Jumping the Ladder

The role of Technological Exploration and Green Innovation in shaping Regional Productivity

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Abstract

This paper investigates the role of technological exploration and green innovation in shaping regional labour productivity across European regions. Building on the literature on technological recombination, we develop a novel indicator of Regional Technological Exploration, defined as the pursuit of previously unexplored technological combinations and distant knowledge domains by inventors in the region. The indicator is constructed by identifying unconventional technological recombinations at the patent level and aggregating them to capture regional exploratory propensity. We compare the indicator with alternative measures of technological diversification, novelty and impact proposed in the literature, and show that it captures a distinct dimension of regional innovation. Using a panel of 1,386 European NUTS3 regions over the period 1980–2019, we examine the dynamic interactions among regional technological exploration, green innovation, and labour productivity. The results reveal that both technological exploration and green innovation lead to subsequent productivity growth, and their effects are persistent. These findings contribute to the literature on regional innovation and innovation policy by highlighting the importance of exploratory strategies and green innovation for long-run productivity growth.

1 Introduction

There have been successful instances of technological "leapfrogging" (Soete, 1985; Brezis et al., 1993; Lee and Malerba, 2017), but these have been relatively rare (Petralia et al., 2017). Innovation efforts exploring new technologies and new uses can make these jumps in regional economic performance more frequent (Amoroso et al., 2022). Since Schumpeter (1939)'s theory of economic development, innovations have been conceived as resulting from the recombination of previous knowledge (Nelson and Winter, 1982; Weitzman, 1998; Arthur, 2009). From a cognitive perspective, recombination can occur between highly proximate components or between more distant ones. Recent literature has employed the concept of technological "unconventionality" for inventions that rely on distant pieces of knowledge or recombination of knowledge that have never been used before (Uzzi et al., 2013; Ke et al., 2026). Building on this perspective, the concept of technological exploration emphasises the search for new recombinations, previously unexplored properties, uses, and internal and external relationships of technologies (Gustafsson and Autio, 2016). Green innovation can be considered another potential driver of jumps in regional productivity. Several studies suggest that green innovation can enhance productivity by fostering resource efficiency, technological upgrading, and new market opportunities (Horbach et al., 2012; Barbieri et al., 2020).

Although both technological exploration and green innovation have been identified as potential drivers of long-term productivity, their actual effects on regional productivity remain underexplored and theoretically distinct. This paper aims to investigate the impact of technological exploration and green innovation, both in terms of size and persistence, on regional labour productivity, assessing their role in achieving technological "leapfrogging" in European regions. Although technological exploration and green innovation are typically treated as separate in the literature, recent findings suggest that regions capable of mastering new combinations of knowledge tend to perform better in generating green innovation (Orsatti et al., 2020a). Investigating this connection is particularly relevant in light of the recent evolution of Smart Specialisation (Foray, 2022), which increasingly combines regional economic growth objectives with broader societal challenges, such as climate change.

To better understand the size and persistence of these impacts, we estimate Panel Vector Autoregression (PVAR) models. The Impulse Response Functions (IRFs) capture to what extent and with what persistence changes in technological exploration and green innovation affect productivity over time. To do that, we exploit the information contained in a rich dataset that combines information from different sources, including PATSTAT, OECD RegPat, and the Annual Regional Database of the European Commission (ARDECO), covering 1,386 NUTS3 EU regions from 1980 to 2019. The evidence indicates that both green innovations and regional technological exploration have a positive and persistent effect on regions' labour productivity. The magnitude of the effect of technological exploration is remarkably greater than that of green innovation. Our evidence also highlights that there is limited synergy between green and unconventional innovation.

This paper contributes to the literature in multiple aspects. First, it introduces a new

indicator to evaluate the relevance of technological exploration in the regional knowledge base, defined as Regional Technological Exploration. We compare this indicator with the main alternative measures of technological diversification, novelty and impact used in the literature, and show that it is only weakly correlated with most of them and remains associated with labour productivity in a two-way fixed-effects setting. Second, it employs an econometric framework with recursive identification restrictions to recover structural impulse responses, offering a dynamic causal view that captures effect, timing, and persistence. This method complements the static findings from existing cross-sectional and fixed-effects studies. Finally, it compares how different types of innovation activities – technological exploration along with green innovation – affect regional labour productivity.

The paper is organised as follows. In Section 2, we review the relevant literature. Section 3 contains a description of the dataset and the presentation of the Regional Technological Exploration (subsection 3.1), together with its comparison with alternative measures from the literature (subsection 3.3). In Section 4, we illustrate the estimation strategy, and, in subsection 4.1, we present the econometric results, followed by robustness checks. The final section of the paper draws to a close by briefly discussing the limitations of the study and highlighting its policy implications.

2 Literature Review

2.1 Technological Exploration and Innovation

Firms and organisations engaging in innovation can recombine existing knowledge or search for new forms (March, 1991). This dichotomy is often referred to as "exploitation" versus "exploration". Exploration is associated with concepts such as search, experimentation, discovery, and risk-taking. Exploitation is associated with production, refinement, implementation, and execution (Li et al., 2008). Exploration towards what is "new to the organisation" yields higher risks than exploitation (Cesaroni et al., 2005). It underpins search efforts for competencies and solutions beyond what an organisation already does. Efforts can be even more risky if the degree of novelty goes beyond what is "new to the organisation," "to the industry," or even "new to the world" (Ahuja and Morris Lampert, 2001). This intrinsic risk makes exploration strategies more convenient in terms of expected rewards. Exploration, when successful, allows for achieving remarkable competitive advantages (Siren et al., 2012; Clauss et al., 2021). Exploitation, instead, seeks the refinement and extension of the recombination of existing knowledge (Levinthal and March, 1993). For this reason, it offers lower rewards with much higher certainty.

Both are fundamental activities for organisational learning strategies, and a good balance of the two is desirable (Lavie et al., 2010; O'Reilly III and Tushman, 2013). However, each of the two activities draws resources from the organisation, imposing tradeoffs in terms of which dimension to prioritise (He and Wong, 2004; Koryak et al., 2018; Farzaneh et al., 2022). The focus of this work is on exploration. Exploration strategies are associated with increases in productivity (Benner and Tushman, 2003), a higher market penetration

(Yalcinkaya et al., 2007), stronger export performances (Perera et al., 2026), and better innovation outcomes (Ferreira et al., 2020). These effects are likely to appear with some delay (Katila and Chen, 2006), since they take some time to sediment and be exploited (Van Looy et al., 2005; Raisch and Birkinshaw, 2008). However, recent literature has highlighted how exploration effects might be very context-specific, depending on characteristics of the industry, operating markets, and organisational structure (Su et al., 2017; Ambroise et al., 2020; Ferreira et al., 2021).

The technological search is one of the most critical focuses of exploration activities (Rosenkopf and Nerkar, 2001; Zahra and George, 2002; Katila, 2008; Duchek, 2020). Innovative technological features take different forms and are constrained in different ways by exploration or exploitation activities. When exploration weighs in technological search, the focus is on developing new technologies (Jayanthi and Sinha, 1998; Lee and Ryu, 2002; Cantwell and Mudambi, 2005; Dowell and Swaminathan, 2006), new skills (Atuahene-Gima, 2005; Mom et al., 2007), hiring new employees (Perretti and Negro, 2007), and starting co-operations and alliances (Hagedoorn and Duysters, 2002a,b; Vanhaverbeke et al., 2007). Such exploratory efforts are rare and risky, as they require high levels of technological capability (Xiao et al., 2018), substantial resources (Petralia et al., 2017), and often strategic assets that are typically held by large multinational firms (Cortinovis et al., 2020). The search for distant knowledge, although more complex, makes radical innovations more likely to emerge (Nerkar and Roberts, 2004), leading to long-term competitive advantages and higher economic returns (Pinheiro et al., 2022).

Scholars conceptualised innovation made by recombining "distant knowledge" as "atypical" (or "unconventional") innovation (Uzzi et al., 2013; Boyack and Klavans, 2014; Berkes and Gaetani, 2021; Ke et al., 2026). Unconventionality indicates the blending of more distant pieces of knowledge and is associated with higher risk and uncertainty (Fleming, 2001). The unconventionality framework suggests that combinations of more distant technological domains result in better innovation outcomes (Keijl et al., 2016). In this sense, there is a close link between technological exploration and unconventional innovation (Xiao et al., 2022). In this work, we build on this link to measure the exploratory intensity of organisations in a given geographical unit by gauging the recombination of distant technological domains in patents (Audia and Goncalo, 2007; Youn et al., 2015). We call this measure the Regional Technological Exploration (RTE).

2.2 Exploration and Green Innovation

In the last decades, given the institutional and political attention, exploration efforts have been increasingly directed towards green innovations (Xue and Swan, 2023). The increasing political and market pressure for environmental sustainability has influenced organisations to explore alternative green solutions (Ambec and Barla, 2002; Ambec et al., 2013). The role of technological change in this paradigm shift is substantial: developing product and process innovations is at the core of green transition efforts, especially in the European Union green strategies (Woo et al., 2014; Zhao et al., 2022; Szélpál and Varga, 2024). The production of green solutions often drives the exploration of new technologies and knowledge with respect to previous non-green alternatives (Wicki and Hansen, 2019;

Awan et al., 2021). In this sense, exploring green alternatives leads to recombining old skills and technologies with more sustainable approaches. These mechanisms make green innovations a relevant area for technological exploration efforts. From this point of view, it is not surprising that patents associated with green innovations are, on average, more unconventional than non-green innovations (Orsatti et al., 2020b; Barbieri et al., 2023).

The effects of green innovation on organisations are multifaceted. Energy and resource efficiency innovations typically increase productivity by lowering input costs (energy, materials) and improving process efficiency (Ghisetti and Rennings, 2014; Rexhäuser and Rammer, 2014; Van Leeuwen and Mohnen, 2017). Cumulative green knowledge eventually leads to productivity gains, but only after a significant threshold (Soltmann et al., 2015) and appears with time lags (Piekkola and Rahko, 2025). At the regional level, green technological development appears to generate positive productivity effects, particularly in areas with strong absorptive capacities and diverse knowledge bases (Orsatti et al., 2020a). This evidence supports the idea that the benefits of green innovation on regional performances are not automatic, but depend on the local context and complementary capabilities.

2.3 The Regional Side of Technological Exploration

This study aims at exploring the innovation dynamics that help regions to jump the ladder of economic development. Innovative activity is neither evenly nor randomly distributed across spatial dimensions. The distribution of talent – that is, individuals with high levels of human capital – is highly concentrated and strongly associated with high-technology industry locations (Florida, 2002; Mellander and Florida, 2021). Technological change is systemic in nature, where firms innovate in collaboration and interdependence with other organisations (Asheim, 2000; Howells, 2002; Fagerberg et al., 2005). Successful technology-based regional development had a transformative effect on areas and regions where high concentrations of human capital are available (Saxenian, 1990; Lawton Smith et al., 2005).

Previous literature has attempted to analyse the ability of the regions to recombine cognitively distant pieces of knowledge through the concept and metric of unrelated variety (Content and Frenken, 2016). However, this concept reflects the capacity of regions to diversify their technological portfolio rather than their ability to generate exploratory innovations. Moreover, there is no consensus in the literature on the effects of unrelated variety on productivity. The empirical evidence is mixed, depending on the time period, the unit of analysis, and the metric employed. In particular, some studies indicate no significant impact on productivity (Quatraro, 2010), while others suggest an inverted U-shaped effect (Rocchetta et al., 2022).

The literature has often discussed exploration at the organisational level (McGrath, 2001; Harrison et al., 2024). By aggregating it at the regional level, we propose new interesting research avenues. First, unconventional innovations are usually concentrated in high-density locations (Mewes, 2019; Berkes and Gaetani, 2021) and driven by links between variously specialised inventor communities (Abbasiharofteh et al., 2023). Technological

exploration, therefore, is more likely to happen in urban settings, where organisations have stronger co-operation links (Kucharska, 2017). A geographical approach allows us to exploit these inter-organisational ties and observe their far-reaching productivity effects. Second, organisations operating in the region face the same ecosystem, similar constraints, and the same place-specificity that model their innovation potential (Filimonovic et al., 2026). Even if not through collaboration, they are influenced by the same factors. The access to and production of new forms of knowledge reflect the skills in the regional specialised workforce, the same institutional setting, and a similar underlying innovation culture (Brown and Ulijn, 2004; Cooke and Piccaluga, 2006; Morgan, 2007; Marques and Morgan, 2021). Place-specific characteristics play a never-overestimated role in defining exploration paths (Redding, 2002). Third, localised knowledge spillovers from industry incumbents might affect exploration behaviours in the same location. These knowledge spillovers include technological know-how (Klepper and Sleeper, 2005; Gambardella et al., 2015), knowledge related to market and regulation (Chatterji, 2009; Bahoo-Torodi and Torrisi, 2022), organisational routines and managerial practices (Feldman et al., 2019; Honoré, 2022), and social ties to external actors (Sorenson and Audia, 2000). Finally, aggregating exploration activities at the regional level allows us to decouple them from exploitation activities. At the organisational level, we cannot separate the two activities, as they are complementary and associated with different stages of innovation (Holmqvist, 2004; Zhou et al., 2023). At the aggregate level, we can measure the scope of exploration activities performed in the region without assuming that it is always the same organisation that performs them. In this sense, the Regional Technological Exploration indicator allows us to catch the scope and the reach of exploration activities.

3 Data and the Regional Technological Exploration

We rely on a rich dataset combining information from multiple sources, covering 1,386 NUTS3 European regions, including the European Union, UK, Norway, and Switzerland, from 1980 to 2019.

We retrieve data on technologies from the EPO PATSTAT 2023 Autumn Edition and RegPat patent databases. We use RegPat for the geographical disambiguation at the NUTS3 level based on patent inventors. We collect information on patents filed at the European Patent Office (EPO) between 1980 and 2019. We use PATSTAT data to analyse patents to measure regional technological characteristics, such as the number of patents, technological exploration, and the share of green patents in the NUTS3 region per year. To identify these characteristics, we use Cooperative Patent Classification (CPC) technology classes at the 4-digit level (subclasses), for a total of 654 subclasses. We explain in subsection 3.1 how we use technology codes to measure the RTE.

We identify green patents using the OECD Environment-Related Technologies Classification (ENV-Tech) developed by Haščič and Migotto (2015). This classification is a selection of International Patent Classification (IPC) and CPC subclasses representing technologies aiming at four major environmental policy objectives, including human health impacts of environmental pollution, addressing water scarcity, ecosystem health, and climate change

mitigation.

Finally, we integrate technological data with information on regions' socio-economic characteristics from the Annual Regional Database of the European Commission (ARDECO).

3.1 The Regional Technological Exploration

We propose a new measure to assess the importance of technological exploration in regions. The measure aims to evaluate the propensity of organisations in the region to undertake processes of technological search and, thus, explore new or rarely used knowledge combinations. While exploration processes can be risky, they can also lead to the creation of technologies that allow expansion of the technological frontier with consequent important regional economic returns. To construct this measure, we employ patent data, using co-occurrences of technology codes (CPC) associated with patents filed by inventors in the region to catch the recombination of knowledge pieces carried out to produce an invention (Breschi et al., 2003). The measure is constructed in three steps.

First, we construct the technology space on which an invention relies to determine how frequent or conventional its combinations of technology codes are. Following previous literature (Breschi et al., 2003), we look at co-occurrences within inventions of technology subclasses – 4-digit CPC codes – j and k across the universe of patents at the European Patent Office (EPO) in year t. By applying the cosine similarity function (SC) to the matrix of co-occurrences, we compute the Technological Proximity (TP) among those subclasses, which will range between 0 and 1. More distant technology classes (technology proximity close to 0) never or rarely occur together in patents and represent an unconventional combination of knowledge. On the contrary, conventional (frequent) combinations of technology subclasses show a proximity close to 1. The Technological Proximity between classes j and k at time t is defined as:

$$TP_{jk,t} = \frac{\sum_i CO_{ji,t} CO_{ki,t}}{\sqrt{\sum_i CO_{ji,t}^2} \sqrt{\sum_i CO_{ki,t}^2}} \tag{1}$$

where COji,t is the number of co-occurrences between subclasses j and i in the universe of patents filed in year t. TPjk,t detects how "conventional" the combination of j and k is at time t. A low TPjk,t represents technological domains that are more distant at time t. Organisations with knowledge in j might seek knowledge in k as a part of technological exploration efforts. If exploration is successful, TPjk,t might increase over time, if more and more patents combining j and k appear.

Second, we use TPjk,t to evaluate how exploratory a patent is, i.e., how much it relies on unconventional combinations of knowledge. Following Uzzi et al. (2013) and Berkes and Gaetani (2021), we sort all pairs of technology classes (j and k) associated with a patent p filed at time t according to their TPjk,t. We derive the cumulative distribution of technological proximity in patent p as Fpt(TPjk,t). This distribution reflects how close the pieces of knowledge recombined in the invention are. To capture how much a patent is

based on unconventional combinations of knowledge, we focus on the bottom part of the distribution of technological proximity in technology classes associated with the patent:

$$PatUnconv_{pt} = 1 - 10^{th}Pct\left[F_{pt}(TP_{jk,t})\right] \tag{2}$$

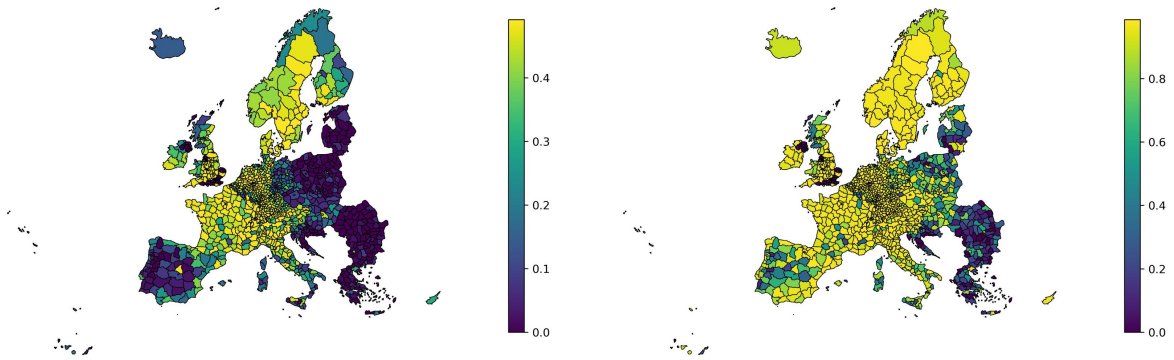
where 10thPct[Fpt(TPjk,t)] is the first decile of the cumulative distribution of technological proximity within p. As low values in TP identify distant knowledge, low values in this decile indicate that the patent strongly relies on unconventional combinations. In order to create a measure that grows with the degree of unconventionality of a patent, we subtract this decile from 1, as TP ranges between 0 and 1. PatUnconvpt allows us to link patents with technological exploration as interpreted in the literature (Audia and Goncalo, 2007). Inventions with high PatUnconvpt explore the technology space to produce new knowledge. They are riskier, but they might have a stronger impact on the direction of technological change.

Third, we measure how much a region relies on exploration to produce new knowledge. Under the assumption that the cumulative distribution of PatUnconvpt conveys information on the overall exploration effort carried out by inventors in the region r at time t, we define this distribution as Φrt(PatUnconvpt). This distribution describes how unconventional the patents produced in the region are. We are interested in detecting the exploratory efforts of organisations in the region, while acknowledging that unconventional patents will represent only a small fraction of the overall regional patent production. For this reason, we focus on the top part of this distribution. Specifically, we define the 90th percentile of Φrt as the Regional Technological Exploration (RTErt) of region r at time t. The index measures how far the exploration carried out by inventors in the region went and how much this is important in the overall regional patent portfolio:

$$RTE_{rt} = 90^{th}Pct\left[\Phi_{rt}(PatUnconv_{pt})\right] \tag{3}$$

In Figure 1, we present the geographical distribution of RTErt in 1980-1999 and 2000-2019. The RTE of European regions increased between these two periods. We observe a substantial increase across all countries, with a significant increase in the Eastern European countries. We also observe persistent regional heterogeneity in laggard regions, such as in Spain, southern Italy, and East Germany. We can conclude that organisations in regions all over Europe improved their exploratory efforts by combining more distant knowledge components, and this is captured by the production of patents more unconventional than before.

Figure 1: The Regional Technological Exploration of the European regions.



(a) 1980–1999 (b) 2000–2019

3.2 Descriptive statistics

In Table 1, we report the descriptive statistics of our variables of interest. Our sample is composed of 1,386 NUTS3 regions observed for 40 years (1980-2019). All technological variables are unsurprisingly skewed at the regional level. The number of patents, for instance, is right-skewed, with most regions patenting little, and a limited number of outliers producing the large majority of patents. The average number of patents is more than six times the median value, bigger than the 75th percentile. The green patents ratio follows a very similar distribution. On the other hand, the RTE presents a good portion of the sample with very low values, and most of the regions with positive values populate the upper part of the range. This distribution depends on the fact that, for non-patenting regions, the RTE is by construction 0. In Figure 2, we show the distribution of the RTE when keeping only non-zero values (38,632 observations). In this case, the RTE distribution presents a handful of regions at the very bottom of the range, and most of the regions concentrate above the 0.8 threshold. Finally, the labour productivity is measured as the real labour productivity per hour worked and presents an average of 35.7, close to its median of 36.0. However, this distribution is pulled at the top by a few outliers, such as Swiss regions and a handful of cities in the Netherlands, Ireland, and Norway.

Table 1: Summary Statistics

	Obs	Mean	Std. Dev.	p25	Median	p75	Min	Max
Num patents	55,440	32.695	142.930	0	5	19	0	4020
Reg Tech Expl	55,440	0.648	0.439	0	0.945	0.972	0	0.9996
Green ratio	55,440	0.077	0.156	0	0	0.100	0	1
Lab prod	50,903	35.676	19.367	26.09	36.01	44.03	1.92	1098.12

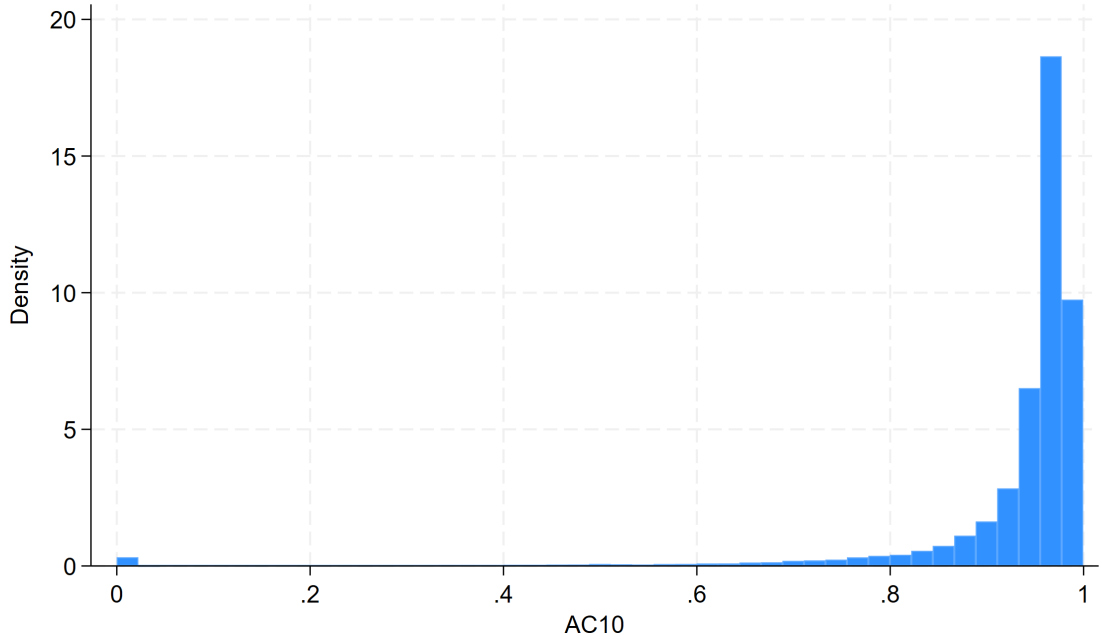
Notes: p25 and p75 denote the 25th and 75th percentiles.

Finally, in Table 2 we present the correlation between our variables. The correlation matrix indicates that none of the main variables is strongly correlated, suggesting that multicollinearity is not a concern in our model.

Table 2: Correlation Matrix

	Num patents	Reg Tech Explo	Green ratio	Lab prod
Num patents	1.0000			
Reg Tech Explo	0.1540	1.0000		
Green ratio	0.0329	0.2859	1.0000	
Lab prod	0.2551	0.3530	0.0774	1.0000

Figure 2: Distribution of non-zero values of the Regional Technological Exploration index



3.3 RTE and alternative measures of technological exploration

In this subsection, we compare RTE with the main measures of technological diversification, novelty and impact proposed in the literature. RTE is only weakly correlated with most of them, is available for a larger and less selected set of regions, and remains associated with labour productivity in a two-way fixed-effects setting. We interpret this evidence as showing that RTE captures a distinct dimension of regional technological exploration, rather than a better proxy for an existing one.

Alternative measures. Table 3 summarises the alternative measures. We group them according to the level at which each is originally computed, before being aggregated to the region–year level. Related and Unrelated Variety are the only measures computed directly at the regional level, from the Shannon entropy of the distribution of IPC classes within a region–year. The share of GPT patents and Component Familiarity are first computed

at the level of the technology class. Breakthrough inventions, Novel Combinations, Originality and Generality are computed at the patent level. Class- and patent-level measures are aggregated to the region–year level using inventors' shares.

Measures computed directly at the regional level

Related and Unrelated Variety. Related Variety and Unrelated Variety (Frenken et al., 2007) are the only measures that are derived directly at the regional level. The Shannon entropy underlying both indices is calculated on the joint distribution of IPC classes within a given region–year cell, and is therefore, by construction, a property of the region. Unrelated Variety captures the degree to which a region's technological base is diversified across distant, unrelated fields. Related Variety captures diversification within technologically related fields.

Measures computed at the IPC class level

Share of patents in General Purpose Technologies (GPT). The General Purpose Technology (GPT) share (Petralia, 2020; Kemeny et al., 2025) assigns to each technology class an exogenous flag indicating whether the class qualifies as general-purpose or disruptive. We directly take the flag as defined by Petralia (2020) in his additional material. Each patent inherits the flag of its associated class(es), weighted by the class's share within the patent (share 4dgt), and the resulting patent-level values are then aggregated to the regional level, based on the inventors' share. This measure captures the presence and intensity of technologies with broad applicability that serve as platforms for further innovation within a region's patent portfolio.

Component Familiarity. This measure gauges how well-established and familiar each individual class already is within the population of prior patents (Fleming, 2001; Arts and Veugelers, 2015). A familiarity stock is first computed for each IPC class in each year, reflecting the extent to which that class has been used by prior patents. This represents the stock of patents in which the class is tagged, discounted by an exponential decay factor that captures the loss of knowledge over time. For each patent, the familiarity values of its constituent IPC classes are then averaged to obtain a patent-level measure. Only at this stage are patent-level values aggregated to the regional level. In the spirit of our metrics, we compute both the average and the 90th percentile of this measure at the regional level.

Measures computed at the patent level

Breakthrough invention. This metric identifies patents that have an exceptional impact on future innovation (Ahuja and Morris Lampert, 2001; Arts and Veugelers, 2015). We first count each patent's forward citations within a five-year window. Then, we flag the patent if it is an extreme outlier relative to the forward-citation distribution of patents in the same IPC class and priority-year cohort. We aggregate this measure to the regional level, based on the inventors' share. In the spirit of our metrics, we compute both the average and the 90th percentile of this measure at the regional level.

Novel Combination. This measure captures new technological recombinations that have never occurred before, at the level of the individual invention (Fleming et al., 2007;

Arts and Veugelers, 2015). We examine all pairwise combinations of IPC classes present in a given patent and flag the patent as novel if at least one such pair has never previously co-occurred in any patent within the global history of the REGPAT database. We aggregate this measure to the regional level, based on the inventors' share.

Originality and Generality. These measures capture, respectively, the breadth of a patent's prior knowledge base and its subsequent technological influence (Trajtenberg et al., 1997; Hall et al., 2001). Originality is the Herfindahl–Hirschman Index (HHI) of the IPC classes of a patent's backward citations. It proxies how many different pieces of knowledge the patent brings together and draws upon. Generality is the HHI of the IPC classes of a patent's forward citations. It captures how many subsequent inventions, across how many different domains, the patent has influenced. We aggregate these measures to the regional level, based on the inventors' share. In the spirit of our metrics, we compute both the average and the 90th percentile of this measure at the regional level.

Measure	Level of computation	What it captures	References

Table 3: Alternative measures of technological exploration

Measure	Level of computation	What it captures	References
Unrelated Variety (UV)	Region	Diversification of the regional technological base across distant, unrelated fields	Frenken et al. (2007)
Related Variety (RV)	Region	Diversification within technologically related fields	Frenken et al. (2007)
GPT share	Technology class	Share of patents in classes flagged as general-purpose or disruptive technologies	Petralia (2020); Kemeny et al. (2025)
Component Familiarity	Technology class	How established each class already is among prior patents (decayed stock of patents tagged with the class)	Fleming (2001); Arts and Veugelers (2015)
Breakthrough share	Patent	Share of patents that are extreme outliers in forward citations (five-year window) within their IPC class and priority-year cohort	Ahuja and Morris Lampert (2001); Arts and Veugelers (2015)
Novel Combination share	Patent	Share of patents with at least one pair of IPC classes never previously combined in REGPAT	Fleming et al. (2007); Arts and Veugelers (2015)
Originality	Patent	Breadth of the knowledge base a patent draws on (HHI of the IPC classes of backward citations)	Trajtenberg et al. (1997); Hall et al. (2001)
Generality	Patent	Breadth of a patent's subsequent influence (HHI of the IPC classes of forward citations)	Trajtenberg et al. (1997); Hall et al. (2001)

Coverage and selection. Unlike RTE, which is defined for all region–years, the alternative measures are missing whenever a region–year has no classifiable patents or fails the citation thresholds the measure requires. Table 4 reports the share of missing values. UV, RV, the GPT share, the Novel Combination share and average Component Familiarity are missing for 24.11% of region–years, i.e. those with no classifiable REGPAT patents. The share is higher for Breakthrough (30.53%), because of the right-censoring introduced by the five-year forward-citation window, and for Originality (34.42%) and Generality (48.05%), which require at least two backward or forward citations per patent.

Table 4: Share of missing values by measure (NUTS3 region–years, 1980–2019)

Measure	Share missing (%)
Unrelated Variety	24.11
Related Variety	24.11
GPT share (fractional count)	24.11
Novel Combination share	24.11
Component Familiarity (mean)	24.11
Breakthrough share ($\geq 3\sigma$)	30.53
Originality (mean)	34.42
Generality (mean)	48.05

Notes: The table reports the measures used in the fixed-effects estimates (Table 7). For several measures we also computed alternative variants: the GPT share as a binary count, in addition to the fractional count; Breakthrough patents, both as a count and as a share of regional patents, at thresholds of 1.5, 2 and 3 standard deviations of the forward-citation distribution; the 90th percentile of Originality, Generality and Component Familiarity, in addition to the regional mean; and Component Familiarity in logs (mean and 90th percentile). Missing shares for all 19 measures and variants are reported in Table A1 in the Appendix.

Missing values are not random with respect to regional size and development. Table 5 compares region–years for which a measure is missing with those for which it is observed. In all cases, region–years with missing values have lower RTE, fewer hours worked, a smaller population, and lower GDP and labour productivity. Missing shares also vary strongly across countries: they are close to zero in Luxembourg, Switzerland and Denmark, but exceed 70% even for the least demanding measures in Bulgaria, Croatia, Greece, Latvia, Lithuania and Romania. The alternative measures are therefore least available precisely for the lagging regions in which the question of leapfrogging is most relevant.

Table 5: Difference in means between region–years with missing and observed measures

	Unrelated Variety	Breakthrough	Originality	Generality	Component Familiarity
RTE	−0.506***	−0.387***	−0.501***	−0.401***	−0.506***
Hours worked	−21.4%***	−11.8%***	−24.3%***	−21.2%***	−21.4%***
Population	−18.6%***	−12.6%***	−19.8%***	−18.3%***	−18.6%***
Real labour productivity	−40.0%***	−23.1%***	−43.8%***	−32.0%***	−40.0%***
GDP (PPS)	−61.0%***	−18.3%***	−71.3%***	−44.6%***	−61.0%***

Notes: Each column compares the mean of the row variable between region–years in which the column measure is missing and region–years in which it is observed. Except for RTE, variables are in logs, so differences are expressed in percentage points. *** $p < 0.01$.

Correlations. Table 6 reports the pairwise correlations between RTE and the alternative measures. RTE is moderately correlated with Unrelated Variety ($r = 0.46$) and weakly with the GPT share ($r = 0.14$); its correlations with the remaining measures are negligible ($|r| \leq 0.07$).

Table 6: Correlation matrix, RTE and alternative measures

	RTE	GPT share	Unrelated Variety	Breakthrough	Originality	Generality	Component Familiarity
GPT share	0.143	1.000					
Unrelated Variety	0.458	0.203	1.000				
Breakthrough	0.046	0.010	0.042	1.000			
Originality	0.019	−0.015	0.022	0.013	1.000		
Generality	−0.066	−0.012	−0.016	0.032	0.003	1.000	
Component Familiarity	−0.038	0.097	0.035	0.012	0.087	−0.086	1.000
Novel Combination	−0.044	−0.033	0.003	−0.012	0.016	0.088	−0.180

Fixed-effects estimates. Table 7 reports two-way fixed-effects regressions of log labour productivity on each measure in turn, controlling for the number of patents (inverse hyperbolic sine) and log population, with NUTS3 region and year fixed effects. No component of the dependent variable is included among the controls. RTE is positively associated with labour productivity both in the full sample (0.0224, column 1) and when the sample is restricted to region–years with at least one patent (0.0167, column 2). The drop between the two columns reflects the exclusion of non-patenting region–years, for which RTE is zero by construction and which are on average smaller and poorer (Table 5). Among the alternative measures, Unrelated and Related Variety are significantly associated with labour productivity, as is average Component Familiarity, although with a coefficient close to zero; the GPT share, the Breakthrough and Novel Combination shares, and average Originality and Generality are not. Since the measures are on different scales, coefficients are not directly comparable across columns.

Table 7: Two-way fixed-effects estimates, log labour productivity on each exploration measure

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
RTE (AC10)	0.0224***	0.0167**								
	(0.0079)	(0.0074)								
Unrelated Variety			0.0137***							
			(0.0039)							
Related Variety				0.0166***						
				(0.0041)						
GPT Patents (fractional count)					0.0001					
					(0.0001)					
Breakthrough Share ($\geq$ 3 sd)						0.0075				
						(0.0158)				
Novel Combination Share							−0.0220			
							(0.0140)			
Originality (mean)								0.0037		
								(0.0072)		
Generality (mean)									−0.0000	
									(0.0026)	
Component Familiarity (mean)										0.0000**
										(0.0000)
Nr. Patents (i.h.s.)	0.0113***	0.0162***	0.0144***	0.0131***	0.0156***	0.0129***	0.0156***	0.0145***	0.0115***	0.0157***
	(0.0041)	(0.0039)	(0.0031)	(0.0030)	(0.0031)	(0.0031)	(0.0031)	(0.0032)	(0.0037)	(0.0031)
Population (log)	−0.1765***	−0.1163*	−0.0965*	−0.1094**	−0.1037*	−0.0906	−0.1038*	−0.0819	−0.0480	−0.1079*
	(0.0581)	(0.0607)	(0.0555)	(0.0555)	(0.0557)	(0.0610)	(0.0557)	(0.0598)	(0.0832)	(0.0557)
Fixed-effects										
NUTS3 Region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics										
Observations	50,903	38,953	40,995	40,995	40,995	37,430	40,995	35,680	28,169	40,995
Within R^2	0.01371	0.00843	0.01021	0.01156	0.00803	0.00540	0.00813	0.00637	0.00312	0.00856

Notes: Dependent variable: log real labour productivity per hour worked. Column (1) uses all values of RTE; column (2) restricts the sample to region–years with at least one patent. Columns (3)–(10) replace RTE with one alternative measure at a time. No component of the dependent variable (hours worked, employment) is included among the controls. All specifications include NUTS3 region and year fixed effects. Clustered (NUTS3 Region) standard-errors in parentheses. Signif. Codes: ***: 0.01, **: 0.05, *: 0.1.

How RTE differs from Unrelated Variety and GPT patents. Among all the alternative measures, RTE relates most closely to Unrelated Variety. RTE appears to capture a different side of unrelated variety, one linked to the technological complementarities that can be fully exploited only when capabilities are geographically within reach. Unrelated Variety, as originally conceived by Frenken et al. (2007), captures diversification per se: a region scores high on UV whenever its patenting activity is spread across many distant technological fields, regardless of whether those fields are actually connected to one another within the region's economic fabric. RTE, by contrast, measures how effectively a region can draw on this breadth. A region can be rich in unrelated variety on paper while its distant capabilities remain isolated and never recombined, generating little of the cross-fertilisation that drives regional technological upgrading.

A second, complementary distinction concerns GPT patents. These patents signal the presence of regional innovation activity in domains considered technological frontiers at the time. Exploration efforts, however, do not need to occur on the frontier: novel and unexpected recombinations can just as easily emerge from more standard, well-established technological fields. Their effects can cumulate alongside ongoing frontier innovation ef-

forts, rather than substitute for them. A region can display substantial atypical recombination activity even where patenting in the frontier is comparatively modest. Rather than proxying for the same underlying phenomenon as the GPT share, RTE isolates a distinct margin of technological exploration, one that operates through the atypical combinations of non-frontier capabilities.

4 Empirical Methods and Results

To design an effective econometric strategy, it is essential to recognise that economic conditions are likely to drive different forms of innovation. In contrast, simultaneously, the evolution of these innovations can impact regional productivity. In addition, changes in the structure of the stock of different forms of innovations could have both immediate and delayed effects on the economy. Cross-sectional and short-panel-based analyses are, therefore, likely to miss essential dynamics and face substantial challenges in identifying causal effects. While fixed-effect models are designed to estimate one-way relationships, Panel Vector Autoregressive (PVAR) models are explicitly built to capture how all variables included in the regression can affect each other over time, allowing each variable in our system of equations to be influenced by its own past values and those of the other variables. Letting the subscripts r and t denote the NUTS3 region r and time t, respectively, we can write our variables of interest as the vector Xrt = [NPrt, RTErt, GIrt, RLPrt]', where NPrt is the stock of patents in region r at time t, RTErt is the level of technological exploration in region r at time t, and GIrt is the variable green innovation that is calculated as the ratio of green patents over the total number of patents in region r at time t. Finally, RLPrt is the regional real labour productivity in region r at time t.

Our reduced-form model can be written as:

$$X_{rt} = \alpha + \sum_{k=1}^{m} \beta_k X_{t-k} + \phi_r + \varepsilon_{rt} \tag{4}$$

where α is a vector of constants, βk is the matrix of coefficients for lag k, ϕr are regional fixed effects and εrt is the error term. To correct for the potential bias in dynamic panels (Nickell, 1981), we use the Generalised Method of Moments for the Helmert-transformed model (Abrigo and Love, 2016). The maximum lag length m is determined according to the method proposed by Andrews and Lu (2001). In our case, these selection criteria suggest that the optimal lag length is one. To correct for the potential for dynamic panel bias, in our main estimation, we apply the Helmert transformation (Abrigo and Love, 2016) and employ "GMM-style" instruments to enhance efficiency by replacing missing values for lagged instruments with zero (Holtz-Eakin et al., 1988). Standard errors are clustered at the regional level. As we aim to trace the dynamic effects of changes in technological exploration and green innovation on labour productivity, we generate Impulse Response Functions (IRF). Each IRF shows the dynamic impact of exogenous changes in one variable on each of the other variables and estimates its persistence. In particular, it allows us to show how a standard deviation exogenous change to a variable affects all the

other variables. IRFs represent the dynamic causal effect of such orthogonalised shocks on our technological variables on the regional labour productivity.

To identify causal effects, we impose a Cholesky decomposition. This entails making assumptions about the order in which shocks propagate through the system. Our ordering is based on the following logic. A variation in the region's technological capabilities – proxied by the number of patents in the region – will affect the capacity of the organisations in the region to make further exploration. As there are more innovations in the regions, there are probabilistically more knowledge components to be potentially recombined. Thus, we allow such shocks to influence Regional Technological Exploration, green innovation, and regional labour productivity contemporaneously. Changes in RTE, which captures the propensity of the region to explore recombination of more distant pieces of knowledge, are assumed to only influence the degree of regional innovation with a lag but can affect green innovation and regional productivity contemporaneously. Shocks to green innovation are assumed to influence the number of patents and regional technological exploration with a lag. This assumption hinges on the idea that changes in the ability to produce green innovation do not immediately translate into new technological capabilities because the development of new scientific and technological knowledge takes time (Nelson, 1959; Dosi, 1982). Finally, the creation of new exploratory and green knowledge will help the regions to push forward their technological frontier, and this will translate into productivity gains. Although we believe that this set of identifying assumptions is plausible, in robustness checks, we also present results for alternative orderings of the shock.

4.1 Results

Table 8 presents the coefficients from our PVAR model. As noted in Section 4, the information criterion indicated that our model should include one lag. Moreover, in our estimation strategy, we use the first two untransformed lags of each variable as GMM-instruments.

Table 8: Panel VAR Estimates (Lag 1)

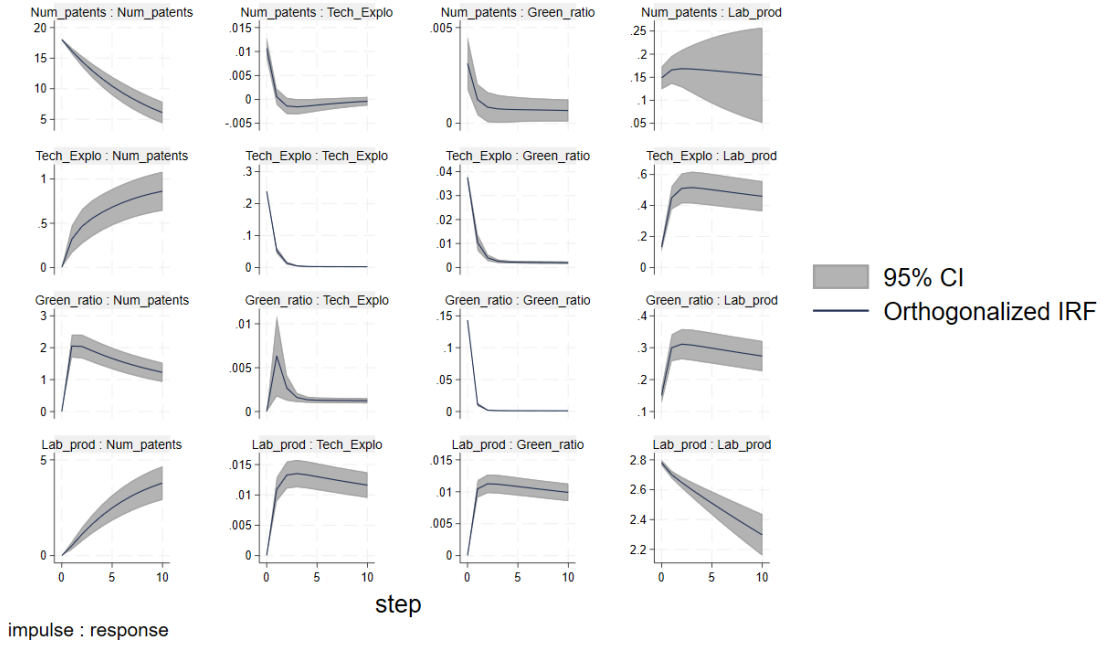
	(1) Num patents$_t$	(2) Tech Explo$_t$	(3) Green ratio$_t$	(4) Lab prod$_t$
Num patents$_{t-1}$	0.8930***	−0.000135***	0.00000703	0.000330
	(0.0132)	(0.000045)	(0.0000223)	(0.000504)
Tech Explo$_{t-1}$	−0.9880***	0.2129***	0.0300***	1.1826***
	(0.2183)	(0.0188)	(0.00757)	(0.1298)
Green ratio$_{t-1}$	14.0856***	0.0399**	0.0732***	1.0704***
	(1.2929)	(0.0161)	(0.00875)	(0.1279)
Lab prod$_{t-1}$	0.1880***	0.00392***	0.00376***	0.9714***
	(0.0367)	(0.000352)	(0.000248)	(0.00319)
Observations	48,137	48,137	48,137	48,137

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The results in Table 8 show that technological exploration is positively associated with regional labour productivity. This result is in line with previous findings and suggests that the ability of a regional economy to improve its performance is stronger when regions reach a higher degree of technological exploration. Similarly, the association between green innovation and labour productivity is positive. Table 8 also shows a positive lagged association between technological exploration and green innovation; however, as the IRFs below show, these effects are short-lived.

By analysing IRFs as described in Section 4, we can assess both the effect of the different forms of innovation on regional labour productivity and the persistence of these effects. Figure 3 displays the orthogonalised IRFs associated with our PVAR models. Each subgraph traces the effects of a time-zero one standard deviation change in the dependent (impulse) variable. The three subgraphs in the upper right quadrant are of particular interest as they depict the effects of the different forms of innovation on regional labour productivity.

Figure 3: Impulse Response Functions



The results in Figure 3 are in line with those reported in Table 8. The evidence presented in Figure 3 indicates that a one standard deviation change in patent counts produces an immediate, persistent, but modest increase in labour productivity, on the order of 0.1-0.15 units. The impact of technological exploration is similarly positive and persistent, but it is greater in magnitude. A one-standard-deviation rise yields a delayed but pronounced productivity response of about 0.4-0.5 units, which emerges after roughly two years and remains elevated throughout the horizon. This pattern supports the view that recombination across distant technological domains fosters structural upgrading and long-run productivity growth.

In the case of green innovation, our evidence suggests that a one standard deviation

change in green innovation produces a positive increase in regional labour productivity, on the order of 0.2-0.3 units, with the effect gradually building and persisting over time. The effect of green innovation on labour productivity is positive, but it is of a smaller magnitude compared to regional technological exploration. This indicates that green innovation, while less transformative than unconventionality, still contributes positively and consistently to regional productivity dynamics.

Therefore, we can infer that the quantity of innovation alone may not be sufficient to enable regions to leapfrog certain developmental stages, as the number of patents led to immediate but modest productivity gains. What type of innovation is being pursued – and how novel or transformative it is – matters considerably more. A shock to technological exploration yields the most potent and most persistent positive effect on labour productivity. The effect is not immediate, but remarkably larger compared to the number of patents. This suggests that regions with more technological exploration are more likely to jump the productivity ladder. Technological exploration also leads to a sustained increase in overall patent activity, reinforcing the idea that frontier innovation can act as a catalyst for broader technological dynamism. Turning to green innovation, the results show that a shock to green innovation has a positive effect on the overall region's innovative capacity, but decreases over time. This result suggests that green innovation is capable of activating broader innovation ecosystems, possibly through spillovers, regulatory incentives, or investment in supporting technologies. Our evidence also suggests that technological exploration and green innovation do not appear to stimulate each other. Although general innovation contributes modestly to regional labour productivity, technological exploration and green innovation emerge as the more potent drivers of long-term productivity growth. Among these, technological exploration has the most significant impact.

4.2 Robustness Checks

We test the robustness of our results by running our estimations using alternative Cholesky orderings. The purpose of changing the Cholesky ordering is to test whether a different order of propagation of the shocks affects the results. If IRFs catch similar propagation dynamics as in the main specification, we can argue that our results are robust and do not depend on the order we have chosen. Notice that the reduced-form results presented in Table 8 are insensitive to alternative Cholesky orderings, and only IRFs change.

Specifically, we test the robustness of our results when adopting the following Cholesky decompositions:

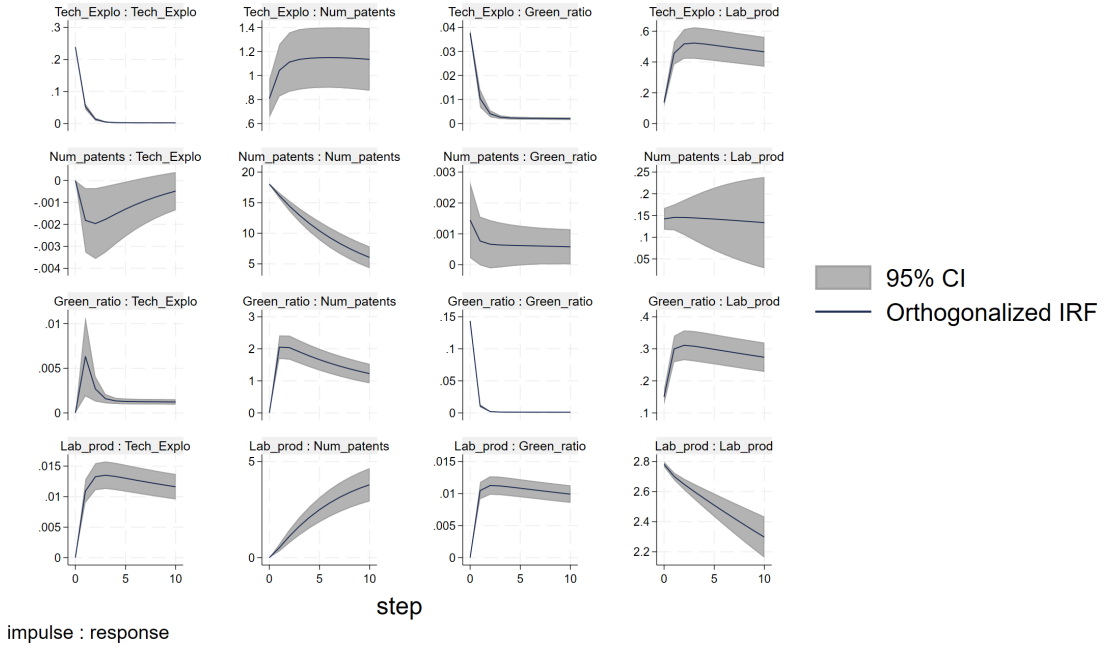
$$RTE \longrightarrow NumPat \longrightarrow GreenRatio \longrightarrow LabProd \tag{5}$$

$$LabProd \longrightarrow RTE \longrightarrow GreenRatio \longrightarrow NumPat \tag{6}$$

In Figure 4, we report the IRFs of the model described in (5). In this model, we assume

that a sudden shock in exploratory activities affects the innovation intensity in the region (number of patents), the production of green innovation (green ratio), and the labour productivity. As in Figure 3, we can see that the effects of the RTE are limited in time on the green ratio and on further technological explorations. However, it presents persistent effects on the number of patents produced in the region and on labour productivity. The second dimension in the model is the number of patents. For the sake of this robustness check, we expect it to affect in turn only the green patent share and labour productivity, but it has no effect at the same time on the RTE. In Figure 4, a shock in the number of patents produces no significant effects on the share of green patents, but it has a positive, even though decaying, impact on labour productivity, with an effect between 0.1 and 0.2 standard deviations. Shocks in the share of green patents have very limited effects on the technological exploration carried out in the region. On the other hand, a standard deviation shock of the green patent shares leads to a persistent effect of around one standard deviation on the number of patents, and between 0.2 and 0.3 standard deviations on labour productivity. Finally, in this robustness check, labour productivity is the only variable that we assume does not have any contemporaneous effects on the other variables. One standard deviation shock in labour productivity induces a 0.01-0.015 standard deviation persistent effect on the regional technological exploration, and 0.1 standard deviations on the share of green patents. The effects on the number of patents are also very interesting, suggesting that the impact is increasing over time, with more and more patents cumulating after the first propagation, up to 5 standard deviations after 10 years. These results are consistent with the IRFs shown in Figure 3.

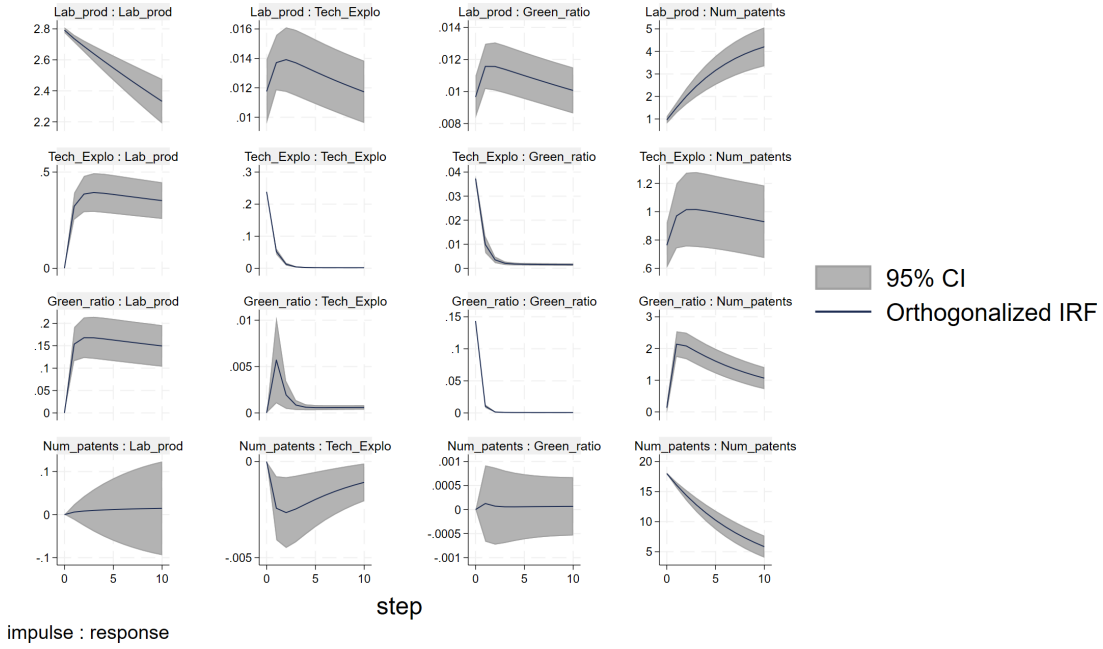
Figure 4: Alternative Impulse Response Functions from eq. (5).



In Figure 5, we display the IRFs from the model based on the Cholesky decomposition reported in equation (6). In this model, we randomise the order of variables. Although this order does not reflect a theoretical order that we deem plausible for the propagation

mechanisms, we aim at showing that the results reported in the main IRFs in Figure 3 are robust to alternative ordering. We assume a structure where labour productivity is the original shock, affecting the shocks in all the other variables at the same time. Then, we assume that a shock in the technological exploration affects the share of green patents and the total number of patents, but not labour productivity in the same period. Finally, we assume that the share of green patents affects only the number of patents in the region, but not the other variables. This Cholesky decomposition is not underpinned by a sound economic theory, but we want to show that an alternative order does not invalidate our results. The effects of labour productivity present the same coefficients and time-persistence as in Figure 3. The same applies to the shocks of RTE, which have a positive and persistent effect on labour productivity and the number of patents, but not on the share of green patents. The impact of the share of green patents, on the other hand, is consistent with the IRFs in Figure 3. Finally, in the last row of Figure 5, we observe that, in this decomposition, one standard deviation in the number of patents produces null effects on labour productivity. Similarly, we find the same pattern in the effects of the number of patents on the green ratio. The effects on regional technological exploration are slightly negative in the short-term, but then they decay in the long-term. Overall, the IRFs coming from this decomposition are consistent with the ones in Figure 3.

Figure 5: Alternative Impulse Response Functions from eq. (6).



4.3 Local Projections

As a further robustness check, we estimate the dynamic responses using Local Projections (Jordà, 2005). PVAR impulse responses are iterated: the response at horizon h chains h one-step-ahead forecasts from the same model, so that even a slight misspecification compounds along the horizon. Local Projections instead estimate the response at each

horizon directly, with a separate regression for each horizon h:

$$y_{r,t+h} = \beta^{(h)} X_{r,t} + \sum_{l=1}^{2} \gamma_l^{(h)} X_{r,t-l} + \phi_r + u_{r,t+h}, \qquad h = 0, \ldots, 12 \tag{7}$$

where y is, in turn, each of the four variables of the system (NP, RTE, GI and RLP), Xr,t is the vector of the four variables at time t, two lags of all variables are included as controls, and ϕr are regional fixed effects. The models are estimated with within-region fixed effects, and standard errors are clustered at the NUTS3 level. Because each horizon is estimated independently and no orthogonalisation is imposed, the Local Projection responses do not depend on a Cholesky ordering. PVAR and Local Projections estimate different objects – cumulative orthogonalised responses versus direct projections at a fixed horizon – so their magnitudes are not directly comparable; we therefore focus on the sign, timing and persistence of the responses.

Table 9 reports the Local Projection estimates at horizon t+2, Table 10 the coefficients on the lagged controls in the same projections, and Figure 6 displays the impulse responses from the Local Projections. The response of labour productivity to technological exploration is positive at all horizons and grows steadily over time, confirming the delayed and persistent effect found in the PVAR. The response of labour productivity to green innovation is also positive: it builds up gradually, peaks after about eight years and then declines. The response to the number of patents is small, positive and increasing over the horizon.

Table 9: Local Projections at t+2

	RTE_{t+2}	NP_{t+2}	GR_{t+2}	RLP_{t+2}
RTE_t	0.1316***	-1.7745***	0.0116*	0.3055***
	(0.0084)	(0.2340)	(0.0045)	(0.0878)
NP_t	0.0000	0.9545***	0.0000	0.0021*
	(0.0000)	(0.0460)	(0.0000)	(0.0011)
GR_t	-0.0054	0.3807	0.0323***	-0.0637
	(0.0115)	(0.3892)	(0.0090)	(0.0884)
RLP_t	0.0012***	0.1004*	0.0006*	0.6418***
	(0.0003)	(0.0492)	(0.0003)	(0.1076)
Obs.	45,371	45,371	45,371	45,371

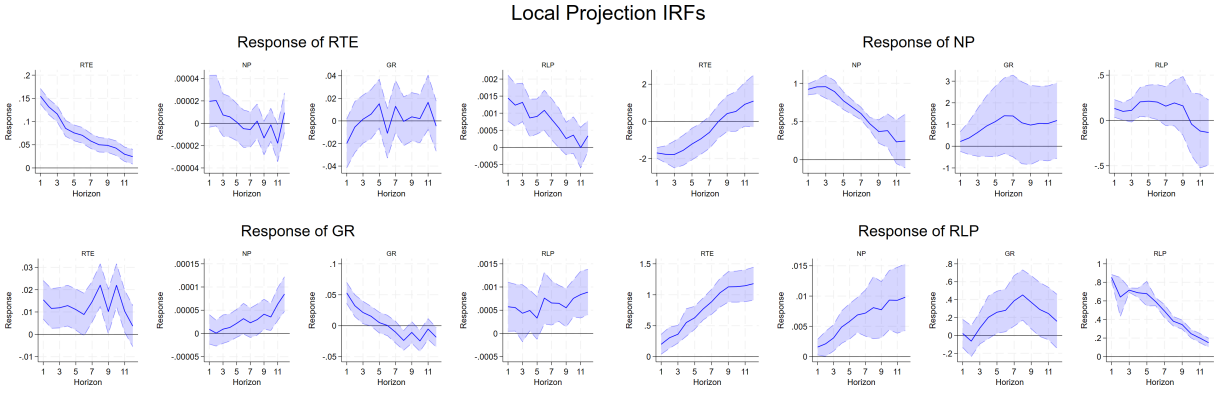
Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. SE in parentheses. Clustered at NUTS3.

Table 10: Local Projections at t+2: lag controls

	RTE_t	NP_t	GR_t	RLP_t
RTE_{t-1}	0.1159***	0.1984	0.0122**	0.3256***
	(0.0084)	(0.1799)	(0.0045)	(0.0954)
NP_{t-1}	-0.0000	0.0659	0.0000	0.0001
	(0.0000)	(0.0348)	(0.0000)	(0.0009)
GR_{t-1}	0.0027	0.3665	0.0197*	0.0762
	(0.0107)	(0.3789)	(0.0088)	(0.0772)
RLP_{t-1}	0.0005	-0.0734	0.0001	0.2393
	(0.0003)	(0.0548)	(0.0002)	(0.1351)
RTE_{t-2}	0.0878***	0.7603***	0.0128**	0.4275***
	(0.0081)	(0.1674)	(0.0043)	(0.1111)
NP_{t-2}	-0.0000**	-0.1339*	0.0000***	0.0014
	(0.0000)	(0.0609)	(0.0000)	(0.0009)
GR_{t-2}	0.0135	0.4086	0.0135	0.1268
	(0.0106)	(0.3541)	(0.0077)	(0.0725)
RLP_{t-2}	0.0001	0.0075	0.0005	-0.0471
	(0.0004)	(0.0469)	(0.0004)	(0.0581)
Obs.	45,371	45,371	45,371	45,371

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. SE in parentheses. Clustered at NUTS3.

Figure 6: Impulse Response Functions from Local Projections



5 Conclusions

This study explores how innovation dynamics might help regions jump the ladder of economic development. We began our contribution by reflecting on how innovation and green innovation interplay with regional technological exploration and are associated with higher regional productivity gains.

On the one hand, we show that the ability of regions to explore more unconventional technological recombination is one of the main drivers of regional productivity growth. This result is aligned with previous evidence. Unconventional recombination of knowledge

is able to push forward the regions' technological frontier (Barbero et al., 2024). That translates into the acquisition of new competitive advantages, which, in turn, translate into productivity gains. On the other hand, we include green innovation due to the significant weight it has acquired in European regional innovation strategies. Similarly to technological exploration, green innovation promotes productivity by fostering resource efficiency, technological upgrading, and by creating market opportunities (Horbach et al., 2012; Barbieri et al., 2020). These similarities weigh in relevant synergies between technological exploration and green innovation, as recent studies (Orsatti et al., 2020a) indicate that regions capable of mastering new combinations of knowledge tend to perform better in generating green innovation.

Our results highlight that technological exploration and green innovation have a persistent positive effect on regional labour productivity. The magnitude of the impact is larger for technological exploration than for green innovation, and both build over time. Nonetheless, the evidence does not corroborate the hypothesis of the presence of synergies between technological exploration and green innovation.

This paper makes three main contributions. First, it introduces a novel indicator of Regional Technological Exploration to capture the ability of the region in proposing risky and potentially disruptive innovations. The comparison with alternative measures from the literature shows that the indicator is distinct from existing measures of diversification, novelty and impact, and that it is available for the lagging regions for which those measures are most often missing. Second, we apply an econometric framework using recursive identification restrictions to recover structural impulse responses, providing a dynamic causal perspective that captures the timing and persistence of effects. This approach complements the static evidence from existing cross-sectional and fixed-effects studies. Lastly, it compares the impact of different types of innovation activities – technological exploration and green innovation – on regional labour productivity.

The study has, of course, limitations. More work is needed to explore the role of technological exploration and green innovation in shaping regional productivity. Future studies should assess this through a sectoral and industrial approach. Additionally, future research might complement these results with a micro-level perspective to identify the mechanisms we present. Despite its limitations, we can draw some policy implications from our findings. Our evidence suggests that regional innovation policy should emphasise the quality and orientation of innovation, encouraging technological exploration – such as supporting risk-taking research, cross-disciplinary collaboration, and frontier experimentation – which can lead to the most significant and sustained productivity gains. Unfortunately, these activities require substantial resources and absorptive capacities, which not all regions possess. Conversely, green innovation provides lasting benefits when integrated into supportive institutional frameworks and aligned with the exploratory strategies performed in the region. From a European perspective, Cohesion Policies and Smart Specialisation 4.0 strategies should be designed to combine frontier and green pathways: advanced regions could be encouraged to push the boundaries of technological exploration, while others can focus on leveraging green innovation niches aligned with local capabilities and policy priorities. Importantly, targeted funding instruments, mission-oriented

incentives, and coordinated governance mechanisms are essential to bridge gaps between frontier and sustainability-oriented innovation, ensuring that the benefits of technological leapfrogging and green transitions are both transformative and inclusive across Europe.

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Appendix

Table A1: Share of Missing Values by Innovation Measure

Measure	Share of NA (%)
Unrelated Variety	24.11%
Related Variety	24.11%
GPT Patents (fractional count)	24.11%
GPT Patents (binary count)	24.11%
Breakthrough Patents ($\geq 1.5\sigma$)	30.53%
Breakthrough Patents ($\geq 2\sigma$)	30.53%
Breakthrough Patents ($\geq 3\sigma$)	30.53%
Breakthrough Share ($\geq 1.5\sigma$)	30.53%
Breakthrough Share ($\geq 2\sigma$)	30.53%
Breakthrough Share ($\geq 3\sigma$)	30.53%
Novel Combination Share	24.11%
Originality (mean)	34.42%
Originality (p90)	42.68%
Generality (mean)	48.05%
Generality (p90)	58.88%
Component Familiarity (mean)	24.11%
Component Familiarity (p90)	29.08%
Component Familiarity, log (mean)	24.11%
Component Familiarity, log (p90)	29.08%