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Papers in Evolutionary Economic Geography

25.03

Utrecht University Human Geography and Planning

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Abstract

This paper investigates the relationship between migrant inventors, informal institutions and the development of green technologies in European regions. We argue that migrant inventors act as an unlocking mechanism that transfers external knowledge to host regions, and that informal institutions (i.e. social capital, migrant acceptance) mediate this effect. The work is based on an original dataset of migrant inventors covering 271 NUTS2 regions in the 27 EU countries, the UK, Switzerland, and Norway. The analysis shows that migrant inventors help their host regions to diversify into green technologies. The regions with the highest levels of both measures of social capital show a higher propensity of migrant inventors to act knowledge brokers. Conversely, regions with lower levels of migrant acceptance and social capital do not seem to contribute to this effect.

Keywords: lock-in, international migration, green innovation, social capital, acceptance, regional diversification, EU regions

JEL Codes: F22, J61, O30, R12, Q55

1. Introduction

Building inclusive and sustainable regional economies is a key policy priority of the EU and an integral part of its regional cohesion agenda (EU, 2019). However, regional economies tend to follow path-dependent trajectories that often lock them into old (fossil fuel) specialisations (Hassink, 2005; Martin, 2010; Martin and Sunley, 2006). Un-locking EU regions from existing fossil fuel technologies therefore requires considerable efforts, diverse skills and appropriate institutions, which not all EU regions possess (Unruh, 2000).

On the one side, green technologies tend to be more complex and diverse than non-green technologies (Barbieri et al. 2020). To build such green knowledge bases, regions need to tap into external capabilities through external linkages (e.g. international cooperation, high-skilled migrants, multinational companies) (Corrocher et al. 2024). External linkages represent relevant pipelines to access novel and non-redundant knowledge (Morrison et al. 2013), which helps regions to de-lock from existing lock in (e.g. technological) and develop new growth paths (Boschma, 2017; Boschma and Martin, 2010). In this paper, we focus on one such external linkages, namely high-skilled migration. High skilled migrants have been regarded as agents of technological change: they carry with them the tacit part of knowledge that, being distinct from the local one, can trigger new local recombinations (Morrison, 2023).

On the other side, regional economies can reap the benefit of external connections only under specific conditions (Giuliani, 2007). The literature has shown for example that social capital can be an important enabling factor to trigger structural change (Muringani et al. 2021). There are extensive gains in developing new technological sectors in a region by linking informal institutions and the entry of new technological industries (Antonietti and Boschma, 2020; Cortinovis, et al. 2017). In addition, social capital has been described as a precondition for innovation because of the interactions and networks through which knowledge flows (Beugelsdijk and van Schaik, 2005). Informal institutions, if inclusive, can also amplify the impact of migration, as they reduce the costs associated with dealing with diversity (Kemeny and Cooke, 2017).

In this paper, we test the impact of high-skilled migrants in fostering the development of green technologies in regions with different level of social capital and social acceptance of migrants.

We rely on a unique dataset of migrant inventors in 257 NUTS2 regions and 22 EU countries plus the UK, Switzerland and Norway over 20 years. We also source information from different waves of the European Value Service in order to build different measures of social capital and migrants acceptance in EU regions.

Our study shows that migrant inventors contribute to the diversification of regions into green technologies. It also finds that informal institutions mediate this effect. In particular, in regions with stronger social capital, the impact of migrant inventor is larger, as compared to regions with lower levels. The effect of acceptance of migrants is instead less clear.

This work contributes to different streams of literature. First of all, it contributes to the literature of carbon lock-in, by investigating how the interplay between exogenous (i.e. migration) and endogenous forces (i.e. local capabilities, informal institutions) help regions to develop green specialisations. This work also adds to the literature on migration and innovation, which has recently cross-fertilised with evolutionary economic geography approaches (Morrison, 2023; Di Iasio and Miguelez, 2022), by adding evidence on the role of migrant inventors for green diversification. We also complement the recent empirical literature on green technological diversification (Santoalha and Boschma, 2021; Montresor and Quatraro, 2020; Fusillo, 2023; Belmartino, 2022), which has looked at external linkages such as FDI and MNCs (Amendolagine et al. 2023; Castellani et al. 2022; Marino and Quatraro et al. 2020).

The work is structured as follows. Section 2 develops the theoretical background while section 3 presents the interpretative framework behind migrants, social capital and green diversification. Section 4 introduces the data and methods and section 5 depicts the descriptive statistics. Section 6 delves into the results, section 7 presents a battery of robustness checks and section 8 concludes.

2. Theoretical background

Patterns of economic and technological change tend to follow a path-dependent process, meaning that current trajectories are shaped by what has happened in the past (Dosi 1997). Path dependency can be the result of serendipitous historical accidents that lead to the choice of a specific technique or standard (David 1985; Arthur, 1988). Network effects and increasing returns to scale act as self-reinforcing mechanisms at the firm and system level, meaning that an established technique can remain the dominant design even it has become less efficient or obsolete (Ruttan, 1997; Arthur, 1988, 1994). Over time, this process overrides potential alternatives and leads an economic or technological system into a lock-in status. Institutional and organisational factors built around a dominant design reinforce this position and bind the whole of society to its use (Unruh, 2000). Path dependent processes unfold also at spatial level, indicating the tendency of regional economies to get trapped in their existing capabilities and specialisations (economic or technological). These processes are specifically bounded to local conditions, which shape their emergence and evolution (Boschma and van der Knaap, 1997). This explains why path dependence has been depicted also as a place dependent process (Martin and Sunley, 2006). A canonical case is provided by Grabher's account of the decline of the industrial complex in the Ruhr region (Grabher 1993), in which socio-political and institutional factors, in addition to economic and technological conditions, were used to explain why actors (local and national) initially overlooked the early signals of crisis and later resisted them. More recently, a path-dependent framework has been used to describe the inertia (or explicit resistance) of certain techno-economic complexes to a sustainable transition (Unruh, 2000). It has been indeed recognised that carbon intensive economic activities and associated technologies follows path-dependent processes (Rosenbloom, 2020). Self-reinforcing mechanisms, which allow the perpetuation of fossil fuel technologies, manifest themselves at different levels, from organisations (e.g. firms) to techno-economic systems and broadly to societies and associated institutions (Seto et al, 2016). In particular, institutional lock-in refers to both formal and information institutions that purposefully reinforce the status quo of a fossil fuel economy (Klitkou et al. 2015). In this debate, it has been noted, that path-dependency has also a positive side for sustainable transition. In regions where green policies have already a significant history of development, and strong constituencies around a green economy have emerged, path dependent mechanisms can support a low-carbon transition (Meckling et al., 2015). The latter suggests that path dependency, besides setting the limits of a system (e.g. economic, technological) also shows its growth opportunities and the direction in which it can change. This resonates with evolutionary approaches in economic geography, which have extensively explored how regions implement processes of related diversification (Boschma, 2017). The attention here shifts to the factors, either endogenous or exogenous, that help regional economies to escape lock in (Martin and Sunley, 2006). The evolutionary idea behind this is that the variety present in the local economy generates novelty that stimulates a process of regional diversification. Over the long term, a higher degree of industrial diversification has been associated with more robust economic systems. The rationale is that by broadening the range of industries within a region, risks are distributed across various sectors, effectively serving as a shelter against economic shocks (Frenken et al., 2007). Additionally, regions that expand their internal industrial variety are better positioned to adapt to structural changes, allowing for the seamless integration of new industries and the phasing out of obsolete ones (Pasinetti & Scazzieri, 2016).

The process that lead to greater variety can be fuelled by virtuous competition among local firms, as it used to happen in industrial clusters (Maskell, 2001) or via spin-off processes, whereby firm founders inherit competences and routines from their parent firm, and in so doing start up new, but related, ventures (Buenstorf and Klepper, 2009; Klepper, 2010). A bourgeoning empirical evidence have shown that regions develop new growth paths by building on their existing capabilities (Neffke et al. 2011; Boschma, 2017). The economic and technological activities in which regions specialise tend to be related to ones already present in the region (Hidalgo et al. 2018; Rigby, 2015).

Besides endogenous forces, de-locking has been associated to external factors. Borrowing from Castaldi and Dosi (2006), Martin and Sunley (2006) coined the term *transplantation* to refer to the "the importation and diffusion of new organisational forms, radical new technologies, industries, firms or institutional arrangements, from outside" (pag. 422). These sources can be the trigger of a profound renewal of a regional economy and spur processes of related diversification.

The role of external factors actors for regional diversification has been explored to some extent in the diversification literature. Neffke et al. (2018) demonstrated that the emergence of new economic activities in Swedish regions was primarily driven by newcomers rather than established firms, particularly when these new firms relocated from outside the region. Similarly, multinational corporations have been identified as key contributors of regional diversification, as seen in the context of Eastern European countries (Elekes et al., 2019) and in China (Qiao et al. 2024). More recently, Kogler et al. (2023) showed that regional diversification processes are facilitated by external collaborative networks, such as co-inventorship. Their findings indicate that co-inventor networks can offset a region's lack of technological relatedness by enabling collaborations within firms across different geographical locations. Some recent works have also explored the role of international co-inventor linkages for green diversification, showing that indeed external connections work as knowledge pipelines, in particular if they bridge between regions with complementary capabilities (Corrocher et al. 2024).

The logic behind this is that extra-regional linkages act as gatekeepers or boundary spanning mechanisms that allow regional economic actors to access non-redundant knowledge (Breschi and Lenzi 2015; Morrison et al. 2013; Martin and Sunley, 2006). As Grabher has shown in the case of the Ruhr, these mechanisms become sclerotic or are absent in locked-in regions. Different strands of literature have explored at length a variety of forces that can perform this catalyst brokering function, including multinationals (Bahar et al. 2014) and R&D networks (Owen-Smith and Powell, 2004) among others. In this work we have focused on high-skilled migrants (Saxenian 2006).

Migrants have emerged as pivotal agents of knowledge transfer (Breschi et al. 2020). Recent quantitative empirical literature shows that they contribute to innovation activities in both host and origin countries (Breschi et al. 2017; Hunt and Gauthier-Loiselle, 2010; Kerr and Lincoln, 2010). Highly skilled and in particular immigrant inventors act as carriers of knowledge (Lissoni and Miguelez, 2024), enabling the dissemination of specialised knowledge and fostering cross-regional exchanges of technical and practical know-how (Kapur & McHale, 2005) as well as scientific knowledge (Ganguli, 2015; Moser et al. 2014);

Another stream of literature has paid attention to the role of immigrants as agents of structural change (Morrison, 2023). For example, Bahar et al. (2020) provide robust evidence that immigrant inventors transfer knowledge from their home countries, significantly influencing the technological trajectory of their host regions. This imported knowledge has been shown to foster technological diversification (Bahar et al., 2020; Diodato et al., 2022; Moser et al., 2014) and, in some cases, reinforce existing specialisations (Caviggioli et al., 2020). Notably, Caviggioli et al. (2020) reveal a negative correlation between the presence of immigrant inventors and regional diversification, as measured by the variety of technologies in which a region is specialised. Miguelez and Morrison (2023) explore different mechanisms through which immigrant inventors affect regional technological diversification: either directly, by using their own personal knowledge; or using the knowledge imported from their home. They show that the impact is greater when their knowledge is not re-combined at the local level, but when it is only reused in teams of migrant inventors. Additionally, recent research highlights that migrants also contribute to diversification in their home countries. Return migration (Diodato et al., 2023) and diaspora networks (Di Iasio & Miguelez, 2022) facilitate technological diversification in origin regions.

However, for migrants to play a transformative role and for their knowledge to be effective, host regions should create the right institutional conditions and be welcoming themselves. Crescenzi and Gagliardi (2015) emphasise that in attracting skilled individuals, regional innovation systems should integrate these human capital inflows into local institutional networks, thereby addressing and mitigating the limitations of insular or narrowly focused knowledge search behaviours. This approach highlights the critical interplay between human mobility and the structural dynamics of regional economic development.

Informal institutions have been shown to play a pivotal role in shaping attitudes and positively moderating the impact of technological change (McMillan & Rodrik, 2011), as well as facilitating the implementation of externally sourced knowledge within regions (Balland & Boschma, 2021). Specifically, social capital has been linked to regional gains in the development of new technological sectors, as it fosters the establishment of informal institutional linkages and the entry of new industries

(Cortinovis, et al. 2017; Muringani, et al., 2021). Furthermore, research highlights the contribution of social capital to regional productivity through innovation (Akçomak and ter Weel, 2009), stronger workers' output (Haus-Reve and Cooke, 2019; Kemeny and Cooke, 2017) and the role of diversity in achieving higher wages in regions characterised by high levels of trust (Kemeny, 2012). The reason behind it is that social capital reduces the costs of coordination when there are people with different backgrounds. This implies that territories with stronger social capital reap the benefit of immigrant diversity better than others. Social capital has also been identified as a critical enabler of innovation, facilitating the interactions and networks through which knowledge is exchanged and disseminated (Crescenzi, et al., 2013). In particular, immigrant inventors are integral part of these processes, with evidence suggesting that their interactions with native populations lead to better outcomes in terms of innovation and productivity (Arkolakis, et al. 2019). In line with the literature on regional lock-in (Martin and Sunley, 2006), this latter evidence indicates that the effectiveness of transplantation stems from the prevailing local conditions either in the form of different level of absorptive capacity or different degree of institutional embeddedness.

We build on these three different streams of literature (i.e. path dependence and regional diversification, migration and innovation, informal institutions) to investigate the impact of immigrant inventors on green technological diversification in EU regions. Below we outline a brief conceptual framework that will guide the empirical analysis.

3. Migrant inventors, social capital and green technological diversification: a interpretative framework

This section introduces a conceptual framework to illustrate the mechanisms through which migrant inventors influence the trajectory of technological change in their host regions, and in this way they help these regions to un-lock. The framework is built around three conceptual pillars: first, technological lock-in emerges in contexts of declining variety; second, de-locking is driven by endogenous (i.e. regional capabilities) as well as exogenous (i.e. migration) factors; third, informal institutions (e.g. social capital, migration acceptance) moderate the effects of the exogenous factors (i.e. migrants).

As to begin with variety, particularly technological variety, is widely recognised to be a driver of economic dynamism (Dosi and Nelson, 1994). However, regions that experience a decline in variety, over time, due to path dependency, see their specialisations continuously reinforced (Martin and Sunley, 2006). This trend poses the risk of long-term lock-in to outdated technologies or industries (Boschma, 2017). Ideally, a process of continuous renewal driven by endogenous positive dynamics is possible.

Regions with a large portfolio of activities can more easily branch out in related sectors and in this way escape cognitive traps. A process of diversification represents for them a typical form of de-locking (Martin and Sunley, 2006).

However, this can be ineffective or not sufficient when the local sources of new knowledge are not feeding properly the regional economic system. This is certainly more likely to be the case when dealing with fossil-fuel technologies and sectors, that face unprecedented threats and challenges. Indeed, green technologies are usually characterised by higher complexity (Barbieri et al. 2020), making diversity even more valuable for their development. Therefore, regions that continue to invest heavily in fossil fuel technologies, infrastructure, and industries are at a significantly higher risk of technological lock-in and economic decline. Additionally, not all regions possess the necessary capabilities to develop or adopt green technologies, particularly at the pace and scale demanded by the current climate crisis.

This is why exogenous factors, such as the knowledge carried by inventor migrants, can serve as a critical channel for regions to escape such lock-in and embrace promptly a renewal path. By leveraging their external networks, immigrant inventors enable regional economies to access novel and complementary knowledge assets. Such non-redundant knowledge introduces variation that fuels the development of new technological trajectories and growth paths (Morrison, 2023).

The positive impact of inventor migrants manifests through several mechanisms. A primary channel is the direct interaction between immigrants and natives, such as within inventor teams. Research shows that cultural diversity in inventor teams enhances creativity, leading to more innovative outcomes (Ferrucci and Lissoni, 2019). Additionally, localised knowledge spillovers generated by immigrant activity indirectly benefit natives, as extensively documented in the literature (Kerr et al., 2016). Another mechanism involves the cross-border transfer of knowledge embedded in migrants themselves. Because tacit knowledge—being personal, idiosyncratic, and non-codified (Polanyi, 1958)—travels with individuals, migration becomes a crucial channel for knowledge diffusion. Migrant inventors carry tacit knowledge not yet available in the destination region, effectively importing expertise from their home countries (Bahar et al., 2020; Diodato et al., 2022). When these inputs complement the knowledge of natives, both groups stand to benefit.

However, for external knowledge to be recombined locally it is crucial that external networks, in our case migrant inventors, are embedded in the local context. We know that network formation is often driven by homophily (Kossinets and Watts, 2009), as people tend to interact with similar alters.

Moreover, diversity can increase transaction costs and discourage potentially fruitful collaborations. Therefore, it cannot be taken for granted that migrants' external knowledge will flow smoothly in the host region and be recombined. In order to facilitate this process and to take full advantage of the diversity induced by migration (Kemeny, 2012), individuals need to trust each other. In fact, social capital enables people to coordinate each other at lower costs and act collectively (Kemeny and Cooke, 2017). This also implies that regions with stronger social capital enable such collective action at lower cost and make the most of the diversity of migrants (Herreros and Criado, 2009). In addition, regions that welcome migrants facilitate their integration, which also enables their embeddedness in professional networks, and in turn facilitates the diffusion of knowledge spillovers (D'Ambrosio et al. 2019). This should in principle be especially true for areas in which the acceptance of migrants is higher. Higher acceptance of migrants facilitates the embeddedness of foreign inventors in the local community, increasing the chances of knowledge diffusion and recombination.

To sum up, we summarise our arguments in Figure 1 below. In the context of de-locking from fossil-fuel based technologies and facilitating a green transition, we investigate the role of migrants as agents of structural change, and how local institutional conditions – specifically in terms of social capital and acceptance of migrants – affect the impact of migrants. Embedding our framework in previous contributions on lock-in and diversification (Martin and Sunley 2006, Boschma 2017), migration (Miguelez and Morrison 2023) and social capital (Putnam 2000; D'Ambrosio et al. 2019). Based on the arguments delineated above and extant evidence, we expect that the positive impact of migrant inventors on the emergence of a new green technology specialisation in the host is amplified in contexts of high levels of social capital and acceptance. Criss-crossing the social capital and acceptance dimensions, we theorise that, on the one hand, high levels of social capital may be a crucial condition for mobilising foreign inventors' knowledge and fostering diversification (i.e. only in the "High Social Capital" row we expect to find a positive relation). The importance of social capital in this respect has to do with the fundamental role of dense network connections for knowledge recombination (Cortinovis et al. 2017; Akçomak and Ter Weel, 2009). At low levels of social capital (i.e. the 'Low Social Capital' row), the limited degree of network embeddedness limits the impact of social capital. So, we expect a null effect. On the other hand, regions characterised by high levels of acceptance and openness to migrants are likely to further enhance the relation between foreign inventors and diversification by facilitating easier and faster integration of high-skill migrants in the local socio-economic context. Similarly, for low level of acceptance, we expect a null effect.

Figure 1 The mediating role of social capital and acceptance of migrants

		Acceptance	
		Low	High
Social Capital	High	++	+++
	Low	Null	Null/+

4. Data development and modelling

4.1 Data development

The main focus of our analysis is the role of inventor migrants in fostering diversification into green technologies in European regions. In terms of data sources, we rely on the OECD REGPAT database for our dependent variable (February 2024 edition), while the information on immigrant inventors comes from the datasets developed by Miguelez & Fink (2013) and by Pellegrino, Penner, & Piguet (2022). Given our interest in de-locking from fossil fuels and green technological transition, we focus on green technologies. To identify green technologies, we use the CPC classification codes listed by the OECD Environmental Technologies "ENVTECH" (OECD, 2015). The OECD regularly updates these codes to identify new inventions that can be potentially included as environmental technologies. We use CPC codes included in the ENVTECH classification at 4-digit level, resulting in 61 different green technologies.

In terms of the time dimension, we split the years 1991-2023 in four non-overlapping periods (1991 to 1998, 1999 to 2005, 2006 to 2012 and 2013 to 2023). We consider a longer time span for the last period, given the rapid growth and increased policy relevance of green technologies in recent years. As described in the next section, we define these time periods in order to be able to compute and compare over time the specialisations of each region in different technologies across time. Our sample covers 272 NUTS2 regions covering 31 countries, including all EU member states, plus Norway, Switzerland and the United Kingdom[1].

[1] The data cleaning efforts allowed us to obtain around 70.158 inventors whose nationalities and places of residence we know, and of whom 6091 are inventors residing in a country different from their nationality.

For the social capital and migrant acceptance variables, we leverage information from the European Value Study survey. This survey, widely used in the social capital literature (Beugelsdijk & van Schaik, 2005; Cortinovis et al. 2017), is conducted every 10 years approximately, in different waves[2] and provides regionalised data on European countries, although with mixed NUTS1 and NUTS2 aggregation[3]. In particular, as discussed below, we use the survey questions concerning trust, participation in voluntary organisations and acceptance of foreign population.

4.2 Dependent Variable: Entry into a new technological field.

Our dependent variable aims at capturing the diversification of a given region in a certain period into a new green technological field. For that, we need to capture the entry of a given European region into a new green technological field, and we can do that by assessing first the technological portfolio that each region has and whether, in the subsequent period, that region enters into a new technological field that was not in its portfolio before. Building upon the methodologies employed in previous studies, such as Hidalgo, et al. (2007), Rigby (2015), Balland, et al. (2019) and Balland & Boschma (2021), we employ the Revealed Technological Advantage (RTA) as a metric for assessing whether a region attains specialisation in a technology that is hitherto unexplored within that region. RTA is a binary variable that takes value 1 when a region exhibits a higher share of patents in a specific technology class, denoted as i, compared to the reference category, which in this case corresponds to the European Union (EU). In cases where this criterion is not met, RTA takes a value of 0. In other words, a region, represented by r within our dataset (where r ranges from 1 to n), is considered to have achieved RTA in the production of technological knowledge, denoted as $'f'$ (where f ranges from 1 to k), if the following condition holds:

$$RTA_{rf}^{t} = \begin{cases} 1 \; if \; \frac{patents_{r,i}^{t} / \Sigma_i patents_{r,i}^{t}}{\Sigma_r patents_{r,i}^{t} / \Sigma_r \Sigma_i patents_{r,i}^{t}} > 1 \\ 0, \; otherwise \end{cases} \quad (1)$$

The variable of interest is then coded as 'entry' with value 1 if a given region r becomes specialised in a given technology f, in which it was not specialised in the previous period t-1. Consequently, that region will be considered as diversified into that new technological portfolio and, therefore, entry into a new technological field. Furthermore, if the region was already specialised in a given technology in period t-1, then we will set that value as missing, as it the 'entry' cannot occur. This can also be expressed as follows:

[2] The different waves used are wave 2, years 1989 and 1990; wave 3, years 1999 and 2000; and wave 4, years 2008 and 2009. Since we used 4 periods of 6 years on the right-hand side of the empirical strategy, we imputed a wave between waves 2 and 3 with the historical trends of those 2 waves.

[3] Data on Germany and France, for instance, are aggregated at the NUTS1 level in certain waves.

$$Entry^{t}_{r,f}\begin{cases}1, if\ RTA^{t}_{r,f} \geq 1 \wedge RTA^{t-1}_{r,f} < 1\\ 0, if\ RTA^{t}_{r,f} < 1 \wedge RTA^{t-1}_{r,f} < 1\\ NA, otherwise\end{cases} \quad (2)$$

4.3 Independent variables: migrant inventors, relatedness density, social capital and acceptance of migrants

Migrant inventors

Our main variable of interest is immigrant inventors, to build it we rely on data collected by Miguelez and Fink (2013). Specifically, we construct for each region, in each technology class and each period if there is any green patent filled by any inventor who is not a national of the country where he or she resides. Following Miguelez & Morrison (2023), we take the cumulative sum of all the inventors that are patenting in a given region r, technology f, in a given period t, assuming that foreign inventors will reside in the same region in the subsequent periods. Note that this variable captures all the green technologies that each migrant inventor patents. For example, if a migrant inventor fills a patent in three different technologies in period t in region r, then we are counting the same inventor in each technology in which she patented. Mathematically, we compute the stock of the number of migrant inventors in each region, technology and period as follows:

$$StMig_{rft} = Mig_{rft} + StMig_{rft-1} (3)$$

Where Mig_{rft} is the number of migrant inventors in region *r* and technology *f* in period *t*; and $StMig_{rft-1}$ is the stacked number of migrant inventors in region *r* and technology *f* in period *t-1.*

Relatedness density

The evolutionary economic geography literature has showed that the current technological capabilities in a region are a major determinant of the entry in new technological classes (Hidalgo et al. 2018). Following this literature, we calculate a measure of relatedness density (RD) to account for this path dependent patterns. Specifically, RD is quantified as the extent of proximity (relatedness) between a specific technology and the technological repertoire of a given region. To calculate the RD, we follow two steps. First, we calculate the pairwise relatedness $\phi_{f,j,t}$ between two technologies (f, j), for the whole set of 654, 4-digit CPC technologies and regions in our sample[4]. This measure, estimated based

[4] In this case, to calculate the relatedness density, we used all the 4-digit technologies available in the portfolio of all regions, not only the green ones that account for 63 4 digits in total.

on the co-occurrence of specialisations in the same local area, is interpreted as a measure of cognitive proximity between each pair of technological classes. Following Hidalgo et al. (2007), we then compute how proximate each technological class (f) in region (r), in period (t) is to the specialisations (j) currently present locally. In more formal terms:

$$RD_{frt} = \frac{\sum_{jf}^{t} RTA_{r,j}^{t} * \phi_{fj}}{\sum_{jf}^{t} \phi_{fj}} * 100 \text{ (4)}$$

RD_{frt} takes values between 0 and 100. It is 0 when there are no technologies related to technology f in region r at time t and 100 when all technologies are related to technology f in region r in time t.

Social Capital and acceptance of migrants

Informal institutions are proxied by the level of social capital and acceptance of migrants in a region. With respect to social capital, we follow the extant literature and focus on the level of participation in voluntary associations as proxy local networks of relation across societal groups and strata. Social capital measures based on associational activities typically distinguish between "bridging" and "bonding" social capital (Knack & Keefer, 1997; Cortinovis et al., 2017; Muringani et al., 2021). The "bridging" type of social capital is conceptually related to participation in groups and organisations which cut across socio-economic divides and connect non-homogeneous groups of people. The intuition is that these types of connections may reduce transaction costs, facilitate collaboration and communication across different groups of the society. To capture this dimension, we use EVS surveys and measure the extent to which interviewees report they voluntarily participate in a associations and organisations which have been identified as bridging different social group, in particular religious associations, women, cultural or recreational groups. Specifically, our measure of bridging capital is computed as the share of the population in a given region that participate in one of the above mentioned associations. Differently, "bonding" social capital aims at capturing stronger links and interactions among homogenous groups of people. Following the literature, we measure bonding social capital as the share of respondents in the survey in a given region that are voluntarily affiliated with either a trade union, a professional association or a political party. Because of the relations captured by bonding social capital are focused on connecting relatively similar individual, it is a priori unclear what the effects of high levels of social capital are on transaction costs, collaboration and communication. The empirical evidence typically suggests that while bridging social capital is associated with higher economic growth, innovation and diversification, bonding social is usually either negatively or unrelated to these phenomena (Knack & Keefer, 1997; Beugelsdijk & van Schaik, 2005; Cortinovis et al., 2017).

To test how the social capital affects the relation between diversification and migrant inventors, we follow Kemeny and Cooke (2017) and combine the information on bridging and bonding social capital. We argue that locations with higher levels of social capital—characterised by networks of trust, mutual support, and cooperation—are more likely to facilitate collaborative efforts among individuals, lower the social and transactional costs associated with integrating newcomers and facilitate individuals from different backgrounds working together. As a result, such locations are better positioned to maximise the benefits of immigrant diversity by reducing barriers to cooperation. To capture the role of social capital we build a composite indicator using a Principal Component Analysis (PCA), consolidating all pertinent variables into a singular variable called 'social capital'. We condense the multiple variables capturing associations (both Bonding and Bridging Social Capital) into one component that might partially capture the Social Capital value of each region, over time. We first get the PCA for each period (wave) individually and then compute the average. We obtain an explanation ratio of about 40% on average, with loadings of the 4th wave (2008) getting higher explanatory power. Since some regions are not covered in all periods, resulting in missing values, we addressed this by imputing the missing data using a nearest-neighbor interpolation technique.

With respect to migrant acceptance, we rely on the EVS, which provides the shares of individuals in a given region who said they would not like to have migrants as neighbours. The higher the share, the more likely the region is to dislike migrants. Therefore, we invert the value so that scores closer to 1 indicate a more positive sentiment, while scores closer to 0 indicate a more negative sentiment. In our analysuis, we use this information as a proxy for the level of acceptance of inventor migrants. As in the case of social capital, the coverage of regions across all periods is unfortunately not complete. As cultural and institutional factors can be expected to change rather slowly over time (Muringani et al. 2021, Rodriguez-Pose and Di Cataldo, 2015), we follow the same approach as for social capital and interpolate the missing values for migrants acceptance using a nearest-neighbour algorithm.

4. Empirical Strategy

We employ a linear probability model (LPM) to assess the likelihood of a region entering a new technological class in which it was not yet specialised as a function of the stock of migrants and the level of social capital and migrant acceptance. Our baseline estimation is as follows:

$$Yentry_{rft} = \beta_0 + \beta_1 StMig_{rft-1} + \beta_2 RD_{rft-1} + \beta_3 SK_{rft-1} + \beta_4 Acc_{rft-1} + \beta_3 SK_{rft-1} * \beta_4 Acc_{rft-1} + \delta X' + \varphi_r + \gamma_f + \vartheta_t + \varepsilon_{rft} \quad (5)$$

Where $Yentry_{rft}$ is a binary variable that captures the entrance of region r, in technology field f at the time t. $StMig_{rft-1}$ is our main variable of interest and measures the stock of migrant inventors[5] that produce at least one patent in a given region-green technological field (Miguelez & Morrison, 2023).

[5] For robustness checks, we also constructed an additional variable, which simply considers the count number of migrant inventors actively patenting in a given period, rather than their cumulative sum.

X' a vector of controls, such as each region's population and its density to control for urbanisation effects, the total number of patents in that region in any technological field and the level of regional GDP. Overall, these controls help us accounting for the effect of differences in size and economic and innovative performance of the region. Furthermore, we include φ_r both region, technology and period fixed effects (respectively, φ_r, γ_f and ϑ_t). All the independent variables were lagged one to reduce the concern for simultaneity bias and the endogeneity caused by reverse causality. In the robustness checks section, we address this endogeneity issue by using an instrumental variable strategy.

We further modify the baseline model reported in Equation 5 to specifically explore the heterogeneity of the relation between technological entry and migrant inventors across different levels of social capital and acceptance of migrants. To this end, we split the sample in four groups of regions (i.e. high social capital & high acceptance, high social capital & low acceptance, low social capital & high acceptance and low social capital & low acceptance) as shown in Figure 1. Empirically, we estimate again the model above for these different scenarios. We perform several robustness checks to substantiate the findings of our study. First, we use a two least stage square regression to address some endogeneity issues related to the path dependency of migrants' settlement. Then, we estimate a probit model to assess the likelihood of entry into a new domain of green technology. Third, we change our main independent variable using the total sum of migrant inventors. Lastly, we use only the proxy for bridging social capital as measure of social capital. As discussed in the next section, our results appear to be robust to these changes.

5. Results

5.1 Descriptive Statistics

Before diving into the results of our empirical analysis, we provide an overview of our main variables of interest. Starting from our dependent variable, Figure 2 below shows the number of green patents in all NUTS2 regions in Europe from 1980 to 2023. Green patents are rather spatially concentrated in more urban and economically advanced regions. In particular, Ile de France (Paris) ranks first on patent production all over the period, with Rhone-Alpes (Lyon) and German regions in the Rhine valley, Stuttgart and Upper Bavaria also among the top performers[6]. Peripheral regions, especially on in the East and South-East parts of Europe tend instead to patent less in green technologies. The right-hand side of the image shows the number of total entries in the whole period per region and condensing all the technologies.

[6] Maps of green patenting activities aggregated at the NUTS2 level per period can be found in the Appendix.

Fig. 2 Total number of green patents and entries in European regions (1980-2023)

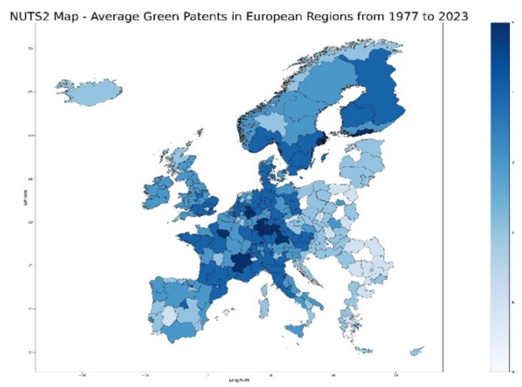
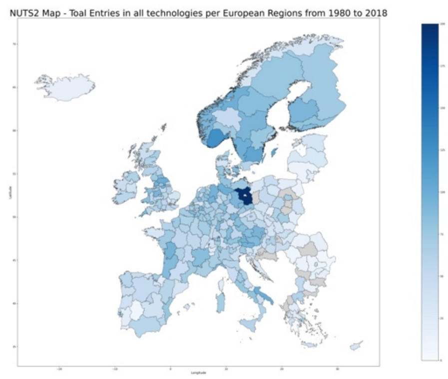
Total number of Green Patents	Total number of Entries
	

Fig. 3 Social capital and acceptance of migrants across European regions

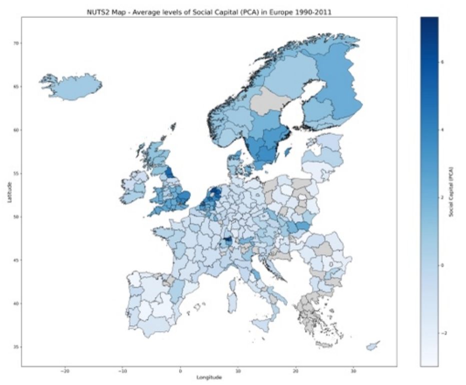
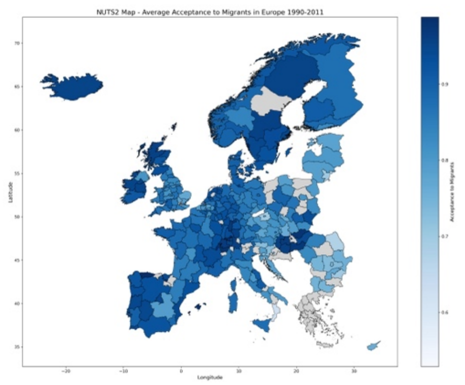
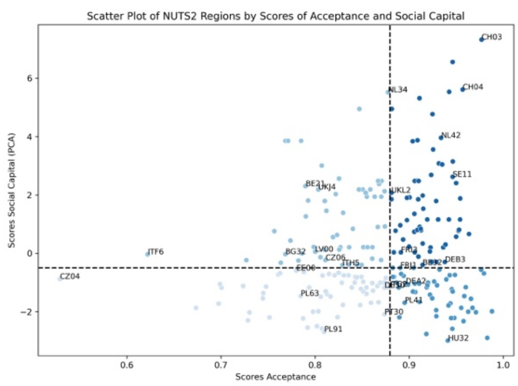
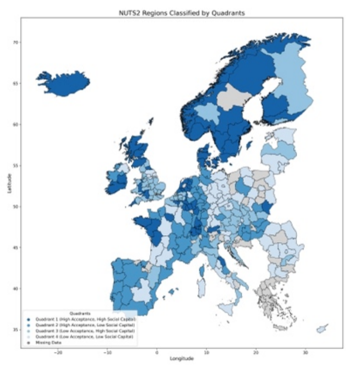
Social capital	Acceptance of migrants
	

Figure 3 shows the spatial distribution of social capital and migrant acceptance across European regions. In terms of social capital, northern European regions, the southern regions of the UK, Scandinavian countries and Benelux report the highest levels of social capital. On the other end of the spectrum, regions in Spain, Southern Italy and Eastern Europe are characterised by lower levels of social capital. The distribution appears somewhat flattened by the top-scoring regions (in particular North-Western Switzerland, Friesland in the Netherlands and Zurich, suggesting a rather significant gap between regions with the highest levels of social capital and areas with an average level. Differently for acceptance, the data from EVS suggests European regions report overall high acceptance levels (often above 70%), with the highest levels typically found in both peripheral (Scandinavian, Spanish, Scotland) and Central-European (South of Germany) regions. Southern Italy and regions in the East and South-East parts of Europe instead seem to present relatively lower scores of acceptance (but always above 50%).

As our analysis groups regions in different categories to assess the heterogeneity of the impacts of migrant inventors, Figure 4 reports a scatterplot showing the distribution of regions along the two dimensions (social capital and acceptance, with the dotted line representing the average scores that we use for splitting the sample) and the spatial distribution of the four categories. The scatterplot on the left-hand side of Figure 4 highlights how – on the horizontal axis – EU regions typically perform relatively well in terms of acceptance, with the average score being well above 80% and only few outlying regions report a score lower than 70%. The range of social capital is instead more evenly scattered (vertical axis), with some outliers presenting extremely high levels, as already noticed in Figure 3. When the two dimensions are criss-crossed, we can see a relatively clear spatial distribution of the different subsamples. Regions in dark blue are characterised by high levels of social capital and acceptance and mostly concentrate in Northern European regions, in particular in Sweden and Norway, Scotland, Ireland, the Netherlands, and along the French-German border. Areas characterised by low levels of social capital and high acceptance (medium-dark blue) are instead mostly concentrated in the Iberian Peninsula and France. Regions in the South of Germany and Northern Italy, together with many regions in England, are categorised as having low levels of acceptance but high levels of social capital (light blue). Lastly, most of the German regions and areas in South-East and Eastern parts of Europe are grouped in the low-social capital and low-acceptance group.

Fig. 4 Social capital and acceptance of migrants levels in European regions

Social capital and acceptance	Spatial distribution of different groups of regions
	

Lastly, Table 1 below shows the summary statistics of all the variables added to the model. Concerning the variable "entry", we can see that the mean is 0.23, meaning that, on average, entries to new green technological fields occur in about one-fourth of the cases. Besides, the variable migrant and stock of migrants seems to be relatively concentrated, with its mean value of migrant inventors in a given region/technology is less than 1 (many regions and technologies with 0 migrant inventors) but its highest value amounting to 236 migrant inventors. As social capital has been computed through PCA, the average value is close to zero but the range of values suggest quite some heterogeneity across regions (as already observed in the maps). Similarly, Table 1 confirms a rather high average value for acceptance (87%), again as already pointed out when discussing Figure 3. More descriptive statistics for the different tiers of regions (high and low social capital and acceptance of migrants) and correlation matrixes can be found in the Appendix.

Table 1. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Entry	63008	0.228	.42	0	1
Migrant Inventors	66368	0.135	1.789	0	234
Migrant Inventors (stock)	66368	0.174	2.074	0	236
Relatedness Density	81557	0.227	0.113	0.001	.525
Social Capital (PCA, avg)	74115	0.033	1.863	-2.95	7.325
Social Capital (PCA)	59292	0.057	2.187	-3.637	11.546
Acceptance to Migrants (avg)	79910	0.87	0.069	0.529	1
Acceptance to Migrants	63928	0.87	0.087	0.4	1
Bridging Social Capital (avg)	74115	0.245	0.096	0.047	0.541
Bridging Social Capital	59292	0.245	0.109	0	0.625
Total Patents	82960	1315.942	3416.105	0	42939.043
GDP	82045	69436.336	165604.45	452.857	2387716.8
Total Population	82045	1779735.9	1433971.2	24238.75	12115140
Population Density	71675	364.388	880.537	3.099	10635.224
Total Area	72590	16328.534	24276.018	109	227120

6.2 Green Technological Diversification

Table 2 reports the results of Equation (5). In column 1 we can see the results of the cumulative number of migrant inventors on the likelihood of regions entering into new green technological fields. Our baseline regressions consistently show a positive and significant coefficient for *Migrant Inventors (stock)*, suggesting that the knowledge and skills brought in the host regions by migrant inventors are associated with a greater probability of diversification into new green technologies. Column 2 to 4 include the variables for social capital and migrant acceptance that, conceptually, may be associated to greater diversification opportunities. Interestingly, our estimates produce positive and significant coefficients for the association between social capital and diversification but non-statistically significant coefficients for migrants' acceptance. This suggests that regions scoring higher in terms of social capital are more likely to diversify into green technologies, but not those regions scoring higher in acceptance to migrants. The lack of significance for acceptance is probably explained by the overall limited variation of this variable. In terms of control variables, the coefficient of the relatedness density is also positive and significant. This suggests that, in line with previous studies (Hidalgo et al. 2007, 2018, Cortinovis et al. 2017), regions are more likely to diversify into a new green technology when already have built capabilities in related technological fields.

Table 2: OLS - Green technological diversification of European regions (full sample)

VARIABLES	(1) Full Sample	(2) Full Sample	(3) Full Sample	(4) Full Sample
Migrant Inventors (stock)	0.052***	0.055***	0.053***	0.055***
	(0.000)	(0.000)	(0.000)	(0.000)
Social Capital (PCA)		0.006***		0.006***
		(0.000)		(0.001)
Acceptance to Migrants			0.002	-0.002
			(0.949)	(0.964)
Relatedness Density	1.313***	1.301***	1.315***	1.301***
	(0.000)	(0.000)	(0.000)	(0.000)
Total Patents (log)	-0.022***	-0.023***	-0.024***	-0.023***
	(0.000)	(0.000)	(0.000)	(0.000)
Population (log)	-0.022***	-0.026***	-0.021***	-0.026***
	(0.000)	(0.000)	(0.000)	(0.000)
GDP (log)	-0.010	-0.002	-0.008	-0.002
	(0.166)	(0.784)	(0.291)	(0.783)
Population Density (log)	0.015***	0.014***	0.015***	0.014***
	(0.000)	(0.001)	(0.001)	(0.001)
Constant	0.302***	0.309***	0.270**	0.311***
	(0.003)	(0.007)	(0.011)	(0.010)
Observations	42,737	37,528	41,076	37,528
R-squared	0.107	0.103	0.105	0.103
Period FE	NO	YES	YES	YES
Regions FE	NO	YES	YES	YES
Technology FE	NO	YES	YES	YES

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: The main independent variable has a hyperbolic sine transformation. Dependent variable: Entry ($\boxed{entry_{rft}}$); Explanatory variable: Cumulative count of migrant inventors ($\boxed{Migrants(stock)_{rft-1}}$), Social Capital (PCA) ($\boxed{SocialCapital_{rft-1})}$ and Acceptance to Migrants ($\boxed{Acceptance_{rft-1}}$). All the independent variables have been lagged for 1 period. The primary independent variable $\boxed{Migrants(stock)_{rft-1}}$ has a hyperbolic sine transformation.

6.3 Heterogeneity across social capital and migrant acceptance

In Table 3 below, we explore the heterogeneity of the relation between diversification and the presence of migrant inventors across regions characterised by different levels of social capital and acceptance. Specifically, we compare the coefficients produced for the same variable (*Migrant Inventors stock*) across different types of regions to investigate whether the relation differ across subsamples. In Column 1 of Table 3 we include the results from Column 1 of Table 2 for comparison. When including in the regression only observations with high values of social capital (Column 2), the estimated coefficient for *Migrant Inventors Stock* is larger than in our baseline model (0.079 vs 0.052), which suggests that the knowledge of migrant inventors is better absorbed and recombined in regions where social capital is higher. Interestingly, when focusing on regions with high acceptance levels (Column 3), the estimated coefficient of interest does not vary from our baseline estimate, pointing towards a less important role of migrant acceptance in enabling and mobilising the knowledge of foreign inventors. When considering simultaneously the level of social capital and acceptance across different regions (Column 4-7), we obtain further interesting insights. Specifically, when regions have high levels of social capital, the impact of migrant inventors on diversification is essentially (and statistically[7]) identical, regardless of the level of migrant acceptance in the area (0.076 vs 0.079). Interestingly, the results in columns 6 suggest that, in regions with low social capital but high acceptance, the impact of foreign inventors is positive and significant but with smaller coefficient (about half) compared to regions with high levels of social capital. Finally, in regions with low levels of both social capital and acceptance, the estimated coefficient of migrant inventors is not significant. Overall, the findings reported in Tables 2 and 3 suggest that migrants are an important driver of green diversification, potentially helping in de-couple European regional economies from technologies based on fossil fuels and opening to a transition based on green technologies. At the same time, the impact of migrant inventors seems to be affected by the level of social capital and, to a lesser extent, of migrant acceptance. Regions with high levels of social capital are better positioned to leverage migrant inventors' skills and knowledge, regardless of their level of acceptance. On the other hand, when the social capital values are low, regions characterised by greater acceptance of migrants tend to benefit, though not as strongly as high-social capital regions.

Table 3: OLS - Green technological diversification of European regions (full sample and scenarios)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Full Sample	High SK	High Acceptance	High SK High Acceptance	High SK Low Acceptance	Low SK High Acceptance	Low SK Low Acceptance

[7] We test whether the point estimates of the two models are different, but the two coefficients are statistically not different from each other.

Migrant Inventors (stock)	0.052***	0.079***	0.053***	0.076***	0.079***	0.037***	0.014
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)	(0.394)
Relatedness Density	1.313***	1.506***	1.283***	1.485***	1.805***	1.183***	1.182***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total Patents (log)	-0.022***	-0.000	-0.010**	0.035***	-0.035***	-0.024***	-0.039***
	(0.000)	(0.968)	(0.047)	(0.003)	(0.000)	(0.000)	(0.000)
Population (log)	-0.022***	-0.071***	-0.040***	-0.099***	-0.079***	0.002	-0.024
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.878)	(0.126)
GDP (log)	-0.010	-0.055***	-0.046***	-0.096***	0.005	0.050**	0.059***
	(0.166)	(0.000)	(0.000)	(0.000)	(0.794)	(0.016)	(0.000)
Population Density (log)	0.015***	0.024***	0.044***	0.014	0.023**	0.036***	-0.012
	(0.000)	(0.000)	(0.000)	(0.276)	(0.014)	(0.001)	(0.192)
Constant	0.302***	1.198***	0.768***	1.818***	0.844***	-0.797***	-0.090
	(0.003)	(0.000)	(0.000)	(0.000)	(0.003)	(0.002)	(0.697)
Observations	42,737	19,237	19,834	9,080	10,157	8,568	9,723
R-squared	0.107	0.097	0.113	0.105	0.110	0.136	0.134
Period FE	YES	YES	YES	YES	YES	YES	YES
Regions FE	YES	YES	YES	YES	YES	YES	YES
Technology FE	YES	YES	YES	YES	YES	YES	YES

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: OLS Regression on the likelihood of Regions entering into a new green technological field on the Full Sample and on different Scenarios, namely High Social Capital, High Acceptance to Migrants, Low Social Capital, and Low Acceptance to Migrants. Dependent variable: Entry ($Yentry_{rft}$); Explanatory variable: Cumulative count of migrant inventors ($StMig_{rft-1}$). All the independent variables have been lagged for 1 period. The primary independent variable (Migrant Inventors) has a hyperbolic sine transformation.

7- Robustness checks

We conduct several robustness checks to assess the stability and validity of the findings reported in Tables 2 and 3. One main concern relates to the sources of endogeneity, in particular the reverse causality that could be driving our findings. We discuss this in the next section. In addition, we further test the validity of our results in particular considering alternative definitions of our variables (e.g. using the currently active migrant inventors rather than the stock of migrants; using only bridging social capital rather than the measure of social capital computed through PCA) and different functional forms (probit rather than a linear probability model).

7.1 Identification: Shift-Share Instrument

One important concern common to many quantitative studies on migration pertains the fact that the decisions on where migrants settle is endogenous to many economic and innovation outcomes. In this sense, migrants are likely to move to areas where there are greater opportunities and better potential outlook for someone with their talents and knowledge. This may imply that migrant inventors working on green technologies are pulled to regions already at the forefront in these activities. To reduce this potential sources of endogeneity we apply an instrumental variable strategy, in particular we rely on the well-known Bartik instrument, which has being widely used also in studies on migration and innovation (Hunt and Gauthier-Loiselle, 2010; Ganguli, 2015). The logic behind this instrument is that migrants, as well as inventor migrants, tend to follow the migration path of other individuals of their same ethnicity (Card, 2001), irrespective the technological profile of the location they move to. The construction of our instrument closely follows the one in Diodato et al. (2022). Mathematically, it is as follows:

$$IV_t^{rf} = \sum_n \frac{MIG_{1977-1991}^{nr}}{MIG_{1977-1991}^{n}} * \left(MIG_t^{nf} - MIG_t^{nrf}\right) \quad (6)$$

the shift part of the instrument $\left(MIG_t^{nf} - MIG_t^{nrf}\right)$ represents the total patent flow in period t from a migrant inventor born in a given country n, who patented in technology class f, importantly it excludes the patents from the region r where he or she settled to remove the endogenous part of the shift. We leverage in this study from the additional dimension provided by our setting, technology, which is not typically available in most migration studies using a shift-share instrument. While for the shift we use the country-of-origin and technology dimensions for the shift, for the share ($\sum_n \frac{MIG_{1977-1991}^{nr}}{MIG_{1977-1991}^{n}}$), we use the country-of-origin and region-of-destination. This share, computed using our period 1 spanning from

1977 to 1991, is exogenous because it includes inventions from country n across all technological classes rather than being specific to the technological class f.

We re-estimate the models which we used for Tables 2 and 3 in a two-stage least square settings. The results are presented in Tables 4 (full sample) and 5 (different scenarios). Our instrumental variable approach appear to be valid, as the F-test of the first stage (reported at the bottom of Tables 4 and 5, respectively) overall indicates our instrument is a relevant predictor of the stock of migrants in a region. In line with our previous findings the estimated coefficient in the second stage is positive and significant. The greater size of the coefficient is somewhat surprising, as it suggests our baselines underestimated the impact of migrant inventors. The same is true for our social capital variable, which is positive, but not significant in Table 2, and which turns positive and highly significant in Table 4. Overall, however, the results of Tables 2 and 4 are well aligned.

Table 4: 2SLS - Green technological diversification of European regions (full sample)

VARIABLES	(1) Full Sample	(2) Full Sample	(3) Full Sample	(4) Full Sample
Migrant Inventors (stock)	0.075**	0.099***	0.084**	0.099***
	(0.033)	(0.009)	(0.020)	(0.009)
Social Capital (PCA)		0.010***		0.010***
		(0.000)		(0.000)
Acceptance to Migrants			0.002	0.003
			(0.960)	(0.950)
Relatedness Density	1.349***	1.361***	1.354***	1.361***
	(0.000)	(0.000)	(0.000)	(0.000)
Total Patents (log)	-0.029***	-0.026***	-0.032***	-0.026***
	(0.000)	(0.000)	(0.000)	(0.000)
Population (log)	-0.020***	-0.032***	-0.017**	-0.032***
	(0.005)	(0.001)	(0.022)	(0.001)
GDP (log)	-0.034***	-0.020*	-0.031***	-0.020*
	(0.001)	(0.088)	(0.003)	(0.090)
Population Density (log)	0.021***	0.018***	0.021***	0.018***
	(0.000)	(0.001)	(0.000)	(0.001)
Constant	0.488***	0.540***	0.443***	0.537***
	(0.000)	(0.000)	(0.001)	(0.000)
Observations	34,091	29,546	32,430	29,546
R-squared	0.100	0.094	0.096	0.094
F (First Stage)_	67.409	62.896	65.962	62.907
Period FE	NO	YES	YES	YES
Regions FE	NO	YES	YES	YES
Technology FE	NO	YES	YES	YES

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: 2SLS Regression on the likelihood of Regions entering a new green technological field. The main independent variable has a hyperbolic sine transformation. Dependent variable: Entry ($\boxed{Yentry_{rft}}$); Explanatory variable: Cumulative count of migrant inventors ($\boxed{Migrants(stock)_{rft-1}}$), Social Capital (PCA) ($\boxed{SocialCapital_{rft-1}}$) and Acceptance to Migrants ($\boxed{Acceptance_{rft-1}}$).). Instrumental variable (iv:

bartik). All the independent variables have been lagged for 1 period. The primary independent variable (Migrant Inventors) has a hyperbolic sine transformation.

Table 5 reports the estimates under different scenarios. One important aspect to notice is that, for one of the subsamples (Column 6, Low Social Capital – High Acceptance), the F-test of the first stage is below the conventional value of 10, suggesting for that portion of the data, the instrument is not strong enough to convincingly predict the endogenous variable. For the other scenarios, we find strong evidence of the positive impact of migrant inventors in regions with high social capital (see Columns 2, 4 and 5). As in the OLS estimates, the coefficient tend to be larger for regions with high social capital and low acceptance, than for areas with both high social capital and migrant acceptance. In regions characterised by low social capital (Columns 6 and 7) instead the impact of migrant inventors is statistically insignificantly different from 0. The discrepancy between Column 6 in Table 3 and in Table 5 may be connected to poor performance of the instrument, also considering that, when only looking at high-acceptance regions (Columns 3), the coefficient for *Migrant Inventors (stock)* is positive and significant.

Table 5 IV- Green technological diversification of European regions (full sample and scenarios)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	IV (Full Sample)	IV (High SK)	IV (High Acceptance)	IV (High SK High Acceptance)	IV (High SK Low Acceptance)	IV (Low SK High Acceptance)	IV (Low SK Low Acceptance)
Migrant Inventors (stock)	0.075**	0.205***	0.065*	0.122*	0.543**	0.045	-0.160
	(0.033)	(0.002)	(0.088)	(0.066)	(0.034)	(0.350)	(0.164)
Relatedness Density	1.349***	1.616***	1.287***	1.516***	1.990***	1.364***	1.536***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total Patents (log)	-0.029***	-0.000	-0.017***	0.035***	-0.050***	-0.044***	-0.101***
	(0.000)	(0.980)	(0.007)	(0.003)	(0.001)	(0.000)	(0.000)
Population (log)	-0.020***	-0.079***	-0.042***	-0.101***	-0.052	-0.013	0.099***
	(0.005)	(0.000)	(0.000)	(0.000)	(0.100)	(0.491)	(0.002)
GDP (log)	-0.034***	-0.074***	-0.052***	-0.097***	-0.086**	0.066**	0.126***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.048)	(0.012)	(0.004)
Population Density (log)	0.021***	0.025***	0.053***	0.011	0.038***	0.124***	-0.050***
	(0.000)	(0.001)	(0.000)	(0.393)	(0.001)	(0.000)	(0.003)

Constant	0.488***	1.447***	0.847***	1.873***	1.304***	-1.090***	-1.934***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Observations	34,091	17,240	17,913	9,080	8,160	7,139	5,167
R-squared	0.100	0.084	0.107	0.103	-0.037	0.135	0.095
F (First Stage)	67.409	22.600	72.382	37.175	3.019	30.396	12.983
Period FE	YES	YES	YES	YES	YES	YES	YES
Regions FE	YES	YES	YES	YES	YES	YES	YES
Technology FE	YES	YES	YES	YES	YES	YES	YES

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: 2SLS Regression on the likelihood of Regions entering into a new green technological field on the Full Sample and on different Scenarios, namely High Social Capital, High Acceptance to Migrants, Low Social Capital, and Low Acceptance to Migrants. Dependent variable: Entry ($Yentry_{rft}$); Explanatory variable: Cumulative count of migrant inventors ($StMig_{rft-1}$). Instrumental variable (iv: bartik). All the independent variables have been lagged for 1 period. The primary independent variable (Migrant Inventors) has a hyperbolic sine transformation. First-stage relevance was reported using the *Kleibergen-Paap F-statistic*.

7.2 Other robustness checks

We conducted three additional robustness checks to verify our results, in particular in terms of definitions of the variables and model specification. First, we use a probit model for the entry model instead of OLS. As shown in Table 12 in the annex, the results remain consistent across all specifications, except for the scenario with high social capital and low acceptance, which shows a clear and strong positive effect. Second, we change our main independent variable to the total number of migrants patenting in technology f in region r during period t. This adjustment assumes that migrant inventors are not present in the region where they previously patented, focusing only on those who patented in the current period. By considering fewer migrant inventors, we strengthen the model and suggest that knowledge spillovers do not accumulate over time. Table 13 in the appendix shows that results hold. Finally, we run a regression using a different measure of social capital, namely bridging social capital. This variable assumes that regions with higher social capital have citizens more engaged in voluntary associations linked to diverse groups seeking cooperation rather than personal gain, in contrast to Bonding Social Capital. This approach is stricter, as our previous composite variable was broader, encompassing various types of networks. Table 14 in the Appendix presents the results from this specification. All results hold, with stronger and more significant coefficients for the scenarios in which regions have higher scores of social capital values. On the contrary, we can observe insignificant coefficients in both scenarios where the levels of social capital are low. This stricter setting allow us to interpret that higher levels of social capital matters. More strikingly, the coefficient of the first quadrant, namely, high social capital and high acceptance to migrants is higher than the specification in which there are higher levels of social capital but lower levels of acceptance to migrants.

8 – Conclusions

Sustainability is part of the agenda in the EU, as highlighted in the European Green Deal and the policies aligned with the United Nations Sustainable Development Goals (SDGs). In the years to come, governments will be pushing harder and moving towards more sustainable solutions as a consequence of the effects of climate change. Developing key technologies to de-lock from fossil technologies and facilitate the green transition is therefore paramount for European regions. At the same time, as the knowledge required for developing such technologies become more complex, accessing the required skills and capabilities represent a crucial challenge. In this respect, the extant literature points to migrants, and in particular migrant inventors, as possible way to overcome current limitations (Rasche, 2023). By bringing with them the embodied knowledge that is diverse from the local knowledge of host economy, they can be a important drivers of structural change.

Building on different streams of the literature on regional lock in, migration and innovation, social capital, this paper shed light on the relationship between migrant inventors and the emergence of green technologies in European regions. In particular, we complement the extant literature by adding an institutional dimension to these processes and consider whether the level of social capital and migrant acceptance in regional economies moderates the relation between migrant inventors and green diversification.

We find that the effect of social capital amplifies the impact of migrants' knowledge in the host regions, and this translates into a higher likelihood of green diversification. The positive effect of social capital is however not stronger when acceptance of migrants is high. In other words, regions with both high and low acceptance, when social capital is high, create a more favorable environment for green innovation. The result indicates that social capital may facilitate cooperation and resource sharing among diverse groups, while acceptance of migrants plays no role, possibly because its variability among European regions, for the period considered, is limited.

Theoretically, this work confirms that both endogenous, i.e. relatedness, and exogenous, i.e. migrant inventors, factors play a role in helping regions to enter new technological trajectories, and in doing so reduce the risk of regional lock in.

For policymakers, the implications are threefold. First, they confirm that highly skilled migrants act as agents of structural change, as they broker the structural holes in terms of knowledge that a region has.

Migrant inventors can bring their knowledge that is recombined with local knowledge, but also considering their diversity might enhance the productivity of complex knowledge recombination such as green patenting. This suggests policy intervention in the direction of easing the mobility with EU countries. Second, the results also show that informal institutions are important, as demonstrated in other empirical papers. In particular, social capital plays a role in building a favourable context for the absorption of migrant's knowledge, and in turn in boosting green diversification. This result point to policy measure that favour trust around foreigners and measure to facilitate their integration in the labour market. Third, we don't find evidence that a welcoming attitude toward migrants significantly boost a region's capacity for innovation. Though theoretically this is surprising, it may be due to the low variability of this indicator across European regions. In fact, on average (and for the years under analysis) present high values of acceptance.

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APPENDIX A: Descriptive Statistics

Table 6. Correlation Matrix

Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) Entry	1.000														
(2) Migrant Inventors	0.068	1.000													
(3) Migrant Inventors (stock)	0.073	0.968	1.000												
(4) Relatedness Density	0.322	0.048	0.055	1.000											
(5) Social Capital (avg)	0.083	0.030	0.034	0.309	1.000										
(6) Social Capital	0.067	0.023	0.027	0.237	0.865	1.000									
(7) Acceptance to Migrants (avg)	0.055	0.034	0.038	0.269	0.127	0.102	1.000								
(8) Acceptance to Migrants	0.044	0.035	0.039	0.228	0.101	0.034	0.816	1.000							
(9) Bridging Social Capital (avg)	0.115	0.033	0.037	0.442	0.896	0.781	0.208	0.166	1.000						
(10) Bridging Social Capital	0.097	0.033	0.037	0.360	0.795	0.863	0.187	0.139	0.885	1.000					
(11) Total Patents	0.028	0.133	0.152	0.274	0.073	0.048	0.177	0.156	0.107	0.096	1.000				
(12) GDP	0.016	0.023	0.029	0.181	0.235	0.287	-0.045	-0.048	0.264	0.294	0.051	1.000			
(13) Total Population	0.002	0.037	0.042	0.137	-0.243	-0.213	0.015	0.018	-0.288	-0.251	0.478	-0.029	1.000		
(14) Population Density	0.001	0.036	0.041	0.092	0.035	0.041	0.027	0.022	0.033	0.033	0.167	0.451	0.045	1.000	
(15) Total Area	-0.027	-0.022	-0.025	-0.141	-0.079	-0.084	0.046	0.043	-0.068	-0.062	-0.099	-0.168	0.084	-0.204	1.000

Table 7. Descriptive Statistics: Regions with High Social Capital

Variable	Obs	Mean	Std. Dev.	Min	Max
Entry	26762	.26	.439	0	1
Migrant Inventors	29036	.184	2.268	0	234
Migrant Inventors (stock)	29036	.235	2.579	0	236
Relatedness Density	35807	.257	.092	.001	.508
Social Capital (PCA, avg)	36295	1.464	1.645	-.473	7.325

Social Capital (PCA)	29036	1.534	2.128	-2.44	11.546
Acceptance to Migrants (avg)	36295	.872	.061	.622	.977
Acceptance to Migrants	29036	.872	.077	.545	1
Bridging Social Capital (avg)	36295	.318	.074	.138	.541
Bridging Social Capital	29036	.318	.094	.096	.625
Total Patents	36295	1559.837	3806.463	0	42939.043
GDP	35685	124171.34	230576.27	580.821	2387716.8
Total Population	35685	1573634.7	1269030.1	230315.5	12115140
Population Density	32635	437.125	1132.232	3.099	10635.224
Total Area	33245	17343.752	31240.415	109	227120

Table 8. Descriptive Statistics: Regions with Low Social Capital

Variable	Obs	Mean	Std. Dev.	Min	Max
Entry	28859	.216	.412	0	1
Migrant Inventors	30256	.116	1.433	0	116
Migrant Inventors (stock)	30256	.15	1.737	0	116
Relatedness Density	37088	.218	.121	.001	.525
Social Capital (PCA, avg)	37820	-1.34	.597	-2.95	-.311
Social Capital (PCA)	30256	-1.36	.962	-3.637	3.483
Acceptance to Migrants (avg)	37820	.865	.076	.529	.988
Acceptance to Migrants	30256	.865	.092	.46	1
Bridging Social Capital (avg)	37820	.176	.054	.047	.267
Bridging Social Capital	30256	.176	.071	0	.396
Total Patents	37820	1350.905	3362.779	0	33200.777
GDP	37515	29268.206	65665.489	452.857	713389.69
Total Population	37515	2216192.2	1538539.9	247659.14	9949120
Population Density	30805	337.422	632.752	20.906	4375.773
Total Area	31110	16676.157	16389.735	316	94225

Table 9. Descriptive Statistics: Regions with High Acceptance to Migrants Capital

Variable	Obs	Mean	Std. Dev.	Min	Max
Entry	30105	.245	.43	0	1
Migrant Inventors	31964	.18	1.87	0	116
Migrant Inventors (stock)	31964	.234	2.291	0	121
Relatedness Density	39833	.245	.106	.002	.525
Social Capital (PCA, avg)	36295	.273	2.093	-2.95	7.325
Social Capital (PCA)	29036	.276	2.371	-3.637	11.546
Acceptance to Migrants (avg)	39955	.924	.027	.88	1
Acceptance to Migrants	31964	.924	.049	.721	1
Bridging Social Capital (avg)	36295	.261	.104	.077	.541
Bridging Social Capital	29036	.261	.115	0	.625
Total Patents	39955	1774.658	3987.51	0	42939.043
GDP	39650	50026.648	152788.94	780.979	2387716.8
Total Population	39650	1790226.4	1676501.6	208997	12115140
Population Density	33245	382.371	1098.478	3.099	10635.224
Total Area	33550	18021.909	25580.665	109	164083

Table 10. Descriptive Statistics: Regions with Low Acceptance to Migrants Capital

Variable	Obs	Mean	Std. Dev.	Min	Max
Entry	30206	.221	.415	0	1
Migrant Inventors	31964	.1	1.773	0	234
Migrant Inventors (stock)	31964	.126	1.917	0	236
Relatedness Density	38735	.219	.114	.001	.522
Social Capital (PCA, avg)	37820	-.198	1.578	-2.688	5.523
Social Capital (PCA)	30256	-.153	1.973	-3.532	10.782
Acceptance to Migrants (avg)	39955	.816	.054	.529	.879
Acceptance to Migrants	31964	.816	.082	.4	1

Bridging Social Capital (avg)	37820	.23	.085	.047	.394
Bridging Social Capital	30256	.23	.101	0	.5
Total Patents	39955	954.696	2804.376	0	33200.777
GDP	39345	93190.065	180242.19	452.857	1189018.8
Total Population	39345	1830149.5	1149692.7	114285	5799043
Population Density	35990	360.882	648.084	5.715	4375.773
Total Area	36600	15123.05	23684.596	316	227120

APPENDIX B: NUTS2 TABLES AND MAPS

Table 11. Social Capital And Acceptance To Migrants Quadrants. Nuts2 Regions

Qua-drant	NUTS2
Lower Left	AT11', 'AT13', 'AT21', 'BG33', 'BG41', 'BG42', 'CY00', 'CZ01', 'CZ02', 'CZ04', 'DE21', 'DE23', 'DE24', 'DE25', 'DE27', 'DE30', 'DE40', 'DE80', 'DE91', 'DE92', 'DEA1', 'DED2', 'DED4', 'DED5', 'DEE0', 'DEG0', 'EE00', 'EL30', 'EL43', 'EL52', 'EL61', 'EL63', 'EL64', 'EL65', 'ES42', 'FRB0', 'FRE2', 'FRF2', 'FRI1', 'FRI2', 'FRJ2', 'HR05', 'ITF3', 'ITG1', 'ITG2', 'ITI2', 'ITI4', 'LT01', 'LT02', 'MT00', 'PL22', 'PL51', 'PL61', 'PL63', 'PL71', 'PL81', 'PL84', 'PL91', 'PT30', 'RO11', 'RO21', 'RO22', 'RO31', 'RO32', 'RO41', 'RO42', 'SI04', 'SK01', 'UKE1', 'UKE2', 'UKE3', 'UKE4', 'UKN0'
Lower Right	CH01', 'CH05', 'DE11', 'DE12', 'DE14', 'DE22', 'DE26', 'DE60', 'DE71', 'DE72', 'DE73', 'DE93', 'DE94', 'DEA2', 'DEA3', 'DEA4', 'DEA5', 'DEF0', 'ES11', 'ES12', 'ES21', 'ES30', 'ES41', 'ES43', 'ES51', 'ES52', 'ES53', 'ES61', 'ES62', 'ES70', 'FRC1', 'FRC2', 'FRD1', 'FRD2', 'FRF1', 'FRF3', 'FRJ1', 'FRK1', 'FRK2', 'FRL0', 'FRM0', 'HU11', 'HU21', 'HU22', 'HU23', 'HU31', 'HU32', 'HU33', 'IE04', 'ITC4', 'ITF1', 'PL21', 'PL41', 'PT11', 'PT15', 'PT16', 'PT17', 'PT18'
Upper Left	AT12', 'AT22', 'AT31', 'AT32', 'BE21', 'BE22', 'BE23', 'BE24', 'BE25', 'BE35', 'BG32', 'CZ03', 'CZ05', 'CZ06', 'CZ07', 'CZ08', 'ES24', 'FI1B', 'FI1D', 'FRE1', 'HR03', 'ITC1', 'ITC3', 'ITF4', 'ITF6', 'ITH3', 'ITH5', 'ITI1', 'LV00', 'NL34', 'NL41', 'NO02', 'SI03', 'SK02', 'SK03', 'SK04', 'UKC2', 'UKD1', 'UKD3', 'UKD4', 'UKD6', 'UKD7', 'UKF1', 'UKF2', 'UKF3', 'UKG1', 'UKG2', 'UKG3', 'UKH1', 'UKH2', 'UKH3', 'UKJ1', 'UKJ2', 'UKJ3', 'UKJ4', 'UKK2', 'UKK4', 'UKL1'
Upper Right	AT33', 'BE10', 'BE31', 'BE32', 'BE33', 'BE34', 'CH02', 'CH03', 'CH04', 'CH06', 'DE13', 'DEB1', 'DEB2', 'DEB3', 'DK01', 'DK02', 'DK03', 'DK04', 'DK05', 'FI19', 'FI1C', 'FR10', 'FRG0', 'FRH0', 'FRI3', 'IE05', 'IE06', 'IS00', 'ITI3', 'LU00', 'NL11', 'NL12', 'NL13', 'NL21', 'NL22', 'NL31', 'NL32', 'NL33', 'NL42', 'NO06', 'NO07', 'NO08', 'NO09', 'NO0A', 'PL82', 'SE11', 'SE12', 'SE21', 'SE22', 'SE23', 'SE31', 'SE33', 'UKC1', 'UKI3', 'UKK1', 'UKK3', 'UKL2', 'UKM5', 'UKM6', 'UKM7', 'UKM9'

Figure 5. Scatter Plot Using Bridging Social Capital

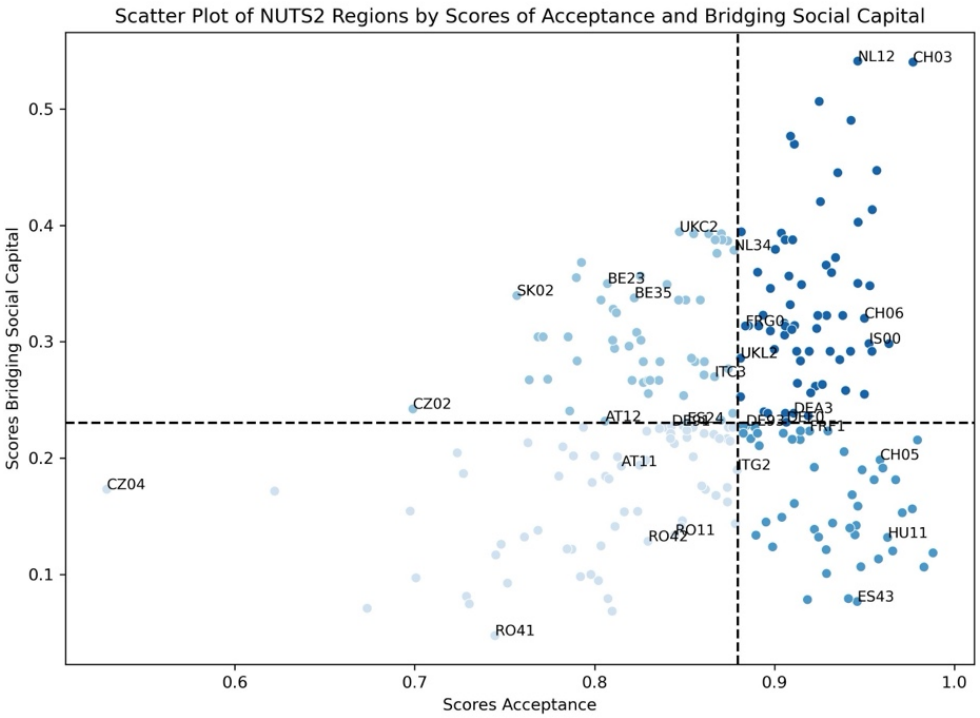
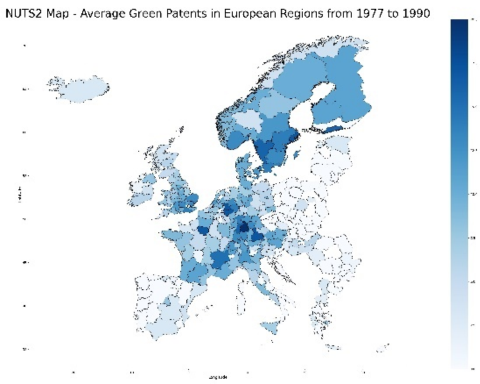
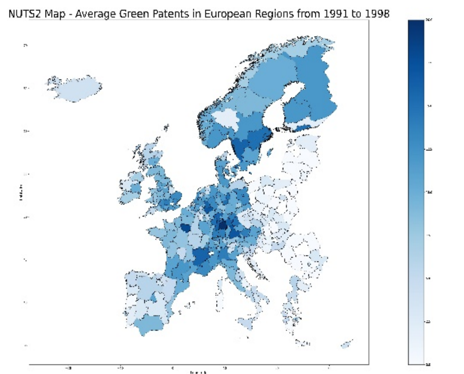
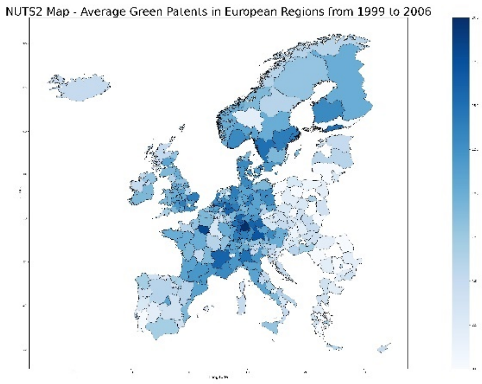
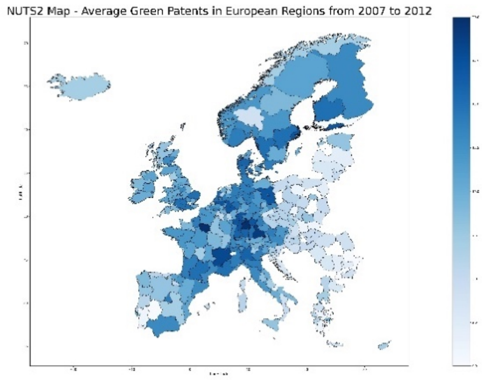


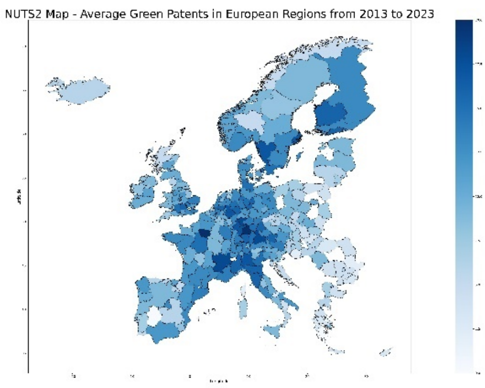
Figure 6. Total green Patents in European regions






NUTS2 Map - Average Green Patents in European Regions from 1999 to 2006


NUTS2 Map - Average Green Patents in European Regions from 2007 to 2012


NUTS2 Map - Average Green Patents in European Regions from 2013 to 2023

APPENDIX C: Robustness Check Tables

Table 12: Probit - Green technological in European regions (full sample and scenarios)

VARIABLES	(1) Probit (Full Sample)	(2) Probit (High SK)	(3) Probit (High Acceptance)	(4) Probit (High SK High Acceptance)	(5) Probit (High SK Low Acceptance)	(6) Probit (Low SK High Acceptance)	(7) Probit (Low SK Low Acceptance)
Migrant Inventors (stock)	0.135***	0.231***	0.140***	0.227***	0.233***	0.093**	0.020
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.012)	(0.666)
Relatedness Density	4.238***	4.901***	4.270***	4.807***	6.034***	4.095***	3.534***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total Patents (log)	-0.063***	0.006	-0.012	0.120***	-0.109***	-0.069**	-0.127***
	(0.000)	(0.782)	(0.575)	(0.003)	(0.000)	(0.017)	(0.000)
Population (log)	-0.075***	-0.257***	-0.153***	-0.339***	-0.297***	0.017	-0.076
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.757)	(0.182)
GDP (log)	-0.016	-0.163***	-0.160***	-0.297***	0.040	0.197**	0.312***
	(0.557)	(0.000)	(0.000)	(0.000)	(0.584)	(0.017)	(0.000)
Population Density (log)	0.045***	0.073***	0.147***	0.037	0.072**	0.132***	-0.056*
	(0.002)	(0.001)	(0.000)	(0.365)	(0.025)	(0.003)	(0.078)
Constant	-0.694*	2.549***	1.217**	4.539***	1.458	-4.927***	-2.816***
	(0.060)	(0.000)	(0.034)	(0.000)	(0.113)	(0.000)	(0.001)
Observations	42,737	19,237	19,834	9,080	10,157	8,568	9,723
Period FE	YES	YES	YES	YES	YES	YES	YES
Regions FE	YES	YES	YES	YES	YES	YES	YES
Technology FE	YES	YES	YES	YES	YES	YES	YES

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Probit Regression on the likelihood of Regions entering into a new green technological field on the Full Sample and on different Scenarios namely High Social Capital High Acceptance to Migrants Low Social Capital and Low Acceptance to Migrants. Dependent variable: Entry; Explanatory variable: Cumulative count of migrant inventors. All the independent variables have been lagged for 1 period. The primary independent variable (Migrant Inventors) has a hyperbolic sine transformation.

Table 13: OLS – Green technological in European regions using simple count of migrant inventors (full sample and scenarios).

VARIABLES	(1) (Full Sample)	(2) (High SK)	(3) (High Acceptance)	(4) (High SK High Acceptance)	(5) (High SK Low Acceptance)	(6) (Low SK High Acceptance)	(7) (Low SK Low Acceptance)
Migrant Inventors	0.059***	0.083***	0.060***	0.079***	0.084***	0.052***	0.021
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.275)
Relatedness Density	1.308***	1.495***	1.276***	1.471***	1.801***	1.181***	1.182***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total Patents (log)	-0.023***	-0.000	-0.011**	0.035***	-0.035***	-0.024***	-0.039***
	(0.000)	(0.968)	(0.042)	(0.003)	(0.000)	(0.000)	(0.000)
Population (log)	-0.022***	-0.070***	-0.039***	-0.097***	-0.078***	0.002	-0.024
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.890)	(0.125)
GDP (log)	-0.011	-0.055***	-0.046***	-0.097***	0.005	0.050**	0.059***
	(0.146)	(0.000)	(0.000)	(0.000)	(0.823)	(0.018)	(0.000)
Population Density (log)	0.015***	0.025***	0.044***	0.015	0.023**	0.035***	-0.012
	(0.000)	(0.000)	(0.000)	(0.230)	(0.013)	(0.001)	(0.194)
Constant	0.299***	1.188***	0.760***	1.792***	0.834***	-0.783***	-0.090
	(0.003)	(0.000)	(0.000)	(0.000)	(0.003)	(0.003)	(0.697)
Observations	42,737	19,237	19,834	9,080	10,157	8,568	9,723
R-squared	0.107	0.097	0.113	0.104	0.109	0.136	0.134
Period FE	YES	YES	YES	YES	YES	YES	YES
Regions FE	YES	YES	YES	YES	YES	YES	YES
Technology FE	YES	YES	YES	YES	YES	YES	YES

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Table 8: OLS Regression on the likelihood of Regions entering into a new green technological field on the Full Sample and on different Scenarios namely High Social Capital
High Acceptance to Migrants Low Social Capital and Low Acceptance to Migrants. Dependent variable: Entry; Explanatory variable: Number of migrant inventors. All the independent variables have been lagged for 1 period. The primary independent variable (Migrant Inventors) has a hyperbolic sine transformation.

Table 14: OLS – Green technological in European regions using bridging social capital (full sample and scenarios).

VARIABLES	(1) (Full Sample)	(2) (High SK)	(3) (High Acceptance)	(4) (High SK High Acceptance)	(5) (High SK Low Acceptance)	(6) (Low SK High Acceptance)	(7) (Low SK Low Acceptance)
Migrant Inventors (stock)	0.052***	0.080***	0.053***	0.079***	0.075***	0.020	0.023
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.149)	(0.181)
Relatedness Density	1.313***	1.425***	1.283***	1.470***	1.770***	1.267***	1.165***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total Patents (log)	-0.022***	-0.000	-0.010**	0.033***	-0.051***	-0.033***	-0.035***
	(0.000)	(0.962)	(0.047)	(0.006)	(0.000)	(0.000)	(0.000)
Population (log)	-0.022***	-0.046***	-0.040***	-0.068***	-0.076***	0.006	-0.030**
	(0.000)	(0.001)	(0.000)	(0.006)	(0.004)	(0.647)	(0.039)
GDP (log)	-0.010	-0.069***	-0.046***	-0.095***	0.009	0.014	0.064***
	(0.166)	(0.000)	(0.000)	(0.000)	(0.716)	(0.527)	(0.000)
Population Density (log)	0.015***	0.024***	0.044***	0.017	0.025***	0.040***	-0.007
	(0.000)	(0.000)	(0.000)	(0.189)	(0.005)	(0.000)	(0.480)
Constant	0.302***	1.016***	0.768***	1.377***	0.891***	-0.271	-0.105
	(0.003)	(0.000)	(0.000)	(0.000)	(0.002)	(0.296)	(0.641)
Observations	42,737	19,395	19,834	9,884	9,511	7,764	10,369
R-squared	0.107	0.093	0.113	0.102	0.109	0.141	0.134
Period FE	YES	YES	YES	YES	YES	YES	YES
Regions FE	YES	YES	YES	YES	YES	YES	YES
Technology FE	YES	YES	YES	YES	YES	YES	YES

Robust pval in parentheses*** p<0.01, ** p<0.05, * p<0.1

Table 9: OLS Regression on the likelihood of Regions entering into a new green technological field on the Full Sample and on different Scenarios namely High Social Capital High Acceptance to Migrants Low Social Capital and Low Acceptance to Migrants. Dependent variable: Entry; Explanatory variable: Cumulative count of migrant inventors. All the independent variables have been lagged for 1 period. The primary independent variable (Migrant Inventors) has a hyperbolic sine transformation.