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Technological diversification and the growth of regions in the short and long run

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ABSTRACT

Technological diversification is crucial for regions to foster innovation and, therefore, to support economic growth. In this paper, we study how different types of technological diversification affect the performance of regional economies. We focus on the effect of changes in technological relatedness and unconventionality – as indicators of related and unrelated diversification – on GDP and employment growth in European regions. Leveraging information on regional economic performances and patents filed at the European Patent Office, we estimate Panel Vector Autoregression models and generate Impulse Response Functions to assess to what extent and with what persistence relatedness and unconventionality affect regional economic performances. Our findings, which have implications for the design of new place-based innovation policies, reveal that increases in technological relatedness have a short-term positive effect on employment growth but a negative effect on GDP growth. Conversely, increases in technological unconventionality have a higher and long-lasting positive impact on GDP growth but no effect on employment growth.

1. Introduction

Innovation can be conceptualised as a path-dependent process of knowledge accumulation and recombination (Dosi, 1982; Scotchmer, 1991). This theme has been developed in various strands of the literature, from the micro-(Fleming and Sorenson, 2001; Wuchty et al., 2007) to the macro-level of analysis (Weitzman, 1998; Jones, 2009). The process of knowledge production is often localised, as it is shaped by place-dependent factors such as the availability of tacit knowledge and the institutional features of local markets and innovation systems (Antonelli et al., 2003; Muller and Zenker, 2001). The resulting stock of knowledge, in turn, influences local economies' development paths. Scholarly interest in the way in which the stock of knowledge and its composition shape local growth dynamics can be traced back to the classic debate on the role of specialisation and diversification in generating Marshallian vis-à-vis Jacobian externalities (Beaudry and Schiffauerova, 2009). Renewed interest in this problem has recently emerged with the growing emphasis on theoretical and analytical perspectives framed around the notion of economic complexity (Arthur, 2021; Balland et al., 2022; Nomaler and Verspagen, 2022).

A diversified portfolio of technological capabilities can increase the probability of knowledge recombination (Antonelli et al., 2022) and mitigate the risk linked to idiosyncratic shocks: on the one hand, it allows for the discovery of new growth opportunities, and, on the other, alleviates the problem of lock-in effects due to product markets or production technologies that are more exposed to external competition, or more vulnerable to exogenous paradigmatic and industry-wide change (Grabher, 1993; Glaeser, 2005; Martin and Sunley, 2006; McCann, 2013; Pinheiro et al., 2022).

At least since Jacobs' work on the rise and exploitation of economies of scope (Jacobs, 1970), the study of agglomeration economies has highlighted the importance of diversification. However, local economies can diversify to different extents and in very different directions, depending on existing capabilities and resources. Knowledge inputs can present configurations that show higher or lower degrees of complementarity and cognitive proximity. Frenken et al. (2007) opened a new strand of literature by providing a robust framework for analysing the complementarities between industries in local economies through the definition of related and unrelated variety as measures of related and unrelated diversification. Related diversification has been identified as a recurrent pattern – a 'stylised fact' – characterising not only technology but a broader range of economic aggregates, including industries, traded products, firm outputs and skills (Li and Neffke,

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2024). In this paper, we focus on technological diversification since the creation of new technological knowledge anticipates industrial transformation and changes in skills at the aggregate level. As shown in Breschi et al. (2003), technological diversification is usually greater than product diversification, and it is important to capture this more granular source of competitive advantage. Moreover, in the majority of cases, technological diversification comes before product and market diversification, as also argued by Pavitt (1998), because technological exploration in a wide range of technologies is a prerequisite for production. With specific reference to technological capabilities, recent literature on related diversification has found a strong association between relatedness and employment growth (Content and Frenken, 2016; Boschma, 2017; Bathelt and Storper, 2023). The role of unrelated diversification has been, instead, much more difficult to establish. This might be due to measurement problems that can be attributed to the use of a priori hierarchical classifications of knowledge inputs that fail to capture the rare or more distant bundles of knowledge driving growth through unrelated diversification. In an attempt to improve existing measures of diversification and combinatorial novelty, Berkes and Gaetani (2021) have used the notion of 'unconventionality' to identify the presence of atypical combinations of technological knowledge in patents. These combinations are knowledge combinations that have rarely been used before, or are entirely new, and blend cognitive inputs more distant from one another in an evolving knowledge space (Uzzi et al., 2013; Fontana et al., 2020; Abbasiharofteh et al., 2023). Unconventional combinations of knowledge can become idiosyncratic sources of competitive advantage. While they have the potential to push local economies towards the technological frontier, they are also riskier and often more costly (Wang et al., 2017).

In this paper, we aim to explore what kind of technological diversification, i.e. recombining more or less related knowledge vs. investing in more or less unconventional combinations of knowledge, is able to improve a region's economic performance. We analyse the effects of variations in regional technological relatedness and unconventionality, as measures of related and unrelated diversification, on the performance of European regions. In doing so, we follow the rich tradition of research that uses patents as one of the most powerful – yet not perfect[1] – indicators of technological knowledge and explore the effects of technological diversification on economic performance. By following existing literature (Balland et al., 2022; Pinheiro et al., 2022; Rocchetta et al., 2022a; Lo Conte et al., 2025), we employ patents as a consistent, codified, and internationally comparable proxy for regional technological capabilities. This approach enables us to trace the structure and novelty of technological knowledge recombination over time, which is widely recognised as a key driver of industrial transformation and long-term growth (Pavitt, 1998). Even though patents do not capture all the innovation activities embedded in a regional economy, their richness, level of detail, and standardisation make them uniquely suited for analysing the evolution of regional technological capabilities. By focusing on the structure of technology co-occurrences within regional patent portfolios, rather than simple counts, our analysis captures the interrelated processes of capability building and diversification that underpin regional development. Specifically, we use data on regional economic performance at the NUTS II level from Eurostat regional statistics and rely on patent data extracted from the European Patent Office (EPO) PATSTAT and OECD RegPat databases. We then estimate Panel Vector Autoregression models and generate Impulse Response Functions (IRFs) that isolate the structural effect of different forms of technological diversification on regional growth. IRFs allow us to estimate to what extent and with what persistence the two distinct types of technological diversification affect, on the one hand, gross domestic product (GDP) and, on the other, employment growth. The evidence indicates that an increase in technological relatedness has a short-term effect on employment growth and a negative effect on GDP growth. Increases in technological unconventionality, instead, have a long-lasting positive impact on GDP growth and no effect on employment growth.

The contribution of this paper is threefold. Firstly, we introduce a new indicator that allows us to evaluate the relevance of unconventional recombination of knowledge in the regional knowledge base. Secondly, we employ an econometric framework that leverages recursive identification restrictions to recover structural impulse responses, offering a dynamic causal perspective that captures the timing and persistence of effects and complements static evidence found in existing cross-sectional and fixed-effects studies. IRF analysed traces the dynamic effects of orthogonalised shocks under standard VAR identification assumptions, rather than making unconditional causal claims. Therefore, this method allows us to assess the effect of increases in technological diversification on regional economic performance, with the aim of suggesting effective regional development policies. Finally, we provide a short- and long-term analysis of the role of different types of technological diversification, uncovering heterogeneous effects on employment vs. output growth.

The paper is organised as follows. In Section 2, we review the relevant literature. In Section 3, we illustrate the methodology. Section 4 contains a description of the dataset and variables. In Section 5, we present the econometric results, which are followed by sensitivity analyses and robustness checks. The final section of the paper draws the contribution to a close by briefly discussing the limitations of the study and highlighting its policy implications.

2. Technological diversification and regional growth

Innovation and technological knowledge have been recognised as key determinants of economic growth (Romer, 1990; Aghion and Howitt, 1992; Grossman and Helpman, 1993). On the one hand, several studies indicated that investments in technological knowledge play a crucial role in shaping employment performances (see, for example, Vivarelli and Pianta (2000) for a discussion of this issue). On the other hand, since the seminal work of Nelson and Winter (1982), innovation has been considered a crucial source of competitive advantages and productivity growth, essential for long-term economic prosperity (see Criscuolo (2009) for an extensive literature review). Since Schumpeter's theory of economic development (Schumpeter, 1939), innovation and the generation of new technological knowledge are conceived as resulting from the recombination of previous knowledge (Nelson and Winter, 1982; Henderson and Clark, 1990; Weitzman, 1998; Fleming and Sorenson, 2001; Jones, 2009). According to this line of thinking, access to a diverse range of ideas, information, and existing technologies is fundamental to having a larger pool of components, perspectives, and challenges to draw from and gaining a competitive advantage in creating innovation (Sorenson, 2023).

Access to a diversified portfolio of technological knowledge – also known as technological diversification – is particularly important for regions (Boschma and Martin, 2010). Regions are essential units of analysis for understanding the innovation process since it is well-known that knowledge has both tacit and codified components, making knowledge bundles highly contextual and sensitive to proximity effects or distance-related decay (Feldman and Kogler, 2010). Moreover, regions are among the economic actors responsible for the implementation of innovation policy. For example, European innovation policies that use technological diversification as a policy instrument have designated NUTS II regions as their primary area of application (e.g., Smart Specialisation Strategies — S3). Technological diversification is crucial for regions, as it expands the components available for recombination, fostering local cross-industry spillovers that drive industrial renewal (Amoroso et al., 2022), innovation, and ultimately economic

[1] Empirical evidence focusing on technological invention only, measured by patents, might overestimate the role of large cities in producing innovation (Castaldi, 2024).

growth (Boschma and Martin, 2010). Recent literature also highlights that more diverse regional economies are likely to experience lower risks of a crisis or gradual decline due to lock-in situations (Martin, 2012; Balland et al., 2015; Xiao et al., 2018). Regions, however, can diversify their portfolios by recombining knowledge components that are more or less related to one another from a cognitive viewpoint (Nooteboom, 2000; Nesta and Saviotti, 2005; Neffke et al., 2011; Caragliu and Nijkamp, 2016; Castaldi et al., 2015; Content and Frenken, 2016).

The literature has extensively studied the importance of related diversification – measured in the empirical literature through related variety or relatedness indicators – along several dimensions, including, but not exclusively, the technological one. The concept of related variety, as the first attempt to measure regional related diversification, was introduced by the seminal work of Frenken and colleagues in 2007 (Frenken et al., 2007), which claims that Jacobian externalities (i.e., diversification externalities) do not always result in knowledge spillovers. Knowledge spillovers are effective only when complementarities exist among sectors in terms of shared competencies. Building on these insights, the literature studying regional diversification has highlighted that diversification within a dynamic framework is not random but follows identifiable patterns. Pinheiro et al. (2022) provide recent evidence on the timing and frequency of diversification. They build on the notion of path dependence in innovation and development (Dosi, 1982; Arthur, 1994), bounded rationality in economic decision-making (Simon, 1990) and absorptive capacity in learning (Cohen and Levinthal, 1990) to argue that diversifying into related fields is relatively easier, overall, less costly, and therefore more probable at any given point in time. This literature also highlights that regional economic performance is influenced by the structure and composition of the stock of regions' economic capabilities (Tanner, 2016; Kogler et al., 2017). Local economies built on more related economic components have been found to outperform those characterised by lower complementarity levels (Frenken et al., 2007; Kogler et al., 2013; Rocchetta et al., 2022b).

Related diversification mainly influences regional employment growth. Regions that diversify into economically related activities – where economic actors leverage complementary competencies – are more likely to engage in interactive learning processes. These processes foster knowledge recombination, which, in turn, facilitates the emergence of new growth paths (Boschma and Frenken, 2011). Ultimately, this leads to the development of related industries and contributes to job creation. This mechanism has been extensively studied in the literature. Early studies measuring the related variety of the regional industrial structure (Frenken et al., 2007; Bishop and Gripaios, 2010; Mameli et al., 2012) suggest that related industrial diversification positively influences employment growth. Similarly, Boschma and Iammarino (2009) highlight that extra-regional knowledge gained from trade with related sectors can enhance regions' employment growth. Additionally, research indicates that higher levels of related variety – whether in skills (Diodato and Weterings, 2015), industry (Holm and Østergaard, 2015), or technology (Rocchetta and Mina, 2019) – strengthen employment performance during crises. In these studies, related variety has often been measured by an entropy-like statistic based on a hierarchical classification of industries, products, occupations, or technologies. However, such indicators may not fully capture the real-world range of possible combinations, as the degree of relatedness between economic components is predetermined by the taxonomy design. Therefore, this approach can overlook real-world cognitive proximity between economic components (Fitjar and Timmermans, 2017; Rocchetta et al., 2022a; Barbero et al., 2024). Moreover, this construction renders the concept of related variety largely static, as it does not allow proximity between economic components to evolve over time due to its reliance on a predefined taxonomy (Martynovich and Taalbi, 2023). To address these limitations, scholars have increasingly employed the co-occurrence of economic components or the similarity of resources used between economic components to define indicators of revealed relatedness between economic components (Neffke and Henning, 2013; Whittle and Kogler, 2020). These outcome-based approaches of relatedness rely on the assumption that the more two industries, occupations, skills, or technologies co-occur or use resources with a high degree of similarity, the more they are related, and their recombination is economically viable (Teece et al., 1994) as there are economies of scope between them. Following this approach, Li and Neffke (2024) corroborate previous findings on the positive association between the presence of related industries and employment growth using different outcome-based measures of relatedness.

There are alternative measures of revealed relatedness that are based on labour mobility. The rationale is that workers tend to change to employers that are either in the same industry or in industries that rely on similar skills and competencies. Consequently, higher levels of mobility between industry pairs are a sign that these industries are more related (Fitjar and Timmermans, 2017). Following the same line of inquiry, Neffke and Henning (2013) claim that a firm will likely focus its diversification efforts in areas that require skills already possessed by its current workforce. Therefore, we can infer that there is more new job creation in regions with a higher level of skill relatedness. This is confirmed by the study of Hane-Weijman et al. (2022), which indicates that increases in occupational relatedness are positively associated with employment growth. Regions generating new jobs in more rather than fewer related occupations would enjoy faster employment growth due to the recombinatory potential and local synergies that arise (Frenken et al., 2007; Hane-Weijman et al., 2022).

As industry relatedness primarily reflects past development paths (Martynovich and Taalbi, 2023), alternative dimensions of related diversification have been investigated by recent literature. Specifically, there has been an increasing interest in the concept of technological relatedness as a measure of proximity between the technologies used by regional economic actors (Boschma and Frenken, 2011). Following the previous literature on relatedness, Kogler et al. (2013) and Boschma and Capone (2015) proposed an operationalisation based on the co-occurrence of patents' technology classes. Scholars engaging in this literature agreed on the idea that the pattern of technological diversification depends on existing capabilities and that technologies related to the regions's pre-existing technologies have a higher probability of entering the technological space of the region (Boschma and Capone, 2015; Rigby, 2015; Kogler et al., 2013; Santoalha et al., 2021). However, this strand of literature generally has been focused more on the evolution of technology rather than on evaluating the impact of technological relatedness on regional development or economic performance (Bathelt and Storper, 2023). Barbero et al. (2024) is an exception in that their results suggest that related technological diversification has a positive effect on regional performances, including employment. Recent studies have also found that a higher level of technological relatedness makes regional economies more able to maintain positive performance in terms of employment growth during crises (Rocchetta and Mina, 2019; Rocchetta et al., 2022a). If local economies develop technological capabilities that are more related, they will be able to adapt more quickly to exogenous changes in market conditions. Technological diversification is a prerequisite for diversification in production (Pavitt, 1998), which in turn contributes to the creation of new jobs. Therefore, when such diversification is related – that is, when new technologies build on capabilities that are similar to the already existing ones, – it facilitates labour mobility across sectors by reducing skill mismatches and lowering retraining costs, thereby decreasing labour market frictions.

While existing studies on related diversification have extensively analysed the short-term (i.e., within a few years) role of relatedness defined along different dimensions (industry, skill, and technology), to the best of our knowledge, the literature has not yet considered the persistence of these effects on regional economic performance. In a dynamic framework aimed at identifying the influence of relatedness on regional economic performance over time (i.e., considering both the short- and long-run), relatedness measures based on technological knowledge (e.g., co-occurrence of patents' technology classes) are superior to indicators of industrial and skill relatedness (Martynovich and Taalbi, 2023). As this paper aims to fill the gap in the literature and capture both the short- and long-run effects of diversification, we consider the technological dimensions in defining regional diversification. Technological relatedness anticipates recombination patterns between industries and skills, mirroring the growth patterns observed in related diversification within industry composition (Lo Conte et al., 2025). The evolution of technological components in the regional knowledge space serves as a crucial 'map' of changing capabilities within the economic opportunity sets of regional actors. Therefore, technological components can be seen as the backbone of industrial competitive advantage and as predictors of regional industry and skill evolution. This approach captures potential relatedness ties that may or may not be realised but still reflect the regional economy's incumbent capabilities.

Since technological relatedness mirrors and anticipates the recombination of skills and industries within each region, and the prior literature suggests that both occupational and industrial relatedness are positively associated with employment growth, we can infer that technological relatedness also has a positive impact on employment growth. This conjecture aligns with the idea that there is a match between incumbent technological capabilities, the demand for skills, and the resulting industry composition (Foray et al., 2009). Indeed, a capabilities-matching approach is likely to drive the reallocation of production factors towards industries where technological capabilities are stronger.

To the best of our knowledge, existing findings have primarily focused on the relationship between related diversification and regional economic performance in a static setting by showing that relatedness is positively associated with employment growth both in cross-sectional and panel fixed-effect analyses. However, as place-based innovation policies increasingly rely on technological relatedness as a tool to enhance regional economic performance, it is also important to evaluate whether increases in technological relatedness have a positive and persistent effect on regional economic performance. When a region's technological relatedness increases, it reflects the development of new technologies that share underlying capabilities. Since technologies often mirror and anticipate the emergence of new industries, we argue that such increases in relatedness can also signal forthcoming job creation in sectors that require similar competencies. As extensively shown in the literature, related diversification is particularly important in the short run. Since knowledge is tacit and sticky, sourcing related knowledge within a region reduces both learning costs and the time required for new knowledge absorption, ultimately facilitating the creation of new jobs in economic activities that rely on related capabilities. However, in addition to facilitating knowledge recombination, technological relatedness influences the resilience of regional industrial bases, which in turn shapes local demand and inter-industry spillovers. New job creation in technology-adjacent sectors can stimulate growth in supporting services – such as retail, logistics, and education – creating multiplier effects consistent with Jacobs-type externalities (Jacobs, 1970; Glaeser, 2005; Beaudry and Schiffauerova, 2009). These dynamics highlight that the benefits of technological relatedness extend beyond patent-intensive sectors, generating employment opportunities even in developing regions where high patenting industries are not dominant (Barbero et al., 2024). By strengthening complementary service ecosystems and fostering cross-sectoral interactions, technological relatedness serves as a key mechanism for broad-based regional development (Boschma and Frenken, 2010; Pinheiro et al., 2022).

This leads us to conjecture the following hypothesis:

HP1: An increase in technological relatedness has a positive effect on regional employment growth in the short run.

There are, of course, trade-offs between regional development strategies favouring more or less related technological diversification. It can be argued that decreasing returns and even risks of technological lock-in might set in if the region follows a knowledge-components diversification path based on technological relatedness in the pursuit of efficiency. In the long run, the exploitation of related knowledge combinations can exhaust their potential as sources of innovation because all possible variants have already been utilised (Fleming, 2001; Aharonson and Schilling, 2016). At some point, the advantages of a highly related set of technological capabilities can be offset by the need for major transformations – to keep up with technological development – and more diversified knowledge, differentiating a regional innovation system from its competitors. This is in line with the findings of Rocchetta et al. (2022b), which provide econometric evidence that the development of related technologies has a positive impact on regional performance. However, this effect is not linear, meaning that economic performance also benefits from the development of technologies that are more distant from the regions's knowledge base. Similarly, Barbero et al. (2024) found that related diversification might be especially effective in less developed regions whose economic structure is not yet fully diversified in technologically related ways and which are relatively distant from the technological frontier. Conversely, in more advanced regions that have a dense and highly related technological space, the impact of related diversification tends to be modest. To achieve sustained and sustainable economic growth, these regions should rather seek to introduce more paradigm-breaking innovations.

Entering into very different areas of specialisation relative to the technological capabilities present in the region is difficult. In the history of economic development, there have been successful instances of 'leapfrogging' (Soete, 1985; Brezis et al., 1993; Lee and Lim, 2001; Lee, 2013; Lee and Malerba, 2017), but these have been relatively infrequent (Petralia et al., 2017; Pinheiro et al., 2022). The reason is that diversifying into unrelated fields requires very high levels of technological capabilities (Xiao et al., 2018), availability of resources (Petralia et al., 2017), and often strategic assets only available to large multinational firms (Cortinovis et al., 2020).

At the same time, the effect of recombining more distant or more unrelated pieces of knowledge is not clear yet. Scholars have not produced conclusive results on the relationship between unrelated diversification of different economic components (such as industry, trade, technologies, and skills) and regional economic performances. By employing a hierarchical-based measure of unrelated diversification analogous to the related variety indicator, Frenken et al. (2007) highlight that unrelated industrial variety dampens unemployment growth. Saviotti and Frenken (2008) found that unrelated export variety promotes growth with a considerable time lag. On the contrary, Quatraro (2010) indicates that unrelated technological variety is insignificant for productivity growth. This evidence inconsistency is possibly due to a measurement bias linked to the hierarchical-based measure of unrelated diversification that has been employed so far. The unrelated variety indicator is complementary and symmetrical to the one of related variety, and it is based on an entropy-like statistic. As highlighted for the related variety, hierarchical-based measures are static and not able to capture the cognitive distance between the components that make up the regions's economic structures.

Despite the inconclusive relationship between unrelated diversification of regions and their economic performance, scholars agreed on the idea that, while relatedness is crucial for generating and sustaining innovation, unrelated diversification is more likely to lead to radical breakthroughs (Martynovich and Taalbi, 2023). Following this line of inquiry, Perruchas et al. (2020) find that unrelated variety was the main driver in the early stages of green technology development in the US. In a similar vein, Castaldi et al. (2015) and Miguelez and Moreno (2018) demonstrate that unrelated variety is positively associated with high-impact breakthrough innovation in the US and EU. Moreover, Mascarini et al. (2023) show that firms in regions with a higher degree of regional unrelated variety are more likely to generate upper-level innovation. This is because recombining knowledge from distant technology fields is perceived to result in more novel and valuable inventions (March, 1991; Trajtenberg et al., 1997; Fleming, 2001). While relatedness facilitates incremental innovation by reinforcing existing patterns, it also limits the potential for breakthrough innovation, as highlighted by Plunket and Starosta de Waldemar (2023). Similarly, Barbieri et al. (2020) highlight that unrelated variety is the main driver of green technology development in the early stages, while related variety becomes more prominent when the technology enters maturity. Therefore, a region needs to combine related and technological diversification to be efficient in producing innovation (Boschma et al., 2023). Unrelated diversification, and especially technological 'unrelatedness', provides regions with the necessary capabilities to propose more innovative contributions by exploiting underexplored areas of the technological space and proposing unusual combinations of knowledge (Plunket and Starosta de Waldemar, 2023).

Berkes and Gaetani (2021) contribute to the debate on the role of unusual knowledge recombination by introducing the concept of 'unconventionality' to identify the presence of atypical combinations (Uzzi et al., 2013) of technological knowledge. Atypical combinations indicate combinations that have rarely been used before or are entirely new, blending more distant and unrelated pieces of knowledge. This new knowledge recombination is often associated with higher risk and uncertainty (Fleming, 2001; Wang et al., 2017). Scholars have long recognised the uncertainty of scientific and technological progress (Nelson, 1959; Arrow, 1962; Rosenberg, 1998) and, in connecting this principle with the Schumpeterian insight that innovation consists in new combinations of previous ideas (Schumpeter, 1939), Fleming (2001) argued that, in theory, in any knowledge system, there are no restrictions to what can be recombined and that what is perceived to 'belong together' by scientists and engineers is the product of habit and social conventions that might change over time. Uzzi et al. (2013) show that the most impactful scientific articles combine conventional combinations of previous works with intrusions of unconventionality. However, the production of unconventional knowledge is usually associated with specific innovation systems. Berkes and Gaetani (2021) point out that only high-density urban locations can diversify and produce unconventional ideas, while Abbasiharofteh et al. (2023) show that innovations based on knowledge unconventionality result from connections between specialised inventor communities.

The notion of unconventionality has already been used in the literature to characterise inventions carried out in local economies (Berkes and Gaetani, 2021; Abbasiharofteh et al., 2023). However, this concept can also be extended at the regional level to analyse the extent of unrelated recombination in regional technological diversification trajectories and provide an output-based measure of unrelated diversification. This measure can overcome the limits of the unrelated variety indicator and provide information on the degree of unrelated technological diversification of regions in a dynamic framework. Moving the concept of unconventionality to the regional level, we can infer that regional technological unconventionality, as a measure of technological diversification, though riskier and less common, can help regions push the boundaries of their technological frontier, leading to new long-term competitive advantages (Pinheiro et al., 2022). Unrelated diversification, indeed, fosters the emergence of more radical innovations, which have the potential to push a regions's technological frontier outward. Barbero et al. (2024) explains this concept by using a technological frontier framework, where the frontier represents the limit of a regions's ability to recombine and exploit existing knowledge, thereby defining the space for achievable growth within a given production paradigm. In this context, increasing technological relatedness allows regions to more efficiently exploit growth opportunities within existing cognitive constraints. In contrast, enhancing technological unrelatedness in a region involves moving beyond these cognitive limits, breaking free from path dependency, and driving structural change. Such processes can lead to an outward shift of the technological frontier itself, creating new growth possibilities for regional economies.

Therefore, while an increase of technological relatedness ensures efficient exploitation of existing knowledge, an increase of technological unconventionality may have a more persistent impact on expanding the level of output in regional economies in the long run. This is because the exploration of unconventional knowledge combinations may lead to performance degradation in the short term, as the search for novel solutions is more prone to failures (Aharonson and Schilling, 2016). As such, the positive impact of an increase in unrelated knowledge recombination is more likely to manifest over the long term. Moreover, the effects of increases in unrelatedness will be more apparent in terms of output growth rather than job market changes, as technological change often leads to creative destruction, which can result in a temporary rise in unemployment.

This motivates the following hypothesis:

HP2. An increase in technological unconventionality has a positive effect on regional output growth in the long run.

In this paper, we test these two hypotheses by focusing on identifying the effects of qualitatively different types of technological diversification on regional economic performance. Specifically, we will consider the effect of increases in technological diversification on two indicators that depict complementary yet different aspects of regional economic performance, i.e. employment and GDP growth. While the first depicts how the job market is evolving, proxying consumer spending and poverty rates, GDP measures the total economic output of a region, including all goods and services produced within its borders. Despite the extensive literature existing on different forms of diversification and regional performances, the available empirical evidence is still descriptive. In trying to assess the effects of diversification, it has been difficult to address endogeneity concerns associated with the path-dependent nature of technological diversification, and identification problems have remained pervasive. Through the application of Panel Vector Autoregression models (PVAR) and the generation of impulse response functions (IRFs), we isolate the causal dynamic effects of technological diversification under clearly defined identification assumptions. This approach allows us to assess not only the magnitude but also the persistence of these effects. By considering both the short- and long-run impact of technological diversification, we fill a gap in the literature that predominantly focuses on short-term effects. In addition, this paper contributes to the existing literature by examining the impact of increases in both technological relatedness and technological unconventionality on employment and GDP growth. This analysis is particularly relevant for the design and implementation of targeted place-based innovation policies. Finally, we provide novel and original evidence on the effects of an increase in technological unconventionality as an outcome-based measure of unrelated diversification, in addition to technological relatedness, on the performance of regional economies.

3. Methodology

As reviewed in the previous section, the extant literature has shown that *ceteris paribus* technological diversification can be associated with different dimensions of economic performance. This relationship has been observed both in cross-sectional analyses (Frenken et al., 2007; Boschma and Iammarino, 2009) and short panel fixed-effect studies (Rocchetta and Mina, 2019; Rocchetta et al., 2022a; Boschma et al., 2023). While both approaches assess the correlation between technological diversification and economic performance, they do not allow one to identify dynamic causal effects while accounting for feedback mechanisms between variables. Contrary to cross-sectional studies, panel fixed-effect analyses, by studying simultaneous variations of dependent and independent variables within a region, control for regional time-invariant characteristics and reduce – but do not remove – endogeneity issues. Residual endogeneity issues can be limited by exploiting the time-series properties of panel data and studying the dynamic relationship between the variables of interest. Moving beyond static correlations, this approach identifies the dynamic causal impact of shocks within a system of interdependent variables, offering a robust empirical foundation for the design of regional innovation policies. Specifically, we can employ Panel Vector Autoregression (PVAR) models to detect the dynamic relationship between various types of technological diversification and different dimensions of economic performance. The PVAR approach extends standard Vector Autoregression (VAR) models to a panel setting, allowing us to account for unobserved regional fixed effects. A primary advantage of this model is that it treats all variables as endogenous, explicitly modelling the intertemporal feedback mechanisms where variables are jointly determined over time. To identify causality within this system, we derive Impulse Response Functions (IRFs) associated with PVAR models. This approach is particularly useful to estimate conditional causal effects in settings where variables are interconnected and jointly endogenous. By imposing a recursive structure, we isolate variations in technological diversification that are contemporaneously independent of other macroeconomic variables. This allows us to interpret the resulting IRFs not merely as correlations, but as the dynamic response of regional economic performance to exogenous variations in technological diversification. The use of a PVAR framework further ensures that these causal estimates are robust to time-invariant regional characteristics.

To design the econometric strategy, it is important to acknowledge that economic conditions are likely to drive technological diversification, while simultaneously, technological diversification can impact regional economic performance. Moreover, changes in the structure of the stock of technological capabilities could have both immediate and delayed effects on the economy. Cross-sectional and short panel-based analyses are therefore likely to miss important dynamics and face substantial challenges in terms of identifying causal effects. While fixed-effect models are designed to estimate one-way relationships, PVAR models are explicitly built to capture how all the variables included in the regression can affect each other over time and allow for 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 region r and time t, respectively, we can write our variables of interest as the vector $X_{rt} = [TU_{rt}\ TR_{rt}\ E_{rt}\ G_{rt}]'$, where TU_{rt} is technological unconventionality in region r at time t, TR_{rt} is technological relatedness (measured through the technological coherence index; see Section 4.1) in region r at time t, E_{rt} is the rate of employment growth in region r at time t, and G_{rt} is the rate of GDP growth in region r at time t (see Section 4.1 for more details). We use growth rates for employment and GDP as tests to indicate that these variables are non-stationary in levels.

Our reduced-form model can be written as:

$$X_{rt} = \alpha + \sum_{i=1}^{p} \beta_i X_{r,t-i} + \phi_r + \epsilon_{rt}, \tag{1}$$

where α is a vector of constants, β_i is the matrix of coefficients for lag i, ϕ_r are regional fixed effects and ϵ_{rt} are the residuals.[2] To correct for the potential for dynamic panel bias (Nickell, 1981), we apply the Helmert transformation (forward orthogonal deviation) and estimate the transformed model using the generalised method of moments (Abrigo and Love, 2016). Lag length, p, is determined by calculating moment model selection criteria proposed by Andrews and Lu (2001). In our case, these section criteria suggest that the optimal lag length is one.[3] Following Holtz-Eakin et al. (1988), we use "GMM-style" instruments to improve efficiency by replacing missing values for lagged instruments with zero.[4] Standard errors are clustered at the regional level.

The generation of Impulse Response Functions (IRFs) resulting from PVAR models allows us to trace the dynamic effects of changes in technological relatedness and technological unconventionality on GDP and employment growth. This is particularly useful for drawing policy implications from our results. 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 (usually referred to as a shock in the literature) to a variable affects all the other variables. In this study, IRFs estimate the dynamic causal effects of orthogonalised shocks to technological diversification indicators on GDP and employment growth, in terms of both magnitude and persistence, conditional on the identification restrictions of the PVAR model.

We present orthogonalised impulse response functions that illustrate the effects of one standard deviation shocks. However, as the terms in ϵ_{rt} are correlated, the changes in one variable will not be independent of the changes to the others. To identify causal effects and isolate technological diversification shocks, we impose a recursive structure via Cholesky decomposition. This approach achieves identification by determining the specific order in which shocks propagate through the system, effectively orthogonalising the error terms. Our ordering is based on the following logic. A variation in the extent to which technological components are combined in an unconventional manner (technological unconventionality) represents a fundamental change to the structure of the regional economy (Berkes and Gaetani, 2021). Thus, we allow such shocks to influence technological relatedness, employment, and economic growth contemporaneously. Changes in technological relatedness, which captures the extent of cognitive proximity across the technological elements that compose the regional knowledge base (Nesta and Saviotti, 2005, 2006), are assumed to only influence the degree of technological unconventionality with a lag but can affect employment and growth contemporaneously. These first assumptions state that technological variations can contemporaneously affect employment and economic growth (Freeman et al., 1982; Grossman and Helpman, 1993). Shocks to employment and economic growth are assumed to influence only both aspects of technological capability with a lag. This assumption hinges on the idea that economic and employment growth changes do not immediately translate into new technological capabilities because the development of new scientific and technological knowledge takes time (Nelson, 1959; Dosi, 1982). Finally, while we allow for variations in employment to influence GDP growth contemporaneously, the latter only operates on the former with a delay. We make this assumption based on the existence of significant labour market frictions in Europe. Although we believe that this set of identified assumptions is plausible, in Appendix A we also present results for alternative orderings of the shocks. The consistency of these results suggests that our conclusions are robust to the recursive structure and are not driven by omitted time-varying factors correlated with the ordering of variables. Confidence intervals are obtained from a Monte Carlo simulation with 1000 draws.

4. Data and variables

We collect data on regional economic performance at the NUTS II level from Eurostat regional statistics.[5] Our data covers the period

[2] The inclusion of regional fixed effects allows us to remove all other time-independent factors that may affect regional economic performance, including regional industrial structure and other forms of innovations. Moreover, the autoregressive nature of this model allows us to isolate the effect of technological diversification on employment and GDP growth while controlling for regional growth paths that might depend on other important factors such as urbanisation, globalisation, or manufacturing decline.

[3] Robustness checks in Appendix A show the main results with more lags.

[4] We use two lags as instruments. However, we test the results by introducing more lags (see Appendix A).

[5] NUTS II regions provide an intermediate level of granularity for statistical analysis and reporting and reflect socio-economic differences within countries

between 1980 and 2014. This information is combined with patent data, used as a proxy of regions' technological capabilities (Balland et al., 2022; Pinheiro et al., 2022; Rocchetta et al., 2022a), extracted from the PATSTAT database of the European Patent Office (EPO) and the OECD RegPat database.[6] We select only patents filed at the EPO and assign those patents to NUTS II regions based on the inventors' residential address and the patent priority year, i.e. the earliest year in which a patent, or the patents in the same family, is filed at a patent office.[7] We then determine the technological diversification of a region in a given year by considering the technology codes assigned to each patent with inventors in that area. Technology codes classify technology hierarchically embedded in patented inventions and are useful for mapping the technological capabilities of regions. Specifically, we use the Cooperative Patent Classification (CPC) at the 4-digit level, obtaining 654 technology codes. We constructed our final sample using all NUTS II regions with consistently available data on employment growth, GDP growth, and patent activity, covering 268 regions over a 35-year period.[8] While patents do not fully capture all innovation activity or its economic value (Pavitt, 1998), they provide detailed and standardised information on the technological composition and novelty of inventive efforts, enabling systematic and cross-regional comparisons over time. This makes them particularly well-suited for analysing knowledge recombination processes and diversification patterns. In this paper, indicators of technological relatedness and unconventionality are derived from the structure of regional patent portfolios rather than simple patent counts, allowing us to map the evolution of capabilities that drive regional economic transformation. From the same databases, we also retrieve control variables used in the robustness checks analysis, i.e. the number of patents and population level.

4.1. Main variables

The main variables of interest are: (i) technological diversification indicators that capture the technological capabilities of regions and their ability to explore new domains at the innovation frontier; (ii) regional economic performance indicators.

We employ two technological diversification indicators to capture different aspects of the regional knowledge base: technological relatedness, measuring related diversification, and technological unconventionality, measuring unrelated diversification. Both measures are based on the analysis of regional patent portfolios. As discussed in Section 2, technological relatedness and unconventionality indicators can be thought of as refined measures of related and unrelated variety indicators applied to technology (Frenken et al., 2007). While the latter indicators represent the first crucial attempts to detect regional industrial and technological diversification, they do not come without limitations. First, their definition is based on hierarchical classifications that are supposed to reflect the degree of relatedness or similarity between industry or technology classes. A key assumption of this approach is that classes are related only if they belong to the same 'high-level class' and all these classes are equally similar to each other. At the same time, all subclasses belonging to different high-level classes are supposed to be equally distant, independent of their characteristics. As an example, in the related and unrelated variety framework, pharmaceutical technologies appear as unrelated (distant) to chemical technologies as they are to transport technologies. Moreover, all pharmaceutical technologies are considered equally related to each other, independently of their application field or chemical structure. The use of hierarchical classifications facilitates the computation of related and unrelated variety indicators but oversimplifies the analysis and can undermine an accurate detection of regional technological relatedness and unconventionality. More recent diversification indicators, including technological relatedness and unconventionality, try to address this limitation by going beyond hierarchical classifications and relying on knowledge or technological spaces that map the relationship between different classes more precisely. Specifically, they infer class similarity based on class co-occurrence in the same region in a given period of time, where co-occurrences are seen as a measure of revealed distance between technology classes. This approach returns a continuous measure of class relatedness that can be used to spot the average regional relatedness as well as the presence of unconventional combinations in the regional diversification strategy. Another crucial limitation of related and unrelated variety is that, by construction, they might be highly correlated. For this reason, it might be difficult to assess their simultaneous effect on regional economic performance. At the same time, considering separately the two dimensions could result in biased estimations, as recently highlighted by Bathelt and Storper (2023). Therefore, going beyond the traditional related and unrelated variety indicators has several advantages. First, it allows us to provide more precise estimations of regional technological diversification by relying on a dynamic technological space to detect class proximity instead of considering pre-determined and fixed hierarchical levels. Second, this approach permits assessing the joint effect of related and unrelated diversification on economic growth.

Technological relatedness. Following previous literature on related diversification (see, e.g., Nesta and Saviotti, 2005; Quatraro, 2010; Rocchetta and Mina, 2019; Rocchetta et al., 2022a), we measure regional technological relatedness by employing the regional technological coherence index. This indicator, defined by Nesta and Saviotti (2005), identifies the average cognitive proximity among the technologies present in a region in a given period. Regions with high technological relatedness show a high degree of homogeneity in their inventions. These regions diversify in technologies that frequently occur together in regional technological portfolios, suggesting that these technologies are likely based on related technological capabilities. The use of patent portfolios to compute the technological relatedness indicator allows us to capture the knowledge base of a region and detect how it evolves over time.

Based on patent portfolios and the associated technology classes (4-digit CPC codes), we can, therefore, detect the technological capabilities of a NUTS II region. Specifically, we define a dummy variable

while maintaining consistency across the EU for comparative purposes. As such, they are appropriate to study the relationship between regional economic performance and technological diversification in an international comparative setting. Analyses at the NUTS III level may prove even more effective, but no comparative data are available to date to guarantee sufficient coverage of European regions.

[6] It is important to stress that patents are not intended to proxy the entire regional economy, but rather to capture the structure and evolution of regions' technological capabilities, which precede and shape broader economic dynamics. We use patents as indicators of regional technological capabilities, and not as a measure of the value of intellectual property to individual firms. Technological capabilities are built before and during the process of patent application (e.g., cumulatively throughout the whole R&D process), and not only after firms can reap (eventually) the commercial benefits of intellectual property. For this reason, we might expect both a short- and long-term effect of technological diversification on regional economic performance. Moreover, we are interested in the structure of technological capabilities more than their volume (the identification of variations in diversification is consistent with this objective), and the use of shorter lags between changes in technological capabilities and regional economic performance may lead to under- rather than over-estimation of effects. Together with the technical considerations discussed in Section 3, these conceptual observations led us to choose a one-year lag structure in our main economic exercises, even if we provide robustness checks with more lags in the Appendix.

[7] Patents with inventors in multiple regions are assigned equally to all the relevant regions. Moreover, we select the priority year of patents to date regional innovation activities to be as close as possible to the year of invention.

[8] Due to the presence of a few missing values in economic performance data, the total number of observations is 7499.

G_{jrt} that is equal to 1 if a region r at time t produces knowledge in the technology class j and 0 otherwise. Thus, the total number of regions with patents in j will be $R_{jt} = \sum_r G_{jrt}$, and R is the total number of regions in the database. Based on this indicator, we can also define the observed co-occurrence (i.e., occurrence in the same region) of two technology classes j and k: $O_{jkt} = \sum_r G_{jrt} G_{krt}$. In this setting, O_{jkt} is the number of regions that have patents in both technologies j and k at time t. By assuming that frequently co-occurring technology classes are associated with similar underlying technological capabilities, we can define the coherence index τ_{jkt} (Teece et al., 1994) associated with each pair of technology classes j and k at time t as their normalised co-occurrence. The normalisation is needed due to the unbalanced distribution of technology classes across regions, and entails the scaling of observed co-occurrences under the hypothesis that technological diversification is random. Therefore, we define the coherence index as:

$$\tau_{jkt} = \frac{O_{jkt} - \mu_{jkt}}{\sigma_{jkt}}, \tag{2}$$

where μ_{jkt} is the expected number of co-occurrences given the size of the two technology classes (i.e., the average of the counterfactual random sample X_{jkt})

$$\mu_{jkt} = E\left(X_{jkt}\right) = \frac{R_{jt} R_{kt}}{R}, \tag{3}$$

and σ_{jkt} is its variance

$$\sigma_{jkt} = \mu_{jkt}\left(1 - \frac{R_{jt}}{R}\right)\left(\frac{R - R_{kt}}{R - 1}\right). \tag{4}$$

Once we have determined the coherence index of technology-code pairs, we can calculate the weighted average relatedness WAR_{jrt} of technology j in a region r at time t:

$$WAR_{jrt} = \frac{\sum_{k \neq j} \tau_{jkt} P_{krt}}{\sum_{k \neq j} P_{krt}}, \tag{5}$$

where P_{krt} is the number of patents associated with technology k in region r at time t. WAR_{jrt} represents the average relatedness of technology j, in a given region and year, to all other technologies k patented in that region. The regional technological relatedness (also known as regional technological coherence) $Tech\_Relatedness_{rt}$ is, therefore, the average WAR_{jrt} of all technologies j patented in the region weighted by the share of patents associated with the different technology classes:

$$Tech\_Relatedness_{rt} = \sum_j WAR_{jrt} \frac{P_{jrt}}{P_{rt}}, \tag{6}$$

where P_{rt} is the total number of patents in region r at time t.

Technological unconventionality. Our second indicator of technological diversification is the regional technological unconventionality index. It captures how regions explore the frontiers of the technological knowledge space by investing in atypical and unprecedented combinations of previous knowledge. Unconventionality is conceived to measure the importance of unrelated technological diversification in regional innovation strategies. It relies on the detection of unconventional pairs of technology classes in the regional patent portfolio, where unconventional pairs are couples of technology classes that rarely occur together in the same region. To detect the relevance of these unconventional pairs in the regional technology diversification strategy, we consider the distribution of the distances between technology classes of patents filed by inventors in the region and select a percentile of this distribution that measures how important unconventional combinations are for each region. Regions with a high share of atypical combinations in their technology portfolio are those that rely on unrelated diversification strategies. Contrary to previous indicators of unrelated variety, this approach is not based on hierarchical classifications and allows us to better distinguish between related and unrelated diversification. Technological unconventionality is indeed orthogonal to technological relatedness since it analyses the presence and relevance of highly diversified technological capabilities instead of focusing on the "core" of these capabilities (as in the relatedness index). In principle, a region could have both high technological relatedness and high technological unconventionality as a signal of its ability to combine a robust knowledge base with the propensity to explore new avenues. To measure technological unconventionality, we propose a generalisation at the regional level of the atypical combination index introduced by Uzzi et al. (2013) and revisited in Berkes and Gaetani (2021) and Fontana et al. (2020).

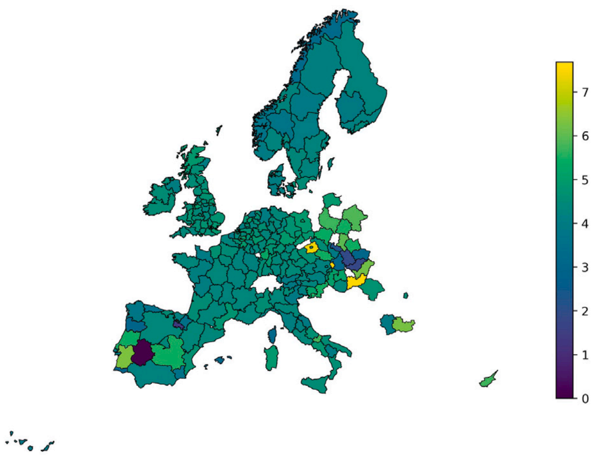
As for the relatedness index, the first step consists of defining a technological knowledge space that allows us to detect atypical (distant) combinations of technological codes. This knowledge space evolves over time and is based on the proximity TP_{jkt} between technology classes j and k at time t. This technological proximity is defined as the normalised co-occurrence of these classes in the same region. In fact, technologies that frequently co-occur together are likely based on similar technology capabilities, while atypical combinations might be related to distant technological skills. We calculate technology proximity in four steps. First, we compute the number of occurrences NO_{jrt} in each region r of the technology class j at time t. It is important to consider the variation over time of this index as a combination of knowledge could be atypical in a certain year and become conventional in the following period. In this context, a dummy variable that simply signals the presence of technology in a region is not suited to detect highly atypical combinations, and a more granular variable, such as the number of occurrences, is required. Second, we use the number of occurrences NO_{jrt} of each technology class in each region at time t to compute the observed number of co-occurrences between two technology classes j and k as $NCO^{obs}_{jkt} = \sum_r NO_{jrt} NO_{krt}$. Third, we proceed with the index normalisation as the number of co-occurrences depends on the size of j and k, as it was for the relatedness index. Following Uzzi et al. (2013), we normalise the observed number of co-occurrences by computing their expected number given the frequency of occurrence for each technology class. Specifically, we create, for each year, a null model of the bipartite network between regions and technology classes.[9] The null model creates a randomised version of such a network that preserves node degrees, i.e. the number of technologies associated with each region and the number of regions in which each technology occurs. We then determine the expected number of co-occurrences among technology classes if technological capabilities were randomly assigned to European regions by creating 100 different randomised bipartite networks[10] and considering the average numbers of co-occurrences between technologies in these randomised networks (b): $NCO^{exp}_{jkt} = \frac{\sum_{b=1}^{100} NCO^{b}_{jkt}}{100}$. Finally, following Berkes and Gaetani (2021) and Fontana et al. (2020), we compare observed and expected values of technology class co-occurrences to define the technological proximity between j and k at time t as[11]:

$$TP_{jkt} = \frac{\arctan\left(\frac{NCO^{obs}_{jkt}}{NCO^{exp}_{jkt}}\right)}{\frac{\pi}{2}}. \tag{7}$$

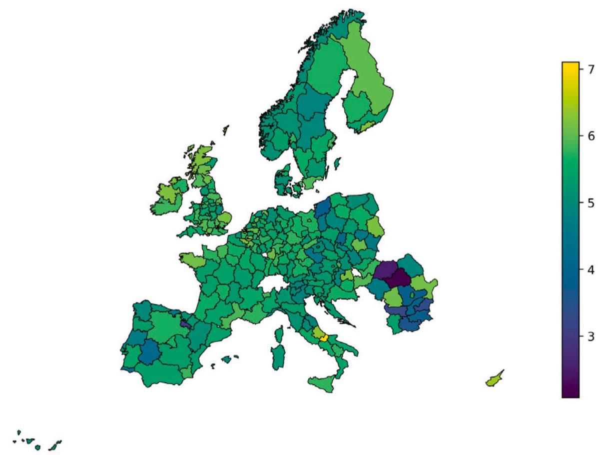
[9] It is worth noticing that Uzzi et al. (2013) focus on unconventionality in scientific articles' backward citations. Therefore, they rely on a null model of the citation network between scientific articles. In this paper, we are instead interested in atypical combinations of technology classes occurring in European regions. For this reason, we consider a bipartite network composed of regions (a set of nodes) and technology classes of patents filed in those regions (the other set of nodes). Edges connect regions with technology classes in which regions' inventors patent, and their weights are equal to the number of occurrences of each technology class in each region.

[10] Following Fontana et al. (2020), we consider 100 different randomised configurations instead of 10, as was suggested by Uzzi et al. (2013), to obtain more precise estimations of expected values.

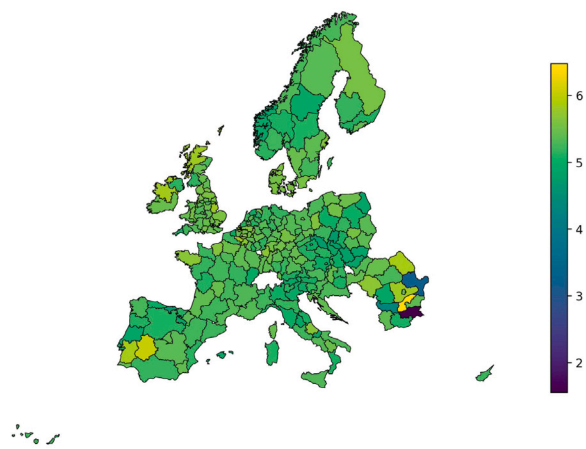
[11] The arc-tangent transformation is helpful to obtain a meaningful value of technological proximity since the ratio between observed and expected



(a) Tech Relatedness 1981–1994.



(b) Tech Relatedness 1995–2004.



(c) Tech Relatedness 2005–2014.

Fig. 1. Evolution of technological relatedness of regions. Average values by decades.

In the resulting technological knowledge space, technologies close to each other are those that frequently co-occur in regions. Examples of atypical combinations of technologies in European regions are 'Manufacture or preparation of tobacco for smoking or chewing' and 'Aircraft; Aviation; Cosmonautics', 'Bakers ovens; Machines or equipment for baking' and 'Digital computers in which all the computation is effected mechanically', 'Nanostructures formed by manipulation of individual atoms, molecules, or limited collections of atoms or molecules as discrete units; Manufacture or treatment thereof' and 'Broadcast communication'. Those technologies require a diversified set of unrelated capabilities that are infrequently present in a single European region. By analysing the relevance and frequency in each region of atypical (distant) technology pairs, we can compute the regional technological unconventionality as:

$$Tech\_Unconventionality_{rt} = 1 - 1^{st}\, percentile \left(F_r t(TC_{jkt}) \right), \tag{8}$$

where $F_r t(TC_{jkt})$ is the cumulative distribution of proximity TP_{jkt} among pairs of technology classes j and k in the region r at time t. By selecting the 1st percentile of this distribution, we detect the relevance of atypical combinations of technologies (that is, technologies with proximity close to 0) in the region. To interpret the index as technological unconventionality, we then subtract to one this percentile.[12]

co-occurrences returns a value ranging between 0 and infinity, where 1 discriminates between unconventional (lower than 1) and conventional (greater than 1) combinations. The arc-tangent transformation and the following normalisation, suggested by Fontana et al. (2020), allow us to obtain a more stationary value in a range comparable to the one of the relatedness index. The resulting indicator assigns 0 technological proximity to technology classes that never occur together, 0.5 to technology pairs that co-occur as expected, and 1 to technology pairs whose expected co-occurrence is zero but occur more than expected. Therefore, the arc-tangent transformation restores the symmetry between unconventional (lower than 0.5) and conventional (greater than 0.5) combinations. This indicator is highly correlated to the one obtained by defining a z-score based on the null model as in Uzzi et al. (2013) (Spearman correlation is 97%). At the same time, it is much more stationary and does not rely on standard deviations whose value might not be reliable for technology classes with few occurrences in the sample. Moreover, the resulting unconventionality index is much more comparable to the relatedness indicator than the one obtained using the original Uzzi et al. (2013) approach, which would run between minus infinity and plus infinity. As such, the approach suggested by Fontana et al. (2020) is more appropriate for our empirical analysis and produces easier interpretable estimates.

[12] The choice of the 1st percentile of the distribution results from the need to detect atypical combinations in regions of different sizes. Since very large regions or regions with a high number of patents have a considerable number of technology pairs, a higher percentile of the distribution may not properly detect unconventional technological pairs. However, we tested the robustness of our results by considering different percentiles of the distribution, and our conclusions hold.

Table 1
Summary statistics.

	Mean	Std	Min	Max	Count
Emp_Growth	0.01	0.02	−0.19	0.32	7499
GDP_Growth	0.02	0.04	−0.64	0.63	7499
Tech_Related	5.04	0.95	0.00	11.64	7499
Tech_Unconv	0.76	0.08	0.12	0.98	7499
No_Patents	238.49	433.23	1	3973	7499
Population	1846.35	1488.57	113.12	12 079.34	7499
Year	1998.75	9.58	1981	2014	7499

Employment and GDP growth. As indicators of economic performance, we use employment growth and GDP growth.[13] For each region r at time t, we define:

$$Emp\_Growth_{rt} = \frac{Emp_{r,t} - Emp_{r,t-1}}{Emp_{r,t-1}}, \tag{9}$$

where $Emp_{r,t}$ is the level of employment of region r at time t, as defined in the Eurostat database. And:

$$GDP\_Growth_{rt} = \frac{GDP_{r,t} - GDP_{r,t-1}}{GDP_{r,t-1}}, \tag{10}$$

where $GDP_{r,t}$ is the level of GDP of region r at time t.

4.2. Descriptive statistics

The final dataset contains 7499 region-year observations[14] and includes information about employment growth, GDP growth, technological relatedness, technological unconventionality, number of patents, and population.

Summary statistics on these variables are shown in Table 1, while Figs. 1 and 2 depict the evolution of regional technological diversification over decades. As shown in the figures, the number of regions with information on technological diversification and economic activities has increased over time since we obtained data on the Balkans and Eastern Europe for more recent years. The average value of technological relatedness is quite uniform across regions and has grown slightly over time (on average), despite the entrance of areas with low technological relatedness. We observe instead a slight decrease in the average value of technological unconventionality due to the entrance of regions with a high degree of technological conventionality. Technologically conventional areas are, indeed, concentrated in Eastern Europe, the Balkans, and the Iberian Peninsula. For both dimensions of technological diversification, we detect a tendency to stabilise on more similar values across European regions in the last decade of observation (2005–2014).

5. Results

Table 2 presents the coefficients from our PVAR model. As noted in Section 4.1 above, the information criterion indicated that our model should include one lag. Moreover, in the estimations we used the first two untransformed lags of each variable as instruments.[15]

Results in Table 2 show that increases in technological relatedness are positively associated with employment growth. This result is in line with previous findings and suggests that the ability of a regional economy to create employment is stronger when its technological structure exhibits a higher degree of cognitive proximity. Conversely, the association between an increase in technological relatedness and GDP growth is negative. Table 2 also shows a positive association between increases in technological unconventionality and GDP growth. This suggests that unconventional combinations of knowledge give rise to more value and more impact.

By analysing impulse response functions as described in Section 3, we can assess both the effect of technological diversification on regional economic performance and the persistence of these effects. The causal interpretation of IRFs is conditional on the recursive identification restrictions imposed via the Cholesky decomposition discussed in Section 3. Fig. 3 displays the orthogonalised impulse response functions associated with our PVAR models. Each subgraph traces the effects of a time-zero one standard deviation change in the dependent (impulse) variable. The four subgraphs in the lower left quadrant are of particular interest as they depict the effects of technological diversification on employment and GDP growth over ten years.

The results in Fig. 3 are in line with those reported in Table 2 and corroborate the conjectures we set out in HP1, showing a short-term effect of increases in regional technological relatedness on employment growth. Evidence presented in Fig. 3 indicates that a one standard deviation change in technological relatedness increases the growth rate of employment by approximately 0.85 percentage points. This effect falls to zero within 5 years. Conversely, a one standard deviation increase in technological relatedness reduces GDP growth by 0.3 percentage points at time zero. This negative effect is statistically significant and persists, though at a diminishing magnitude, for ten years. These results suggest that technological relatedness has a positive short-term impact on employment growth, but a negative and persistent one on more general indicators of regional economic performance.

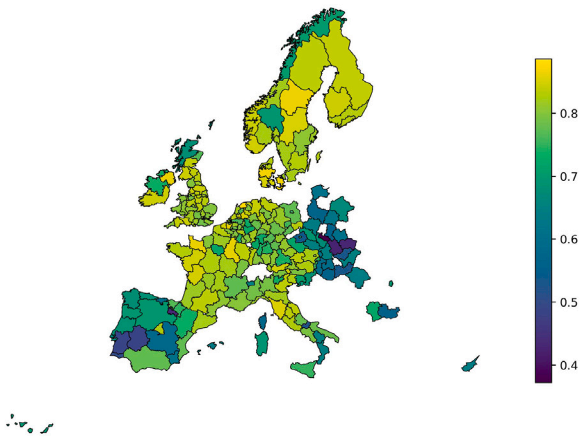
When we move to the analysis of technological unconventionality and its increase, the results presented in Fig. 3 on the effect on GDP growth support the claim outlined in our HP2. A positive change in technological unconventionality has an initial positive effect on GDP growth of 0.1 percentage points. Not only is the impact of a different sign to that of technological relatedness, but the effect of this time-zero change is larger in subsequent periods and remains statistically significant and positive. We find no evidence of a statistically significant influence of technological unconventionality on employment growth. Thus, regional technological unconventionality has a long-term positive effect on GDP growth but no impact on regional employment. Moreover, the effect of a standard deviation increase in technological unconventionality on GDP growth is higher in magnitude than the effect of a standard deviation increase in technological relatedness on employment growth.

The subgraphs in the top right quadrant of Fig. 3 show the effects of GDP and employment growth on technological diversification. We can observe that these results are symmetrical to the ones in the bottom left quadrant. GDP has significant negative effects over a sustained period on technological relatedness and positive effects on unconventionality. Specifically, a standard deviation increase in GDP growth reduces technological relatedness by 1.5 percentage points while increasing technological unconventionality by 0.75 per cent. Employment fosters greater levels of relatedness, namely a standard deviation change in employment growth increases technological relatedness by 7 percentage points. The initial effects on unconventionality are statistically insignificant, but later periods show a small negative effect of employment growth on this variable. Finally, the bottom right quadrant of Fig. 3 demonstrates that one technological feature has a negative effect on the other. These effects persist over our ten-year horizon.

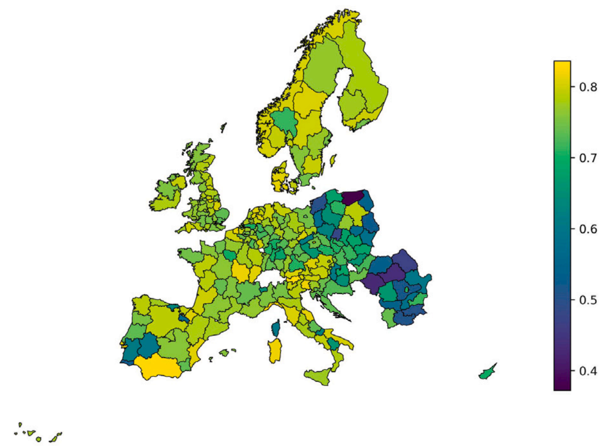
[13] We acknowledge that GDP, while widely employed as a measure of economic output, is subject to potential measurement biases when used over long time periods due to structural shifts in the global economy and evolving national accounting practices. Nonetheless, it remains the most widely accepted and comparable indicator of economic performance over time. Sensitivity analyses provided in the Appendix confirm that our results are robust to the exclusion of potential outliers, suggesting that measurement noise within the regional accounts does not bias our primary estimates.

[14] The number of observations in the econometric models is lower – 6929 – due to the use of lagged variables in PVAR and impulse response estimations.

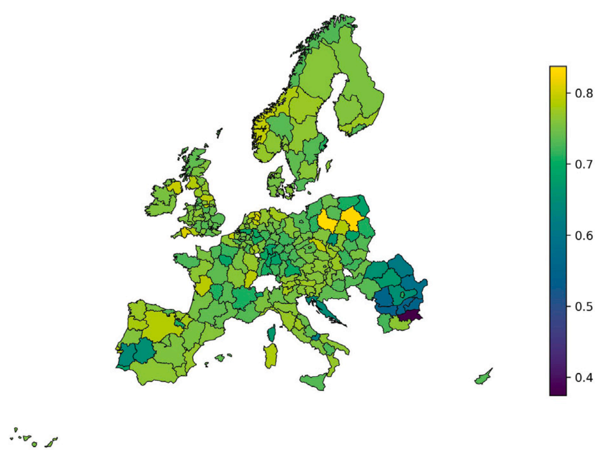
[15] Our results are robust to 2nd order VAR and use more lags as instruments (see Appendix A).



(a) Tech Unconventionality 1981–1994.



(b) Tech Unconventionality 1995–2004.



(c) Tech Unconventionality 2005–2014.

Fig. 2. Evolution of technological unconventionality of regions. Average values by decades.

5.1. Heterogeneous effects

In this section, we explore heterogeneous effects across regions with different characteristics. First, we split the sample into core and periphery regions by considering their GDP per capita. Second, we identify technologically advanced and technologically lagging regions by employing the number of patents whose inventors are located in the region. These analyses are important from a theoretical viewpoint, given the very different histories and composition of these economies, as well as from a developmental policy viewpoint, given the need to adapt regional development policies to different regional characteristics.

Core and periphery regions. The first heterogeneity test aims to study whether regions at the European core experience the same effects of technological diversification on economic performance as regions at the European periphery. The core comprises NUTS II regions with an average GDP per capita exceeding the European median, while the periphery includes regions with an average GDP per capita below the median.[16] Those subsets of regions are characterised by different development paths and are at different development stages. Therefore, we might expect different impacts of technological relatedness and unconventionality on regional economic performance in these two sets of regions.

Table 2
Main results.

	(1) $Tech\_Unconv_t$	(2) $Tech\_Related_t$	(3) Emp_Growth_t	(4) GDP_Growth_t
$Tech\_Unconv_{t-1}$	0.162^{***}	-1.205^{*}	0.002	0.034^{***}
	(0.043)	(0.691)	(0.009)	(0.013)
$Tech\_Related_{t-1}$	-0.022^{***}	0.470^{***}	0.002^{***}	-0.001^{**}
	(0.003)	(0.040)	(0.001)	(0.001)
Emp_Growth_{t-1}	-0.082^{*}	6.035^{***}	0.256^{***}	-0.099^{***}
	(0.048)	(0.660)	(0.039)	(0.025)
GDP_Growth_{t-1}	0.190^{***}	-5.267^{***}	0.141^{***}	0.520^{***}
	(0.039)	(0.594)	(0.013)	(0.029)
Observations	6929	6929	6929	6929

Notes: 1-lag PVAR estimations of the following reduced form model: $X_{rt} = \alpha + \sum_{i=1}^{p} \beta_i X_{r,t-i} + \phi_r + \epsilon_{rt}$. The main variables are technological unconventionality, technological relatedness, employment growth and GDP growth at time t in region r. All regressions include region-fixed effects. Standard errors are clustered at the regional level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3 reports the coefficients of the PVAR model applied to the subsets of core regions vs. the relationship in the remaining regions, while Fig. 4 presents the orthogonalised impulse response functions associated with those PVAR models. While the complementary effects of technological diversification on employment and GDP growth in

[16] We first compute the average GDP per capita for all European regions included in the sample. Then, we split regions according to the median value of the average GDP per capita. Results are analogous when we divide regions according to their GDP.

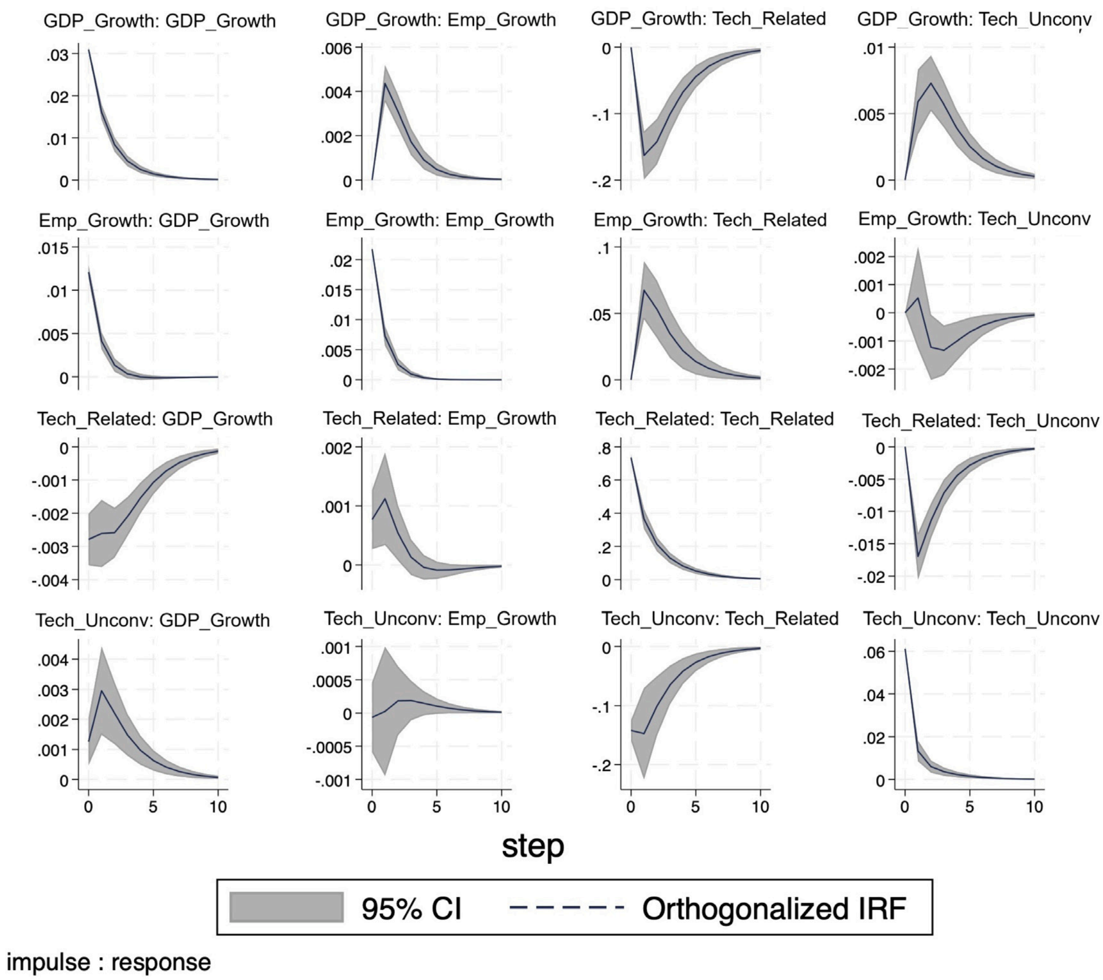


Fig. 3. Impulse response: Main results.
Notes: IRF shows the effect of a standard deviation change of the impulse variable on one unit of the response variable over 10 years. Error bars (in grey) are generated by Monte Carlo simulations using 1000 draws.

the short and long run are confirmed for core regions, the impact is negligible in the other regions.

Specifically, in the core regions, a standard deviation increase in technological relatedness leads to an initial 0.1 per cent growth in employment. In the subsequent period, employment growth increases by 0.15 per cent points. These results are in line with the evidence presented in Table 2 and Fig. 3. Following our previous findings, the effect of technological unconventionality is significant only on GDP growth, and one standard deviation increase results in an initial increase of 0.15 per cents points in GDP growth. In the following period, GDP growth increases by 0.25 per cent points. Conversely, increases in technological relatedness initially have a positive effect on GDP growth (0.1 per cent), which turns persistently negative after a few years.

Concerning Table 3b, we can observe that in periphery regions, technological relatedness is positively associated with employment growth while technological unconventionality is positively associated with GDP growth (while these correlations are less pronounced than for core regions). This evidence corroborates the idea that technologically coherent knowledge bases allow regions to produce incremental new knowledge that improves employment performance, while unconventional knowledge impacts economic output. However, the dynamic effects of technological diversification are negligible in peripheral regions. Fig. 4(b) shows that variations in technological diversification have non-significant effects in those regions except for the relationship between technological relatedness and GDP growth. Specifically, a standard deviation increase in technological relatedness initially reduces GDP growth by 0.5 per cent in periphery regions. The negative effect phases out over time.

Technologically advanced and technologically lagging regions. As a second heterogeneity test, we split the regions based on their number of patents, distinguishing between technologically advanced and technologically lagging regions. Specifically, we divided the sample into two equal groups according to the median of the average number of patents filed by inventors in the regions over the period covered by our database. Regions with more than 83.21 patents on average between 1980 and 2014 – corresponding to the median value of patents across regions – are classified as technologically advanced.[17] This test is designed to capture regional differences that may not have been detected in the previous heterogeneity analysis.

Table 4 reports the PVAR results and Fig. 5 shows the corresponding impulse response functions. From Table 4a and Fig. 5(a), we can confirm the statistically significant (and positive) effects of increases in technological diversification on employment and GDP growth in technologically advanced regions, both in the short and long run. It is worth noticing that, in this case, the effect of increases in technological relatedness is also positive on GDP growth. Similarly, technological unconventionality has a long-lasting positive effect on employment

[17] We prefer the average number of patents to the total number of patents as our panel is unbalanced.

Table 3
Effects of technological diversification in core and periphery regions.

(a) Core regions.

	(1) $Tech\_Unconv_t$	(2) $Tech\_Related_t$	(3) Emp_Growth_t	(4) GDP_Growth_t
$Tech\_Unconv_{t-1}$	0.280***	−0.010	0.007	0.043**
	(0.052)	(0.836)	(0.016)	(0.020)
$Tech\_Related_{t-1}$	−0.029***	0.799***	0.003**	−0.003**
	(0.003)	(0.058)	(0.001)	(0.001)
Emp_Growth_{t-1}	0.037	1.134**	0.276***	−0.000
	(0.035)	(0.553)	(0.034)	(0.036)
GDP_Growth_{t-1}	0.073**	2.481***	0.144***	0.326***
	(0.032)	(0.287)	(0.016)	(0.039)
Observations	3916	3916	3916	3916

Notes: 1-lag PVAR estimations of the following reduced form model on core regions: $X_{rt} = \alpha + \sum_{i=1}^{p} \beta_i X_{r,t-i} + \phi_r + \epsilon_{rt}$. The main variables are technological unconventionality, technological relatedness, employment growth and GDP growth at time t in region r. All regressions include region-fixed effects. Standard errors are clustered at the regional level and obtained by Monte Carlo simulations using 1000 draws. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

(b) Periphery regions.

	(1) $Tech\_Unconv_t$	(2) $Tech\_Related_t$	(3) Emp_Growth_t	(4) GDP_Growth_t
$Tech\_Unconv_{t-1}$	0.101**	−1.368*	0.006	0.036**
	(0.049)	(0.752)	(0.010)	(0.016)
$Tech\_Related_{t-1}$	−0.013***	0.260***	0.001**	0.000
	(0.003)	(0.043)	(0.001)	(0.001)
Emp_Growth_{t-1}	0.060	7.008***	0.210***	−0.089***
	(0.070)	(1.123)	(0.064)	(0.033)
GDP_Growth_{t-1}	−0.118*	−8.897***	0.145***	0.552***
	(0.061)	(1.076)	(0.018)	(0.039)
Observations	3013	3013	3013	3013

Notes: 1-lag PVAR estimations of the following reduced form model on periphery regions: $X_{rt} = \alpha + \sum_{i=1}^{p} \beta_i X_{r,t-i} + \phi_r + \epsilon_{rt}$. The main variables are technological unconventionality, technological relatedness, employment growth and GDP growth at time t in region r. All regressions include region-fixed effects. Standard errors are clustered at the regional level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4
Effects of technological diversification in technologically advanced and technologically lagging regions.

(a) Technologically advanced regions.

	(1) $Tech\_Unconv_t$	(2) $Tech\_Related_t$	(3) Emp_Growth_t	(4) GDP_Growth_t
$Tech\_Unconv_{t-1}$	0.417***	5.093***	0.022	0.322***
	(0.034)	(0.304)	(0.014)	(0.027)
$Tech\_Related_{t-1}$	−0.023***	1.138***	0.004***	0.015***
	(0.002)	(0.020)	(0.001)	(0.002)
Emp_Growth_{t-1}	−0.219***	3.222***	0.189***	−0.070
	(0.029)	(0.373)	(0.033)	(0.052)
GDP_Growth_{t-1}	0.187***	−1.263***	0.128***	0.167***
	(0.021)	(0.179)	(0.013)	(0.050)
Observations	3962	3962	3962	3962

Notes: 1-lag PVAR estimations of the following reduced form model on technologically advanced regions: $X_{rt} = \alpha + \sum_{i=1}^{p} \beta_i X_{r,t-i} + \phi_r + \epsilon_{rt}$. The main variables are technological unconventionality, technological relatedness, employment growth and GDP growth at time t in region r. All regressions include region-fixed effects. Standard errors are clustered at the regional level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

(b) Technologically lagging regions.

	(1) $Tech\_Unconv_t$	(2) $Tech\_Related_t$	(3) Emp_Growth_t	(4) GDP_Growth_t
$Tech\_Unconv_{t-1}$	0.105**	−1.233*	0.006	0.024
	(0.043)	(0.637)	(0.010)	(0.015)
$Tech\_Related_{t-1}$	−0.009***	0.194***	0.001**	−0.000
	(0.003)	(0.041)	(0.001)	(0.001)
Emp_Growth_{t-1}	0.264***	7.456***	0.224***	−0.089***
	(0.072)	(1.121)	(0.062)	(0.031)
GDP_Growth_{t-1}	−0.410***	−11.030***	0.188***	0.654***
	(0.080)	(1.271)	(0.023)	(0.037)
Observations	2967	2967	2967	2967

Notes: 1-lag PVAR estimations of the following reduced form model on technologically lagging regions: $X_{rt} = \alpha + \sum_{i=1}^{p} \beta_i X_{r,t-i} + \phi_r + \epsilon_{rt}$. The main variables are technological unconventionality, technological relatedness, employment growth and GDP growth at time t in region r. All regressions include region-fixed effects. Standard errors are clustered at the regional level and obtained by Monte Carlo simulations using 1000 draws. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

growth. For what concerns technologically lagging regions (Table 4b and Fig. 5(b)), instead, there is no effect of variations in technological unconventionality on economic growth. Although these regions are relatively less technically advanced, we can still observe an effect of technological relatedness on employment growth, even though the dynamics of this effect are uncertain. Our main results are, therefore, driven by technologically advanced regions with advanced and diversified technological capabilities that allow them to apply different regional diversification strategies.

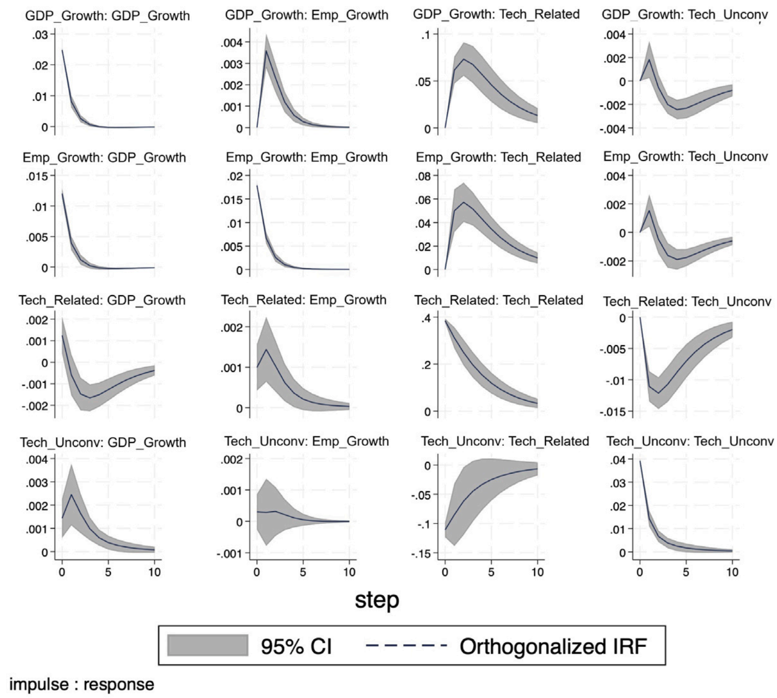
5.2. Robustness checks

We test the robustness of our results by adding exogenous controls at the regional level, such as population level and number of patents, in Table A10 and Figure A10. We also assess the robustness of our results to different subsets of our data. In a first set of additional tests, since our sample includes regions that experienced major geopolitical transformations in the last 40 years, we run estimations excluding Germany (reunified only in 1989) or removing countries originating from the dissolution of the Soviet Union and Yugoslavia. Secondly, as the propensity to innovate varies across regions, we exclude regions with low innovation rates (regions whose average number of patents is below the tenth percentile of the average number of patents). Third, we remove the country-capital regions to rule out the possibility that our results are driven by the economic and institutional centres, where companies' headquarters are usually located. Finally, we run estimations that exclude regions with extreme values (top tenth and bottom tenth percentile of the average distribution) of employment and GDP growth. We also check the sensitivity of our results to extreme values by winsorizing below the 10th and above the 90th percentile of employment and GDP growth. Results of these robustness checks are reported in Tables A3, A4, A5, A6, A7, A8, and A9 and Figures A3, A4, A5, A6, A7, A8, and A9.

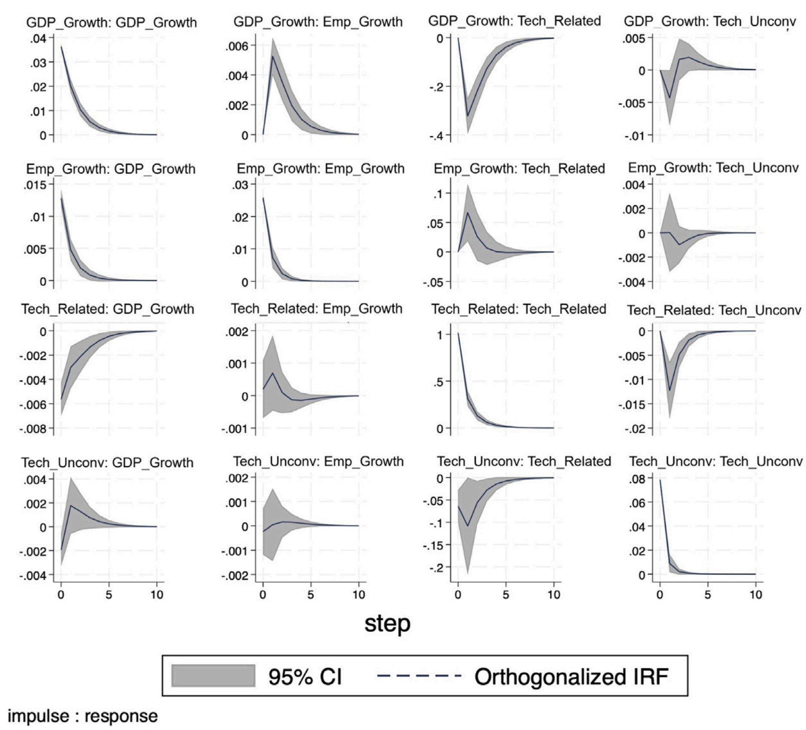
In Table A10 and Figure A10, instead, we examine whether our results are affected by the number of lags in the "GMM-style" instrument. Specifically, we estimate our main model using three "GMM-style" instruments instead of two. We also assess the robustness of the results for lag selection in our PVAR model. To check whether our results are driven by the selection of the lag length, we estimate our PVAR model using two lags. We present the results in Table A11 and Figure A11. Finally, we show in Table A12 and Figure A12 and Table A13 and Figure A13 our estimations using two alternative Cholesky decomposition orderings.

Finally, we test whether the results are robust to alternative definitions of our main variables. First, we replace GDP growth with labour productivity growth as an indicator of regional economic performance. Results are reported in Table A14 and Figure A14. Then, we propose alternative definitions of technological unconventionality by considering different percentiles of the cumulative technological proximity distribution that allows us to detect the relevance of atypical combinations in regional technology portfolios.[18] Tables A15, A16 and A17 and Figures A15, A16 and A17 show the results. To further assess the robustness of

[18] We consider the second, fifth, and tenth (as in the original definition by Uzzi et al. (2013)) percentiles of the distribution instead of the first percentile. By increasing the percentile of the distribution, we are incrementally considering less unconventional combinations.

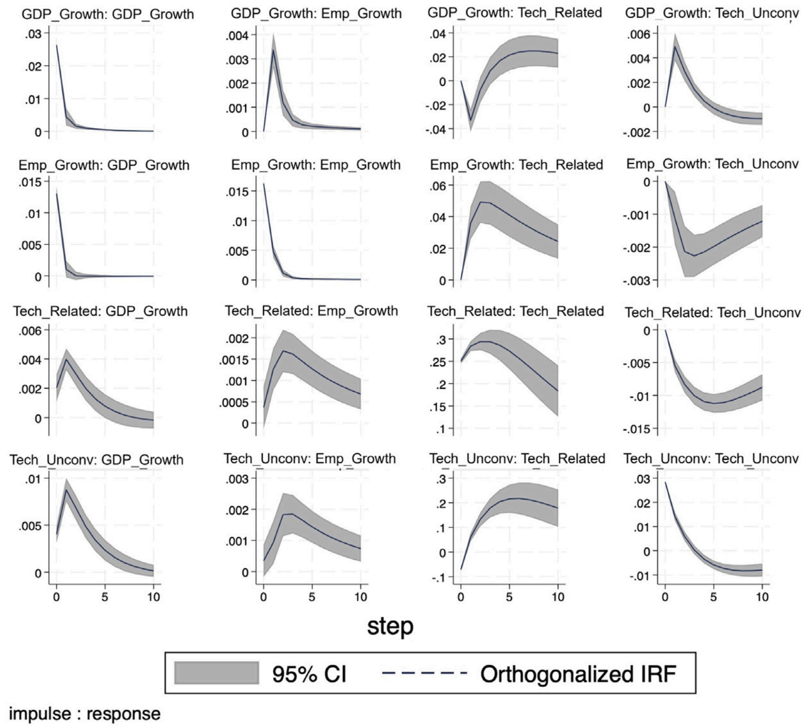


(a) Core regions.

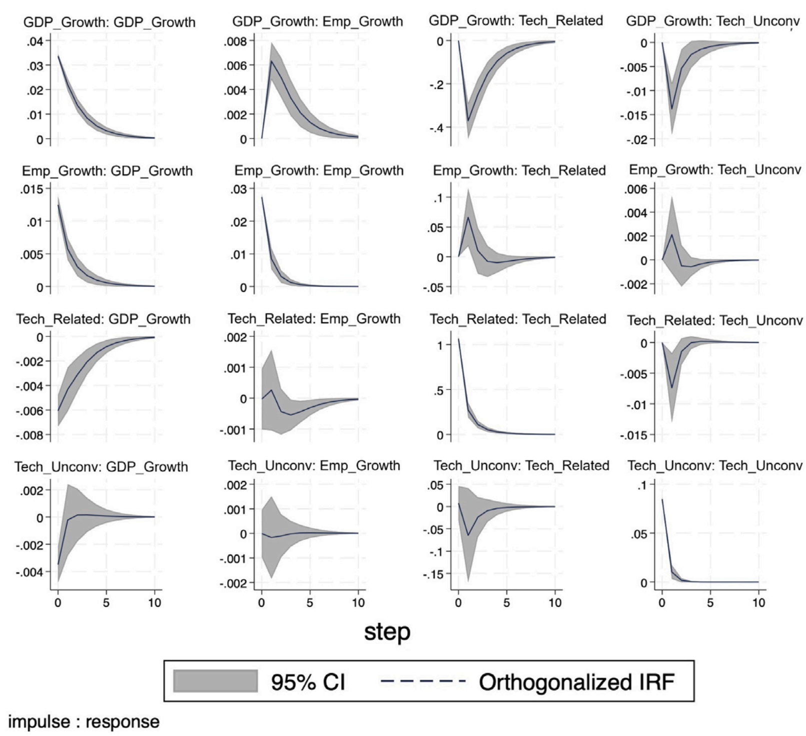


(b) Periphery regions.

Fig. 4. Impulse response: Core and periphery regions.
Notes: IRF shows the effect of a standard deviation change of the impulse variable on one unit of the response variable over 10 years. Error bars (in grey) are generated by Monte Carlo simulations using 1000 draws.



(a) Technologically advanced regions.



(b) Technologically lagging regions.

Fig. 5. Impulse response: Technologically advanced and technologically lagging regions.
Notes: IRF shows the effect of a standard deviation change of the impulse variable on one unit of the response variable over 10 years. Results refer to the subsample of less innovative regions. Error bars (in grey) are generated by Monte Carlo simulations using 1000 draws.

our findings to alternative definitions of technological diversification, we also employ the average relatedness indicator defined in Kogler et al. (2013) as a measure of related diversification (Kogler et al., 2017; Boschma et al., 2014). Unlike the regional technological coherence indicator, this index defines technology proximity based on the co-occurrence of technology classes at the patent level.[19] In the same robustness check, we modify the technological unconventionality index by calculating technological proximity (see Eq. (7)) using technology class co-occurrences within patents rather than regions. The results are presented in Table A18 and Figure A18.

All these additional results, presented in Appendix A, confirm that increases in technological relatedness have a short-term effect on employment growth and a negative effect on GDP growth. Increases in technological unconventionality, instead, have a longer-lasting positive impact on GDP growth and no effect, or negligible effects, on employment growth. This evidence corroborates our main results, suggesting a complementary impact of technological relatedness and technological unconventionality both in terms of the persistence of the effect and the economic performance variable affected by the different types of technological diversification patterns.

6. Conclusions

This study explores what kind of regional technological diversification – in terms of recombining more or less similar knowledge in more or less conventional ways – is conducive to superior economic performance in the short and long run. We began our contribution by reflecting on what type of knowledge diversification patterns may be associated with regional competitive advantages. On the one hand, we considered the relatedness of technological capabilities in a region, and, on the other, the presence of rare knowledge or more distant combinations as an indicator of technological unconventionality. These indicators reflect two crucial and complementary aspects of technological diversification. Local economies may build their technological portfolios by exploiting existing technologies or branching into related ones and, at the same time, be prepared to catch new technological opportunities by exploring unprecedented and rare combinations of technological inputs. While recombining more related technologies ensures easier adaptation to changes in market conditions, unconventional combinations help regions to move towards new technological frontiers. An increase in technological relatedness has a positive effect on employment in the short run and a negative effect in the long run on the local economies' level of output. Conversely, an increase in technological unconventionality positively affects output growth in the long run, while it does not significantly affect employment growth. Notably, not all regions possess the necessary capabilities to exploit the advantages of technological diversification. More specifically, our results highlight that increases in technological relatedness have a significant positive effect on employment growth only in core (i.e., regions with higher GDP per capita) and technologically advanced regions. In technologically advanced regions, technological relatedness also positively affects GDP growth. In core regions, this effect is positive only in the short run, while it becomes negative in the long run. Similarly, the effects of a technological unconventionality increase on GDP growth are positive only for core and technologically advanced regions. In periphery regions, technological relatedness and technological unconventionality are positively associated with employment growth and GDP growth, respectively. However, these correlations do not translate into significant effects on regional economic performance when we analyse the impact of changes in technological diversification. In technologically lagging regions, we observe a positive relationship only between technological relatedness and employment growth, while there are no significant dynamic effects between the two variables. These contrasting results might stem from the necessity of technological asset investment in these regions.

In addition to its novel empirical findings, the paper also makes theoretical and methodological contributions. First, we elaborated on the direction and the short- vs. long-term effects of increases in different forms of technological diversification on regions' economic performance. We also adopted a methodological framework that leverages recursive identification restrictions to isolate the causal dynamic effects of technological diversification. This approach, despite its limitations, seeks to address the endogeneity challenges that have limited causal claims in economic geography literature. Furthermore, by showing the dynamic effects of changes in technological diversification, our analysis provides a basis for deriving policy implications. Finally, and differently from the prior literature on regional technological diversification, we used a new measure of technological unconventionality to complement the more established indicator of technological relatedness in a performance framework.

The study has, of course, limitations. More needs to be done to unpack the role of technological capabilities in shaping employment and GDP growth in regions with different levels of economic, industrial and technological development. Furthermore, future studies should consider the effect of different profiles of technological capabilities within and across sectors and how these could increase competitive gaps between top-performing and laggard regions. In addition, future research should adopt a micro-level approach to identify the specific actors who shape regional technological capabilities and drive economic growth. It would also be interesting to explore through firm-level studies how different types of firms (e.g. local SMEs vs. multinational corporations), as well as different ownership structures and firms' positions in value chains, influence these dynamics.

Our findings have relevant implications for the design of appropriate regional development policy instruments. Our results confirm that effective regional development strategies should be characterised by a careful assessment of the structure of the regional knowledge base. Importantly, different diversification strategies yield distinct – and differently persistent – effects on GDP and employment. Identifying existing technological capabilities is thus essential for designing appropriate incentive schemes. Our evidence on both more and less developed areas, as well as technologically advanced and lagging regions, highlights the need to tailor diversification strategies to regional capabilities and innovation potential. More broadly, in terms of innovation policy design, if a region seeks to improve its employment growth performance, it should prioritise policies that promote the recombination of related pieces of knowledge. Exploiting related knowledge components through recombinant search allows local economies to generate new knowledge that is related to the existing components of the technological space. This smoother evolution of the technological space favours the short-term adaptation of the region's economic actors. Conversely, if the policy goal is long-term GDP growth, regions may benefit from promoting the recombination of knowledge that is more distant from existing technological capabilities. The exploration of unconventional combinations favours the long-term competitive advantages of regional economies. Identifying which technological diversification choices can affect the desired macroeconomic outcome is key to designing an appropriate place-based policy *mix*, and overcoming the potential limits of Smart Specialisation strategies (S3) in order to facilitate the re-orientation of local development trajectories from S3 to the new S4+ policies. While exploiting already existing local technological knowledge is important to maintain satisfactory performance in the job market, it is equally important to explore unconventional combinations to generate long-term growth potential. With specific reference to Smart Specialisation strategies, our study points to key differences in impacts depending on whether we consider the short or the long term. It will be important to take into account the possibility that the

[19] Since this approach may overlook potential local synergies between complementary technologies, we favour the widely used definition of regional technology relatedness presented in Section 4.1.

short-term effects of place-based policies based on relatedness could be positive, but not particularly persistent. On the other hand, it is possible that investments in unconventional knowledge combinations might succeed in the long run, but might fail to produce positive effects on employment. Therefore, it will be important to assess whether output growth induced by place-based policies will translate into higher wages or will further contribute to the decline in the labour share of output that has characterised modern macroeconomic trends associated with growing income inequalities. These insights are particularly important since recent reports (McCann et al., 2020) highlight that new place-based innovation policies will focus on transformative changes that have to balance competitiveness with broader regional societal challenges.

CRediT authorship contribution statement

Silvia Rocchetta: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **Martina Iori:** Writing – review & editing, Writing – original draft, Visualization, Software, Formal analysis, Data curation, Conceptualization. **Andrea Mina:** Writing – review & editing, Supervision, Conceptualization. **Robert Gillanders:** Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Additional results

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.respol.2026.105445.

Data availability

Data will be made available on request.

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