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Abstract

This work investigates the role of external exchanges of green knowledge on the regional development of new green technological specializations. We extend the recombinant knowledge framework to commodity-embodied knowledge and posit that inter-industry inter-regional flows of commodities, in which new green knowledge gets incorporated, are a channel through which regions can increase their opportunities of specializing in new green technologies and diversify in a more exploratory manner. We further expect these dynamics to be stronger when foreign rather than domestic embodied flows are concerned. By combining the EUREGIO input-output database with patent data, we test our hypotheses on a sample of 237 EU (NUTS2) regions over the period 2000-2019. We measure the regions' centrality in the network of inter-regional flows of embodied green knowledge ($GreenFlowNet$) and exploit regional network centrality in a model of related diversification for green technologies. Results show that the centrality of regions in the network is positively associated with green diversification, making this process more exploratory. We also find that the regional ability to acquire new green-techs is mainly associated with the centrality in outward flows of green knowledge towards other regions rather than inward ones. Lastly, we find that regions' green-tech diversification seems to be enabled (at the extensive margin) primarily by their centrality in the *foreign* network and accelerated (at the intensive margin) by their centrality in the *domestic* one. Policy implications are drawn accordingly.

Keywords: green technologies, diversification, relatedness, knowledge networks

JEL codes: R11, R15, O52, O33

1 Introduction

The development and adoption of new environmental technologies constitute a pivotal catalyst for advancing the green transition (EC, 2019; IEA, 2020). Nevertheless, the accessibility of these emerging green technologies varies significantly among countries and even more so among sub-national regions (Barbieri et al., 2023). This asymmetry adds to the varying levels of vulnerability that regions exhibit to the changes entailed by the green transition (Rodríguez-Pose and Bartalucci, 2023), and raises the concern of its "spatial justness" (Garvey et al., 2022). This issue calls for the attention of policymakers who are encouraged to address it, particularly by implementing regional policies that target the drivers of regional green-tech diversification.

A rapidly accumulating body of research on the topic indicates that this diversification takes shape as a form of technological *branching* (Tanner, 2014), wherein regions specialize in new green technologies that are cognitively closer, i.e., *related*, to their pre-existing ones (Montresor and Quatraro, 2020). This makes regional green-tech diversification inherently path-dependent and, while it aids regions already on the green trajectory, it runs the risk of disadvantaging regions lagging behind in both green and non-green technological capabilities. This may in turn exacerbate the lack of justness in the green transition.

In this scenario, it becomes important to understand which additional factors can facilitate green-tech diversification and possibly attenuate (i.e., negatively moderate) the role of relatedness, rendering it more exploratory. The extant literature has primarily focused on the beyond-relatedness determinants of green-tech diversification within the regional boundaries and identified them in a set of *internal factors*. However, these internal factors are strongly linked to the local degree of socio-economic development, on which regions have limited scope to act in the short-run. In the same respect, a more manageable set of determinants is represented by *external factors* through which regions – and the peripheral ones in particular – can reach knowledge and capabilities developed beyond their boundaries, which can be possibly transferred and absorbed for the sake of their new green-tech development (Boschma, 2022). Yet, the extant literature on green-tech diversification has paid only limited attention to these external factors and is mostly confined to the role of Foreign Direct Investments (FDIs). Conversely, other external factors, which have been shown to facilitate the technological diversification of regions in generic terms (Balland and Boschma, 2021a), have not yet been addressed in the analysis of the green-tech one.

Among these, an important missing factor is represented by the flows of innovative knowledge that regions exchange among them as embodied (i.e., incorporated) in their respective flows of intermediate commodities. Indeed, previous studies have shown that these intersectoral flows of intermediate commodities can act as carriers of the innovative knowledge developed by a focal industry. However, the extent to which this transmitted knowledge enriches the knowledge base of regions and facilitates their capacity of combining local and external knowledge for diversification purposes, has been marginally and indirectly investigated so far, and only with respect to generic technologies (Fusillo et al., 2023). Given the pervasiveness of such flows, which span across several and heterogeneous locations through domestic and international trade (Karlsson et al., 2019), this gap is particularly unfortunate.

By drawing on the literature about input-output based innovation networks and extending the recombinant innovation framework to commodity-embodied knowledge, we contribute the analysis of regional green-tech diversification in three respects. Firstly, we maintain that the embodied exchange – both inward and outward – of green knowledge among regional industries represents an important channel through which the regional knowledge base can be enriched with new recombination opportunities for the development of new green technologies. Secondly, we argue that by getting exposed to the network of inter-regional flows of (industry) embodied green knowledge, regions can diversify into new green technologies that are more cognitively distant from their existing ones. Thirdly, we also maintain that the extent to which the previous arguments hold is greater when foreign rather than domestic flows of the kind are considered.

We combine the EUREGIO input-output database with patent data from OECD RegPat, and test these arguments on a sample of 237 EU (NUTS2) regions over the period 2000-2019. From a methodological point of view, we first build up the network of inter-regional flows of embodied green knowledge (*GreenFlowNet*) and measure each region's degree centrality, in total, in-degree, and out-degree terms. We then employ these centrality indicators in a model of related diversification for green technologies, augmented with the interaction between centrality and the relatedness indicator between new green and existing technologies.

Results confirm our expectations on the role of the *GreenFlowNet* in green-tech technological diversification, but primarily for outward flows of green knowledge towards other regions rather than inward ones. Furthermore, we find that regions' green-tech diversification appears enabled (at the extensive margin) by their centrality in the *foreign GreenFlowNet* – capturing flows among regional industries across different countries – and accelerated (at the intensive margin) by their centrality in the *domestic GreenFlowNet* – made up of flows between regional industries within the same countries. Policy implications are drawn accordingly.

The remaining of the paper proceeds as follows. Section 2 illustrates the background literature and our research hypotheses. Section 3 presents the data employed, the construction of focal indicators, and a description of the empirical strategy. Section 4 provides estimation results and delves into further empirical analyses and robustness checks. Section 5 provides concluding remarks, exploring the main policy implications of the results.

2 Background literature and research hypotheses

Within the field of innovation geography, the body of literature on regional technological diversification has experienced substantial growth over the past decade (Shearmur et al., 2016). Building on evolutionary economic geography principles, a key tenet of its analysis posits that regions primarily – and ideally – diversify by branching from their existing technologies. In essence, to mitigate the risks associated with overly hazardous and potentially unsuccessful diversification endeavors (Balland et al., 2019), regions develop new technologies that are marked by higher cognitive *relatedness* to their pre-existing ones, as they leverage similar capabilities (Boschma, 2017).

Drawing on and refining prior literature, recent analyses have shifted attention to the regions' ability to engage in eco-innovation and diversify their green technologies – a domain where our understanding remains limited (for a review, see Losacker et al. (2023)). Adopting a relatedness approach, extant studies have generally found that regions diversify also their green technologies through branching (Tanner, 2014), relying on both green and non-green pre-existing capabilities (Montresor and Quatraro, 2020). However, like in the case of technological diversification in general, different factors have been found to combine with, and moderate – usually negatively (i.e. attenuating) – the impact of relatedness on green-tech branching. The majority of the available studies have focused on *internal factors* to the regions that can play this role.[1] Conversely, only limited attention has been paid to factors that affect the green-tech diversification of regions by acting across their boundaries, i.e., *external factors*. The primary emphasis has been on the role of Foreign Direct Investments (FDIs), both in inward (received by regions) and outward (made abroad by regional actors) terms. The argument posits that multinational corporations can serve as conduits for global "pipelines" of green knowledge, intersecting with the local "buzz" of domestic knowledge and thereby enhancing regional green-tech capabilities (Bathelt et al., 2004). Castellani et al. (2022) have found that inward innovative FDIs (i.e., in R&D activities) occurring in green industries, positively impact a region's specialization in green technologies. This effect is larger in regions whose prior knowledge base is highly unrelated to environmental technologies. Indeed, it is only for high levels of unrelatedness that the same kind of FDIs help regions acquire a green-tech specialization ex novo. Along a similar line, in Bello et al. (2023) inward innovative FDIs from home-countries' MNCs to host-regions are found to be significantly and positively associated with the backward citations that the green patents of the latter make to the patents obtained in the former. Quite interestingly, this does not occur with respect to outward innovative FDIs. However, outward FDIs can be claimed to serve in establishing external connections and in facilitating local access to external resources through other channels. Indeed, Belmartino et al. (2023) find a positive relationship between environmental innovation in European regions and their outward FDIs, especially when the

[1] Among these factors the most studied concern: the regions' endowment of Key Enabling Technologies (KETs) (Montresor and Quatraro, 2020) and of Artificial Intelligence (AI) knowledge (Cicerone et al., 2023); the political support they give to environmental issues (e.g. in times of elections) (Santoalha and Boschma, 2021); and the intensity of local digital skills (Santoalha et al., 2021).

latter target regions with higher availability of green patents and trademarks.

While important, FDIs are not the only channel through which regions can gain access to external knowledge, especially of a green kind, to facilitate their green-tech diversification. External knowledge flows can pass through the inter-regional mobility of other *non-local actors* than MNCs, like migrant inventors (Miguelez and Morrison, 2023) and foreign entrepreneurs (Neffke et al., 2018; Elekes et al., 2019). *Local actors* themselves can also entertain or/and be exposed to extra-regional linkages. This can occur both in knowledge creation – like in cross-regional inventors' collaborations – and in knowledge diffusion – through processes of knowledge transfer across regions. In both domains, inter-regional relationships have been found to affect regional innovation and technological diversification in general terms (Balland and Boschma, 2021b; Kogler et al., 2023). Furthermore, and possibly in a more pervasive way, regions also engage in trade relationships, which stimulate the regions' development of new industries (Andersson et al., 2013; Boschma et al., 2017). As recently argued by Boschma (2022), regions draw important opportunities to diversify their technologies by participating to Global Value Chains (GVC), and the same holds true for their belonging to Global Production and Innovation Networks (GPN and GIN) that spread across the World (Cooke, 2013). Nevertheless, the relevance of external relationships linked to this kind of networks has been overlooked in the analysis of regional green-tech diversification so far.[2]

Aiming to fill this gap, we propose to extend and refine with respect to the green-tech realm the recent contribution proposed in Fusillo et al. (2023), who relate regions' technological diversification, in general terms, to their exposure to the global network of embodied R&D knowledge (GNRD). Following the embodied diffusion channel of technology (Papaconstantinou et al., 1996), industrial providers that invest in R&D make their intermediate commodities more innovative; and their industrial customers benefit (in the form of rent spillovers) from the innovative knowledge these commodities "embody" by buying them. Exchanges of R&D-embodied knowledge among the industries of different countries create a

[2]An exception is the work by Bachtrögler-Unger et al. (2023), which, however, employs a different framework and considers the role of co-inventorship across regions for the regional development of twin (i.e., digital and green) technologies.

global network of embodied R&D (GNRD) (Fusillo et al., 2024). Through these relationships, innovative knowledge can be created, moved and benefited across the World also for the sake of technological diversification. Accordingly, Fusillo et al. (2023) find that regions, by increasing their “exposure" to the most “central” nodes of this GNRD (through the target of their local inventive activities), can both increase their diversification capacity and render it more exploratory in the search of new technologies.

The approach proposed in this study can be extended and refined to investigate the role of the same kind of external driver in regional green-tech diversification. The starting point of this extension is the consideration that regional industries – rather than country-industries as in Fusillo et al. (2023, 2024) – can be deemed the most salient unit of analysis at which to map the flows of embodied knowledge from which regions can benefit for diversifying. Indeed, through the engagement of their firms in R&D, patenting, and other green inventive activities, regional industries can access new green technological knowledge that can be both used locally (within the region) and transferred externally (outside the region). In the latter case, the embodied diffusion of innovation across industries of *different regions* does appear particularly relevant. Through the development of new green knowledge, the industries of a focal region can increase the “greenness” of the commodities obtained by their firms – e.g., in terms of energy and resource efficiency, or of used pollutants. In turn, the underlying knowledge through which such greenness has been improved can be benefited by the customer industries of other regions through the acquisition of the relative ameliorated commodities.[3] In analytical terms, the flows of embodied green knowledge that regional industries exchange among them generate a network that we can term the *GreenFlowNet*. Within the network, new green knowledge is created and circulated, from which regions can benefit more (in developing new green technologies), the more “central” their sub-network of industries is in

[3] It is worth stressing that this kind of embodied diffusion of green knowledge also occurs among the industries of the same regions. Nevertheless, given the diversity in industrial structures among regions and the variations in innovation among regional systems, the most significant and impactful novelty in the acquired embodied knowledge is likely to originate externally: that is, through inter-regional (industry) exchanges encompassing both domestic interactions (regions within the same country) and foreign interactions (regions from other countries). Indeed, *intra-regional* flows of the same kind arguably accrue from learning-by-interacting of local industries and thus augment the regional capacity of mastering new green technologies only marginally.

it.[4]

Elaborating upon the recombinant knowledge framework (Weitzman, 1998), supporting the relatedness approach to technological diversification, the described benefit from centrality in the *GreenFlowNet* is twofold and leads us to formulate two main research hypotheses, plus one. Firstly, we can argue that the most central a region – through its regional sub-system is in the *GreenFlowNet*, the more pervasively its local industries exchange embodied green knowledge with outer (extra-regional) industries, and the more intensively they can access diverse bits of knowledge to be combined and recombined in the development of new green technologies (Montresor and Quatraro, 2020). In principle, this can occur with respect to both the acquisition and the diffusion of the kind of knowledge under consideration. In the former case, more inward-central regions (i.e., central by looking at inward flows) absorb more diverse green knowledge inputs by acting more intensively as buyers of environmentally improved commodities developed elsewhere. In the latter case, more outward-central regions are so to say exposed to more diverse green knowledge by serving more intensively as suppliers of environmentally improved commodities that are demanded elsewhere. As both channels can be equally knowledge conveying, we do not have a theoretical a priori about their distinctive effect, which would be however interesting to disentangle. Accordingly, we put forward our first research hypothesis:

HP1: *Regions that are more central in the GreenFlowNet – either in inward or outward terms (or both) – have a higher capacity to acquire new green technologies.*

The second benefit concerns its capacity to attenuate the path-dependence from their pre-existing technologies. In technical terms, this centrality can be expected to downplay the diversification-enabling effect played by the cognitive proximity (i.e., relatedness) between pre-existing and new green technologies (Boschma, 2017). Mimicking the arguments put forward in relation to other external channels of knowledge diffusion, like FDIs (Castellani et al., 2022), we can argue that the centrality at stake can play such a role. Indeed, not

[4]For the sake of clarity, we refer to the centrality of a region – i.e., of its sub-network of industries, in the *GreenFlowNet* as a proxy of its importance. A detailed discussion on this meaning is presented in Section 3.

only can more central regions be expected to have more diverse green knowledge inputs to be combined and thus a wider recombinatory potential. A more varied green knowledge, made available by more (externally) interacting suppliers and customers of green-improved commodities, also fuels the "architectural" knowledge on which regions rely to recombine their modular one into new green technologies. In other words, the architectural knowledge base of more central regions is capable of recombining their pre-existing modular knowledge with more degrees of freedom and enabling them to diversify in the green realm in a more exploratory manner, i.e., in less cognitively related new green technologies. Once more, this could occur either for inward and outward central regions in the *GreenFlowNet* and leads us to put forward our second research hypothesis:

HP2: *Regions that are more central in the GreenFlowNet – either in inward or outward terms (or both) – are capable to acquire new green technologies that are less cognitively related to their pre-existing ones.*

In addition to these two hypotheses, a third one can be put forth in order to enrich them. As anticipated, with respect to a focal region, the extra-regional linkages of embodied green knowledge that constitute the *GreenFlowNet* can be either domestic – i.e., pertaining to other regions located in the same country – or foreign – i.e., referring to regions located in other countries. As extensively shown by the literature about national systems of innovation and by its recent evolution into global ones (Fusillo et al., 2024), cross-country differences in industrial structures and in innovation performances still matter and add an additional and possibly stronger element of discontinuity to cross-regional ones. Accordingly, it can be argued that the green-knowledge novelty to which the regions' centrality in the *GreenFlowNet* gives access is greater when its foreign rather than domestic flows are considered. Accordingly, we formulate our third hypothesis as follows:

HP3: *The effects to which HP1 and HP2 refer are stronger for the foreign rather than the domestic flows of the GreenFlowNet.*

3 Empirical analysis

3.1 Data

Our empirical analysis rests on a new dataset of 237 European (NUTS2) regions and 14 industries from 2000 to 2019, assembled by combining different sources. The primary data source of our analysis, employed to build up the *GreenFlowNet*, is represented by the EUropean REGional Input-Output (EUREGIO) database. This is the first time-series – annual, from 2000 to 2010 – of global Input-Output tables offering regional granularity across the extensive trading block of the European Union. The tables integrate data from World Input-Output Dataset (WIOD) (2013 release) with regional economic accounts and interregional trade estimates developed by PBL and with survey-based regional input-output data for select countries(Thissen et al., 2018).

Our second main data source is the OECD REGPAT data (February 2022 version), from which we extract patent data, regionalized according to the address of the inventors. Following recent literature, the green technologies to which our dependent variable of green-tech diversification refers, as well as other regressors and controls, are identified by exploiting the Y-tagging Cooperative Patent Classification (CPC) scheme of technology classes assigned to patent documents at the 4-digit level (Favot et al., 2023). More precisely, patents are identified as green if they are classified in at least one of the "Climate Change Mitigation technologies" defined by the EPO CPC classes Y02-Y04S.

Lastly, we complemented this information with regional- (and country-) data, such as population and gross domestic product (GDP, at the current market prices), from Eurostat and the index of environmental policy stringency from the OECD (OECD, 2016).

3.2 Variables construction

3.2.1 Dependent variables

The dependent variables of our analysis measure the green-tech diversification of regions by looking at the green technologies that enter region r at time t, with t spanning from 2000 to

2019. Following the extant literature (e.g. Montresor and Quatraro, 2020), such an entry is denoted by a dummy variable $GreenTechEntry_{s,r,t}$, which takes value 1 if region r acquires a Revealed Technological Advantage (RTA) in a generic green-tech s at time t, which it did not have at $t-1$, and 0 otherwise.[5] Formally:

$$GreenTechEntry_{s,r,t} = 1 \quad \text{if } RTA_{s,r,t} = 1 \text{ and } 0 \leq RTA_{s,r,t-1} \leq 1 \tag{1}$$

where $RTA_{s,r,t}$ is defined as follows:

$$RTA_{s,r,t} = \frac{\frac{PAT_{s,r,t}}{\sum_t PAT_{s,r,t}}}{\frac{\sum_r PAT_{s,r,t}}{\sum_t \sum_r PAT_{s,r,t}}} \tag{2}$$

with $PAT_{s,r,t}$ denoting the number of patents region r holds in technology s at time t, with the standard implication that the region is (not) specialized in the same technology when $(0 \leq RTA_{s,r,t} \leq 1)$ $RTA_{s,r,t} = 1$.

Following Fusillo et al. (2023), we measure diversification (in the green tech) both at the extensive and intensive margin. At the *extensive margin* (EM), we focus on the focal region's capacity to enter the green-tech realm, regardless of the intensity at which it does it. Accordingly, we measure green-tech diversification at the EM with a dummy variable $GreenTechEntryEM_{r,t}$, defined as:

$$GreenTechEntryEM_{r,t} = 1 \quad \text{if } GreenTechEntry_{s,r,t} = 1 \text{ for at least one } s\text{,and 0 otherwise} \tag{3}$$

At the *intensive margin* (IM), we instead focus on the strength with which the focal region diversifies its technologies in the green realm. To do that, we define the following

[5]This is a reference time lag in the literature (Montresor and Quatraro, 2020), for which other lags have been tried ($k = 1, \ldots 3$), without substantially altering the results

variable $GreenTechEntryIM_{r,t}$:

$$GreenTechEntryIM_{r,t} = \sum_s GreenTechEntry_{s,r,t} \quad (4)$$

In other words, $GreenTechEntryIM_{r,t}$ simply counts the number of $GreenTechEntry_{s,r,t}$ that occurred at time t.

3.2.2 Explanatory variables

Our main regressor aims at measuring the importance that region r reveals in the $GreenFlowNet$ at t: i.e., the network identified by the inter-regional flows of embodied green knowledge that regional industries exchange among them.

First, to build up the $GreenFlowNet$ we rest on the hypothesis, widely accepted in the relevant literature (Montresor and Marzetti, 2008), that the (green-tech) knowledge developed by the focal regional industry diffuses to other regional industries proportionally to their input-output exchanges of intermediate commodities.[6] This hypothesis can be operationalized with the following matrix multiplication, whose outcome represents the adjacency matrix behind the construction of the $GreenFlowNet$:

$$\mathbf{GreenFlowNet}_t = \mathbf{GreenKnow}_t \times \mathbf{A}_t \quad (5)$$

In equation 5, $\mathbf{GreenKnow}_t$ is the diagonal vector ($nm\times nm$) of the green-tech knowledge obtained by the regional industries (where n and m represent the numbers of regions and industries, respectively), over the temporal span 2000-2019. Following the extant literature (Acs et al., 2002), the green knowledge of regions can be detected by counting the number of green patents whose inventors reside in them. As for their allocation across regional industries,

[6] For the pros and cons of this hypothesis, see Montresor and Vittucci Marzetti (2007); Montresor and Marzetti (2008).

we instead resort to the Algorithmic Links with Probabilities (ALP) approach developed by Lybbert and Zolas (2014) and use the probability weights with which green patents refer to industries, for each year and for each region.[7]

$\mathbf{A}_t$ in equation 5 is the matrix of input-output coefficients obtained on the basis of the inter-sectoral flows of intermediate commodities measured by the EUREGIO dataset at time t. Its generic element, $a_{dz,ew,t}$, measures the value of the intermediate commodities produced at t by industry d in region z, which is acquired by industry e in region w to obtain one unit of its final output (see Miller and Blair, 2009). Following the proportionality assumption in knowledge embodiment, these coefficients represent the weights through which the green knowledge obtained by regional industries can be distributed across the other ones.[8] Unfortunately, as anticipated, EUREGIO data availability only enables us to build up the $\mathbf{A}_t$ matrix over the period 2000-2010. Accordingly, despite the availability of patent data allows us to measure the $GreenKnow_t$ until 2019, the use of yearly input-output coefficients in Eq.5, would prevent the possibility of obtaining the $GreenFlowNet_t$ beyond 2010. To avoid this temporal loss and maximize the temporal coverage of our empirical estimation, we decided to amend Eq.5 by using an alternative $\mathbf{A}_{Avg}$ matrix, obtained by calculating the average values of the $\mathbf{A}_t$ elements over 2000-2010. In so doing, we rely on the fact that, being a structural feature of national and regional economies, input-output coefficients can be expected to change only gradually over time and mainly in the long run. The average values of these coefficients find the 2000-2010 decade are arguably not excessively dissimilar from those of the years from 2000 to 2019. Accordingly, the coefficients of $\mathbf{A}_{Avg}$ can be retained as a reliable proxy of the structural relationships along which the $\mathbf{GreenKnow}_t$ obtained in the same years circulate in an embodied way and affect $GreenTechEntry_{r,t}$ and $GreenTechEntryCount_{r,t}$.

In sum, the $GreenFlowNet_t$ matrix obtained from Eq.5 allows us to measure the kind

[7] Precisely, we map CPC technology classes at the 4-digits level into the corresponding ISIC rev.4 industry classification, together with their probability weights. Then, since EUREGIO data only covers 14 industries (table), we aggregate and match patent counts (at the ISIC rev.4 industry classification) with the 14 EUREGIO industries, following the concordance table provided in Table A6 in paper Appendix.

[8] Further details on the choice of these and possibly other input-output based weights are provided in Montresor and Vittucci Marzetti (2007); Montresor and Marzetti (2008).

of flows we are focusing on. Its generic element $GreenFlowNet_{dz,ew}$, in fact, denotes the amount of green knowledge obtained by industry d in region z, which diffuses to industry e in region w. It may well be that $z = w$, capturing inter-industry flows within the same region, or that z and w refer to the same country, or to different countries. The $GreenFlowNet_t$ matrix can thus be treated as a weighted adjacency matrix, configuring a weighted directed network whose nodes refer to region-industry pairs.

By referring to this network, we can eventually measure the positioning of regions in terms of network centrality. Among the different possible measures of centrality available in network analysis (Borgatti, 2005), the simplest and most employed proxy of the importance of nodes in terms of their connectivity is the *Degree Centrality*. In a binary network, degree centrality simply measures the number of links incident upon a node. In a network in which links are directed, degree centrality can be split into in-degree and out-degree, as nodes may have a different number of inwards and outwards connections, respectively. Degree centrality can also be extended to the case of weighted connections. In such a case, degree centrality measures the sum of the weights of the links incident upon a node, and its calculation can be further extended, and its decomposition into inward and outward applied to, weighted directed linkages.

As described above, the $GreenFlowNet$ is a weighted directed network, with nodes corresponding to region-industries pair. However, our interest lies in the centrality position of a region in the network. Further, because of the nature of the links in the $GreenFlowNet$, we aim at capturing the extent to which regions are embedded into the array of embodied green knowledge flows both in terms of range and amount of such exchanges. Hence, we measure the centrality of regions in the $GreenFlowNet$ by calculating the weighted group degree centrality (Borgatti, 2006). To do so, we build up the regional indicator of $TotalDegreeCentrality_{rt}$, which sums the weights of the links of non-group members (extra-regional industries) connected to group members (regional industries) by incoming and outgoing edges at t with respect to each region r. Furthermore, we also calculate for each region and indicator of group- $InDegreeCentrality_{rt}$ and $OutDegreeCentrality_{rt}$ by only considering, respectively, incoming edges or outgoing edges with respect to each region r at time t. A higher value of $InDegreeCentrality_{rt}$ thus informs us about the extent to which a region acquires embodied green knowledge flows from outside. On the other hand, higher values of $OutDegreeCentrality_{rt}$ are associated with a larger outreach (diffusion) of regional industries in providing green knowledge to other regions via its embodiment into the intermediate good exchanges.[9] At the same time, a region with a higher in-degree centrality may not necessarily also have a higher out-degree centrality.

Following our Hp1 we expect these three centrality indicators of the $GreenFlowNet$ to be positively correlated with the regions' capacity to diversify their green technologies and, following Hp2, to negatively moderate the impact of relatedness on the same capacity. As for Hp3, we calculate the same centrality indicators with respect to two "artificial" sub-sets of the $GreenFlowNet$, which capture its domestic and foreign portions. The *network of domestic flows* ($GreenFlowNetDomestic$) is obtained by retaining the industry knowledge flows of the $GreenFlowNet$ that, for every country, each region exchanges with those of the same country, that is, by still maintaining external links, but not going beyond the country border. The *network of foreign flows* ($GreenFlowNetForeign$) is instead obtained by considering only the embodied flows of industry knowledge that, for each region of a certain country, go to (or come from) regions of other countries.

Our second focal explanatory variable is represented by the average relatedness density of new green technologies to those pre-existing in the regional knowledge space: $Avg\_RD_{r,t}$.

Following consolidated regional branching literature and its application to the green-tech diversification case (Hidalgo and Hausmann, 2009; Neffke et al., 2011; Montresor and Quatraro, 2017, 2020), the construction of the average relatedness density indicator entails the following steps. First, we define a measure of proximity between each technology i and j at a given time, $\phi_{i,j,t}$, exploiting the co-occurrence of 4-digit CPC classes in regional patent documents. In line with previous literature, proximity is defined as the minimum pairwise conditional probability that a region has a specialization ($RTA_i > 1$) in technology i provided that it is

[9] Weighted group degree centralities are calculated through the algorithm provided by the *keyplayer* package in RStudio.

already specialized ($RTA_j > 1$) in technology j:

$$\phi_{i,j} = \min(P(RTA_i > 1|RTA_j > 1), P(RTA_j > 1|RTA_i > 1)) \tag{6}$$

Secondly, we derive the density of the proximity indicator between each new green-technology specialization i and all technologies j in which a region r was specialized in $t-1$:

$$RD_{r,i,t} = \frac{\sum_{i \neq j} X_{r,j,t-1} \cdot \phi_{i,j,t}}{\sum_{i \neq j} \phi_{i,j,t}} \tag{7}$$

Lastly, for each region, we calculate the average relatedness density of these distances by weighting them with the RTAs the region gained in green technologies:

$$Avg\_RD_{r,t} = \sum_{J \neq i} RD_{r,i,t} \frac{X_{r,i,t}}{\sum_{i \neq J} X_{r,i,t}} \tag{8}$$

The interpretation of $Avg\_RD_{r,t}$ is the standard one in these studies. The higher this indicator is, the more cognitively closer are the new green technologies that enter the regional knowledge space to those that already populate it. Accordingly, in line with previous literature, we expect this to be positively correlated with $GreenTechEntryEM_{r,t}$ and $GreenTechEntryIM_{r,t}$.

In addition to our two focal regressors, we include a set of control variables. First, following the debate on the positive effect of higher income on environmental awareness (see, among others, Kruize et al., 2007; Santoalha and Boschma, 2021), we include *GDP per capita* to account for the economic wealth of the region. We then include the *stringency of the environmental policy* at a country level, assuming regions with higher levels of environmental stringency would be more inclined to produce greener technologies to comply with the standards.

3.3 Empirical strategy

The empirical strategy employed to test our three hypotheses rests on two models. The first model refers to the regional green-tech diversification at the extensive margin and, by using $GreenTechEntryEM_{r,t}$ as dependent (dichotomic) variable, estimates with a two-way fixed effects Linear Probability Model (with binary choice) the following equation 9:

$$\begin{aligned} GreenTechEntryEM_{r,t} = {} & \alpha + \beta_1 \cdot Avg\_RD_{r,t-1} + \beta_2 \cdot DegreeCentrality_{r,t-1} \\ & + \beta_3 \cdot Avg\_RD_{r,t-1} \cdot DegreeCentrality_{r,t-1} \\ & + \beta_4 \cdot Controls_{t-1} + FE_r + FE_t + \varepsilon_{r,t} \end{aligned} \tag{9}$$

where subscripts r and t refer to *regions* and *time* respectively. In equation 9, $DegreeCentrality_{r,t-1}$ denotes what we have defined as $TotalDegreeCentrality_{r,t-1}$ in a first specification; the $InDegreeCentrality_{r,t-1}$ and $OutDegreeCentrality_{r,t-1}$ as two independent regressors in a second specification; the previous two versions of degree centrality in the $GreenFlowNetDomestic$ and in $GreenFlowNetForeign$ network in a third specification. FE_r and FE_t denote, respectively, region- and year-fixed effects included to control for remaining unobservable time-invariant region-specific factors and time factors. $\epsilon_{r,t}$ is an idiosyncratic error term.

The second model employs as dependent (count) variable $GreenTechEntryIM_{r,t}$ and estimates with a two-way fixed effects OLS model the following equation:

$$\begin{aligned} GreenTechEntriesIM_{r,t} = {} & \alpha + \beta_1 \cdot Avg\_RD_{r,t-1} + \beta_2 \cdot DegreeCentrality_{r,t-1} \\ & + \beta_3 \cdot Avg\_RD_{r,t-1} \cdot DegreeCentrality_{r,t-1} \\ & + \beta_4 \cdot Controls_{t-1} + FE_r + FE_t + \varepsilon_{r,t} \end{aligned} \tag{10}$$

Model in equation 10 is also estimated by first considering $TotalDegreeCentrality_{r,t-1}$ as the main focal regressor, and then by considering in another specification $InDegreeCentrality_{r,t-1}$ and $OutDegreeCentrality_{r,t-1}$ as separated independent regressors. In all models, to alleviate endogeneity issues, we lag the regressors by one period with respect to the dependent variable.[10]

In line with our first hypothesis, we would expect β_2 to be significant and positive. The higher the centrality of a region in the network of inter-regional green knowledge (industry) flows, the wider its set of opportunities to branch existing green technologies into new ones. As discussed in Section 2, we would also expect that, following our Hp2, a more central role of the region in the network at stake could make its green-tech diversification more exploratory in nature and less affected by the binding role played by pre-existing technologies. We thus expect that $DegreeCentrality_{r,t-1}$ might negatively moderate the role of $Avg\_RD_{r,t-1}$ and that β_3 is statistically significant with a negative sign. As for our Hp3, the expectation is that β_2 turns out to be higher when $DegreeCentrality_{r,t-1}$ is constructed with respect to foreign than for domestic flows in the $GreenFlowNet$.

Summary statistics of the variables employed are reported in Table 1.

[TABLE 1 ABOUT HERE]

4 Results

4.1 Green-tech diversification and embodied green knowledge flows

Tables 2 and 3 report the results of our estimates when total regional degree centrality – i.e., considering both inward and outward regional flows – is modeled as explanatory variable in regional green-tech diversification at the extensive and intensive margins, respectively. In both cases, column (1) refers to the model including controls and average relatedness density,

[10] It is worth noting that lagging independent variables might not rule out other potential sources of endogeneity. For this reason, we avoid interpreting the relationships found with our estimates making causality claims.

column (2) to the model augmented with the centrality measure, and column (3) to the model with the interaction term between average relatedness density and centrality.

As expected, in both estimations and all models, Avg_RD reveals a positive and statistically significant coefficient. In line with previous research (Montresor et al., 2022; Santoalha and Boschma, 2021), this result confirms that the region's capacity to diversify its technologies in the green realm is greater when green-tech entries are cognitively closer to the technologies in the regional knowledge space. In brief, the development of new green technologies is path-dependent and occurs in the form of branching.

Retaining the average level of the relatedness variable, in Model 2 of both tables, the total centrality of regions in the network of inter-regional embodied green knowledge is statistically significant and positive. This supports our Hp1 when inward and outward flows are indistinguishably retained.

When we move to Model 3, which conditions the effect of regions' centrality in the $NetwGreenFlow$ on relatedness, not only turns our focal regressor statistically significant. But it also negatively moderates the role of the average relatedness density on green-tech diversification.

All in all, our first two hypotheses – Hp1 and Hp2 – appear confirmed when we pull together inward and outward flows of the $GrenFlowNet$.

Quite interestingly, the results reported in Tables 2 and 3 support our two hypotheses at both margins, with no appreciable differences between the extensive and the intensive one. However, the two processes of green-tech diversification are still different, as reflected by some heterogeneity in the controls. Indeed, while GDP per capita appears significant and negative in the two cases - pointing to a possible greater scope of relatively less developed regions in acquiring new green-techs from a still incomplete knowledge base - the stringency of environmental policy appears to help regions only in diversifying at the intensive margin.

[TABLE 2 ABOUT HERE]

[TABLE 3 ABOUT HERE]

Table 4 delves into the specificity of the network connectivity, illustrating estimation results with respect to different centrality measures: *in-degree centrality out-degree centrality*. At both the extensive and the intensive margin, an interesting result emerges. The positive association between degree centrality and green-tech diversification appears driven by its out-degree component. At the extensive margin (Table 4, columns 1 and 2), in-degree centrality apparently and unexpectedly reduces the regional capacity to green-tech diversify, and it complements, rather than substituting, the green-tech diversification role of relatedness (i.e., $AvgRD$). However, the significance of the two coefficients is weak. At the intensive margin, (Table 4, columns 3 and 4), this latter role also vanishes, and green-tech diversification correlates only with the out-degree centrality of regions in the $GreenFlowNet$: both directly and indirectly (i.e., by negatively moderating the positive effect of $AvgRD$).

All in all, our two hypotheses (Hp1 and Hp2) appear confirmed mainly with respect to the out-degree centrality of regions in the network at stake. This is quite interesting and suggests that, for the sake of green-tech diversification (Hp1) and of its exploratory degree (Hp2) (especially at the intensive margin), it is not so important for regions to be pivotal in acquiring embodied green knowledge from the outside. Rather, what seems to be crucial is the regions' importance in diffusing outside new green knowledge developed internally. In other words, the inter-regional exchanges of the $GreenFlowNet$ appear to spur green-tech diversification mainly by exposing regional suppliers to the demand for greener local commodities by extra-regional customers; rather than by making regional customers exposed to the offer of greener commodities by extra-regional suppliers. In this last respect, the green knowledge developed internally is apparently more relevant than that acquired externally for the sake of green-tech diversification.

[TABLE 4 ABOUT HERE]

Moving to the test of our Hp3, the relative importance of regional centrality in foreign vs.

domestic $GreenFlowNet$ appears different with respect to extensive and intensive green-tech diversification. At the *extensive margin*, the degree centrality of regions (in general terms) appears to matter only with respect to the foreign portion of the $GreenFlowNet$ (columns 1) and 2) in Table 5), for which our general results (i.e, for the entire $GreenFlowNet$) appear confirmed. Indeed, at the same margin, degree centrality in the domestic network is not significantly correlated with green-tech diversification and does not significantly moderate the role of relatedness either. In brief, by supporting our Hp3, foreign flows do matter more than domestic ones for regions to gain a new green-tech diversification; as unlike the former, the latter do not seem to matter.

At the *intensive margin*, previous results get reversed. Indeed, the degree centrality of regions in the domestic network correlates with $GreenTechEntryIM$ more than that in the foreign network (columns 3) and 4) in Table 5). Furthermore, the centrality of regions in the domestic network is the only one that significantly and negatively moderates relatedness, as from our Hp2. In other words, domestic flows matter more than foreign ones for regions to increase the number of new green-tech entries and they are the only ones that matter for doing that in a more exploratory manner.

Results about Hp3 are particularly interesting, as they suggest a sort of "labour division", between centrality in the foreign and domestic $GreenFlowNet$, in facilitating regional green-tech diversification. On the one hand, the former (foreign), which possibly conveys in regions the more diversified kind of external embodied green knowledge, appears to act as an *enabler* of green-tech diversification: more central regions in the foreign $GreenFlowNet$ are in fact more capable to enter in the green-tech realm, while this does not happen for their centrality in the domestic network. On the other hand, degree centrality in the domestic $GreenFlowNet$ serves as an *accelerator* of green-tech diversification: more central regions in this network are more capable to acquire a greater number of new green technologies; the same role is also played by regions centrality in the foreign $GreenFlowNet$, but to a lesser extent.

[TABLE 5 ABOUT HERE]

All in all, while the (total) centrality of regions in the foreign *GreenFlowNet* is the only one that matters both for the sake of their extensive and intensive green-tech diversification, our Hp3 appears confirmed only at the extensive margin. With respect to the intensive margin, unlike Hp3 predicts, it is instead the centrality in the domestic network that matters more both in affecting green-tech diversification (Hp1) and in making it more exploratory (Hp2).

4.2 Robustness checks and further analysis

In order to check for the robustness of our previous findings, we carry out a number of robustness checks. Furthermore, interesting nuances emerge when we carry out additional analysis to those presented in the baseline.

First, to overcome the assumption regarding the stability of the input-output coefficients of matrix A_t in building up the *GreenFlowNet* (as from Eq.5) over the period 2000-2019, we have re-run our estimates by letting input-output coefficients vary over the period 2000-2010 – for which data are indeed available–. We then compare these estimates with the results obtained by averaging input-output coefficients over the same restricted period. Tables A1 and A2 show that, at both the extensive and the intensive margin, respectively, Hp1 and Hp2 are confirmed with the specification we made in the baseline. The correlation between green-tech diversification and regional total degree centrality is significant and positive (Hp1), and the same centrality negatively moderates the positive correlation between relatedness and green-tech diversification (Hp2). Yearly-based results (Columns (4) and (5)) are consistent with average-based ones (Columns (1), (2), and (3).)

As a second robustness check, we re-estimate the model that counts the number of new green-tech entries (i.e., diversification at the intensive margin) using a FE Poisson model. Table A3 shows that the results are consistent with the baseline.

In the third and last robustness check, we augment our baseline model by retaining among the controls the extent to which regions are central in the complement network to the $GreenFlowNet$, that is, $Non - GreenFlowNet$. This network is constructed by using the same methodology adopted to obtain the $GreenFlowNet$ (see Section 3.2.2) but considering all the regional industry patents, excluding the green ones. In this way, we measure inter-industry flows across regions of embodied non-green knowledge. Indeed, this could help us understand whether it is the environmental nature of the (industry-specific embodied) knowledge that is exchanged among regions that matter for the sake of their green-tech diversification or, rather, their openness of any kind and even non-green. Tables A4 and A5 show that our results are robust to the inclusion of this last control. Furthermore, quite interestingly, being central in the $Non - GreenFlowNet$ does not seem to help regions with their green-tech diversification. On the contrary, though with weak statistical significance, this kind of centrality apparently reduces the regions' capacity to master new green technologies, especially at the intensive margin. Speculatively, this could be accounted for by the fact that this centrality rather helps regions with their non-green-tech diversification.

5 Concluding remarks

The regional capacity to diversify existing green technologies represents a crucial leverage for local sustainable growth. This green-tech diversification allows regions to escape lock-in traps in pre-existing knowledge domains and trigger resilient reactions to move effectively along the desired green transition. Extant research has shown that regional green-tech diversification requires a wide range of factors, among which the attention has been placed on the regional capacity to branch out existing technological competencies into new, related ones by extending and diversifying existing technological competencies into new, related areas. Conversely, the literature has paid limited attention to regional external drivers, such as regional participation in Global Value Chains and, in particular, in Global Knowledge Networks of different kinds.

In contributing to filling this gap, in this paper, we have focused on the exchanges of embodied green knowledge that regions make among them through the flows of intermediate commodities occurring among their industries. In particular, by extending the relatedness approach to regional technological diversification, along the lines suggested by Fusillo et al. (2023), we have argued that these embodied green knowledge flows constitute a network, enabling regions to increase their green-tech diversification capacity and make it more exploratory. We have tested these expectations empirically with respect to 237 EU regions (NUTS2) observed from 2000 to 2019. The analysis has been carried out by building up a new dataset, which combines the EUREGIO input-output database with green patent data from OECD RegPat, and by employing network analysis indicators in a related diversification model.

Our analysis yields three main results, bearing important policy implications. Firstly, we found that more central regions in the embodied extra-regional exchange of green knowledge are more capable of gaining new green technologies. In other words, such a centrality helps regions diversify in the green-tech realm. Furthermore, it also makes regions more capable to diversify in an exploratory manner, that is, by targeting new green technologies that are cognitively more distant from pre-existing ones. This result has important policy implications, as it suggests to regional policy-makers an additional leverage to escape the risk of lock-in in pre-existing (possibly brown) technologies. This passes through the policy support to their inter-regional and international trade of intermediate commodities, which should be retained in the policy-mix to pursue smart and sustainable growth.

Secondly, we found that regional green-tech diversification is fostered, along the lines of the previous result, by the regions' selling, rather than acquiring embodied green-tech knowledge in the network that regional industries create. In terms of policy implications, this result suggests that policy-makers can foster the entry of new green technologies in their regions by supporting the local providers of intermediate commodities, which could incorporate local green knowledge, rather than the local customers of green knowledge developed elsewhere and incorporated in foreign intermediate commodities.

Thirdly, our results show interesting heterogeneity with respect to the geographical extension of the inter-regional flows of embodied green knowledge we have considered. Being more central in the network of foreign flows of this kind is the only channel through which regions can increase their capacity to make the shift in the green-tech realm, that is, specializing in any new green technology. Conversely, a higher centrality in the network of domestic flows makes regions more capable to acquire a higher number of new green technologies, i.e., of accelerating the green-tech transition in intensive terms. Centrality in the foreign network can ease this process but to a lower extent compared to the centrality in the domestic one. Drawing on this result, local policy-makers should consider that targeting the domestic rather than the foreign network in terms of centrality should be informed also and above all by the need their regions express with respect to the green-tech transition, in turn, related to their position along it.

The results of our empirical analysis are not free from limitations. A first limitation concerns the kind of knowledge flows on which we focus with our $GreenFlowNet$. Indeed, although following consolidated literature, in the construction of the $GreenFlowNet$ we implicitly assumed that the green knowledge gets embodied in the production of the industry to a full extent. Further, the input-output matrix A_t is specified following the proportionality assumption in knowledge embodiment. An alternative approach would be to describe production relationships in terms of vertically integrated sectors (Montresor and Vittucci Marzetti, 2007; Montresor and Marzetti, 2008). This would imply assuming that green knowledge in a sector flows proportionally to all the production exchanges between industries in different regions, considering all the interconnected production rounds, thus combining both direct and indirect green knowledge flows between two industries. However, for the purpose of our analysis, both direct and indirect linkages among region-industries pair are relevant in mapping the regional importance in the network of green knowledge exchanges, thus, we choose not to use the concept of vertically integrated sectors in our analysis. Yet, the extension toward a disembodied kind of green knowledge flows, would represent an interesting avenue for future research.

A second limitation concerns the fact that the EUREGIO data are highly aggregated in terms of industrial coverage, with data available for 14 industries. This may lead to an over-aggregation of industries, which, in turn, could have resulted in a potential overestimation of the green knowledge exchanges. Future research may overcome such limitation by calling for greater efforts toward the provision of extensive regionalized worldwide input–output tables, such as the development of multi-regional input-output tables (e.g., RHOMOLO) and the provision of more advanced estimation techniques (going beyond the RAS method).

The last concern is related to the choice of the appropriate centrality indicator to measure the importance of regions in the network of green knowledge exchanges. Indeed, different network centrality measures are meant to capture different aspects of the positioning of nodes within the network and its consequent impact. Future research might exploit such heterogeneity by comparing different centrality measures, and aiming at assessing their potential differential role in stimulating regional technological diversification and development.

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Tables

Table 1: Summary statistics

	N	Mean	St. Dev.	Min	Max
Green Tech Entry EM	3,683	0.610	0.488	0	1
Green Tech Entry IM	3,683	1.063	1.109	0	7
Avg RD	3,683	0.960	1.041	0.000	5.027
Total Degree Centrality	3,683	31.291	98.619	0.994	1,443.511
In Degree Centrality	3,683	9.514	5.308	0.994	37.211
Out Degree Centrality	3,683	21.777	98.670	0.000	1,434.287
GDP cap	3,683	0.026	0.012	0.003	0.102
Env. Policy String.	3,683	2.867	0.687	0.528	4.722

Table 2: Green-tech diversification at the extensive margin (EM) and total degree centrality.

	GreenTech Entry EM		
	(1)	(2)	(3)
Avg RD	0.4510***	0.4480***	0.7051***
	(0.0167)	(0.0165)	(0.0486)
GDP cap	-5.964*	-6.129**	-6.268**
	(3.128)	(3.104)	(2.971)
Env. Policy String.	0.0045	0.0116	0.0077
	(0.0192)	(0.0193)	(0.0193)
Tot. Degree Cent.		0.1131***	0.1878***
		(0.0324)	(0.0344)
Avg RD × Tot. Degree Cent.			-0.0765***
			(0.0121)
Observations	3,683	3,683	3,683
R^2	0.69723	0.69826	0.72078
Within R^2	0.61783	0.61913	0.64756
Region FE	✓	✓	✓
Year FE	✓	✓	✓

Dep var: regional entry in a generic green-tech. Explanatory variables are lagged by one year, GDP per capita and Total Degree Centrality are log-transformed. All models are estimated through a linear probability model. Heteroskedastic-robust standard errors, reported in parentheses, are clustered at the NUTS2 level. *p<0.1; **p<0.05; ***p<0.01

Table 3: Green-tech diversification at the intensive margin (IM) and total degree centrality.

	GreenTech Entry IM		
	(1)	(2)	(3)
Avg RD	0.4350***	0.4274***	0.6698***
	(0.0157)	(0.0152)	(0.0468)
GDP cap	-3.001	-3.407	-3.538
	(3.528)	(3.422)	(3.326)
Env. Policy String.	0.0472**	0.0647***	0.0610***
	(0.0222)	(0.0221)	(0.0217)
Tot. Degree Cent.		0.2792***	0.3496***
		(0.0475)	(0.0481)
Avg RD × Tot. Degree Cent.			-0.0721***
			(0.0117)
Observations	3,683	3,683	3,683
R^2	0.58065	0.58607	0.60339
Within R^2	0.48416	0.49083	0.51213
Region FE	✓	✓	✓
Year FE	✓	✓	✓

Dep var: (log) number of regional entry in green-techs. Explanatory variables are lagged by one year, GDP per capita and Total Degree are log-transformed. All models are estimated using two-way fixed effects OLS. Heteroskedastic-robust standard errors, reported in parentheses, are clustered at the NUTS2 level. *p<0.1; **p<0.05; ***p<0.01

Table 4: Green-tech diversification at the EM and IM, in-degree vs. out-degree centrality.

	GreenTech Entry EM		GreenTech Entry IM	
	(1)	(2)	(3)	(4)
Avg RD	0.4417***	0.4919***	0.4190***	0.5135***
	(0.0161)	(0.0795)	(0.0145)	(0.0754)
InDegree Cent.	-0.1759	-0.1995*	-0.1721	-0.1741
	(0.1170)	(0.1159)	(0.1343)	(0.1300)
OutDegree Cent.	0.1286***	0.1678***	0.2196***	0.2564***
	(0.0173)	(0.0173)	(0.0211)	(0.0213)
GDP cap	-6.875**	-7.395**	-4.531	-4.863
	(3.105)	(3.097)	(3.418)	(3.404)
Env. Policy String.	-0.0026	-0.0055	0.0432**	0.0403*
	(0.0193)	(0.0189)	(0.0217)	(0.0208)
Avg RD × InDegree Cent.		0.0485*		0.0213
		(0.0257)		(0.0249)
Avg RD × OutDegree Cent.		-0.0637***		-0.0570***
		(0.0081)		(0.0077)
Observations	3,683	3,683	3,683	3,683
R^2	0.70480	0.74193	0.59945	0.62455
Within R^2	0.62739	0.67426	0.50729	0.53816
Region FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Dep var: regional entry in a generic green-tech in columns 1 and 2 (extensive margin); (log) number of regional entry in green-techs in columns 3 and 4 (intensive margin). Explanatory variables are lagged by one year, GDP per capita and Degree centrality variables are log-transformed. Models in columns 1 and 2 are estimated through a linear probability model; Models in columns 3 and 4 are estimated using two-way fixed effects OLS. Heteroskedastic-robust standard errors, reported in parentheses, are clustered at the NUTS2 level. *p<0.1; **p<0.05; ***p<0.01

Table 5: Green-tech diversification at the EM and IM, degree centrality in domestic vs. foreign network

	GreenTech Entry EM		GreenTech Entry IM	
	(1)	(2)	(3)	(4)
Avg RD	0.4486***	0.6327***	0.4279***	0.5848***
	(0.0165)	(0.0557)	(0.0151)	(0.0399)
Tot. Degree Cent. Foreign	0.1062***	0.1648***	0.1157*	0.1449**
	(0.0359)	(0.0420)	(0.0679)	(0.0674)
Tot. Degree Cent. Domestic	-0.0019	-0.0003	0.1462***	0.2310***
	(0.0015)	(0.0014)	(0.0461)	(0.0453)
GDP cap	-6.013*	-6.233**	-3.012	-4.013
	(3.118)	(2.999)	(3.408)	(3.577)
Env. Policy String.	0.0084	0.0047	0.0635***	0.0598***
	(0.0192)	(0.0192)	(0.0222)	(0.0218)
Avg RD × Tot. Degree Cent. Foreign		-0.0548***		0.0128
		(0.0180)		(0.0166)
Avg RD × Tot. Degree Cent.Domestic		-0.0009		-0.1024***
		(0.0006)		(0.0150)
Observations	3,683	3,683	3,683	3,683
R^2	0.69788	0.71749	0.58617	0.61170
Within R^2	0.61866	0.64341	0.49094	0.52235
Region FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Dep var: regional entry in a generic green-tech in columns 1 and 2 (extensive margin); (log) number of regional entry in green-techs in columns 3 and 4 (intensive margin). Domestic degree refers to in-group degree centrality in the network of domestic flows; Foreign degree refers to in-group degree centrality in the network of foreign flows. Explanatory variables are lagged by one year, GDP per capita and Degree centrality variables are log-transformed. Models in columns 1 and 2 are estimated through a linear probability model; Models in columns 3 and 4 are estimated using two-way fixed effects OLS. Heteroskedastic-robust standard errors, reported in parentheses, are clustered at the NUTS2 level. *p<0.1; **p<0.05; ***p<0.01

Appendix A

Table A1: Robustness: Green-tech diversification at the EM and total degree centrality over 2000-2010.

	Green Entry EM				
	(1)	(2)	(3)	(4)	(5)
Av.Rel Dens	0.4370***	0.4306***	0.7028***	0.4344***	0.7005***
	(0.0192)	(0.0188)	(0.0574)	(0.0191)	(0.0554)
GDP cap	-18.47***	-19.33***	-18.24***	-18.67***	-17.78***
	(6.149)	(6.318)	(6.204)	(6.346)	(6.372)
Env. Policy String.	0.0464	0.0460	0.0391	0.0444	0.0342
	(0.0330)	(0.0327)	(0.0319)	(0.0329)	(0.0323)
Tot. Degree Cent.		0.1898***	0.2714***		
		(0.0449)	(0.0457)		
Av.Rel Dens × Tot. Degree Cent.			-0.0832***		
			(0.0141)		
Tot. Degree Cent.Y				0.0736**	0.1434***
				(0.0327)	(0.0354)
Av.Rel Dens × Tot. Degree Cent.Y					-0.0811***
					(0.0133)
Observations	1,903	1,903	1,903	1,903	1,903
R^2	0.69410	0.69658	0.72004	0.69476	0.71750
Within R^2	0.57710	0.58053	0.61297	0.57801	0.60945
Region FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓

Dep var: regional entry in a generic green-tech. The sample is reduced to the period 2000-2010. Total degree centrality in columns 1), 2), and 3) refer to the network with average-based input-output coefficients. Total degree centrality Y, in columns 4) and 5), is calculated allowing input-output coefficients to vary yearly. Explanatory variables are lagged by one year, GDP per capita and degree variables are log-transformed. All models are estimated through a linear probability model. Heteroskedastic-robust standard errors, reported in parentheses, are clustered at the NUTS2 level. *p<0.1; **p<0.05; ***p<0.01

Table A2: Robustness: Green-tech diversification at the IM and total degree centrality over 2000-2010.

	Green Entry IM				
	(1)	(2)	(3)	(4)	(5)
Av.Rel Dens	0.4298***	0.4166***	0.6787***	0.4231***	0.6783***
	(0.0176)	(0.0166)	(0.0536)	(0.0171)	(0.0519)
GDP cap	-13.03**	-14.79**	-13.74**	-13.54**	-12.68*
	(6.263)	(6.460)	(6.445)	(6.537)	(6.631)
Env. Policy String.	0.0858**	0.0849**	0.0783**	0.0806**	0.0708*
	(0.0384)	(0.0382)	(0.0376)	(0.0384)	(0.0380)
Tot. Degree Cent.		0.3900***	0.4686***		
		(0.0578)	(0.0576)		
Av.Rel Dens × Tot. Degree Cent.			-0.0801***		
			(0.0131)		
Tot. Degree Cent.Y				0.1914***	0.2583***
				(0.0446)	(0.0474)
Av.Rel Dens × Tot. Degree Cent.Y					-0.0778***
					(0.0124)
Observations	1,903	1,903	1,903	1,903	1,903
R^2	0.58777	0.59679	0.61552	0.59159	0.60963
Within R^2	0.45752	0.46939	0.49405	0.46255	0.48629
Region FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓

Dep var: (log) number of regional entry in green-techs. The sample is reduced to the period 2000-2010. Total degree centrality in columns 1), 2), and 3) refer to the network with average-based input-output coefficients. Total degree centrality Y, in columns 4) and 5), is calculated allowing input-output coefficients to vary yearly. Explanatory variables are lagged by one year, GDP per capita, and degree variables are log-transformed. All models are estimated using two-way fixed effects OLS. Heteroskedastic-robust standard errors, reported in parentheses, are clustered at the NUTS2 level. *p<0.1; **p<0.05; ***p<0.01

Table A3: Robustness: Green-tech diversification at the IM, fixed-effects Poisson regression.

	GreenTech Entry IM		
	(1)	(2)	(3)
Av.Rel Dens	1.081***	1.061***	1.578***
	(0.0431)	(0.0425)	(0.1028)
GDP cap	-2.824	-2.976	-1.458
	(9.831)	(9.594)	(9.947)
Env. Policy String.	0.1105*	0.1414**	0.1356**
	(0.0591)	(0.0591)	(0.0602)
Tot. Degree Cent.		0.4860***	0.7844***
		(0.1098)	(0.1184)
Av.Rel Dens × Tot. Degree Cent.			-0.1663***
			(0.0268)
Observations	3,626	3,626	3,626
Squared Correlation	0.35265	0.35626	0.36411
Pseudo R^2	0.21262	0.21453	0.21870
BIC	9,711.1	9,700.0	9,666.1
Region FE	✓	✓	✓
Year FE	✓	✓	✓

Dep var: number of regional entry in green-techs. Explanatory variables are lagged by one year, GDP per capita and Total Degree are log-transformed. All models are estimated using two-way fixed effects Poisson regressions. Heteroskedastic-robust standard errors, reported in parentheses, are clustered at the NUTS2 level. *p<0.1; **p<0.05; ***p<0.01

Table A4: Robustness: Green-tech diversification at the EM and total degree centrality in the non-green network.

	Green Entry EM		
	(1)	(2)	(3)
Av.Rel Dens	0.4510***	0.4479***	0.7075***
	(0.0167)	(0.0165)	(0.0490)
GDP cap	-5.964*	-6.359**	-6.659**
	(3.128)	(3.115)	(2.950)
Env. Policy String.	0.0045	0.0103	0.0054
	(0.0192)	(0.0194)	(0.0193)
Tot. Degree Cent. Green		0.1249***	0.2086***
		(0.0320)	(0.0339)
Tot. Degree Cent. Non-Green		-0.0834	-0.1408*
		(0.0790)	(0.0779)
Av.Rel Dens × Tot. Degree Cent. Green			-0.0772***
			(0.0122)
Observations	3,683	3,683	3,683
R^2	0.69723	0.69845	0.72133
Within R^2	0.61783	0.61938	0.64826
Region FE	✓	✓	✓
Year FE	✓	✓	✓

Dep var: regional entry in a generic green-tech. No-Green Total degree refers to the in-group centrality in the network of non-green embodied knowledge flows, obtained by multiplying the input-output matrix by a diagonal vector of non-green knowledge. Explanatory variables are lagged by one year, GDP per capita and Total Degree are log-transformed. All models are estimated through a linear probability model. Heteroskedastic-robust standard errors, reported in parentheses, are clustered at the NUTS2 level. *p<0.1; **p<0.05; ***p<0.01

Table A5: Robustness: Green-tech diversification at the IM and total degree centrality in the non-green network.

	Green Entry IM		
	(1)	(2)	(3)
Av.Rel Dens	0.4350***	0.4273***	0.6738***
	(0.0157)	(0.0152)	(0.0475)
GDP cap	-3.001	-3.900	-4.184
	(3.528)	(3.399)	(3.261)
Env. Policy String.	0.0472**	0.0619***	0.0572***
	(0.0222)	(0.0221)	(0.0215)
Tot. Degree Cent. Green		0.3044***	0.3838***
		(0.0481)	(0.0486)
Tot. Degree Cent. Non-Green		-0.1781*	-0.2326**
		(0.0948)	(0.0919)
Av.Rel Dens × Tot. Degree Cent. Green			-0.0733***
			(0.0120)
Observations	3,683	3,683	3,683
R^2	0.58065	0.58684	0.60469
Within R^2	0.48416	0.49177	0.51373
Region FE	✓	✓	✓
Year FE	✓	✓	✓

Dep var: (log) number of regional entry in green-techs. No-Green Total degree refers to the in-group centrality in the network of non-green embodied knowledge flows, obtained by multiplying the input-output matrix by a diagonal vector of non-green knowledge. Explanatory variables are lagged by one year, GDP per capita and Total Degree are log-transformed. All models are estimated using two-way fixed effects OLS. Heteroskedastic-robust standard errors, reported in parentheses, are clustered at the NUTS2 level. *p<0.1; **p<0.05; ***p<0.01

EUREGIO		ISIC (rev.4)	
ss1	Agriculture	A01	Crop and animal production, hunting and related service activities
ss2	Mining_quarrying_and_energy_supply	B05	Mining of coal and lignite
ss2		B06	Extraction of crude petroleum and natural gas
ss2		B07	Mining of metal ores
ss2		B08	Other mining and quarrying
ss3	Food_beverages_and_tobacco	C10	Manufacture of food products
ss3		C11	Manufacture of beverages
ss3		C12	Manufacture of tobacco products
ss4	Textiles_and_leather_etc	C13	Manufacture of textiles
ss4		C14	Manufacture of wearing apparel
ss4		C15	Manufacture of leather and related products
ss5	Coke_refined_petroleum_nuclear_fuel_and_chemicals_etc	C19	Manufacture of coke and refined petroleum products
ss5		C20	Manufacture of chemicals and chemical products
ss6	Electrical_and_optical_equipment_and_Transport_equipment	C26	Manufacture of computer, electronic and optical products
ss6		C27	Manufacture of electrical equipment
ss6		C30	Manufacture of other transport equipment
ss8	Other_manufacturing	C16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
ss8		C17	Manufacture of paper and paper products
ss8		C18	Printing and reproduction of recorded media
ss8		C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
ss8		C22	Manufacture of rubber products
ss8		C23	Manufacture of other non-metallic mineral products
ss8		C24	Manufacture of basic metals
ss8		C25	Manufacture of fabricated metal products, except machinery and equipment
ss9	Construction	F41	Construction of buildings
ss9		F42	Civil engineering
ss10	Distribution	J58	Publishing activities
ss10		J59	Motion picture, video and television programme production, sound recording and music publishing activities
ss10		J60	Programming and broadcasting activities
ss10		J61	Telecommunications
ss10		J62	Computer programming, consultancy and related activities
ss10		J63	Information service activities
ss11	Hotels_and_restaurants	I55	Accommodation
ss11		I56	Food and beverage service activities
ss12	Transport_storage_and_communication	H49	Land transport and transport via pipelines
ss12		H50	Water transport
ss12		H51	Air transport
ss12		H52	Warehousing and support activities for transportation
ss12		H53	Postal and courier activities
ss13	Financial_intermediation	K64	Financial service activities, except insurance and pension funding
ss13		K65	Insurance, reinsurance and pension funding, except compulsory social security
ss13		K66	Activities auxiliary to financial service and insurance activities
ss14	Real_estate_renting_and_business_activities	L68	Real estate activities
ss14		M69	Legal and accounting activities
ss14		M70	Activities of head offices; management consultancy activities
ss14		M71	Architectural and engineering activities; technical testing and analysis
ss14		M72	Scientific research and development
ss14		M73	Advertising and market research
ss14		M74	Other professional, scientific and technical activities
ss14		M75	Veterinary activities
ss14		N77	Rental and leasing activities
ss14		N78	Employment activities
ss14		N79	Travel agency, tour operator, reservation service and related activities
ss14		N80	Security and investigation activities
ss14		N81	Services to buildings and landscape activities
ss14		N82	Office administrative, office support and other business support activities
ss15	Non_Market_services	S94	Activities of membership organizations
ss15		S95	Repair of computers and personal and household goods
ss15		S96	Other personal service activities
ss15		T97	Activities of households as employers of domestic personnel
ss15		T98	Undifferentiated goods- and services-producing activities of private households for own use
ss15		U99	Activities of extraterritorial organizations and bodies

Table A6: EUREGIO and ISIC industrial concordance table