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Do digital skills foster green diversification?

A study of European regions

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Abstract

Within the debate on smart specialisation, there is growing attention towards the features that favour or thwart regions' ability to pursue sustainable development through eco-innovation. Against this backdrop, the present paper proposes an empirical analysis of the role of local capabilities, of related diversification and of their interaction in a panel of 225 European regions (NUTS 2) between 2002 and 2013. The main novelty is the explicit consideration of digital skills, workforce capabilities associated with the use and development of digital technologies. We find that the e-skills endowment is positively correlated with the probability that regions specialise in new green technological domains. Moreover, digital competences positively moderate the effect of technological relatedness on green diversification. Our results highlight the potential of complementarities between two emerging general-purpose technologies, ICTs and eco-innovations, in the transition towards a greener economy.

Keywords: Eco-innovation; ICTs; digital skills; technological relatedness; green diversification; smart specialisation

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1. Introduction

The present paper contributes to research at the intersection of economic geography and environmental innovation (Coenen and Truffer, 2012; Hansen and Coenen, 2015) by studying the role of local capabilities in regional green specialisation. The analysis of the nature, the sources and the diffusion of eco-innovation is at the centre of an intense debate among academics and policy makers alike. Tackling and preventing the negative effects of climate change call for a paradigm shift driven by structural change and innovation (Ayres and van den Bergh, 2005). The consensus is that accelerating the development of new low-carbon technologies and promoting their global application are both crucial steps towards enhancing environmental efficiency (e.g. Carrión-Flores and Innes, 2010; Costantini et al., 2013; Voigt et al, 2014; Ghisetti and Quatraro, 2017). At the same time, the belief is that technology alone will not suffice (United Nations, 2017), especially when rebound effects are at play (Michaels, 2012). Parallel to this, economic geographers debate the role of local capabilities in spurring the emergence of new specialisations. The expectation is that effective policies can stimulate bottom-up learning and open up opportunities for innovation and development by exploiting existing know-how (Foray et al, 2009). But besides prior capacity local technological and non-technological infrastructures are pivotal in the pursuit of smart specialisation. We follow up recent literature that emphasises a gap on the role of general-purpose technologies (GPTs) in the development of new regional specialisations (Sörvik et al, 2014; Pattinson et al, 2015; Foray, 2015; Montresor and Quatraro, 2017). More in detail, we focus on the characteristics of the regional knowledge base associated with a particular GPT, Information and Communication Technologies (ICTs). Although these technologies assist the generation of new products, production processes and services, their enduring effects in modern economies is in the form of new knowledge (Bristow, 2005). Given the pervasive character of these GPTs, digital literacy consists not just in specific technical knowledge (i.e. programming) but also in the hybridisation of traditional competences to heighten capacity of reading, writing, researching and communicating. Different from prior literature, we do not focus on the endowment of physical technologies but, rather, on the workforce skills that are needed to operate effectively these GPTs.

Bringing together the above threads, we propose that studying whether and to what extent the local knowledge base can trigger the latent potential of innovation is crucial to understanding why some regions fare better than others in the face of societal challenges such as climate change. While prior literature has elucidated the spatial dynamics of green activities, the role

of workforce skills has been somewhat neglected. In broad strokes, high levels of human capital facilitate local economic development through a variety of channels (Glaeser et al, 1995; Audretsch et al., 2005), but no study has so far explored the empirical regularities and the specific mechanisms in relation to green innovation. As Boschma (2017) notes, in the regional diversification literature capabilities are defined in a broad fashion and are identified in empirical analysis at best indirectly, following the principle of similar resource requirements (i.e. co-location, co-occurrence). We tackle this gap by focussing on the digital skills in the workplace that are needed to use, adapt and design ICTs across various context. E-skills carry a general-purpose character (Carretero et al, 2017; CEEMET, 2018; Castellacci et al, 2019) that is deemed important in the face of major societal transitions, such as environmental sustainability, which entail the creation of new activities as well as the adaptation of existing ones.

Our expectation is that these local capabilities are important in opening up new technological and industrial profiles across regions. The proposed approach also adds to empirical literature based on the use of patenting as a proxy for invention capacity while, at the same time, offering a more nuanced perspective of the extent to which technologies are absorbed into work routines. Put otherwise, being based on the direct observation of skills used within work activities, our analysis is closer to the context of use rather than of creation of technology. Our analysis of the role of digital skills in green technological diversification in a panel of 225 European regions (NUTS 2)³ between 2002 and 2013 yields three main findings. First, the level of e-skills in the workforce is a positive predictor that a region specialises in a new green technological domain. Second, both green and non-green relatedness are found to matter for the development of a new green specialisation. Third, digital competences magnify the positive effect of both types of technological relatedness on green technological diversification. In general terms, the idea that digitalization and ICTs may foster the transition towards a greener economy is paramount, but the complementarity between these two GPTs has received very limited scholarly attention so far (Cecere et al., 2014). By showing that digital skills matter for green diversification, the present paper takes a first step towards bridging the gap between ICTs research and transition studies.

The paper is organized as follows. Section 2 provides an overview of prior literature on regional diversification and eco-innovation in the context of digital economies. Building on these strands of work, we formulate our main hypotheses in Section 3. Sections 4 and 5 detail

³ UK is an exception: we use data regionalized by NUTS 1.

the variable construction, data sources and the descriptive statistics. After the regression analysis and a detailed comment of the empirical results in Section 6, the last section concludes and briefly discusses the policy implications of our findings.

2. Literature review

Responding to societal challenges like climate change requires a vast array of transformations in the way resources are generated and used. Both the adaptation of old activities and the emergence of new ones are expected to be highly uneven across space since territories display significant heterogeneity in exposure to climate events as well as in their ability to adjust. The literature on economic geography has long since established that the generation and diffusion of relevant know-how rely on the institutional set up that, together with the attendant socioeconomic and cultural system, determine whether local economies succeed or fail to upgrade in the face of new societal challenges (Capello and Lenzi, 2018). A key question for the goal of the present paper, is: to what extent do local characteristics promote, or thwart, adaptation in the face of green growth?

2.1 – Regional diversification and eco-innovation

A now consolidated literature in evolutionary economic geography emphasises that regional development consists of both qualitative and quantitative transformations. The underlying proviso, dating to the pioneering studies of Norton and Rees (1979), is that innovation cum structural change allows regions to develop new industries and outperform regions that are locked into mature industries. Such an intuition gave the way to alternative interpretations of agglomeration economies beyond the traditional Marshallian specialisation tenet, and based on Jane Jacobs' (1969) argument that new industries require diversified local economies. Taking the cue from this, Glaeser et al (1992) extended the agglomeration externalities framework with a view to assess the effect of the local industrial structure. Building on that, Henderson et al (1995) showed that mature industries benefit from 'Marshallian' localization externalities in specialized cities whereas new hi-tech industries tended to emerge in diversified cities, where Jacobs' type of externalities were at work. Subsequently, Duranton and Puga (2001) put forth the notion of nursery cities in relation to how agglomeration benefits from the local environment depend on firms' maturity. These seminal works paved the way to empirical studies on whether and how much existing local capabilities affect regional specialisation into new industries (Neffke et al 2011), new technologies (Rigby, 2015), as well as regions' overall capacity to diversify (Boschma and Capone, 2015). This

literature also shaped the conceptual framework of relatedness (Boschma and Martin, 2007; Apa et al., 2019), whose main tenet is that areas tend to attract new activities that are technologically related to the existing know-how. As Frenken and Boschma (2007) put it, regional industrial paths branch out of related pre-existing activities. Empirical evidence lends support to this hypothesis in a variety of sectoral and geographical contexts (Frenken et al, 2007; Neffke et al, 2011).

Recently, research on regional diversification has turned towards the empirical analysis of green activities. The evidence however remains mixed. Van den Berge and Weterings (2014) find a connection between eco-innovation and pre-existing specialisation in related domains in European regions. Likewise, Tanner (2016) shows that relatedness played a significant role in the emergence of the fuel cell industry in European regions. More recently, Montresor and Quatraro (2019), again on European regions, report positive effects of relatedness in both green and non-green knowledge on the emergence of new green technological specialisations. Conversely, Corradini (2019) finds an inverted U-shaped relationship between the entry of regions in green technologies and the relatedness to local green knowledge. A study on US states by Barbieri et al. (2018b) proposes a different approach based on the empirical identification of the life cycle, and shows that unrelated variety is more prominent for green technologies at early stages of development, while related variety becomes more important as the technologies consolidate into maturity. Likewise, the cross-country analysis by Perruchas et al (2019) reports that, while prior competence in related domains is important for diversification and specialisation, the maturity of the green technology matters more than the level of countries' development. This is consistent with other studies arguing that green activities are more complex than non-green ones, in the sense that they recombine bits of know-how that are cognitively distant (Barbieri et al, 2018a; Quatraro and Scandura, 2019).

By and large these studies do not deal, at least not explicitly, with the role of human capital in green technology development. Yet the ample literature on the mutual significance between innovation and the skills of the workforce (Aghion et al., 1998; Coe, 2005; Charlot et al., 2015) would lead to expect that such a relationship matters also in relation to environmental sustainability. As a matter of fact, empirical evidence indicates that green activities tend to rely on particular forms of know-how via the labour market (Vona et al., 2019). But to the best of our knowledge, no prior study has explicitly connected the two domains, and analysed whether and to what extent new varieties of environmental innovations in regions are associated with the workforce's skills. The present paper seeks to fill this gap.

2.2 – Eco-innovation in digital economies

While it seems plausible that local technological and non-technological infrastructures are pivotal in enabling (green) diversification, only recently has the literature explicitly considered the role of General Purpose Technologies (GPTs). In particular, studies from both the policy (Sörvik et al, 2014; Pattinson et al, 2015) and the scholarly front (Foray, 2015; Montresor and Quatraro, 2017) have analysed emerging functional domains, or Key Enabling Technologies, that embrace a wide spectrum of products and industrial processes, and that are expected to facilitate smart specialisation in modern knowledge economies. The present paper does not deal with these technologies but shares the spirit of prior literature in accounting for GPTs in the development of new regional specialisations. Rather, we focus on Information and Communication Technologies.

Two specific properties make ICTs relevant for the present study. First, their horizontal adaptability and, thus, the potential to trigger complementarities across different domains of use. Second, their potential to trigger forward complementarities between inventions and applications (Frenken et al, 2012). Although the magnitude of their impact is still debated (see e.g. the review by Karlsson et al, 2010), the combination of digitalisation and the Internet has had broader applicability than previous GPTs, in that the effects have not been limited to manufacturing industries but reached out also to services (Carlsson, 2003). More than this, beyond the generation of new products, production processes and services (Kahin and Brynjolfsson, 2000) the enduring effects of ICTs reside in the emergence of new knowledge (Bristow, 2005). Indeed, physical ICTs change over time as a result of scientific advances and learning improvements that both reduce costs and expand the potential of application. More fundamentally, however, these GPTs alter the selection environment that includes non-technological factors – i.e. markets, labour supply, training, infrastructures and institutional factors – that, to a varying degree, affect the innovation potential as well as the capacity to attract the necessary skills.

Recent policy contributions praise the high potential of ICTs to help meeting Sustainable Development Goals (SDGs) more effectively and faster (Earth Institute and Ericsson, 2016). But ICTs have been long perceived as being both ‘part of the problem’ as well as ‘part of the solution’ (Berkhout and Hertin, 2001; Hilty et al, 2015). In particular, the specialised literature points to a threefold interaction between ICTs and the environment.

First, these technologies exert direct negative environmental effects due to growing demand for materials and energy. Further, the production, use, and disposal of these technologies pose significant environmental burdens. To illustrate, the ICT-producing sector alone has been estimated to produce 2% of global greenhouse gas emissions (Mingay, 2007). Conversely, the increase of energy consumption related to the production of equipment and the running of the infrastructure has been estimated to contribute up to 2.8% of total global emissions by 2020 (European Commission, 2009). Under this view, the production, use and disposal of ICTs are therefore problems to be mitigated (Dedrick, 2010).

Second, and to balance the former, digital technologies can trigger indirect positive effects by aiding changes in production processes, products, and distribution systems (Faucheux and Nicolai, 2011; Cecere et al., 2014). The literature calls attention to substitution effects, whereby the use of ICTs replaces the use of environmentally harmful resources (e.g., an e-book reader replacing printed books, as well as optimization effects, whereby the use of ICTs reduces the use of other resources (e.g., less energy is used for heating in a smart home that knows where the people who live in it are located, which windows are open, what weather is forecast, etc.). To illustrate, a report by the International Energy Agency (2018) shows that global investments on the digitalisation of energy date back to the 1970s, and have grown by 20% per year over the last decade. Further, a study on a panel of 142 countries between 1995 and 2010 finds that the relationship between ICT adoption and CO₂ emissions has an inverted U-shape form (Higón et al, 2017).

A third type of effects, often referred to as ‘systemic’, consists of behavioral changes in lifestyles and the promotion of sustainable consumption i.e. through active participation of citizens’ in online platforms. Lebel and Lorek (2008) identify key enabling mechanisms for this effect, namely: co-design, environmental certification and labelling, ethical marketing, educating consumers to responsible consumption. By facilitating the availability of information, digital technologies can help overcoming this gap by connecting relevant actors, by making new opportunities for consumption accessible, by enabling monitoring mechanisms at individual level.

The connection between human capital and the diffusion of ICTs goes beyond the immediate benefits such as higher efficiency in gathering, organising and interpreting information. Adequate digital literacy involves also the hybridisation of traditional competences to heighten capacity of researching, communicating, planning and organising. Accordingly, our analysis focuses on qualitative aspects of human capital that are relevant to the challenges of

climate change and, in particular, on a class of capabilities that are prominent in the modern digital economy. In our view, digitalisation is not merely the scaling-up of computing power upon traditional economic structures but, rather, a radical reorganisation of the possibilities available to both users and producers. Because digital media are so diverse and widespread, they also call for appropriate skills to successfully master an expanded spectrum of options. These are so-called e-skills, which may be defined as capabilities required for researching, developing and designing, managing, producing, consulting, marketing and selling, integrating, installing and administrating, maintaining, supporting and service of ICT systems (Gareis et al., 2014).

Advanced digital literacy entails the hybridisation of traditional competences to heighten capacity of reading, writing, researching and communicating. Accounting for e-skills endowments affords a more nuanced analysis of regional diversification in that it bypasses the generic role of technologies and encompasses more explicitly the way in which work routines tied to digital technologies are embedded in local production and distribution systems.

3. Hypotheses

The complex relationship between green technology, human capital and ICTs calls upon empirical analysis of the circumstances that favour or impede regions to engage the transition towards sustainable growth. Bringing together the various threads outlined above, we develop three main hypotheses.

As already pointed out, infrastructural conditions such as the endowment of ICTs are important but do not per se ensure faster and more efficient green transition. The potential of digital technologies must be enriched and embedded within a very broad set of innovation and knowledge related factors (De Marchi, 2012; Kesidou and Demirel, 2012). In the current technological paradigm, ICTs are expected to play an active role in tackling or preventing the hazards of climate change. However, considering the nature of the complementarities and the high degree of uncertainty at this relatively early stage of tackling climate change, the adaptability and flexibility of the local knowledge base is equally, if not arguably, more important. This resonates with the tenet of economic geography reviewed in section 2.1 whereby the endowment of local capabilities is a key prerequisite for the emergence of specific regional green industrial and technological profiles (Rigby and Essletzbichler, 1997).

This calls attention to the digital skills of the workforce. Our first hypothesis is that these digital skills are important for fostering green technological diversification. Three related

arguments support this idea. First, digital skills of the workforce are arguably stronger in regions that are specialized in ICT-related industries. In these regions, diversifying towards green technologies may be easier because of the close connection between ICTs domains and green innovations (Faucheux and Nicolai, 2011; Cecere et al., 2014). Examples of the intrinsic relationship between ICTs and green GPTs abound for instance in the energy sector. Digitally-enabled tasks such as data processing, modelling, simulation and optimization have been pivotal to the transformation of energy sectors since the 1970s (e.g. smart grids to measure electricity consumption); and they have progressively acquired prominence in other environmentally-sensitive domains such as transport, buildings and industry (IEA, 2018).

However, digital skills are not only important for regions that are specialized in ICTs but also for areas in which the workforce has on average a high level of digital competence, regardless of the specific local industrial specialization. Our second argument is that e-skills enable rapid codification and imitation of complex advanced knowledge that is available in other regions and/or in other industries, thus fostering non-localized spillovers and inter-industry knowledge diffusion (Castellacci et al., 2019). Further, they facilitate access to advanced knowledge stemming from the public science system, which is important for early stage and emerging green domains. Last but not least, ICTs can help overcome path-dependence in established technologies by enabling the swift creation of new network externalities, which increase users' incentives to switch from older to new green technologies.

Third, green innovations are typically based on complex competences that often require recombination of distant bits of knowledge (Quatraro and Scandura, 2019; Messeni Petruzzelli et al., 2011). Digital skills can enhance the introduction of “recombinant innovations” (Frenken et al., 2012) by enabling the codification and use of different pieces and components of knowledge related to distinct domains and technologies. Further, ICTs also enable collaboration among innovative agents (inventors) that are not co-located or are cognitively distant (Pershina et al., 2019), which has been shown to strengthen technological diversification (Santoalha, 2019). In summary, based on the three arguments noted above, we point out the following hypothesis:

H1: *The local endowment of digital skills is positively associated with the development of new regional green technological specialisations.*

The second hypothesis speaks to the debate on whether and to what extent prior competence matters for the development of new regional specialisations, and hence the role of relatedness

for the technological diversification. The existing literature points out that cognitive proximity favours the development of new technology by reducing search costs while at the same time favouring knowledge spillovers across related domains (Boschma, 2017; Tanner, 2016; van den Berge and Weterings, 2014; Corradini 2019). There is contradictory evidence, however, on the nature of the specific know-how that is relevant for green technologies. In general, green activities are more complex than non-green ones and, as a consequence, draw on a broad pool of know-how, both related and unrelated (Barbieri et al, 2018b; Quatraro and Scandura, 2019). Green innovations are often based on recombinations that partly draw on non-green technologies. There are several examples of this. For instance, the hybrid car combines a conventional combustion engine with a new electric propulsion system (Quatraro and Scandura, 2019). Another illustration is the emergence of offshore wind power in Norway, which is largely based on the dominant oil and gas industry (Makitie et al., 2018), and the development of solar photovoltaics that is closely based on competences drawn from the well-established silicon industry (Hanson, 2018). In short, since green technologies are overall at an early stage of their development in the life cycle, they cannot only relate to other green innovations but often require relatedness to existing non-green technological domains (Montresor and Quatraro, 2019; Barbieri et al., 2018b). Therefore, recognizing that both types of relatedness matter, we posit the following hypothesis:

H2: *Both green and non-green relatedness matter for a region's ability to develop new green technological specialisations.*

Taking stock from the first two hypotheses, we combine the above insights and inquire whether digital skills have a moderating effect on the relationship between relatedness and regional green diversification. In other words: do e-skills make relatedness more or less important? The answer to this question is not clear cut. Digital skills can in principle have two contrasting effects on the relatedness-diversification relationship. The first is a substitution effect. As noted above, e-skills can facilitate knowledge diffusion and inter-industry spillovers, thus in principle making relatedness less important for regional diversification (Castellacci et al., 2019). This argument was also advanced and empirically supported in very recent research, which shows the moderating role of General Purpose Technologies (Montresor and Quatraro, 2019) and of academic inventors (Quatraro and Scandura, 2019) in the relationship between relatedness and green diversification / green innovation. On the other hand, however, the opposite is possible, namely that e-skills complement and strengthen the role of relatedness for regional green diversification. As noted above, new green technologies

are on the whole at an early stage of the life cycle (Barbieri et al., 2018b; Perruchas et al., 2019) and rely on relatedness between non-green established technologies and new and emerging green technologies. The complementarity effect posits that digital skills will make relatedness between old (non-green) and new (green) innovations more relevant. This complementarity effect may specifically be related to the following aspect.

Green innovations in emerging domains are often “*carried out by established firms through the acquisition of new competencies outside their core area of technological expertise*” (Cecere et al., 2014: 1837). So, firms (e.g. large incumbent firms and oligopolistic innovators that dominate established technological domains) are often reluctant to undertake R&D investments in new green directions due to high uncertainty about future rewards that characterizes these emerging domains (Messeni Petruzzelli et al., 2011). In regions that are specialized in ICTs, and where companies have high digital skills, incumbents will more likely diversify and enter green technological domains that are close to the existing regional knowledge base because green innovations require recombination of distant knowledge between old and emerging domains (Quatraro and Scandura, 2019). Such a combination calls upon the management of complex knowledge, often close to the scientific frontier, and requires advanced non-routine analytical skills and stronger levels of formal education and human capital (Consoli et al., 2016). Digital skills are closely related to, and enable, the codification and access to these complex knowledge and analytical skills. Digital expertise may therefore foster the introduction of “recombinant innovations”, by enabling the codification and use of different components of knowledge related to older and emerging domains and technologies. Due to the intrinsic association between green technologies and ICTs, digital competences favour the hybridization and recombination of the local technological capabilities that are dispersed across different firms and other regional actors, thus reorienting them towards the development green technologies.

On the whole, the substitution and complementarity effects will have different impacts on relatedness, making it less or more relevant, respectively. The prevalence of one or the other effect is an empirical matter, and is hard to hypothesize ex-ante. However, for the reasons noted above, we posit that the complementarity effect will be relatively more important for green technologies, and we therefore expect that digital skills will strengthen the relationship between relatedness and green technological diversification.

H3: *The local endowment of digital skills positively moderates the role of relatedness on the development of new regional green technological specialisations.*

The remainder of the paper operationalises the relevant concepts and proposes an empirical analysis to test these hypotheses.

4. Variables

4.1. Dependent variable: entry of technological specializations in regions

Following previous research on regional technological diversification (Boschma et al., 2015; Rigby, 2015; Balland et al., 2019), we investigate the emergence of new technological specializations in European regions. First, for each year and region in the sample we compute the Revealed Comparative Advantage (RCA) for each technology (both green and non-green):

$$RCA_{izt} = \frac{PAT_{izt}}{\sum_{z=1}^n PAT_{izt}} / \frac{\sum_{i=1}^m PAT_{izt}}{\sum_{i=1}^m \sum_{z=1}^n PAT_{izt}} \quad (1)$$

where RCA_{izt} represents the Revealed Comparative Advantage of region i , in technology z , at year t , while PAT_{izt} is the number of patent applications attributed to technological field z in region i and year t . This indicator assesses the relative strength of a given region, at a given time, in technology z , in comparison to all other regions. If RCA is greater than 1, that means region i is specialized in technology z , in year t .

Our analysis focuses on the development of new technological specializations. To this end, we include all pairs of regions and technologies z in which a given region is not specialized at moment t . The dependent variable represents the regional acquisition of new technological specializations, and it is defined as follows:

$$S_{izt+2} = 1 \text{ if } RCA_{izt} \leq 1 \wedge RCA_{izt+2} > 1 \quad (2)$$

$$S_{izt+2} = 0 \text{ if } RCA_{izt} \leq 1 \wedge RCA_{izt+2} \leq 1$$

where S_{izt+2} is a dummy variable that takes the value 1 if region i , which did not have a specialization in technology z at time t , acquires that specialization at time $t+2$. Otherwise, S_{izt+2} takes the value 0, which means region i has not acquired a specialization in technology z between t and $t+2$. Z can be either a green or a non-green technological category.

4.2 - Explanatory variables

4.2.1 – E-skills

The study of local human capital has traditionally relied on the notion that the level of education in the population is a reliable proxy of a territory's capacity to innovate and to

grow. Such an approach, however, is rather crude *vis-à-vis* the need to uncover the structural aspects of skills and know-how in relation to innovation and technological diversification. Human capital is a multi-faceted and dynamic process, and the main issue is not ‘how much’ of it is needed to achieve desired levels of productivity and competitiveness but, rather, ‘what’ type’ best suits the opportunities and challenges of the attendant technology frontier. The alternative is to focus on work tasks. Using occupations as the unit of analysis, one can think of vectors wherein occupation-specific tasks and workers’ skills match to fulfil job duties (Autor et al. 2003). In aggregate, the configuration of occupations is a proxy of the knowledge mix that is relevant in a particular context (i.e. industrial sector or geographical region). By the same token, as industry or regional needs change, occupations evolve and so do the agreed tasks and the relevant skill mix (Vona and Consoli 2015). In short, by emphasizing the connection between work tasks and the knowledge that is needed to carry them out, this alternative route restates the importance of focusing on individual characteristics to grasp the multi-dimensional character of human capital. Coherent with the proviso that human capital is best understood as an occupation-specific characteristic, e-skill endowment is operationalized using employment data and information on the skill content of occupations. We expect that looking at workers’ skills directly enhances our understanding of the degree to which routines associated with the use, adaptation and design of digital technologies have been absorbed into regions’ production systems.

To operationalise this tenet, we use employment data from Eurostat European Union Labour Force Survey (EU LFS). This is a large household survey on labour force participation of people aged 15 and over containing data on employment status and place of residence. Following prior literature that focuses on the composition of the regional labour force, we exclude military employment. Occupations are coded by one-digit International Standard Classification of Occupations (ISCO-2008) codes. We sum employment within region-sector-year cells to obtain our variable for labour demand estimates.

The main source of information on the e-skill Task Intensity index is the first release of the European Classification of Skills/Competences, Qualifications and Occupations (ESCO) by the European Commission (2013). ESCO is similar to US data sources like DOT and O*NET, in that it matches information about competences and qualifications for all occupations in Europe. Our objective is to identify e-skills, that is, job specific competences that are associated with the use of digital technologies. Accordingly, we identify 69 e-skills items on

the basis of textual description in ESCO (for further details see Castellacci et al., 2019).⁴

E-skills are matched with 4-digit ISCO occupations when the job entails one or more digital competences. The occupational intensity of e-skills is computed as the sum of e-skills weighed by the number of 4-digit jobs under each 1-digit level ISCO category:

$$ESKILLS_INTENSITY_j = \frac{\sum_{y=1}^{P_j} ESKILLS_{y,j}}{P_j} \quad (3)$$

ESKILLS is the number of e-skills identified in the description of each 4-digit occupational category within each 1-digit occupational category j . P_j is the total number of 4-digit occupational groups y within each 1-digit occupational group j . Finally, ESKILLS_INTENSITY is the average number of e-skills in each 4-digit occupation within any 1-digit occupation j . Subsequently, ESKILLS_INTENSITY is standardized to have a zero mean and unit standard deviation across 1-digit occupations. To measure routine task intensity at the level of NUTS-2, we compute for each region i an employment-share weighted index across all occupations j :

$$REG_ESKILLS_INTENSITY_i = \sum_{j=1}^9 (ShareOccup_{ji} * STD_ESKILLS_INTENSITY_j) \quad (4)$$

STD_ESKILLS_INTENSITY is the standardized version of the variable described in (3), while ShareOccup represents the share of the labour force in 1-digit occupation j in region i . REG_ESKILLS_INTENSITY represents the intensity of the labour force of region i in terms of e-skills. This will be our main explanatory variable when testing for the effect of e-skill endowment in the local labour force on the development of new green technological specializations in European regions.

4.2.2 – Green and non-green technologies

This paper uses patent data from the OECD REGPAT database. To identify green technologies, IPC/CPC codes of patent applications have been recoded according to the search strategies for the identification of selected environment-related technologies (OECD, 2016; Barbieri et al., 2016). Using the detailed classification of environment-related technologies proposed by OECD ENV-TECH (i.e. 3-digits) we select 107 different 3-digit categories of environment-related technologies. OECD (2016) identifies for each category of

⁴ These detailed data afford the opportunity of understanding how jobs differ from one another, not just in terms of job title, but also by considering work content and, therefore, the type of know-how that is needed to perform in that occupation. The main limitation is that the skill scores are subjective assessments. Both these points have been widely debated in the labour economics literature (see e.g. Autor et al., 2003).

environment-related technologies the corresponding set of IPC/CPC-codes. Compared to other empirical strategies to study green technologies, the recodification of IPC/CPC codes into OECD ENV-TECH 3-digit categories is more precise. In fact, prior research assumes that if the first digits of a given IPC code is environment-related, all patents within that digit are environment-related (see i.e. Montresor & Quatraro, 2019; van den Berge & Weterings, 2014). In the method proposed here, since the recodification is based on full IPC /CPC codes, and not only the initial digits, there is no risk of overestimating the number of green patent applications.

Although the universe of OECD ENV-TECH 3-digit technological categories consists of 107 items, in the OECD REGPAT database there are only patents in 52 of these categories.⁵ Since this paper focuses specifically on the development of green technological specializations, we created a dummy variable to measure whether the technologies in our sample are green. This variable is defined as follows:

$$G_z = 1 \text{ if } z \in \text{Green} \quad (5)$$

$$G_z = 0 \text{ if } z \notin \text{Green}$$

where G is a dummy variable that takes the value 1 if technology z belongs to the set of green technologies (Green) and 0 otherwise. Non-green technologies are operationalized, as usual, using IPC and CPC codes at 3-digit level. The only particularity here is that patent applications that are environment-related (according to the criteria described above), are not taken into account to determine the number of patents by each 3-digit IPC / CPC code.

4.2.3 – Relatedness Density

Following hypothesis 2 in section 3, we seek to capture to what extent technologies in which the regions are not specialized at time t are related to existing specializations. This requires computing the degree of proximity (DoP) between pairs of technologies. To do so, we compute all pairs of technological domains for which a given region, in a given year, has at least a share in a patent application. Next, we compute the DoP between technologies composing a pair, following the formula below, where a and b represent two different technological fields and RCA is defined as in (1):

$$\Omega_{ab} = \min \{P(RCA_a > 1 \mid RCA_b > 1), P(RCA_b > 1 \mid RCA_a > 1)\}, \quad (6)$$

⁵ This is mainly because group 9 (“Climate change mitigation technologies in the production or processing of goods”) contains no patent applications in REGPAT. Table A1 in the Appendix shows the full list of 3-digit environment-related technological categories for which there is data on patent applications.

$$\text{where } P(RCA_a > 1 \mid RCA_b > 1) = \frac{P(RCA_a > 1 \cap RCA_b > 1)}{P(RCA_b > 1)} \quad (7)$$

In (6) Ω_{ab} indicates the DoP between technologies a and b, while the expression $P(RCA_a > 1 \mid RCA_b > 1)$ represents the conditional probability of there being, in the sample, cases where technology a has an $RCA > 1$ given that for technology b $RCA > 1$. For computing Ω_{ab} and its underlying probabilities, in the sample one observation is a pair consisting of a region and a year. In total, the sample contains 3443 pairs of years (2000–2013) and regions. The DoP between two technological fields is computed based on the frequency of finding the spatial co-occurrence of a specialization ($RCA > 1$) in these fields.

Subsequently we compute the relatedness between each technology z in which region i is not specialized at time t and the technological specializations s of region i at moment t. To do so, we compute a density index as proposed by Hausmann and Klinger (2007):

$$\text{Density}_{izt} = \frac{\sum_{z=1}^n \Omega_{zs} S_{ist}}{\sum_{z=1}^n \Omega_{zs}} \quad (8)$$

such that:

$$S_{ist} = 1 \text{ if } RCA_{ist} > 1 \quad (9)$$

$$S_{ist} = 0 \text{ if } RCA_{ist} \leq 1$$

where Density_{izt} represents the density of a given technology z in which the region i is not specialized at time t, by comparison to the set of technologies s in which region i at time t is already specialized. In a nutshell, this density indicator compares for each technology z at time t, the total proximity between z and the technological specializations existing in region i at time t (numerator) and the total proximity between z and all technological fields s in our sample of observations (denominator). This indicator ranges between 0 and 1, where 0 means that the degree of proximity between a given technology z and all technological specializations s in region i at time t is 0. Reversely, the value 1 represents a situation in which all technologies that have a certain degree of proximity ($\Omega > 0$) with a given technological domain z are those in which region i has a specialization at time t.

This paper computes three different variations of the density indicator (8). In each one, s represents a different group of technologies. In the first case, s represents all technological domains (both green and non-green) available in our sample of observations. However, in the remaining versions of (8), s corresponds to subsets of technological fields: green technologies and non-green technologies.

Depending on the version of the density indicator (8) computed, our empirical analysis will use three indicators:

1. Relatedness between a given technology z and all technological domains s ;
2. G_Relatedness between a given technology z and all green technological domains s ;
3. NG_Relatedness between technological category z and all non-green technological domains s ;

4.2.4 – Control variables

In the econometric model, we also include a set of standard controls such as: regional economic development (GDP per capita), technological capacity (R&D percentage of GDP), age structure of the population (% of population older than 65 years), the gender structure of the workforce (share of female workers), and the unemployment rate. All variables are collected from the Eurostat regional statistics, with the exception of the gender structure of the labour force, which is drawn from Eurostat Labour Force Survey.

5. Data and descriptive statistics

Our main source of information for technological specialization is the OECD REGPAT patent database. In particular, we seek to analyse whether new technological specializations enter a given region for 4 non-overlapping periods of three years each, starting in 2002-2004 and including all three-year periods up to 2011-2013. Most of control variables and the main explanatory variable (e-skills of the labour force) are computed as the average of the 3 years prior to the values of diversification, with the only exception of relatedness that is used as per the previous section. This means that data on most of control variables and e-skills are collected as averages over the following periods: 1999-2001, 2002-2004, 2005-2007 and 2008-2010. The analysis covers 27 European countries⁶ and 225 regions (NUTS-2, except in UK where the territorial units of analysis are NUTS-1).

Table 1 shows the summary statistics of the variables that are used in the econometric analysis. The dataset contains 119192 observations (i.e. triplets constituted by a region, a 3-year period and a given technology z in which the region is not specialized at the beginning of each period). The development of a new technological specialization by a given region only

⁶ EU-28 plus Norway, except Malta and Netherlands. These two countries do not have EU-LFS data in order to compute the e-skills variable.

happens in 11% of the cases. Out of all observations considered in our analysis (that include both green and non-green technologies), 32% concern green technologies.

TABLE ONE ABOUT HERE

Figure 1 depicts the distribution of the success rate in the acquisition of new technological specializations across European regions. The map on the left-hand side of figure 1 represents the average success rate in the acquisition of new technological specializations in general (both green and non-green). The map on the right-hand side of figure 1 illustrates the average success rate of exclusively green technologies and the remarkable differences across European regions. Moreover, comparing quartiles in the legend of the map on the left-hand side with the corresponding quartiles on the right-hand side, suggests that the development of green technological specializations is more unlikely than the acquisition of new non-green technological specializations.

FIGURE ONE ABOUT HERE

Figure 2 represents the average (of the 4 periods considered in our analysis) distribution of e-skills endowments across European regions. Here, the pattern is clearer: regions with highest e-skills scores are mostly in the core of the continent and in the North (Scandinavian Peninsula), while the lowest scores are in the Eastern and Southern periphery of Europe. The correlation matrix in Table 2 shows a weakly positive, but statistically significant, correlation between the entry of new technological specializations and e-skills endowment. In the next section, we investigate further such a relationship.

FIGURE TWO AND TABLE TWO ABOUT HERE

6. Empirical analysis

In order to test the hypotheses outlined in section 3, we estimate the following model:

$$S_{izt,t+2} = \alpha + \beta_1 \text{ESKILLS}_{it-1,t-3} + \beta_2 \text{RELATEDNESS}_{izt,t+2} + \beta_3 G_z + \gamma^k \text{Controls}_{it-1,t-3}^k + \eta_i + \theta_t + \varepsilon_{it} \quad (10)$$

where i indicates the region, z the technology, and t the year. S is defined as described above in equation (2). ESKILLS is the lagged 3-year average of the e-skills variable described in (4). RELATEDNESS denotes the density variable as in (8). As described in section 4, RELATEDNESS can take the form of three different indicators: Relatedness , $G_Relatedness$ and $NG_Relatedness$; as explained below, the three indicators are used alternately in different

models. Controls is the set of k control variables that are added to the regressions with a lagged 3-year average. η_i is region fixed effects, θ_t is time fixed effects (a dummy for each of the 4 three-year periods), and ε is the error term. Our econometric specification also includes the dummy variable G that identifies green technologies (see equation 5). The reason for including this dummy (rather than a dependent variable that uses exclusively data on green technologies) is to investigate to what extent the empirical patterns we obtain differ between green and non-green technologies. This provides a clearer understanding of relevant differences that may exist between these two groups of technologies

Following previous research on technological diversification in regions (Balland et al. 2019), our econometric analysis uses a linear probability model (LPM). Besides region and time fixed-effects, the estimation also includes country fixed-effects. Moreover, we weight all regressions by population density of the regions as an additional way to account for unexplained variation at country level (see Solon et al 2015).

Table 3 shows the results of the first group of regressions on all technologies (both green and non-green). The first three columns show the main coefficients of interest, namely: the green dummy, the e-skills indicator and their interaction term. In the last column of the table is our favourite specification containing the full set of control variables. The negative coefficient of the green dummy variable indicates that regions in our sample tend to specialise significantly more in non-green technologies. This is not surprising, since these represent the bulk of existing and well-established technological paradigms. When the e-skill indicator is included (col 2), the estimation results indicate no significant effect. It is useful to explore whether the probability that a region specialises in a new technology differs depending on whether the technology is green and over various values of local e-skill endowment. This is tested by adding the interaction between these two variables. Recall that the premise is that regions endowed with greater ability to use, develop and adapt ICTs to different domains of use enjoy greater capacity to exploit advanced knowledge and to introduce recombinant innovations, which, according to the literature in economic geography, are pivotal for the emergence of novel forms of technological specialisation. The positive and significant coefficient of the interaction term (col 3) resonates with the above and lends support to hypothesis 1: the level of e-skills in the workforce is a positive predictor of the probability that a region acquires

Revealed Comparative Advantage in a new green technological domain. Our finding is robust to the inclusion of the control variables (col 4).⁷

TABLE THREE ABOUT HERE

Table 4 illustrates the second set of findings, concerning relatedness. The key conceptual premise is that regions engage successfully new domains if these rely on capabilities that are not too distant from the region's knowledge base (see i.e. Frenken and Boschma, 2007). This proximity reduces barriers and therefore promotes knowledge spillovers. The specification in column 1 confirms that, in line with prior literature, relatedness is positively correlated with regional technological diversification. Given the peculiarities of the empirical setting at hand, we check whether this depends on the type of relatedness, and specifically on whether the crucial competences are strictly related to dealing with environmental issues. Montresor and Quatraro (2019) have recently tackled such a question by studying the role of Key Enabling Technologies in regional technological specialisation. Using the same rationale, we include the new explanatory variables Green Relatedness (col 2) and Non-Green Relatedness (col 3) to our model and find that the associated coefficients are both positive and significant, and thus in line with the expectations of hypothesis 2. This is confirmed also when we check whether the observed effect holds if a technology is green. The last two models (col 4 and 5) include interaction terms between the green dummy and the two types of relatedness. Here we observe that, again both green and non-green relatedness are positively correlated with the probability that a region develops a new specialisation in green technologies. The coefficients of the interaction terms are positive and statistically significant, which means that in presence of related technological capabilities (both green and non-green) the development of new green technological specializations is less unlikely.

TABLE 4 ABOUT HERE

The last set of results (Table 5) concerns the last hypothesis, namely whether the regional e-skills endowment positively moderates relatedness. The new specifications build on previous models (Table 4, col 2 and 3) with the addition of the e-skills indicator (see Table 5, col 1 and 2). Hence, to test hypothesis 3, the regressions reported in columns 3 and 4 include all possible combinations of interaction effects among our main variables (green dummy, relatedness, e-skills). The coefficients in columns 1 and 2 indicate that e-skills endowment is

⁷ Our main findings are also robust when green technologies are unpacked into two main sub-domains of Adaptation and Mitigation technologies. See Appendix A1 and the tables listed therein.

a positive predictor of the probability that regions enter new technological domains while both the relatedness coefficients remain positive and significant. The following two specifications (col 3 and 4) feature the addition of interaction terms. Here, the main coefficient of interest is the three-way interaction between e-skills, relatedness (green / non-green) and the green dummy: both are positive and significant, and thus in line with hypothesis 3. If a given technology is green, there is complementarity between e-skills and relatedness and e-skills strengthen the role of local capabilities in developing new technological specializations.

TABLE FIVE ABOUT HERE

To quantify the magnitude of these interaction effects, Table 6 illustrates the marginal effects of green and non-green relatedness for different levels of e-skill endowment (minimum, first quartile, second quartile or median, third quartile and maximum) when the technology is green (i.e. Green Dummy=1). The two blocks of Table 6 show the marginal effects of relatedness in specifications 3 and 4 in the previous Table 5. The coefficients indicate that when the technology is green the effect of both green and non-green relatedness increases with the levels of e-skill endowments in regions. In particular, an increase of 0.1 in green relatedness increases the probability that a region engages a new green technological specialization between 6 and 15 percentage points. The effect of non-green relatedness is higher and ranges between 11 and 23 percentage points, meaning that related competences outside of the environmental domain are more important. This finding is in line with the recent results of Montresor and Quatraro (2019) and resonates with the argument that, because green technologies are at early stages of development, they tend to draw on an ample pool of know-how both related and unrelated to environmental competences (Barbieri et al, 2018a; Barbieri et al, 2018b). Besides, path-dependence stemming from consolidated ways of doing things in existing industrial systems will likely have an effect. This is why hybrid competences, i.e. mixing green and non-green know-how, characterise the current phase of the transition (Barbieri and Consoli, 2019; Quatraro and Scandura, 2019).

TABLE SIX ABOUT HERE

These results discussed above also provide further support to hypothesis 3, namely that e-skills positively moderates relatedness. This contrasts with the findings of Montresor and Quatraro (2019), in particular that regional specialisation in Key Enabling Technologies negatively moderates the impact of both green and non-green relatedness. The implication therein is that KETs favour regional transition towards sustainability by enlarging the search

space towards more distant green technologies while, at the same time, bypassing the complementarity between new green technologies and the existing ‘standard’ (sic) ones. Our finding that e-skills positively moderate green and non-green relatedness points in a different direction. In the case under analysis, higher know-how associated with – it is worth reiterating – the use, adaptation and design of digital technologies is complementary to – rather than a substitute for – technological green and non-green relatedness. The main reason behind the differences between our results and those of Montresor and Quatraro (2019), in our view, is that their analysis focuses on patenting in KETs as a proxy for regional invention capacity while our main explanatory variable, based on the direct observation of workforce skills, is a more general proxy of regional absorptive capacity in the context of digital economies. Put otherwise, our analysis of the competences used in the context of work activities is closer to the domain of use of innovation, rather than of invention only. Moreover, e-skills carry a general-purpose character that favours the identification, assimilation and adaptation of useful know-how into work activities (Carretero et al, 2017; CEEMET, 2018; Castellacci et al, 2019). In the case at hand, digital competences are tools to navigate related green and non-green domains of practice. The positive interaction between e-skills and relatedness indicates that in the current early stages of green technology life cycle (Barbieri et al, 2018b) the relevant know-how is still fluid and not routinized, thus implying complementarity rather than substitutability between digital competences and other regional capabilities. Under this perspective, our finding resonates with prior literature arguing that digital technologies, and the attending capabilities, enable horizontal complementarities, viz. adaptability across different domains of use, as well as forward complementarities, viz. bridging invention and application (van den Bergh 2008; Frenken et al, 2012).

As a further check, we ran a regression based on the latest specification including a dummy variable equal to one if each of the technologies in which a region is not specialized at t is non-green. In so doing, we invert the terms of the variables in equation (5) so that, by construction, all the coefficients will have the opposite sign of those in Table 5. As expected, e-skills *negatively* moderate the effect of – or be a substitute for – relatedness on non-green technological diversification (in line with the empirical results of Castellacci et al., 2019). Likewise, the marginal effects of relatedness on entry for different levels of e-skills, this time for non-green technology, are still statistically significant (Table 7). This confirms that the sign of the moderation effect of e-skills on relatedness depends on the direction, i.e. green or non-green, of the development of technological specialisations in a region.

Finally, we carried out two further robustness exercises to assess whether our results are driven by specific sub-groups of green technologies. To this end, we have, first, repeated the same regressions with the inclusion of dummies to distinguish between adaptation and mitigation technologies (results are reported in the online appendix). Second, more in detail, we have also re-run the regressions for each of the seven groups of green technologies individually. The results of the three hypotheses tests are basically the same as our baseline findings. The only exception is the result for hypothesis 3 for two groups of green technologies (group 1 - environmental management; group 7 - climate change mitigation technologies related to buildings), for which, exclusively in the case of green relatedness, we do not find support for the complementarity effect as for all other groups.

TABLE SEVEN ABOUT HERE

7. Conclusions

This paper has proposed an analysis of the role of e-skills and relatedness in green technological diversification in a panel of European regions. The backdrop is the intersection of three interrelated debates. The first concerns the need to prepare or accelerate the transition towards low-carbon economies along a paradigm driven by innovation and structural change (Ayres and van den Bergh, 2005). Since climate change is a global phenomenon with strongly localised character, we articulate this through a regional-level analysis for assessing the progress, or lack of thereof, towards this societal challenge. The second debate concerns the extent to which regions, especially European, can leverage their existing competences to pursue smart specialisation – not necessarily in relation to environmental issues (Foray et al, 2009). Empirical studies focus on the extent to which local technological and non-technological infrastructures assist the pursuit of smart specialisation (Pattinson et al, 2015; Foray, 2015; Montresor and Quatraro, 2017; 2019). The third relevant thread is the appreciation that modern economies rely heavily on digital infrastructures that permeate their very organisation across production, distribution and consumption. In relation to this, we have argued that e-skills represent an important aspect of human capital for regions' ability to access, replicate and recombine advanced knowledge, and ultimately pursue new paths of technological specialization. The focus on e-skills is motivated by the identification of a gap at the intersection of these literatures. As a thorough review by Boschma (2017) highlights, in spite of widespread agreement on their importance, the literature on regional diversification defines and operationalises capabilities broadly and indirectly. We tackle this gap by

focussing on the digital skills in the workplace that are needed to use, adapt and design ICTs across various context. Digital skills carry a general-purpose character that is important in the face of a major transition – such as sustainability – which entails creation of new activities as well as adaptation of existing ones. We therefore complement empirical literature by offering a more nuanced perspective of the extent to which technologies are absorbed into work routines, and the magnitude of the importance of the latter for the development of the former.

The empirical analysis on a panel of 225 European regions (NUTS 2) between 2002 and 2013 yields three main findings. First, the level of e-skills in the workforce is a positive predictor that a region specialises in new green technological domains. While this may not be surprising in general, since e-skill endowment is a reflection of broader institutional commitment to digital infrastructure and knowledge diffusion in a region, the positive significant correlation speaks to the general-purpose nature of these competences and their role in facilitating the transition towards low-carbon societies. The implication is that policies aiming at fostering green smart specialization should focus on the creation or the reinforcement of digital competences in the workforce. The second main finding is that both green and non-green relatedness matter for green technological diversification. This is in line with recent empirical literature showing that green technologies at early stages of the life-cycle and draw on an ample pool of know-how. This calls for policies that enable connectivity across domains by fostering hybrid competences, i.e. green and non-green know-how. The third result of the empirical analysis is that digital competences positively moderate the effects of both green and non-green technological relatedness on green technological diversification.

It is worth emphasising that there is very little research on these issues and hope that the present study offers a starting point for future work on these dynamics. On the whole, our finding of complementarity between digital skills and relatedness should be read as ‘good news’ for most regions: the domain of useful know-how need not be restricted by prior specialisation in environmental activities. However, this finding also entails that backward regions with little or no prior technological specialization may struggle to make the first step and enter green domains. This signals the potential of growing divergence in environmental, and ultimately developmental, performance across regions, which future research should investigate further.

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Table 1: Descriptive statistics

Variables	N	mean	max	min	std dev
Entry	119192	0.11	1	0	0.31
Green	119192	0.32	1	0	0.47
Eskills intensity - Total (std)	119192	0.27	0.76	-0.18	0.15
Relatedness	119192	0.18	0.59	0.00	0.11
Green Relatedness	119192	0.12	0.62	0.00	0.11
Non-green Relatedness	119192	0.20	0.63	0.00	0.12
GDP per capita	119192	21831.60	64666.67	3733.33	8752.24
R&D	119192	1.33	7.36	0.08	1.14
Share female workers	119192	0.44	0.50	0.29	0.04
Share elderly population	119192	0.17	0.27	0.10	0.03
Unemployment rate	119192	8.81	26.80	2.17	4.58

Table 2: Correlation matrix

	Entry		Green		Eskills (std)		Relatedness		Green Relatedness		Non-green Relatedness		GDP per capita		R&D		Share female workers		Share elderly population		Unemployment rate	
Entry	1																					
Green	-0.085	***	1																			
Eskills (std)	0.077	***	0.00	**	1																	
Relatedness	0.224	***	-0.093	***	0.438	***	1															
Green Relatedness	0.180	***	-0.104	***	0.432	***	0.812	***	1													
Non-green Relatedness	0.210	***	-0.051	***	0.416	***	0.983	***	0.702	***	1											
GDP per capita	0.095	***	0.008	***	0.668	***	0.544	***	0.523	***	0.520	***	1									
R&D	0.080	***	0.004		0.616	***	0.464	***	0.482	***	0.433	***	0.526	***	1							
Share female workers	0.023	***	0.001		0.279	***	0.150	***	0.157	***	0.140	***	0.030	***	0.266	***	1					
Share elderly population	0.032	***	0.008	***	0.081	***	0.228	***	0.174	***	0.232	***	0.202	***	0.124	***	-0.102	***	1			
Unemployment rate	-0.053	***	-0.010	***	-0.222	***	-0.297	***	-0.204	***	-0.308	***	-0.445	***	-0.260	***	-0.219	***	-0.171	***	1	

* p<0.1, ** p<0.05, *** p<0.01

Figure 1: Distribution of new technological specializations in European regions

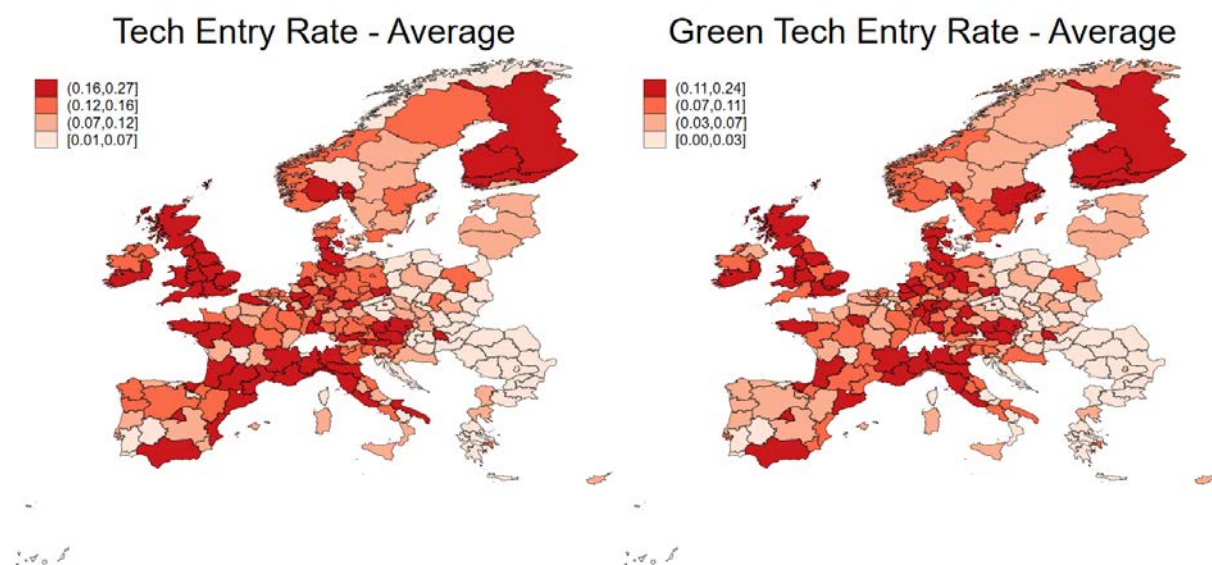


Figure 2: Distribution of e-skills in European regions

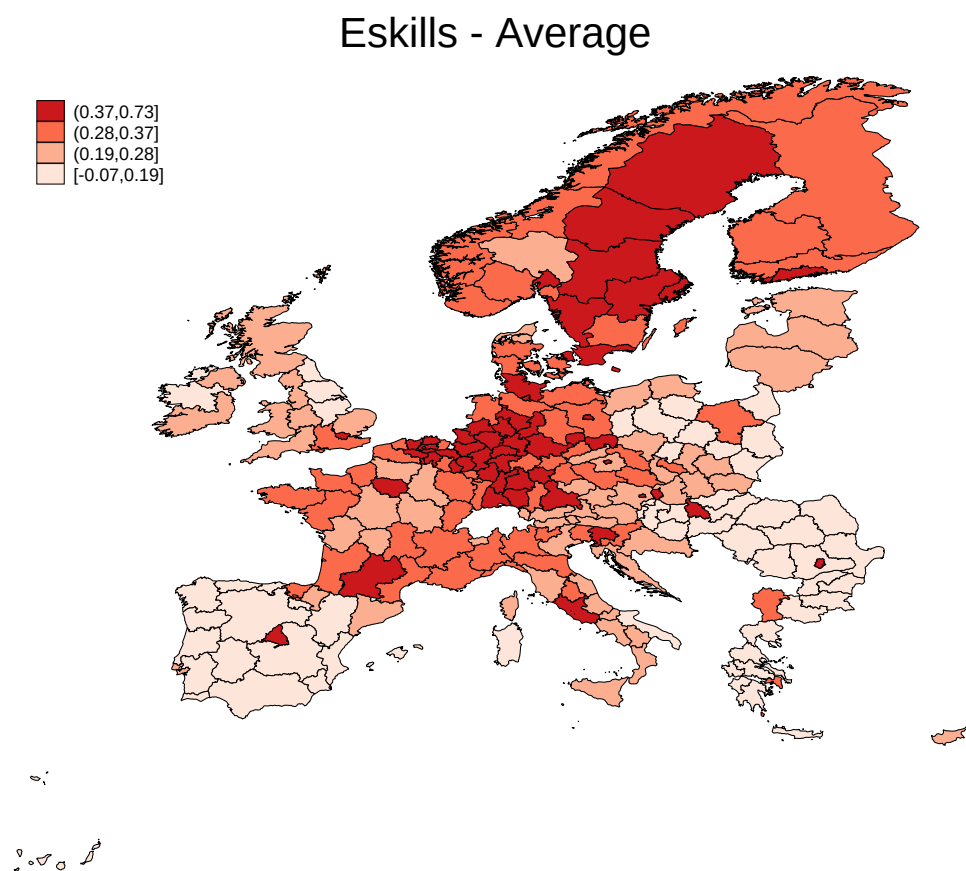


Table 3: Test of hypothesis 1 (effects of e-skills on green diversification)

	(1)	(2)	(3)	(4)
green	-0.041169*** (0.005770)	-0.041207*** (0.005764)	-0.087408*** (0.007739)	-0.087217*** (0.007732)
e-skills		0.137541 (0.109100)	0.102922 (0.108716)	0.158748 (0.108620)
e-skills*green			0.114746*** (0.027553)	0.114187*** (0.027529)
gdp_pc				-0.000003* (0.000002)
rd				-0.008372 (0.014305)
female_workers				0.010178 (0.213880)
old_pop				0.028980 (0.537414)
un				-0.000113 (0.000914)
Constant	0.091397*** (0.012221)	0.070711*** (0.019450)	0.084858*** (0.019405)	0.113877 (0.152072)
R-sqr	0.022	0.022	0.023	0.023
N	119192	119192	119192	119192

* p<0.10, ** p<0.05, *** p<0.01

Table 4: Test of hypothesis 2 (effects of relatedness on green diversification)

	(1)	(2)	(3)	(4)	(5)
green	-0.007878 (0.006092)	-0.030644*** (0.005947)	-0.021568*** (0.005915)	-0.068481*** (0.008373)	-0.037177*** (0.007038)
relatedness	1.377731*** (0.059445)				
g_rel		0.415432*** (0.044669)		0.352478*** (0.046252)	
ng_rel			1.184982*** (0.059766)		1.167563*** (0.059582)
green*g_rel				0.231732*** (0.049807)	
green*ng_rel					0.068450* (0.035668)
gdp_pc	-0.000009*** (0.000001)	-0.000005*** (0.000001)	-0.000008*** (0.000001)	-0.000005*** (0.000001)	-0.000008*** (0.000001)
rd	0.008953 (0.014715)	0.001933 (0.014788)	0.005642 (0.014817)	0.001835 (0.014758)	0.005741 (0.014818)
female_workers	-0.424460** (0.211592)	-0.133308 (0.214726)	-0.298196 (0.212212)	-0.142691 (0.214502)	-0.298033 (0.212193)
old_pop	-0.389670 (0.537863)	0.421890 (0.544515)	-0.728548 (0.534231)	0.446457 (0.544248)	-0.731450 (0.534138)
un	0.000166 (0.000941)	0.000832 (0.000948)	-0.000484 (0.000935)	0.000838 (0.000947)	-0.000490 (0.000935)
Constant	0.380696** (0.151500)	0.133131 (0.155762)	0.364500** (0.150994)	0.144552 (0.155911)	0.369951** (0.151041)
R-sqr	0.047	0.028	0.040	0.029	0.040
N	119192	119192	119192	119192	119192

* p<0.10, ** p<0.05, *** p<0.01

Table 5: Test of hypothesis 3 (moderation effects of e-skills on the relationship between relatedness and green diversification)

	(1)	(2)	(3)	(4)
green	-0.030328*** (0.005946)	-0.021595*** (0.005907)	-0.038831*** (0.009872)	0.004120 (0.010061)
e-skills	0.362239*** (0.105145)	0.029049 (0.108168)	0.517937*** (0.109513)	0.096291 (0.121414)
g_rel	0.431573*** (0.043878)		0.766909*** (0.071804)	
ng_rel		1.183805*** (0.060136)		1.287856*** (0.094138)
e-skills*g_rel			-0.989504*** (0.214109)	
e-skills*ng_rel				-0.436081 (0.315760)
e-skills*green			-0.080157 (0.050148)	-0.171699*** (0.051732)
green*g_rel			-0.146013 (0.092555)	
green*e-skills*g_rel			0.890474*** (0.278250)	
green*ng_rel				-0.360837*** (0.075262)
green*e-skills*ng_rel				1.314671*** (0.294596)
gdp_pc	-0.000007*** (0.000001)	-0.000008*** (0.000002)	-0.000005*** (0.000002)	-0.000008*** (0.000002)
rd	-0.005535 (0.014221)	0.005014 (0.014153)	-0.002011 (0.014163)	0.004931 (0.014198)
female_workers	-0.245549 (0.211842)	-0.306193 (0.210648)	-0.324034 (0.210674)	-0.291967 (0.216607)
old_pop	0.226862 (0.536023)	-0.744177 (0.525576)	0.088191 (0.531103)	-0.737105 (0.523669)
un	0.000474 (0.000916)	-0.000514 (0.000902)	0.000881 (0.000900)	-0.000473 (0.000882)
Constant	0.199362 (0.152057)	0.369291** (0.148074)	0.199204 (0.151920)	0.350061** (0.151248)
R-sqr	0.028	0.040	0.031	0.041
N	119192	119192	119192	119192

* p<0.10, ** p<0.05, *** p<0.01

Table 6: Marginal effects of relatedness on green diversification at different quartiles of the e-skills distribution

Type of relatedness	Marginal effect of relatedness on entry if green dummy=1		E-skills
Green Relatedness	0.61	***	min
	0.93	***	Q1
	1.00	***	Q2
	1.08	***	Q3
	1.45	***	max
Non-Green Relatedness	1.05	***	min
	1.52	***	Q1
	1.63	***	Q2
	1.75	***	Q3
	2.29	***	max

* p<0.1, ** p<0.05, *** p<0.01

Table 7: Marginal effects of relatedness on non-green diversification at different quartiles of the e-skills distribution

Type of relatedness	Marginal effect of relatedness on entry if non-green dummy=1		E-skills
Green Relatedness	0.78	***	min
	0.46	***	Q1
	0.39	**	Q2
	0.31	*	Q3
	-0.06		max
Non-Green Relatedness	1.16	***	min
	0.69	***	Q1
	0.58	***	Q2
	0.46	***	Q3
	-0.08		max

* p<0.1, ** p<0.05, *** p<0.01

Appendix

Appendix

Table A1: List of green technology classes

Green Technology group code		Green Technological group name
1 digit	3 digits	
Adaptation Technologies		
1	1.2.1.	Water and wastewater treatment
1	1.3.1.	Solid waste collection
1	1.3.2.	Material recovery, recycling and re-use
1	1.4.0.	Soil remediation
2	2.1.1.	Indoor water conservation
Mitigation Technologies		
4	4.1.1.	Wind energy
4	4.1.2.	Solar thermal energy
4	4.1.3.	Solar photovoltaic (PV) energy
4	4.1.4.	Solar thermal-PV hybrids
4	4.1.5.	Solar thermal-PV hybrids
4	4.1.6.	Marine energy
4	4.1.7.	Hydro energy
4	4.2.1.	Biofuels
4	4.2.2.	Fuel from waste
4	4.3.1.	Technologies for improved output efficiency (Combined heat and power, combined cycles, etc.)
4	4.3.2.	Technologies for improved input efficiency (Efficient combustion or heat usage)
4	4.4.1.	Nuclear fusion reactors
4	4.4.2.	Nuclear fission reactors
4	4.5.1.	Superconducting electric elements or equipment
4	4.5.2.	Not elsewhere classified
4	4.6.1.	Energy storage
4	4.6.2.	Hydrogen technology
4	4.6.3.	Fuel cells
4	4.6.4.	Smart grids in the energy sector
4	4.7.0.	Other energy conversion or management systems reducing GHG emissions
5	5.1.0.	CO2 capture or storage (CCS)
5	5.2.0.	Capture or disposal of greenhouse gases other than CO2
6	6.1.1.	Conventional vehicles (based on internal combustion engine)
6	6.1.2.	Hybrid vehicles
6	6.1.3.	Electric vehicles
6	6.1.4.	Fuel efficiency-improving vehicle design (common to all road vehicles)
6	6.2.0.	Rail transport

6	6.3.0.	Air transport
6	6.4.0.	Maritime or waterways transport
6	6.5.1.	Electric vehicle charging
6	6.5.2.	Application of fuel cell and hydrogen technology to transportation
7	7.1.0.	Integration of renewable energy sources in buildings
7	7.2.1.	Lighting
7	7.2.2.	Heating, ventilation or air conditioning [HVAC]
7	7.2.3.	Home appliances
7	7.2.4.	Elevators, escalators and moving walkways
7	7.2.5.	Information and communication technologies
7	7.2.6.	End-user side
7	7.3.0.	Architectural or constructional elements improving the thermal performance of buildings
7	7.4.0.	Enabling technologies in buildings
8	8.1.0.	Wastewater treatment
8	8.2.1.	Waste collection, transportation, transfer or storage
8	8.2.2.	Waste processing or separation
8	8.2.3.	Landfill technologies aiming to mitigate methane emissions
8	8.2.4.	Bio-organic fraction processing; Production of fertilisers from the organic fraction of waste or refuse
8	8.2.5.	Reuse, recycling or recovery technologies
8	8.3.0.	Enabling technologies or technologies with a potential or indirect contribution to GHG mitigation

Robustness checks: mitigation and adaptation green technology

The analysis in the main text considers green technologies as a unique bundle with no differentiation between different typologies. However, policy efforts to deal with climate change have been traditionally channelled in two different directions. Adaptation strategies concern the ability of an anthropogenic system to adjust to climate change by moderating potential damage. Mitigation strategies consist of actions taken to permanently eliminate or reduce the long-term risk and hazards of climate change. In a nutshell, one can think of the former as adjustment of existing routines and of the latter as generating entirely new routines. Accordingly, options within the adaptation paradigm entail infrastructure development, process optimization, integrated natural resources management, risk transfer, creation of information systems to support early warning and proactive planning. Conversely, implementing mitigation strategies implies a range of sector-specific structural changes to reduce emission intensity and to improve energy and resource efficiency. From this, it follows that climate change adaptation and mitigation technologies differ significantly as regards the opportunities, the challenges, the trade-offs and the barriers to adoption. Building on this

premise, this subsection follows the empirical strategy used above and presents the results of estimations on these two sub-groups of green technologies.

For the purpose of our analysis, we distinguish green technologies depending on whether they belong to two broad classes: mitigation and adaptation. The former technologies are environment-related technologies of group 1 (environmental management) and group 2 (water-related adaptation technologies) as per the OECD (2016). The remaining green technological groups for which we find patent data in our database belong to the family of mitigation technologies (groups 4, 5, 6, 7, and 8). Accordingly, we create two additional dummy variables (A and M), each taking the value 1 if case technology z belongs to either group (Adaptation or Mitigation), and 0 otherwise:

$A_z/M_z = 1$ if $z \in \text{Adaptation/Mitigation}$

$A_z/M_z = 0$ if $z \notin \text{Adaptation/Mitigation}$

The regressions in Table A2 replicate our favourite specification of Table 3 (see col 4) for, respectively adaptation (col 1) and mitigation (col 2) technologies. The main coefficient of interest, the interaction with the e-skills indicator, is positive and significant for mitigation technologies but not for adaptation. Accordingly, our prior findings relative to hypothesis 1 hold only for the former group: the probability that a region acquires Revealed Comparative Advantage in a new green mitigation technology increases with the level of e-skills in the workforce.

TABLE A2 ABOUT HERE

Moving to the regressions concerning relatedness, Tables A3 and A4, we observe that in both cases only the interaction with green relatedness is positive and significant. This provides only partial support to hypothesis 2 in that, different from the general case of Table 4, non-green relatedness now exhibits no significant correlation with the probability of regions developing new green technologies, be they mitigation or adaptation.

TABLES A3 AND A4 ABOUT HERE

Turning to the relation between relatedness and e-skills, the coefficients in Table A5 and A6 point to some differences from the baseline regressions (Table 5). In particular, at first glance, hypothesis 3 is only confirmed for the mitigation group. Thereby, apparently, the local endowment of e-skills augments the positive effects of relatedness only for technologies that aim at radical new ways to eliminate or contain the hazards of climate change. Note that this holds for both green and non-green relatedness (col 3 and 4, Table A6).

TABLES A5 AND A6 ABOUT HERE

Nevertheless, to gain a clearer picture of these interaction effects, we computed the marginal effects of green and non-green relatedness for different levels of regional e-skill endowments. The marginal effects of Tables A7 and A8 indicate that, akin the general case of Table 6, the role of relatedness in the likelihood of developing new specialisations increases for green and non-green relatedness together with e-skills. This holds for both adaptation and mitigation technologies. Also similar to the general case, marginal effects are stronger for non-green relatedness than for green relatedness. At the same time however, e-skills strengthens the role of relatedness more for mitigation relative to adaptation technologies. To illustrate, the marginal effect on green relatedness is rather low and essentially invariant to the level of e-skills for adaptation technologies (Upper part of Table A7), whereas the correspondent effect for mitigation technologies increases together with the levels of regional e-skills endowment (Upper part of Table A8). As regards non-green relatedness, the percent change between the minimum and the maximum of e-skill endowment is twice as large for mitigation technologies relative to adaptation (+117.0% versus +35.2%).

TABLES A7 AND A8 ABOUT HERE

Our reading of these differences is that solutions for climate change adaptation are usually less capital intensive and more amenable to small-scale interventions, and thus encompass a mix of “hard” – e.g. new irrigation systems or drought-resistant seeds - and “soft” technologies – e.g. insurance schemes or changing crop rotation. The point is that adaptation strategies may be already underway, in one way or another, in some regions and therefore

likely to happen ‘under the radar’ of our regression approach. Mitigation strategies on the other hand involve investments at all stages of the technology development process, from R&D upstream to demonstration, deployment, and diffusion. In particular, empirical evidence suggests that most emerging low-carbon energy technologies are subject to sizeable “learning effects”, i.e. their costs decrease as experience accumulates through cumulative production (IEA, 2008). Further, and closer to our analysis, the first wave of mitigation technologies carried a specific rather than general-purpose nature (e.g. wind, solar and nuclear energy to power generation, hydrogen and biofuels to transport, etc.) while more recently, efforts point to more multi-purpose and cross-sectoral inventions (Sbardella et al, 2018). This leads to expect a more prominent role for competences like e-skills that ensure interoperability and seamless diffusion across contexts of use. Doing so, digital competences favour the linking and recombination of regional capabilities that are spread across different sectors and regional actors, and that are necessary for this more recent wave of mitigation technologies.

Table A2: Tests of hypothesis 1: Comparing adaptation and mitigation technologies

	(1)	(2)
adapt	-0.051187** (0.022939)	
mitig		-0.084525*** (0.007836)
e-skills	0.184168* (0.109051)	0.165451 (0.108621)
e-skills*adapt	0.124979 (0.079044)	
e-skills*mitig		0.101432*** (0.028120)
gdp_pc	-0.000003* (0.000002)	-0.000003* (0.000002)
rd	-0.008343 (0.014326)	-0.008412 (0.014311)
female_workers	0.017062 (0.214514)	0.010895 (0.213828)
old_pop	0.023070 (0.537621)	0.028459 (0.537092)
un	-0.000128 (0.000917)	-0.000116 (0.000914)
Constant	0.087188 (0.152432)	0.110547 (0.151960)
R-sqr	0.019	0.023
N	119192	119192

* p<0.10, ** p<0.05, *** p<0.01

Table A3: Tests of hypothesis 2 for green adaptation technologies

	(1)	(2)	(3)	(4)	(5)
adapt	0.024849 (0.017504)	0.010052 (0.017773)	0.013876 (0.017591)	-0.026913 (0.022673)	-0.009121 (0.021596)
relatedness	1.411851*** (0.055058)				
g_rel		0.460417*** (0.043519)		0.454092*** (0.043577)	
ng_rel			1.238657*** (0.057200)		1.235822*** (0.057149)
adapt*g_rel				0.234027* (0.140527)	
adapt*ng_rel					0.101928 (0.109555)
gdp_pc	-0.000010*** (0.000001)	-0.000006*** (0.000001)	-0.000008*** (0.000001)	-0.000006*** (0.000001)	-0.000008*** (0.000001)
rd	0.009275 (0.014709)	0.002591 (0.014791)	0.006079 (0.014816)	0.002593 (0.014797)	0.006091 (0.014817)
female_workers	-0.436799** (0.211859)	-0.155238 (0.215327)	-0.314812 (0.212654)	-0.153156 (0.215296)	-0.314597 (0.212665)
old_pop	-0.407650 (0.538360)	0.439862 (0.544324)	-0.777054 (0.534945)	0.441822 (0.544448)	-0.776474 (0.534958)
un	0.000162 (0.000941)	0.000897 (0.000949)	-0.000521 (0.000937)	0.000890 (0.000949)	-0.000522 (0.000937)
Constant	0.386637** (0.151790)	0.133411 (0.155975)	0.372960** (0.151276)	0.133063 (0.155981)	0.373379** (0.151265)
R-sqr	0.047	0.026	0.040	0.026	0.040
N	119192	119192	119192	119192	119192

* p<0.10, ** p<0.05, *** p<0.01

Table A4: Tests of hypothesis 2 for green mitigation technologies

	(1)	(2)	(3)	(4)	(5)
mitig	-0.012187** (0.006110)	-0.033821*** (0.005994)	-0.024881*** (0.005973)	-0.067802*** (0.008547)	-0.037969*** (0.007042)
relatedness	1.367591*** (0.058559)				
g_rel		0.416509*** (0.044327)		0.365716*** (0.045751)	
ng_rel			1.182603*** (0.059416)		1.169656*** (0.059284)
mitig*g_rel				0.209679*** (0.051795)	
mitig*ng_rel					0.057517 (0.036308)
gdp_pc	-0.000009*** (0.000001)	-0.000005*** (0.000001)	-0.000008*** (0.000001)	-0.000005*** (0.000001)	-0.000008*** (0.000001)
rd	0.008857 (0.014715)	0.001948 (0.014793)	0.005622 (0.014820)	0.001866 (0.014760)	0.005699 (0.014820)
female_workers	-0.420911** (0.211563)	-0.134040 (0.214690)	-0.297611 (0.212186)	-0.144646 (0.214508)	-0.297625 (0.212167)
old_pop	-0.385222 (0.537827)	0.420983 (0.544129)	-0.727641 (0.534042)	0.441628 (0.543743)	-0.730493 (0.534007)
un	0.000166 (0.000941)	0.000831 (0.000948)	-0.000484 (0.000935)	0.000844 (0.000947)	-0.000488 (0.000935)
Constant	0.379262** (0.151489)	0.133838 (0.155667)	0.364505** (0.150946)	0.144503 (0.155817)	0.368865** (0.151030)
R-sqr	0.047	0.028	0.041	0.029	0.041
N	119192	119192	119192	119192	119192

* p<0.10, ** p<0.05, *** p<0.01

Table A5: Tests of hypothesis 3 for green adaptation technologies

	(1)	(2)	(3)	(4)
adapt	0.010297 (0.017747)	0.013863 (0.017590)	-0.041501 (0.026867)	-0.015531 (0.030306)
e-skills	0.375855*** (0.105071)	0.018541 (0.108426)	0.521607*** (0.108924)	0.064287 (0.119829)
g_rel	0.476742*** (0.042655)		0.820611*** (0.068489)	
ng_rel		1.237943*** (0.057628)		1.335292*** (0.090555)
e-skills*g_rel			-0.862302*** (0.199538)	
e-skills*ng_rel				-0.265347 (0.299844)
e-skills*adapt			0.048766 (0.130171)	0.007587 (0.151737)
adapt*g_rel			0.194213 (0.299703)	
adapt*e-skills*g_rel			0.015661 (0.739202)	
adapt*ng_rel				-0.081705 (0.203660)
adapt*e-skills*ng_rel				0.463791 (0.797450)
gdp_pc	-0.000008*** (0.000002)	-0.000008*** (0.000002)	-0.000006*** (0.000002)	-0.000008*** (0.000002)
rd	-0.005164 (0.014214)	0.005678 (0.014143)	-0.001320 (0.014227)	0.004952 (0.014213)
female_workers	-0.271494 (0.212387)	-0.319928 (0.211016)	-0.338589 (0.211620)	-0.278114 (0.216861)
old_pop	0.237321 (0.536026)	-0.787062 (0.526199)	0.041891 (0.531764)	-0.764545 (0.525016)
un	0.000525 (0.000916)	-0.000540 (0.000904)	0.000977 (0.000903)	-0.000415 (0.000885)
Constant	0.202136 (0.152303)	0.376023** (0.148310)	0.198382 (0.152400)	0.336467** (0.151859)
R-sqr	0.027	0.040	0.028	0.040
N	119192	119192	119192	119192

* p<0.10, ** p<0.05, *** p<0.01

Table A6: Tests of hypothesis 3 for green mitigation technologies

	(1)	(2)	(3)	(4)
mitig	-0.033524*** (0.005992)	-0.024906*** (0.005967)	-0.034299*** (0.010057)	0.007085 (0.010127)
e-skills	0.362423*** (0.105061)	0.029339 (0.108161)	0.522246*** (0.109420)	0.099047 (0.121164)
g_rel	0.432583*** (0.043521)		0.780059*** (0.071480)	
ng_rel		1.181423*** (0.059795)		1.290613*** (0.093661)
e-skills*g_rel			-0.991715*** (0.212035)	
e-skills*ng_rel				-0.424681 (0.313427)
e-skills*mitig			-0.092113* (0.051254)	-0.183322*** (0.052189)
mitig*g_rel			-0.180247* (0.094935)	
mitig*e-skills*g_rel			0.932662*** (0.289406)	
mitig*ng_rel				-0.367923*** (0.077133)
mitig*e-skills*ng_rel				1.317691*** (0.302057)
gdp_pc	-0.000007*** (0.000001)	-0.000008*** (0.000002)	-0.000005*** (0.000002)	-0.000008*** (0.000002)
rd	-0.005525 (0.014226)	0.004988 (0.014156)	-0.002023 (0.014160)	0.004788 (0.014196)
female_workers	-0.246300 (0.211799)	-0.305691 (0.210611)	-0.326474 (0.210742)	-0.287297 (0.216521)
old_pop	0.225837 (0.535682)	-0.743435 (0.525382)	0.081234 (0.530634)	-0.737754 (0.523613)
un	0.000473 (0.000915)	-0.000514 (0.000902)	0.000898 (0.000900)	-0.000461 (0.000882)
Constant	0.200096 (0.151971)	0.369346** (0.148023)	0.198270 (0.151851)	0.345872** (0.151149)
R-sqr	0.029	0.041	0.031	0.041
N	119192	119192	119192	119192

* p<0.10, ** p<0.05, *** p<0.01

Table A7: Marginal effects of relatedness on green diversification for adaptation technologies

Type of relatedness	Marginal effect of relatedness on entry if adaptation dummy=1		E-skills
Green Relatedness	0.82	***	min
	0.82	***	Q1
	0.82	***	Q2
	0.83	***	Q3
	0.83		max
Non-Green Relatedness	1.25	***	min
	1.42	***	Q1
	1.46	***	Q2
	1.50	***	Q3
	1.69	***	max

* p<0.1, ** p<0.05, *** p<0.01

Table A8: Marginal effects of relatedness on green diversification for mitigation technologies

Type of relatedness	Marginal effect of relatedness on entry if mitigation dummy=1		E-skills
Green Relatedness	0.61	***	min
	0.95	***	Q1
	1.02	***	Q2
	1.11	***	Q3
	1.49	***	max
Non-Green Relatedness	1.06	***	min
	1.53	***	Q1
	1.63	***	Q2
	1.76	***	Q3
	2.30	***	max

* p<0.1, ** p<0.05, *** p<0.01