levinsohn and Petrin (2003) and applied by industrial economics literature (Howell, 2020). The key assumptions of this method are: (1) firms are profit-maximizing; (2) intermediate inputs are monotonic in productivity; and (3) intermediate inputs are monotonic in productivity. Firms are profit-maximizing A Cobb-Douglas production function is expressed as:

$$y_{it} = \beta_0 + \beta_l L_{it} + \beta_k K_{it} + \beta_m M_{it} + \omega_{it} + \eta_{it} \qquad Eq.(A.1)$$

where y_{it} is the logarithm of output, L_{it}, K_{it}, M_{it} are logarithm of labour, capital and input materials for firm *i* in year *t*. The error term ω_{it} is called "transmission bias" that impact the firm's input decisions but are unobserved by the econometrician. This leads to the possible endogeneity problem due to the correlation between the production inputs and the error terms. η_{it} is the error term that is a random productivity shock and is uncorrelated with inputs decisions. To tackle the "transmission bias", Levinsohn and Petrin (2003) propose using input materials M_{it} to proxy the unobserved firm-specific shock ω_{it}.

Demand for the input materials M_{it} is assumed to be determined by K_{it} and ω_{it}:

$$M_{it} = M_{it}(K_{it}, \omega_{it}) \qquad Eq.(A.2)$$

Assuming the above demand function is monotonically increasing in ω_{it}, the inversion of the above demand function can be re-written as:

$$\omega_{it} = \omega_{it}(K_{it}, M_{it}) \qquad Eq.(A.3)$$

An additional assumption is that productivity follows a first-order Markov process:

$$\omega_{it} = E[\omega_{it}|\omega_{it-1}] + \xi_{it} \qquad Eq.(A.4)$$

When the output is measured by logarithm value added (VA_{it}), the production function can be expressed as:

$$VA_{it} = \beta_0 + \beta_l L_{it} + \beta_k K_{it} + \omega_{it} + \eta_{it} = \beta_l L_{it} + \phi_{it}(K_{it}, M_{it}) + \eta_{it} \qquad Eq.(A.5)$$

where:

$$\phi_{it}(K_{it}, M_{it}) = \beta_0 + \beta_k K_{it} + \omega_{it}(K_{it}, M_{it}) \qquad Eq.(A.6)$$

Adding a third-order polynomial in capital K_{it} and input materials M_{it}, value added can be expressed as:

$$VA_{it} = \delta_0 + \beta_l L_{it} + \sum_{b=0}^{3}\sum_{c=0}^{3-b} \delta_{bc} K_{it}^{b} M_{it}^{c} + \eta_{it} \qquad Eq.(A.7)$$

This equation is estimated by two steps. The first step is an ordinary least squares estimation to consistently estimate labour elasticity β_l. The second stage takes the estimated β_l and minimise the sample residual obtained in the first step:

$$\min_{\beta_k^*} \sum_{it} (VA_{it} - \widehat{\beta_l} L_{it} - \beta_k^* K_{it} - E(\widehat{\omega_{it}|\omega_{it-1}}))^2 \qquad Eq.(A.8)$$

Standard errors for $\widehat{\beta_l}$ and $\widehat{\beta_k}$ are estimated using a bootstrap approach. The estimation follows the method suggested by Petrin, Poi and Levinsohn (2004).

Appendix B: Multilevel modelling vs. Linear fixed effects

The dependent variable is measured at the firm level, while explanatory variables exist at both the firm and regional levels. Firms are nested within regions, creating a hierarchical data structure. Multilevel modeling is specifically designed to account for such nesting, allowing for more accurate estimation of effects at each level.

Multilevel modeling correctly models hierarchical dependencies by explicitly model the nested structure of the data. It accounts for the non-independence of observations within regions, avoiding biased standard errors that can arise when ignoring clustering. The empirical model can be re-written as:

$$Productivity_{tir} = \underbrace{\beta_0 + \beta_1 x_{tir} + \beta_2 z_{tr}}_{Fixed\ part} + \underbrace{v_r + u_{ir} + e_{tir}}_{Random\ part}$$

$$v_r \sim N(0, \sigma_v^2\ )$$

$$u_{ir} \sim N(0, \sigma_u^2\ )$$

$$e_{tir} \sim N(0, \sigma_e^2\ )$$

where $Productivity_{tir}$ is an SME i's productivity in time *t* in a NUTS-2 region *r*. The first level of the hierarchy is year *t*, representing each observation. Each observation is nested within each SME *i*, which is the second level of the structure. Each SME is then nested within each NUTS-2 region which is the third level of the structure. β_0 is the overall intercept across all observations. x_{tir} are the firm-level predictors. z_{tr} are the region-level predictors. v_r, u_{ir}, and e_{tir} are the level-3, level-2 and level-1 random effect, respectively. The random effects are assumed normally distributed with mean 0, and independent across units and levels. σ_v^2 measures the extent to which an SME's productivity varies between different NUTS-2 regions. σ_u^2 measures the extent to which SME's productivity varies within one NUTS-2 region and between different SMEs. σ_e^2 measures the extent to which each SMEs' productivity varies between different years.

Each NUTS-2 region *r* has their own random intercept:

$$\beta_{0r} = \beta_0 + v_r$$

Each SME *i* has its own random intercept:

$$\beta_{0ir} = \beta_0 + v_r + u_{ir}$$

As a result, multilevel modeling enables modelling of firm-specific and region-specific intercepts, capturing unobserved heterogeneity across regions more flexibly than fixed effects. It accounts for the fact that region-level variables affect all firms in that region, and adjusts standard errors accordingly.

By comparison, a standard panel fixed effects regression assumes:

$$y_{tir} = \beta_0 + \beta_1 x_{ti} + \beta_2 z_r + \varepsilon_{ti}$$

which treats all observations as independent, ignoring the fact that SMEs within the same NUTS-2 region share context.

Mathematically, in a standard fixed effects regression model, we assume:

$$Cov(\varepsilon_{ij}, \varepsilon_{i'j'}) = 0 \;\; for \;\; all \;\; i \neq i', j \neq j'$$

This means all residuals are independent and there is no correlation between SMEs, even within the same region. But in reality, SMEs within the same region may share unobserved characteristics:

$$Cov(\varepsilon_{ij}, \varepsilon_{i'j'}) \neq 0 \;\; for \;\; all \;\; i \neq i'$$

Ignoring this leads to underestimated standard errors, inflating the risk of false positives.

Multilevel modeling corrects this by introducing a region-level random effect by explicitly estimates the intra-region correlation, adjusting standard errors accordingly:

$$Cov(productivity_{ij}, productivity_{i'j'}) = \sigma_v^2 \ for \ i \neq i'$$

Moreover, fixed effects models with panel data control for all time-invariant characteristics of the unit by demeaning or differencing. Panel fixed effects are useful for controlling for unobserved heterogeneity at the firm level, but they absorb all between-region variation. If region-level variables are time-invariant, it gets dropped from the fixed effects model because it is collinear with the fixed effect. However, the region-level variables in this paper are time-varying, which means they can be included in a firm-level fixed effects model. But even then, fixed effects models do not account for clustering interactions as cleanly as multilevel modelling.

Appendix C: Variable measurements

Using Orbis Intellectual Property data, patent stock of each firm *i* is generated by using the perpetual inventory method (Guellec and Potterie, 2004).

$$Patent\_stock_{it} = Patent\_flow_{it} + (1 - \delta) * Patent\_stock_{it-1}$$

where $Patent\_stock_{it}$ is the patent stock of firm *i* in year t; $Patent\_flow_{it}$ is the number of new patents published by firm *i* in year *t*. the rate of obsolescence is assumed to be annually constant at 15% following the literature (Colombelli and Quatraro, 2019). Green patent stock is measured in a similar way.

Using Orbis data, Herfindahl-Hirschman index is calculated as:

$$HHI = \sum_{i=1}^{N} s_i^2$$

where s_i is the market share of firm *i* and N is the total number of firms in the industry. The maximum value of the Herfindahl-Hirschman index is 1 when there is a single monopoly producer, while the minimum value of the Herfindahl-Hirschman index is 1/N when the industry consists of N equal-sized firms.

Appendix D: Practical implications

The smart specialisation initiative in European countries has faced criticism for not adequately prioritising policy support based on place-based capabilities (Deegan *et al.,* 2021). Apart from Europe, there is a notable gap in corresponding studies for the UK, which examine how regions can identify opportunities and leverage existing strength to build comparative advantages.

Our categorisation of UK NUTS2 regions is based on patent data following the methodology of Hidalgo and Hausmann (2009), which allows for the measurement of green knowledge relatedness and complexity. Policymakers can use these indicators to examine which green technological domains have developed revealed technological advantage (RTA), which domains are more related to their region's existing knowledge base, and which are more complex and thus likely to generate higher economic returns. This approach provides a practical framework for identifying regional strengths and gaps in green innovation capacity. By mapping regions according to these dimensions, policymakers can target support toward developing either more related or more complex green knowledge, depending on the region's position and potential.

Drawing inspiration from Balland *et al.* (2019), Figure 3 illustrates the UK NUTS-2 regions according to their average green relatedness density for technological domains with RTA (*i.e.,* RTA = 1) on the x-axis, and their average green knowledge complexity for technological domains that have RTA on the y-axis during 2013-2020.

Regions positioned to the right of the vertical black line have developed a relatively high level of related green knowledge with RTA, whereas those on the left lack such related knowledge. Similarly, regions above the horizontal black line have developed a certain degree of complex green knowledge where they have RTA, while those below this line lack complex green knowledge. The size of the bubbles represents the total number of green patents, capturing the extent of green patenting activities.

Regions in the top-right quadrant exhibit relatively high green knowledge relatedness and complexity, with a revealed technological advantage (RTA) in green technologies. For instance, Berkshire, Buckinghamshire, and Oxfordshire (UKJ1) rank highest in both dimensions and boast a substantial number of green patents. It is expected to have highly productive firms. Such regions do not need to diversify significantly away from their current specialised green technologies. They also have considerable potential to specialise in new green technological domains, as they possess the necessary related green knowledge that serves as a driver for economic growth.

Regions in the bottom-right quadrant exhibit highly related green technologies but lack complexity in their green knowledge. For example, Inner West London (UKI3) possesses a substantial number of green patents, yet its green knowledge structure remains relatively simple. To enhance green knowledge complexity and productivity, these regions could strategically invest in non-ubiquitous green technology domains. Implementing supportive policies aimed at fostering such investments would be crucial in achieving these objectives.

The top-left quadrant encompasses regions with high green knowledge complexity, but their green technologies are situated in relatively distant knowledge domains. These regions possess significant potential to enhance productivity by leveraging complex green knowledge, although developing related green knowledge may present challenges. For regions such as North Yorkshire (UKE2) and West Wales and the Valleys (UKL1), which have relatively isolated green technological domains, productivity could be substantially increased if policies were implemented to encourage investment in related green technological domains.

The bottom-left quadrant comprises regions with low green knowledge relatedness and complexity. Regions such as Leicestershire, Rutland, and Northamptonshire (UKF2) still have the potential to develop both dimensions, given the relatively large quantities of green patents produced. Overall, the majority of regions in this quadrant possess some degree of related green technologies and may enhance either complexity or relatedness to drive economic development.

Figure 4 illustrates the UK NUTS-2 regions based on their average green relatedness density (x-axis) and their potential gain from green knowledge complexity (y-axis) during the period of 2013-2020. Following Pintar and Scherngell (2021), potential gain is defined as the ratio of the average green knowledge complexity index of technological domains in which the focal region has not yet developed specialisation (*i.e.,* RTA = 0) to the average green knowledge complexity of technological domains in which the focal region has already demonstrated specialisation (*i.e.,* RTA = 1). Regions above the horizontal black line exhibit higher potential gains. Regions to the right of the vertical black line possess a high level of green related knowledge. The size of the bubbles represents the total number of green patents, indicating the extent of green patenting activities.

The top-right quadrant comprises regions with considerable potential gains and highly related green knowledge. These regions have a significant opportunity to reap economic benefits. Policies could assist firms in prioritising green technological domains for development, requiring minimal funding due to their existing robust technological structure. Regions such as Outer London West and North (UKI7), Lancashire (UKD4), Cheshire (UKD6), and Bedfordshire and Hertfordshire (UKH2) fall into this category.

The bottom-right quadrant includes regions with a low level of potential gains but a high level of green relatedness density. These regions do not need to diversify significantly from their existing technological path. Regions such as Berkshire, Buckinghamshire, and Oxfordshire (UKJ1), Inner London (UKI3, UKI4), and East Anglia (UKH2) fall into this category.

The top-left quadrant comprises regions with high potential gains, but their green technological domains are relatively distant. Developing more related green knowledge in these regions may involve significant costs and risks. Regions such as Cornwall (UKK3), North Yorkshire (UKE2), and Lincolnshire (UKF3) could benefit from policies that encourage investment in green technological domains with a relatively high level of relatedness. Such policies would help mitigate risks while enabling these regions to capitalise on their high potential gains.

The bottom-left quadrant includes regions with low potential gains and low green knowledge relatedness. Although these regions specialise in some complex green technological domains, these fields are relatively distant. Significant investment may be required to either develop related knowledge to avoid being locked into a few distant green technological domains or to enhance their green knowledge complexity in areas where they have not yet specialised. Regions such as Leicestershire, Rutland, and Northamptonshire (UKF2), Outer London East and North East (UKI5), and North Eastern Scotland (UKM5) fall into this category.

The classification of UK NUTS2 regions into quadrants based on green knowledge relatedness and complexity is not merely descriptive but is grounded in the empirical framework developed in this study. These typologies are constructed using patent-based indicators following Hidalgo and Hausmann (2009), and they reflect the structural characteristics of regional green technological capabilities. Crucially, the same measures of relatedness and complexity are used in our regression analysis, where we find statistically significant associations with SME productivity. The quadrant typology thus serves as a policy-relevant lens through which regional innovation potential can be interpreted. Furthermore, the robustness of our findings across subsample and interaction analyses reinforces the validity of these dimensions as predictors of firm-level outcomes.

Figure 3: Practical application

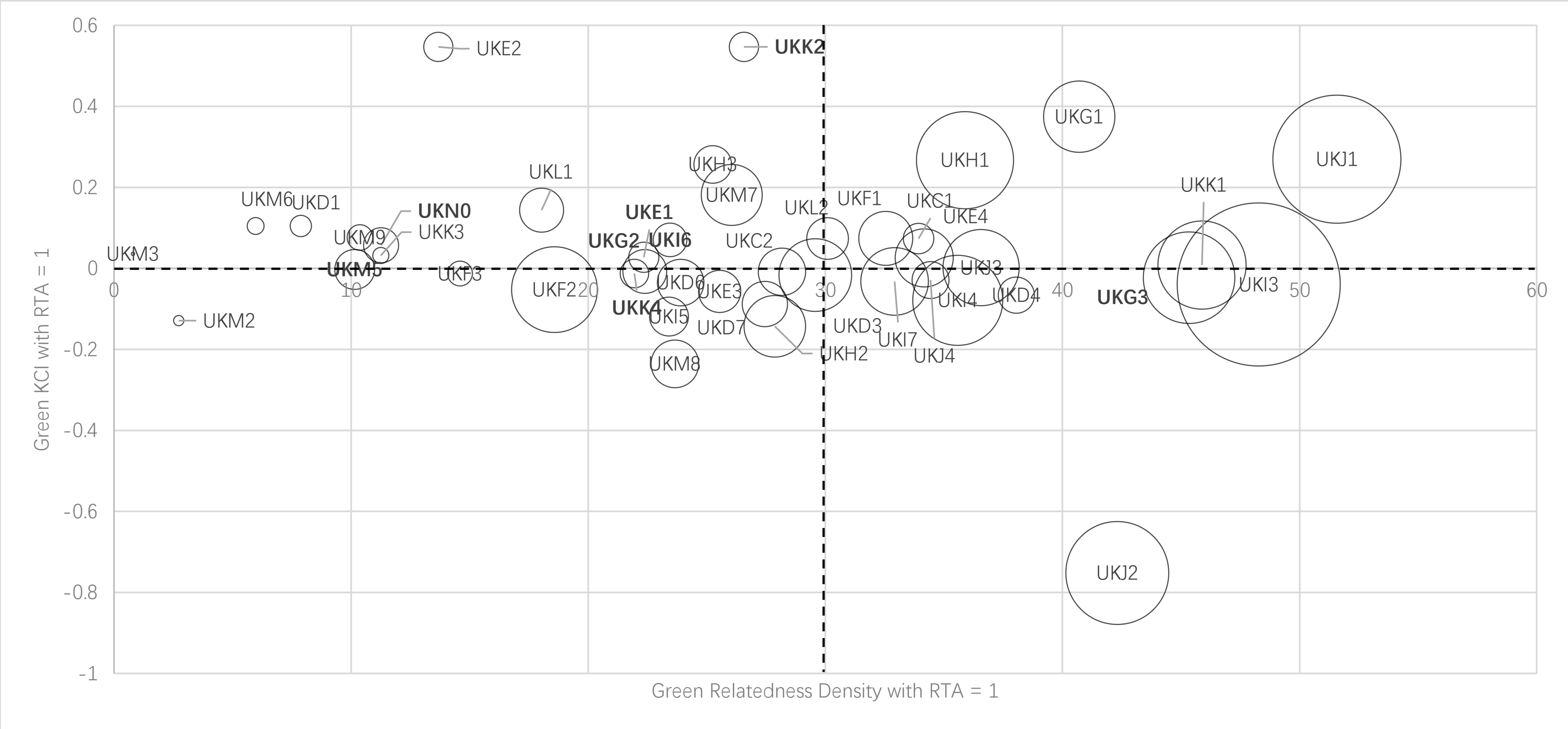
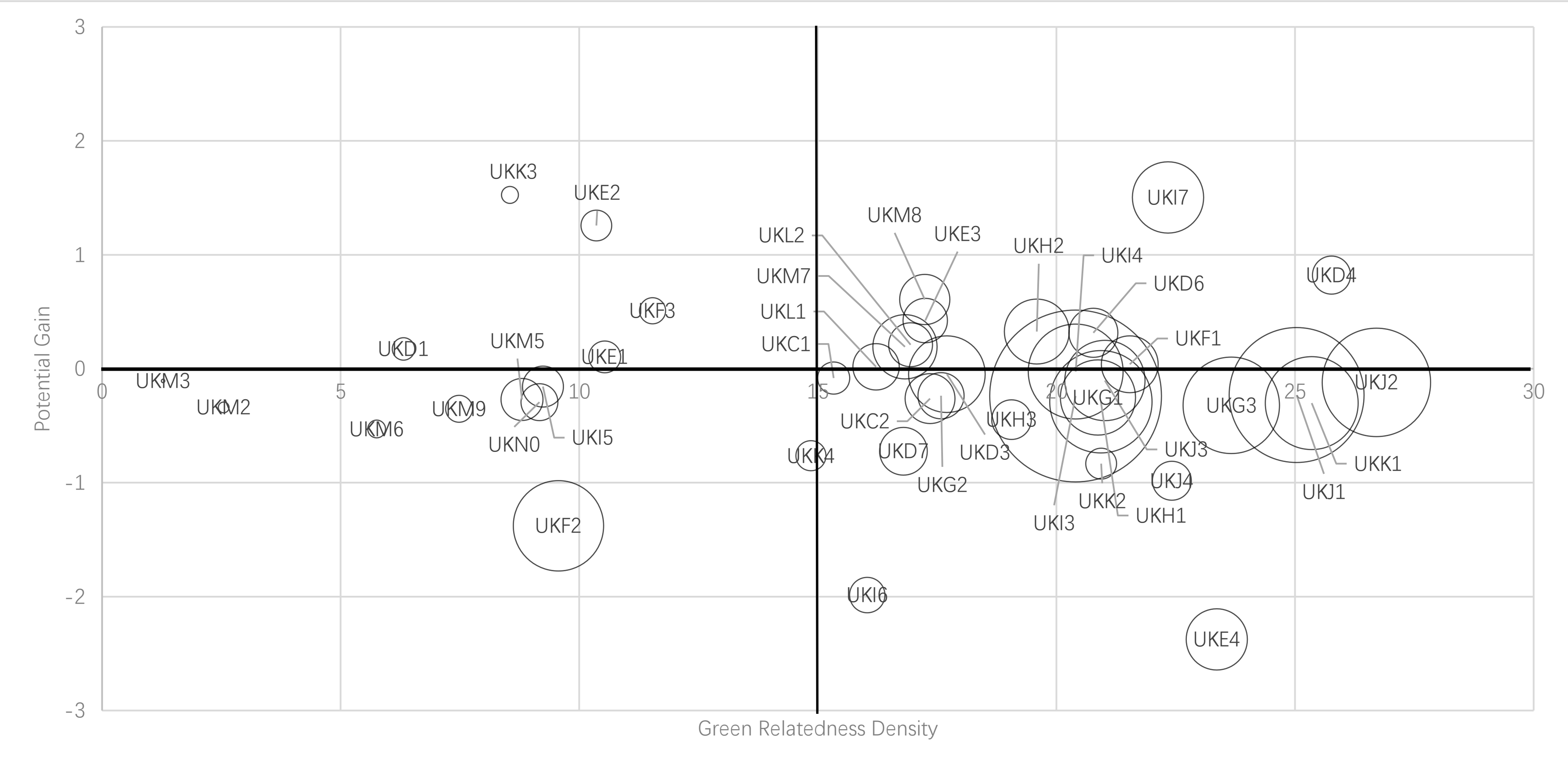


Figure 4: Potential Gain



Appendix E: Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Total factor productivity	1													
(2) Labour productivity	0.898	1												
(3) Green knowledge relatedness	-0.026	-0.019	1											
(4) Green knowledge complexity	-0.036	-0.025	0.235	1										
(5) Green patent stock share	-0.037	-0.050	0.007	-0.007	1									
(6) Intangible assets	0.053	0.065	-0.002	-0.011	0.046	1								
(7) Firm size	0.048	-0.189	-0.118	-0.102	0.061	0.124	1							
(8) Firm age	-0.027	-0.071	-0.026	-0.041	0.043	-0.080	0.292	1						
(9) Regional technological diversification index	-0.033	-0.025	0.985	0.254	0.006	-0.005	-0.130	-0.032	1					
(10) Herfindahl index	-0.240	-0.236	-0.026	-0.031	0.025	0.011	0.084	0.038	-0.025	1				
(11) Industry size	0.209	0.177	0.024	0.051	-0.032	-0.030	-0.069	-0.061	0.031	-0.256	1			
(12) Industry sales growth	-0.027	-0.023	0.004	-0.026	-0.008	-0.003	0.008	-0.006	0.007	0.203	0.027	1		
(13) Transport (motorways and roads) length (logarithm)	0.024	0.004	-0.044	-0.166	0.026	0.036	0.162	0.087	-0.077	0.073	-0.083	-0.005	1	
(14) Share of high-technology manufacturing employment in total employment	0.044	0.041	0.193	-0.090	0.007	0.041	0.044	0.040	0.177	0.027	-0.037	-0.014	0.545	1

Appendix F: Dependent variable total factor productivity: with additional regional control variables

	(1)	(2)	(3)	(4)	(5)	(6)
	All regions	All regions	High green knowledge relatedness regions	Low green knowledge relatedness regions	High green knowledge complexity regions	Low green knowledge complexity regions
Green Knowledge Spillovers						
Green knowledge relatedness	0.004*	0.004**	-0.005	0.005	0.009**	0.005
	(0.002)	(0.002)	(0.005)	(0.003)	(0.004)	(0.004)
Green knowledge complexity	0.039***	0.041***	0.048**	-0.043*	0.060**	-0.138*
	(0.011)	(0.011)	(0.023)	(0.022)	(0.029)	(0.075)
Green knowledge relatedness * Green knowledge complexity		0.004***	0.018**	-0.007**	0.009***	-0.012**
		(0.001)	(0.008)	(0.004)	(0.003)	(0.005)
Firm Characteristics						
Share of green patent stock	0.002***	0.002***	0.002**	0.002***	0.003***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Intangible Assets (logarithm)	0.032***	0.032***	0.022***	0.041***	0.032***	0.038***
	(0.003)	(0.003)	(0.005)	(0.004)	(0.004)	(0.004)
Firm size (logarithm)	0.359***	0.359***	0.401***	0.382***	0.409***	0.439***
	(0.006)	(0.006)	(0.010)	(0.007)	(0.008)	(0.008)
Firm age	0.008***	0.008***	0.008***	0.004***	0.005***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Region and Industry Control Variables						
Regional technological diversification index	-0.006***	-0.007***	0.000	-0.005*	-0.007**	-0.009***
	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.003)
Herfindahl-Hirschman index	-0.015	-0.015	0.006	0.008	0.024	0.016
	(0.029)	(0.029)	(0.055)	(0.034)	(0.044)	(0.045)
Industry size	0.169***	0.168***	0.176***	0.139***	0.123***	0.160***
	(0.020)	(0.020)	(0.036)	(0.024)	(0.031)	(0.029)
Industry sales growth	0.021**	0.021**	0.046***	0.003	0.014	0.012
	(0.009)	(0.009)	(0.017)	(0.011)	(0.013)	(0.015)
Transport (motorways and roads) length (logarithm)	0.063	0.067	-0.059	-0.023	0.106	0.043
	(0.098)	(0.098)	(0.158)	(0.075)	(0.104)	(0.110)
Share of high-technology manufacturing employment in total employment	0.008	0.005	-0.050	0.034*	0.020	-0.028
	(0.017)	(0.017)	(0.035)	(0.020)	(0.025)	(0.028)
Constant	-1.838*	-1.785*	0.078	-1.122	-2.209*	-1.515
	(1.082)	(1.085)	(1.787)	(0.878)	(1.200)	(1.274)
Observations	82,668	82,668	35,719	46,949	38,713	43,955
Number of groups	12	12	11	12	12	12

Notes: (1) The dependent variable is firm-level total factor productivity. (2) Multilevel modelling estimation is used. (3) Year dummies and NACE2 industry dummies are included in all estimations. (4) *** p<0.01, ** p<0.05, * p<0.10.

Appendix G: Additional interaction effects with firm-level green patent stock

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High (Low) green knowledge relatedness/complexity defined by above (below) median values				High green knowledge relatedness/complexity defined by above 75 percentiles; Low green knowledge relatedness/complexity defined by below 25 percentiles			
	High green knowledge relatedness regions	Low green knowledge relatedness regions	High green knowledge complexity regions	Low green knowledge complexity regions	High green knowledge relatedness regions	Low green knowledge relatedness regions	High green knowledge complexity regions	Low green knowledge complexity regions
Green Knowledge Spillovers								
Green knowledge relatedness	-0.005	0.004	0.009**	0.004	-0.022*	0.008*	0.009	-0.000
	(0.005)	(0.003)	(0.004)	(0.004)	(0.011)	(0.005)	(0.008)	(0.006)
Green knowledge complexity	0.043*	-0.044*	0.057**	-0.132*	0.204***	-0.003	0.001	-0.342***
	(0.023)	(0.022)	(0.029)	(0.074)	(0.036)	(0.025)	(0.099)	(0.116)
Green knowledge relatedness * Green knowledge complexity	0.022***	-0.007*	0.009***	-0.011**	0.074***	-0.002	0.003	-0.028***
	(0.008)	(0.004)	(0.003)	(0.005)	(0.018)	(0.006)	(0.007)	(0.008)
Share of green patent stock * Green knowledge relatedness * Green knowledge complexity	-0.001	-0.000	-0.000	-0.000	-0.002	0.000	-0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)	(0.000)	(0.000)
Firm Characteristics								
Share of green patent stock	0.002**	0.002***	0.003***	0.001	0.002	0.003**	0.003**	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Intangible Assets (logarithm)	0.023***	0.041***	0.033***	0.040***	0.027***	0.037***	0.027***	0.041***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.009)	(0.005)	(0.008)	(0.006)
Firm size (logarithm)	0.403***	0.383***	0.410***	0.441***	0.442***	0.412***	0.480***	0.499***
	(0.010)	(0.007)	(0.008)	(0.008)	(0.017)	(0.009)	(0.013)	(0.010)
Firm age	0.008***	0.004***	0.005***	0.006***	0.007***	0.003***	0.005***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Region and Industry Control Variables								
Regional technological diversification index	-0.001	-0.004	-0.007*	-0.009***	0.003	-0.005	-0.006	-0.005
	(0.004)	(0.003)	(0.003)	(0.003)	(0.010)	(0.004)	(0.007)	(0.005)
Herfindahl-Hirschman index	0.004	0.008	0.025	0.013	0.149	-0.012	0.026	0.037
	(0.055)	(0.034)	(0.044)	(0.045)	(0.103)	(0.049)	(0.081)	(0.063)
Industry size	0.178***	0.140***	0.123***	0.161***	0.217***	0.137***	0.180***	0.174***
	(0.036)	(0.024)	(0.031)	(0.029)	(0.059)	(0.033)	(0.063)	(0.044)
Industry sales growth	0.044***	0.003	0.014	0.011	0.049	0.015	0.041*	0.019
	(0.017)	(0.011)	(0.013)	(0.015)	(0.031)	(0.016)	(0.023)	(0.021)
Constant	-1.739***	-1.271***	-1.012**	-1.605***	-2.373***	-1.349***	-1.925**	-2.035***
	(0.474)	(0.305)	(0.398)	(0.379)	(0.816)	(0.422)	(0.806)	(0.563)
Observations	35,719	46,949	38,713	43,955	16,100	24,625	16,378	25,009
Number of groups	19	37	41	41	10	29	28	40

Notes: (1) The dependent variable is firm-level total factor productivity. (2) Multilevel modelling estimation is used. (3) Year dummies and NACE2 industry dummies are included in all estimations. (4) *** p<0.01, ** p<0.05, * p<0.10.

Appendix H: Additional interaction effects with firm-level intangible assets

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High (Low) green knowledge relatedness/complexity defined by above (below) median values				High green knowledge relatedness/complexity defined by above 75 percentiles; Low green knowledge relatedness/complexity defined by below 25 percentiles			
Green Knowledge Spillovers	High green knowledge relatedness regions	Low green knowledge relatedness regions	High green knowledge complexity regions	Low green knowledge complexity regions	High green knowledge relatedness regions	Low green knowledge relatedness regions	High green knowledge complexity regions	Low green knowledge complexity regions
Green knowledge relatedness	0.045*	-0.043*	0.056*	-0.133*	0.199***	-0.003	0.002	-0.342***
	(0.023)	(0.022)	(0.029)	(0.074)	(0.036)	(0.025)	(0.099)	(0.116)
Green knowledge complexity	-0.005	0.004	0.009**	0.004	-0.021*	0.008*	0.009	-0.000
	(0.005)	(0.003)	(0.004)	(0.004)	(0.011)	(0.005)	(0.008)	(0.006)
Green knowledge relatedness * Green knowledge complexity	0.021***	-0.007**	0.008**	-0.011**	0.077***	-0.002	0.003	-0.027***
	(0.008)	(0.004)	(0.003)	(0.005)	(0.018)	(0.006)	(0.007)	(0.008)
Intangible Assets * Green knowledge relatedness * Green knowledge complexity	0.001	-0.001	-0.003	0.001	0.015*	0.001	-0.001	0.002
	(0.005)	(0.002)	(0.002)	(0.002)	(0.009)	(0.004)	(0.002)	(0.002)
Firm Characteristics								
Share of green patent stock	0.002**	0.002***	0.003***	0.001	0.003	0.003**	0.003**	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Intangible Assets (logarithm)	0.023***	0.042***	0.033***	0.040***	0.027***	0.037***	0.027***	0.041***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.009)	(0.005)	(0.008)	(0.006)
Firm size (logarithm)	0.403***	0.383***	0.410***	0.441***	0.443***	0.412***	0.480***	0.499***
	(0.010)	(0.007)	(0.008)	(0.008)	(0.017)	(0.009)	(0.013)	(0.010)
Firm age	0.008***	0.004***	0.005***	0.006***	0.007***	0.003***	0.005***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Region and Industry Control Variables								
Regional technological diversification index	-0.001	-0.004	-0.007*	-0.009***	0.003	-0.005	-0.006	-0.005

	(0.004)	(0.003)	(0.003)	(0.003)	(0.010)	(0.004)	(0.007)	(0.005)
Herfindahl-Hirschman index	0.004	0.008	0.026	0.013	0.154	-0.012	0.026	0.037
	(0.055)	(0.034)	(0.044)	(0.045)	(0.103)	(0.049)	(0.081)	(0.063)
Industry size	0.177***	0.139***	0.123***	0.161***	0.219***	0.137***	0.180***	0.175***
	(0.036)	(0.024)	(0.031)	(0.029)	(0.059)	(0.033)	(0.063)	(0.044)
Industry sales growth	0.044***	0.003	0.014	0.011	0.049	0.015	0.041*	0.019
	(0.017)	(0.011)	(0.013)	(0.015)	(0.031)	(0.016)	(0.023)	(0.021)
Constant	-1.721***	-1.245***	-0.993**	-1.583***	-2.378***	-1.330***	-1.916**	-2.020***
	(0.474)	(0.305)	(0.398)	(0.379)	(0.816)	(0.422)	(0.806)	(0.563)
Observations	35,719	46,949	38,713	43,955	16,100	24,625	16,378	25,009
Number of groups	19	37	41	41	10	29	28	40

Notes: (1) The dependent variable is firm-level total factor productivity. (2) Multilevel modelling estimation is used. (3) Year dummies and NACE2 industry dummies are included in all estimations. (4) *** p<0.01, ** p<0.05, * p<0.10. (5) The interactions between firms' absorptive capacity and innovation intensity and green knowledge relatedness and complexity are statistically insignificant, suggesting that in our sample, firms with higher share of green knowledge stock or intangible assets do not derive significantly greater productivity benefits from green knowledge relatedness or complexity than others. It is possible that the nature of green knowledge—particularly its tacit and collaborative dimensions—makes external networks and regional context more influential than firm-level absorptive capacity. While this result may reflect the broad accessibility of green knowledge spillovers to SMEs regardless of their internal capabilities, it may also indicate limitations in our proxy measure or sample composition. We interpret this as a valuable insight for policy, as it implies that external green knowledge may be leveraged by a wide range of firms, not only those with high absorptive capacity.

Appendix I: Alternative dependent variable: labour productivity

	(1)	(2)	(3)	(4)	(5)	(6)
	All regions	All regions	High green knowledge relatedness regions	Low green knowledge relatedness regions	High green knowledge complexity regions	Low green knowledge complexity regions
Green Knowledge Spillovers						
Green knowledge relatedness	0.004*	0.004*	-0.003	0.002	0.007*	0.005
	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.003)
Green knowledge complexity	0.022**	0.023**	0.023	-0.036*	0.028	-0.077
	(0.010)	(0.010)	(0.020)	(0.021)	(0.027)	(0.067)
Green knowledge relatedness * Green knowledge complexity		0.003***	0.018***	-0.004	0.002	-0.006
		(0.001)	(0.007)	(0.004)	(0.003)	(0.005)
Firm Characteristics						
Share of green patent stock	0.001**	0.001**	0.001	0.002**	0.002**	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Intangible Assets (logarithm)	0.076***	0.076***	0.062***	0.090***	0.083***	0.081***
	(0.003)	(0.003)	(0.005)	(0.003)	(0.004)	(0.004)
Firm size (logarithm)	-0.189***	-0.189***	-0.142***	-0.173***	-0.130***	-0.116***
	(0.005)	(0.005)	(0.009)	(0.006)	(0.007)	(0.007)
Firm age	0.009***	0.009***	0.009***	0.006***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Region and Industry Control Variables						
Regional technological diversification index	-0.005**	-0.005***	-0.000	-0.001	-0.005	-0.008***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Herfindahl-Hirschman index	0.043	0.043	-0.006	0.105***	0.110***	0.047
	(0.027)	(0.027)	(0.048)	(0.033)	(0.042)	(0.041)
Industry size	0.136***	0.135***	0.178***	0.083***	0.108***	0.130***
	(0.018)	(0.018)	(0.031)	(0.023)	(0.029)	(0.026)
Industry sales growth	0.037***	0.037***	0.056***	0.024**	0.041***	0.030**
	(0.008)	(0.008)	(0.015)	(0.010)	(0.013)	(0.013)
Constant	0.308	0.380	-0.343	0.893***	0.545	0.282
	(0.236)	(0.238)	(0.416)	(0.292)	(0.378)	(0.341)
Observations	82,668	82,668	35,719	46,949	38,713	43,955
Number of groups	41	41	19	37	41	41

Notes: (1) The dependent variable is firm-level labour productivity proxied by value added per employee in logarithm form. (2) Multilevel modelling estimation is used. (3) Year dummies and NACE2 industry dummies are included in all estimations. (4) *** p<0.01, ** p<0.05, * p<0.10.

Appendix J: Dependent variable labour productivity: with additional regional control variables

	(1)	(2)	(3)	(4)	(5)	(6)
	All regions	All regions	High green knowledge relatedness regions	Low green knowledge relatedness regions	High green knowledge complexity regions	Low green knowledge complexity regions
Green Knowledge Spillovers						
Green knowledge relatedness	0.003*	0.003*	-0.003	0.002	0.006*	0.006*
	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.003)
Green knowledge complexity	0.023**	0.024**	0.026	-0.039*	0.024	-0.102
	(0.010)	(0.010)	(0.020)	(0.021)	(0.028)	(0.067)
Green knowledge relatedness * Green knowledge complexity		0.003***	0.016**	-0.004	0.002	-0.008
		(0.001)	(0.007)	(0.004)	(0.003)	(0.005)
Firm Characteristics						
Share of green patent stock	0.001**	0.001**	0.001	0.002**	0.002**	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Intangible Assets (logarithm)	0.074***	0.074***	0.059***	0.090***	0.083***	0.078***
	(0.003)	(0.003)	(0.005)	(0.003)	(0.004)	(0.004)
Firm size (logarithm)	-0.190***	-0.190***	-0.144***	-0.174***	-0.132***	-0.118***
	(0.005)	(0.005)	(0.009)	(0.006)	(0.007)	(0.007)
Firm age	0.009***	0.009***	0.009***	0.006***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Region and Industry Control Variables						
Regional technological diversification index	-0.004**	-0.004**	0.001	-0.001	-0.005	-0.009***
	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)	(0.003)
Herfindahl-Hirschman index	0.046*	0.046*	0.001	0.105***	0.108***	0.054
	(0.027)	(0.027)	(0.048)	(0.033)	(0.042)	(0.041)
Industry size	0.135***	0.134***	0.177***	0.082***	0.108***	0.129***
	(0.018)	(0.018)	(0.031)	(0.023)	(0.029)	(0.026)
Industry sales growth	0.037***	0.037***	0.058***	0.023**	0.040***	0.031**
	(0.008)	(0.008)	(0.015)	(0.010)	(0.013)	(0.013)
Transport (motorways and roads) length (logarithm)	0.042	0.045	-0.087	-0.004	0.088	0.022
	(0.088)	(0.088)	(0.140)	(0.064)	(0.092)	(0.099)
Share of high-technology manufacturing employment in total employment	-0.016	-0.019	-0.022	-0.018	-0.000	-0.079***
	(0.015)	(0.015)	(0.031)	(0.019)	(0.024)	(0.025)
Constant	0.289	0.329	1.514	1.098	-0.259	0.741
	(0.971)	(0.973)	(1.578)	(0.769)	(1.076)	(1.139)
Observations	82,668	82,668	35,719	46,949	38,713	43,955
Number of groups	12	12	11	12	12	12

Notes: (1) The dependent variable is firm-level labour productivity. (2) Multilevel modelling estimation is used. (3) Year dummies and NACE2 industry dummies are included in all estimations. (4) *** p<0.01, ** p<0.05, * p<0.10.