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

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

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Abstract

We study the effects of different types of technological diversification on the performance of regional economies. We focus on the relatedness and unconventionality of technological capabilities as drivers of GDP and employment growth. Using economic indicators from Eurostat regional statistics and patent records from the European Patent Office (EPO) PATSTAT and the OECD RegPat databases, we estimate Panel Vector Autoregression models and generate Impulse Response Functions to assess to what extent and with what persistence relatedness and unconventionality affect growth. Our findings, which have implications for place-based innovation policies, reveal that technological relatedness has short-term effects on employment growth and negative effects on GDP growth, whereas technological unconventionality has a long-lasting positive impact on GDP growth and no effect on employment growth.

Keywords: Technological capabilities; Diversification; Relatedness; Unconventionality; Innovation; Regional development

JEL codes: O33; R11

1 Introduction

Innovation is a path-dependent process of knowledge accumulation and recombination (Dosi, 1982; Scotchmer, 1991). This Schumpeterian theme (Schumpeter et al., 1939) has been developed in various strands of the literature, from the micro- (Fleming, 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 a variety of factors that are place-dependent, including 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, the development paths of local economies. 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. Related diversification has been identified as a recurrent pattern – a 'stylised fact' – characterising not only technology, but a broader range of economic aggregates, including traded products, firm outputs and skills (Li and Neffke, 2022).

With specific reference to technological capabilities, the literature has found a strong association between relatedness and employment growth (Frenken et al., 2007; Content and Frenken, 2016; Boschma, 2017; Bathelt and Storper, 2022; Rocchetta et al., 2022). However, the role of recombinatorial novelty has been much more difficult to establish because of measurement problems that can be attributed to the use of a priori classifications of knowledge inputs that fail to capture the more rare or more distant bundles of knowledge driving growth through unrelated diversification. Recently, Berkes and Gaetani (2021) have used the notion of 'unconventionality' to identify the presence of atypical combinations of technological knowledge. Atypical combinations are knowledge combinations that have rarely been used before, or are entirely new, and blend together cognitive inputs more distant from one another in a evolving knowledge space (Uzzi et al., 2013; Fontana et al., 2020). Unconventional or atypical 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 apply the notion of coherence to capture relatedness, and the notion of unconventionality to capture unrelated diversification. We then analyse the effects of coherence and unconventionality on the performance of European regions. 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 as proxies for regional innovation. We then estimate Panel Vector Autoregression models and generate Impulse Response Functions (IRF) capable of identifying the causal relationship between different forms of technological diversification and regional growth. Moreover, IRF allows 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 technological relatedness has a short-term effect on employment growth and a negative effect on GDP growth. Technological unconventionality, instead, has 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 use an econometric approach that is superior in terms of identification strategy relative to those that can be found in the literature on this topic, including instrumental variable approaches, which may suffer from weak instrument problems and violate the exclusion restriction. 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

Since Schumpeter's seminal theory of economic development (Schumpeter et al., 1939), knowledge recombination has been recognised as a key determinant of economic growth. Following this line of inquiry, diversification in technological capabilities is a feature of regional economies that has been explored at length in the innovation and economic geography literature of Schumpeterian descent (Boschma and Martin, 2010). Firstly, having a diversified portfolio of technological knowledge is important because this portfolio contains the potential components for recombination and for the emergence of local cross-sectoral spillovers capable of fostering growth (Boschma and Frenken, 2010). Secondly, technological diversification can trigger industrial renewal by favouring the accumulation of new capabilities and the access to new product markets (Amoroso et al., 2022). Thirdly, more diverse 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).

The central argument is that the economic performance of regions is not only a function of knowledge stocks, but also of the structure and composition of these stocks of intangibles (Tanner, 2016; Kogler et al., 2017). As a particular instantiation of knowledge, technology stocks appear in different combinations that are more or less similar to one another from a cognitive viewpoint, and more or less complementary to one another within and across sectors (Nooteboom, 2000; Nesta and Saviotti, 2005; Neffke et al., 2011; Caragliu and Nijkamp, 2016; Castaldi et al., 2015; Content and Frenken, 2016).

Moreover, in a dynamic framework, diversification does not occur at random across technology fields. 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, Levinthal, et al., 1990), to argue that diversifying into related fields is relatively easier, overall less costly, and therefore more probable at any given point in time. Indeed this feature of technological change mirrors the patterns of growth through related diversification found in the industry composition (Frenken and Boschma, 2007; Neffke et al., 2011) and trade mix (Hidalgo et al., 2007; Hausmann et al., 2014) of countries and regions.

In terms of economic performance, local economies built on technologies or industries that are more related to one another have been found to outperform those specialised in technologies and industries with lower complementarity levels (Frenken et al., 2007; Kogler et al., 2013). Interestingly, these effects seem to be more pronounced in the short run and during times of crisis. Diodato and Weterings (2015) reports that the cognitive proximity between workers' skills plays a positive role against both general and sector-specific shocks. This finding is consistent with the view that skill mobility and capability recombination are easier between related fields, where adjustments and learning costs are lower. Several studies also found that higher levels of industrial and/or technological relatedness make regional economies more resilient to crises, thus emphasising again the greater efficiency of related diversification in the phases of the business cycle with stronger financial constraints and market frictions (Holm and Østergaard, 2015; Rocchetta and Mina, 2019; Rocchetta et al., 2022). If local economies develop technological capabilities that are more related, they will be able to adapt more quickly to exogenous changes in market conditions, for example through lower labour market frictions when workers migrate between sectors that require more similar skills and lower re-training costs.

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 ever-increasing complementarities 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 been already 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.

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).[1] Moreover, the different costs and opportunities to innovate stemming from the choice of what kind of knowledge to recombine and where to locate new activities result in a highly heterogeneous geographical distribution of technologies that reflect varying combinations of Marshallian (Marshall, 1890) and Jacobian (Jacobs, 1970) externalities (Berkes and Gaetani, 2021).

In characterising the novelty of innovation, rather than its relatedness or unrelatedness to existing technological capabilities, Fleming (2001) addressed the role of uncertainty in recombinant innovation processes. 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 ideas (Schumpeter et al., 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. Moreover, this changes over time. Whereas conventional combinations of ideas are more certain, unconventional combinations can have greater value and more impact. A technological diversification trajectory based only on the recombination of similar knowledge may lead regional economies to be locked into too-specialised technological or industrial paths (Balland et al., 2019) because the technological frontier does not expand. Although unrelated diversification is more risky and uncommon, it can allow regions to explore new technological frontiers and therefore gain new long-term competitive advantages (Pinheiro et al., 2022). In the short term, however, the exploration of atypical knowledge combinations might cause performance degradation because the search for novel solutions is more subject to failures (Aharonson and Schilling, 2016).

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, to the best of our knowledge, we incorporate for the first time this concept to analyse the extent of unconventional recombinations in regional technological diversification trajectories. It is not yet clear in the literature, indeed, to what extent the unconventionality of regional technological recombinations favours the growth of local economies, bearing in mind the uncertainty associated with combinations that are less tried and tested remains an open question.

Following this line of inquiry, in this paper we focus on identifying the effects of qualitatively

[1] For a discussion of the institutional contexts favouring unrelated diversification, even though the paper focuses on traded products rather than technologies, see (Boschma and Capone, 2015).

different types of technological diversification on regional growth. Specifically, we will consider the effect of 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 related diversification and its economic benefits, the available empirical evidence is overwhelmingly descriptive. In trying to assess the causal 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 impulse response functions (IRF), we obtain reliable estimates of the effects of variations in two complementary yet opposing types of technological diversification trajectory on regional economic performance. Moreover, we assess not only the size but also the persistence of these effects. Secondly, we provide novel and original evidence on the effects of technological unconventionality, in addition to relatedness, on the performance of regional economies. Interestingly, as we shall see, relatedness and unconventionality affect GDP and employment in different ways. To the best of our knowledge, causal evidence of these mechanisms, which are highly relevant to the ongoing debate on diversification, is still lacking.

3 Methodology

To design the econometric strategy, it is important to acknowledge that changes in the structure of the stock of technological capabilities could have both immediate and delayed effects on the economy. Moreover, shocks to the economy are likely to influence technology. Cross-sectional analyses and short panel-based analyses are therefore likely to miss important dynamics and face substantial challenges in terms of identifying causal effects. Panel Vector Autoregression (PVAR) models 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 $X_{rt} = [TU_{rt}\ TC_{rt}\ E_{rt}\ G_{rt}]'$, where TU_{rt} is technological unconventionality, TC_{rt} is technological relatedness (measured through the technological coherence index), E_{rt} is the rate of employment growth, and G_{rt} is the rate of GDP growth (see Section 4.1 for more details). We use growth rates for employment and GDP as tests 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. 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.[2] Following Holtz-Eakin et al. (1988), we use "GMM-style" instruments to improve efficiency by replacing missing values for lagged instruments with zero.[3] Standard errors are clustered at the regional level.

As in this paper we aim to trace the dynamic effects of changes in technological relatedness, and technological unconventionality on GDP and employment growth, we generate Impulse Response Functions (IRF). IRF show the dynamic impact of exogenous changes in one variable on each of the other variables. In particular, it allows us to show how one standard deviation exogenous shock to a variable affects all the other variables. For the purpose of this study, IRF estimates the unbiased causal dynamic effect of changes in technological diversification indicators and GDP and employment growth in terms of both magnitude and persistence. In our estimations, the shock represents an unexpected positive increase in the variables included in our modelling exercise.

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 shocks in one variable will not be independent of the shocks to the others. To identify causal effects, we impose a Cholesky decomposition. This entails making assumptions about the order in which shocks propagate through the system. Our ordering is based on the following logic. A shock in the extent to which technological components are combined in an unconventional manner (technological unconventionality) represents a fundamental shock 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. Shocks to technological relatedness, which captures the extent

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

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

of cognitive proximity across the technological elements that compose the regional knowledge base (Nesta and Saviotti, 2005; Nesta and Saviotti, 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 shocks 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 shocks 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 shocks to 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. These changes do not alter the findings and our conclusions. 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. Our data covers the period between 1980 and 2014. This information is combined with patent data, used as a proxy for the innovative activities carried out in the region (Griliches, 1990; Hall et al., 2001), extracted from the PATSTAT database of the European Patent Office (EPO) and the OECD RegPat database. 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.[4] 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. The final sample includes 251 regions

[4]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.

over 35 years.[5] 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 frontiers; ii) regional economic performance indicators.

We consider two technological diversification indicators to capture distinct features of the regional knowledge base. Both measures are based on the analysis of regional patent portfolios.

Technological Relatedness. First of all, we introduce an indicator of regional technological relatedness, measured through 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 and proximity among their technologies in the knowledge space. The use of patent portfolios to compute this indicator allows us to capture the technological frontier of a region and detect how it evolves over time.

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

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

[5] Due to the presence of a few missing values in economic performance data, the total number of observations is 7,350.

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 coherence $Tech\_Coherence_{rt}$ 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:

$$Tech\_Coherence_{rt} = \sum_{j} WAR_{jrt} \frac{P_{jrt}}{P_{rt}}, \tag{6}$$

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. This index is 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 coherence 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). Approaches based on the detection of atypical combinations have already been used in the literature to detect unconventional innovations (Berkes and Gaetani, 2021; Kim et al., 2016; Abbasiharofteh et al., 2023).

The first step consists of computing 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 between technology classes. Technological proximity TP_{jkt} between two technological classes j and k is similar to the coherence index τ_{jk} but, since our focus here is on distant and unconventional combinations of knowledge, it is calculated considering the number of occurrences NO_{jrt} in each region r of the technological class j at time t and not simply the dummy variable G_{jr}. In fact, a combination of knowledge could be atypical in a certain year and become conventional in the following period. Therefore, it is important to consider the variation over time of this index. Moreover, an aggregated variable, such as a dummy variable that signals the presence of technology in a region, is not suited to detect highly atypical combinations and a more granular variable (the number of occurrences) is needed.

From the number of occurrences NO_{jrt} of each technological class in each region at time t, we can compute the observed number of co-occurrences between two technology classes j and k as $NCO^{obs}_{jkt} = \sum_r NO_{jrt} NO_{krt}$. Also in this case, the number of co-occurrences will depend on the size of j and k, and we proceed with the index normalisation. Following Uzzi et al. (2013), we create, for each year, a null model of the weighted bipartite network with regions and technology classes as nodes. Edges connect regions with technology classes in which they patent, and edge weights are equal to the number of occurrences of each technological class in each region. The null model creates a randomised version of the weighted bipartite network that preserves node degrees, i.e. the weighted number of technologies associated with each region and the weighted number of regions in which each technology occurs. Then we can determine the expected number of co-occurrences among technological classes if the technological capabilities were randomly assigned to European regions by creating 100 different randomised bipartite networks and computing the corresponding numbers of co-occurrences between technologies: $NCO^{exp}_{jkt} = \frac{\sum_{b=1}^{100} NCO^{b}_{jkt}}{100}$, where NCO^{b}_{jkt} is the number of co-occurrences between technologies j and k at time t in the randomised bipartite network b. Finally, the technological proximity between j and k at time t is:

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

The arc-tangent transformation and normalisation ($\pi/2$) allow us to obtain a more stationary variable ranging between 0 (unconventional or atypical combinations) and 1 (conventional and typical combinations).

In the resulting technological knowledge space, technologies close to each other are those that frequently co-occur in regions. By analysing the relevance in each region of atypical (distant) technology pairs, we can instead compute the regional technological unconventionality:

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

where $F_r t(TC_{jkt})$ is the cumulative distribution of proximity among pairs of technology classes j and k in the region r at time t. By selecting the 1^{st} per centile 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 per centile.[6]

Employment and GDP growth. As indicators of economic performance, we use employment growth and GDP growth. 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 7,350 region-year observations[7] and includes information about employment growth, GDP growth, technological coherence, technological unconventionality, number of patents, and population.

[6] The choice of the 1^{st} per centile 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 per centile of the distribution may not properly detect unconventional technological pairs. However, we tested the robustness of our results by considering different per centiles of the distribution and our conclusions hold.

[7] The number of observation in the econometric models is lower – 6,794 – due to the use of lagged variables in PVAR and impulse response estimations.

Summary statistics on these variables are shown in Table 1, while Figures 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 coherence 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 Balkan, 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).

Table 1: Summary statistics

	Mean	Std	Min	Max	Count
Emp_Growth	0.01	0.02	-0.21	0.28	7350
GDP_Growth	0.02	0.04	-0.64	0.63	7350
Tech_Coherence	4.98	0.94	0.00	11.87	7350
Tech_Unconv	0.76	0.08	0.12	0.98	7350
No_Patents	242.65	436.55	1.00	3973.00	7350
Population (thousands)	1853.95	1497.34	113.12	12079.34	7350
Year	1998.74	9.59	1981	2014	7350

Figure 1: Evolution of technological coherence of regions. Average values by decades.

(a) Tech Coherence 1981–1994

(b) Tech Coherence 1995–2004

(c) Tech Coherence 2005–2014

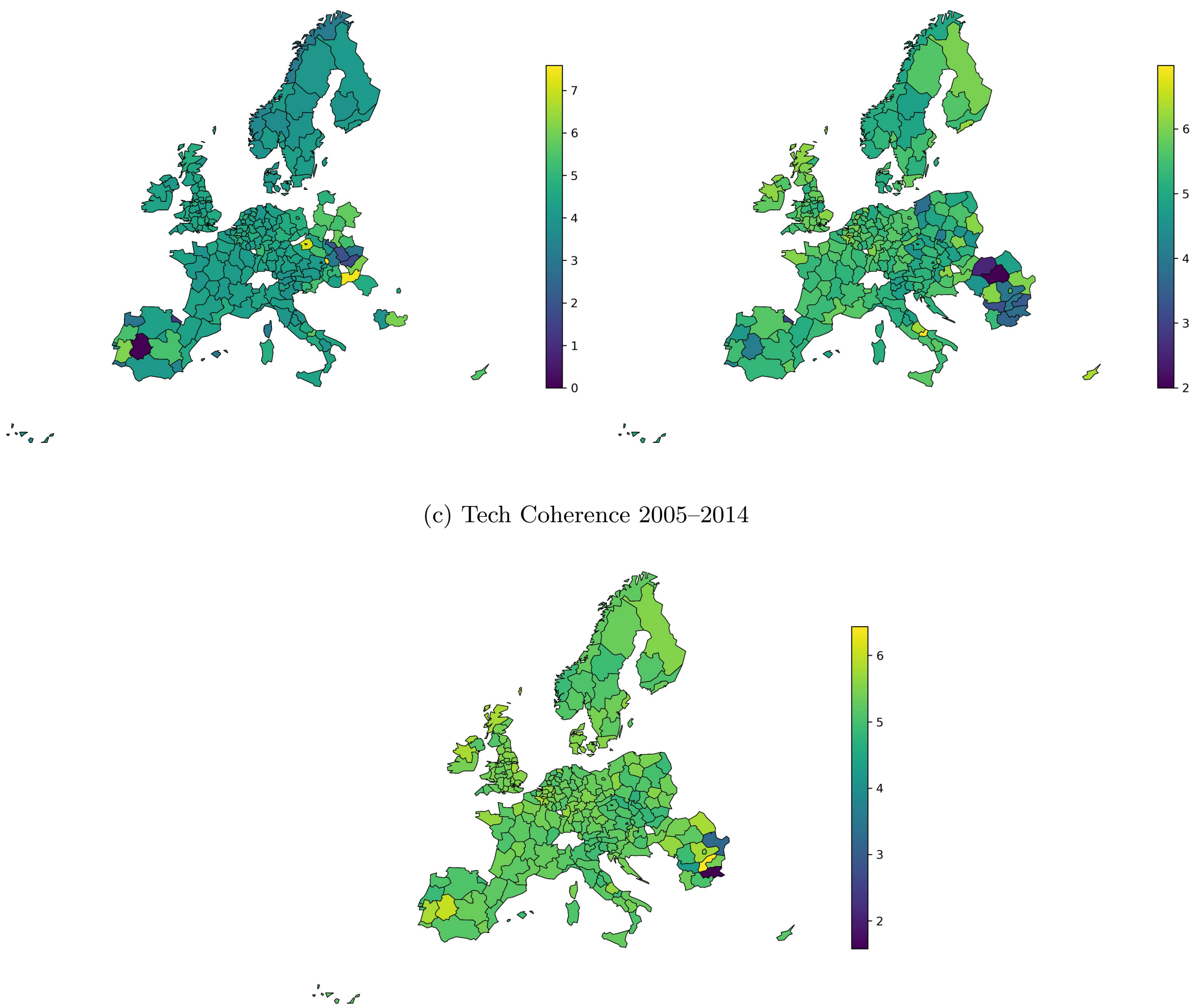
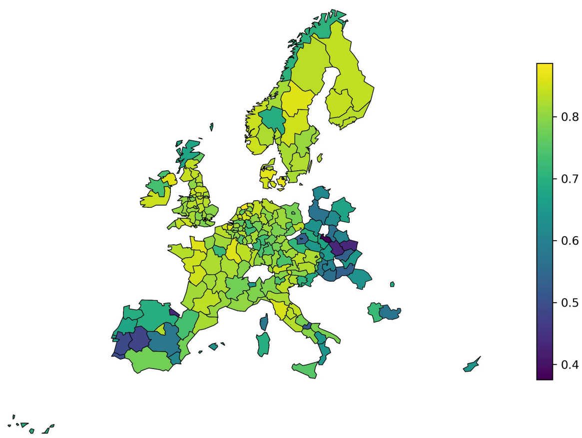
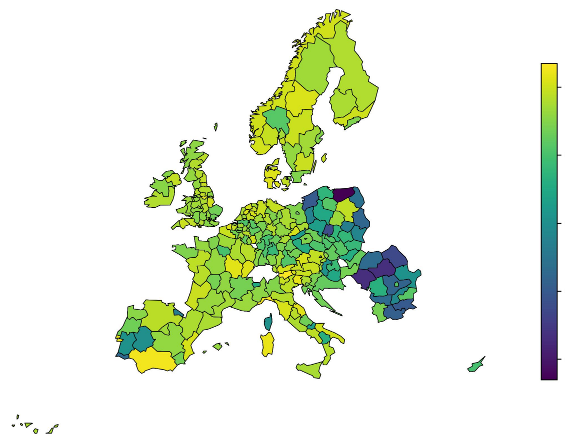


Figure 2: Evolution of technological unconventionality of regions. Average values by decades.

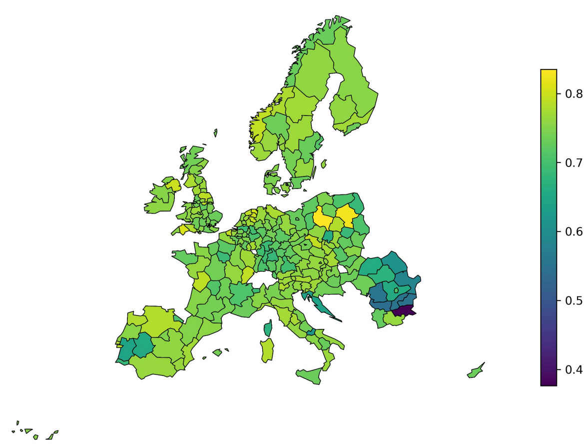
(a) Tech Unconventionality 1981–1994



(b) Tech Unconventionality 1995–2004



(c) Tech Unconventionality 2005–2014



5 Results

Table 2 presents the coefficients from our PVAR model and Figure 3 displays the associated orthogonalised impulse response functions. Each subgraph traces the effects of a time-zero one standard deviation shock in the impulse variable. 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.[8]

Table 2: Main results

	(1) Tech_Unconv_t	(2) Tech_Coherence_t	(3) Emp_Growth_t	(4) GDP_Growth_t
Tech_Unconv_{t-1}	0.159***	-0.988	0.000209	0.0302**
	(0.0450)	(0.754)	(0.00928)	(0.0140)
$\text{Tech\_Coherence}_{t-1}$	-0.0233***	0.515***	0.00178***	-0.00167**
	(0.00250)	(0.0425)	(0.000576)	(0.000736)
Emp_Growth_{t-1}	-0.0772	5.485***	0.239***	-0.105***
	(0.0486)	(0.661)	(0.0400)	(0.0258)
GDP_Growth_{t-1}	0.168***	-5.009***	0.138***	0.511***
	(0.0397)	(0.590)	(0.0133)	(0.0297)
Observations	6,794	6,794	6,794	6,794

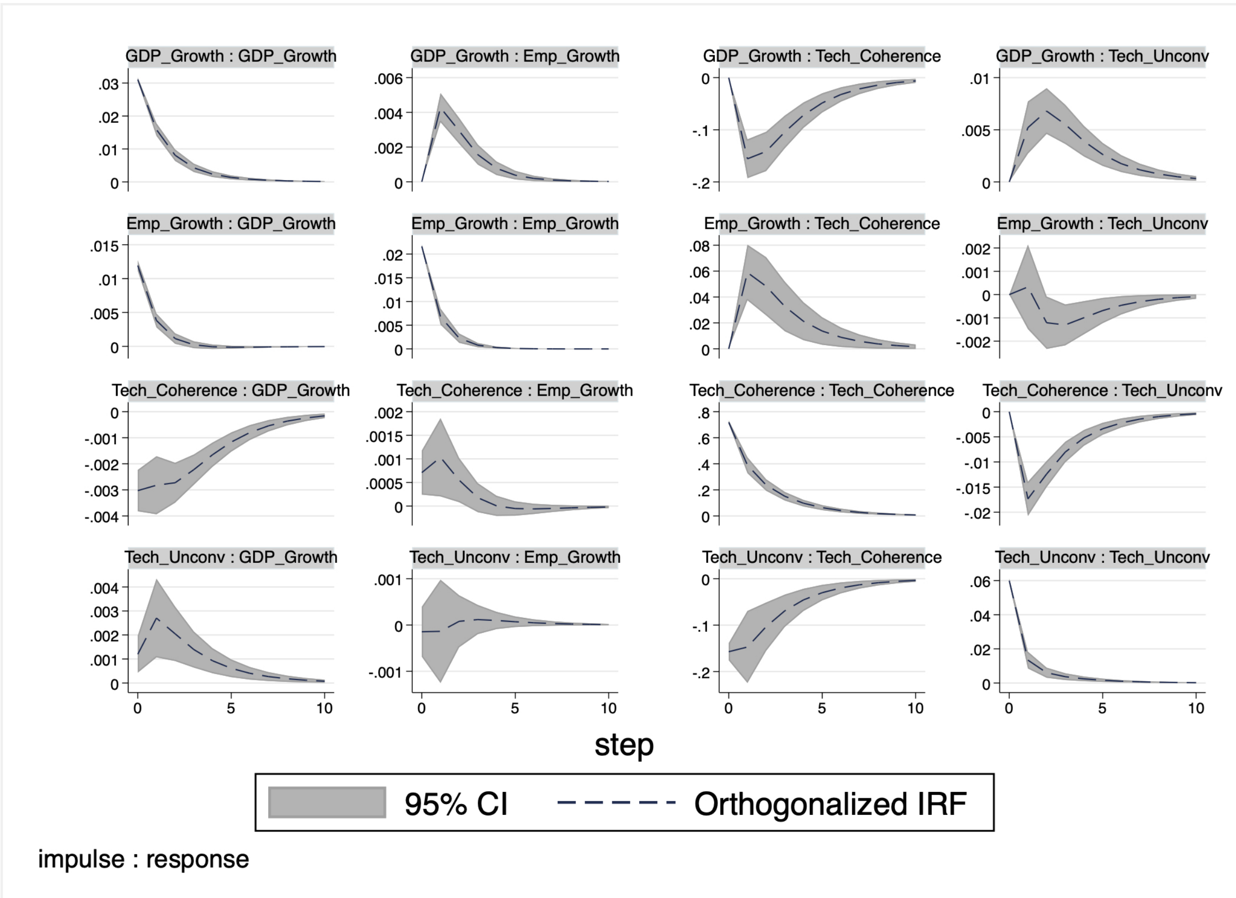
Notes: 1-lag PVAR estimations of the following reduced form model: $X_{rt} = \alpha + \sum_{i=1}^{p} \beta_i X_{r,t-i} + \phi_r + \epsilon_{rt}$. The main variables are technological unconventionality, technological coherence (as a measure of technological relatedness), employment growth and GDP growth 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

The four subgraphs in the lower left quadrant of Figure 3 are of particular interest as they depict the effects of technological diversification on employment and GDP growth over ten years.

The results in Figure 3 and Table 2 corroborate the findings of previous contributions on the short-term effects of technological relatedness and employment growth (see, for example, Rocchetta et al., 2022). Evidence presented in Figure 3 indicates that one standard deviation shock to technological relatedness increases the growth rate of employment by approximately 0.75 percentage points. This effect falls to zero within 5 years. This result 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 effect of technological relatedness on GDP growth is negative. A one standard deviation shock on technological relatedness reduces GDP growth by 0.3 percentage points in time zero. This negative effect is statistically significant and persists, though

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

Figure 3: Impulse response: Main results



Notes: IRF shows the effect of a standard deviation shock 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 1,000 draws.

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 effects, results presented in Figure 3 and Table 2 on the effect on GDP growth are in line with the idea that unconventional combinations of knowledge give rise to more value and more impact. A shock to 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 shock 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.

The subgraphs in the top right quadrant of Figure 3 show the effects of GDP and employment on technological diversification. GDP has significant negative effects over a sustained period on technological relatedness and positive effects on unconventionality. Employment fosters greater levels of relatedness. The initial effects on unconventionality are statistically insignificant, but later periods show a small negative effect. Finally, the bottom right quadrant of Figure 3 demonstrates that one technological feature has a negative effect on the other. These effects persist over our ten year horizon.

5.1 Heterogeneous effects

In this section, we explore heterogeneous effects across regions with different characteristics. First, we split the sample according to whether the regions belong (or not) to the EU15 area (the composition of the European Union from 1995 to 2004)[9] and Norway. Second, we identify the most and least innovative regions by employing the average of the total number of patents whose inventors are located in the region.

Regions in and outside EU15 Table 3 reports the coefficients of the PVAR model applied to the subsets of regions of EU15 and Norway vs. the effects in the remaining countries, while Figure 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 the

[9] EU15 includes the following countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden, and the UK.

short and long run are confirmed for regions in EU15 or Norway, the impact is negligible or null in all the other regions. Our main results are therefore driven by regions belonging to EU15 countries and Norway.

Specifically, in the EU15 and Norway regions, a standard deviation shock in technological relatedness leads to an initial 0.05 per cent growth in employment and a decrease of 0.2 per cent points GDP growth. In the subsequent period, one standard deviation shock in technological relatedness increases employment growth by 0.15 per cent points. These results are in line with the evidence presented in Table 2 and Figure 3. Following our previous findings, the effect of technological unconventionality is significant only on GDP growth, and one standard deviation shock results in an initial increase of 0.2 per cents points in GDP growth. In the following period, the effect of one standard deviation shock of technological unconventionality increases GDP growth by 0.4 per cent points.

Concerning Figure 4b and Table 3b, we can observe that in non-EU15 European regions, technological relatedness has an initial positive effect on employment growth of 0.09. This evidence corroborates the idea that technologically coherent knowledge bases allow regions to produce incremental new knowledge that improves employment performance. Figure 4b also highlights that technological relatedness leads to an initial negative effect of 0.2 on GDP growth. In regions outside the EU15, we observe a negative effect of technological unconventionality on GDP growth. In particular, Figure 4b highlights that a standard deviation shock in technological unconventionality leads to a fall in GDP growth of around 0.7 per cent points. However, Figure 4b also indicates that a standard deviation shock in technological unconventionality leads to an increase of 0.1 per cent points in employment growth. It is possible that in regions with a less mature industrial structure, unconventional technological combinations may lead to the emergence of new industries and, therefore, the creation of new jobs.

Table 3: Effects of technological diversification in regions in and outside EU15 and Norway.

(a) Regions in EU15 and Norway.

	(1) Tech_Unconv$_t$	(2) Tech_Coherence$_t$	(3) Emp_Growth$_t$	(4) GDP_Growth$_t$
Tech_Unconv$_{t-1}$	0.129**	1.163*	0.0148	0.0521***
	(0.0530)	(0.662)	(0.00943)	(0.0166)
Tech_Coherence$_{t-1}$	-0.0288***	0.788***	0.00255***	-0.00203**
	(0.00328)	(0.0481)	(0.000611)	(0.000916)
Emp_Growth$_{t-1}$	-0.148***	2.350***	0.272***	0.0589*
	(0.0563)	(0.822)	(0.0528)	(0.0304)
GDP_Growth$_{t-1}$	0.240***	0.536	0.139***	0.316***
	(0.0441)	(0.444)	(0.0140)	(0.0322)
Observations	5,944	5,944	5,944	5,944

Notes: 1-lag PVAR estimations of the following reduced form model on EU15 and Norway 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 coherence (as a measure of 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 1,000 draws. *** p<0.01, ** p<0.05, * p<0.1

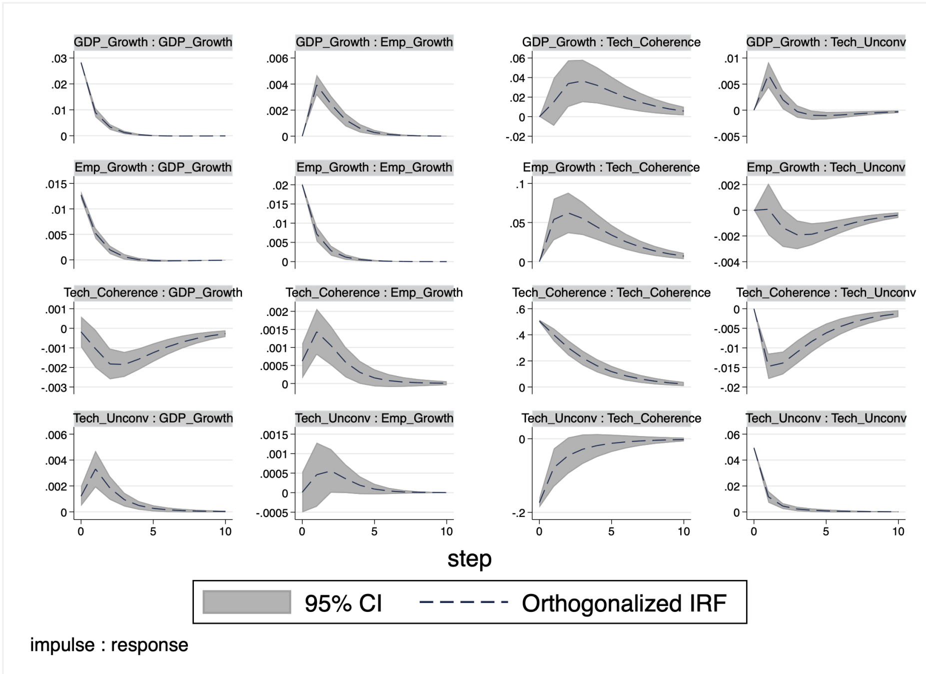
(b) European regions not in EU15 or Norway.

	(1) Tech_Unconv$_t$	(2) Tech_Coherence$_t$	(3) Emp_Growth$_t$	(4) GDP_Growth$_t$
Tech_Unconv$_{t-1}$	0.219***	-1.349*	0.00899	0.0215
	(0.0569)	(0.730)	(0.0154)	(0.0184)
Tech_Coherence$_{t-1}$	-0.00767**	0.0476	0.000927	0.000398
	(0.00340)	(0.0555)	(0.000852)	(0.00119)
Emp_Growth$_{t-1}$	0.683***	2.391	0.199***	-0.152***
	(0.118)	(1.561)	(0.0457)	(0.0517)
GDP_Growth$_{t-1}$	-0.877***	-3.294**	0.0561	0.676***
	(0.157)	(1.309)	(0.0369)	(0.0590)
Observations	1,103	1,103	1,103	1,103

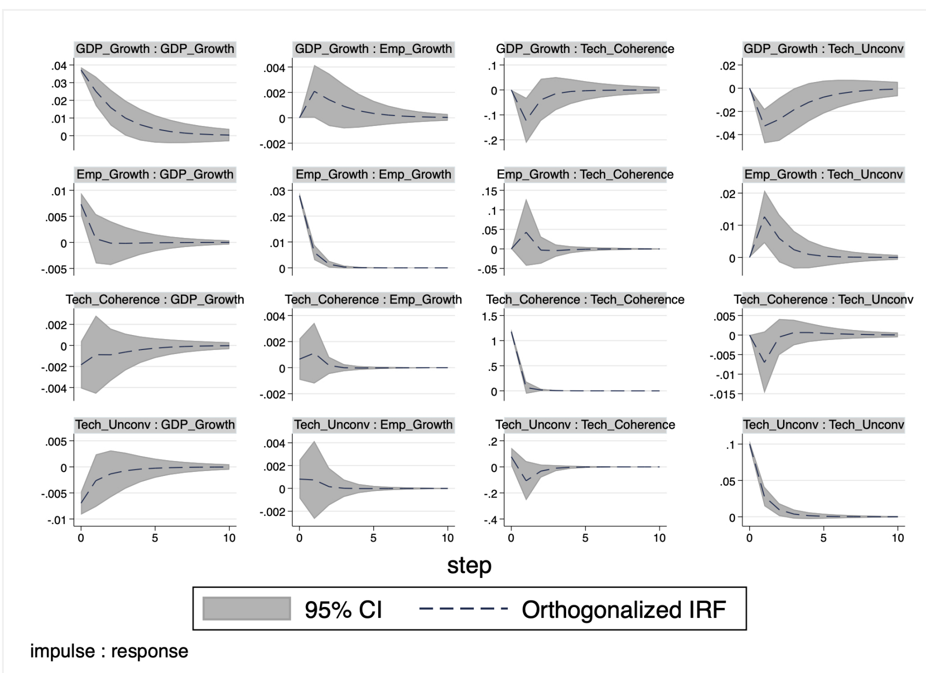
Notes: 1-lag PVAR estimations of the following reduced form model on regions that do not belong to EU15: $X_{rt} = \alpha + \sum_{i=1}^{p} \beta_i X_{r,t-i} + \phi_r + \epsilon_{rt}$. The main variables are technological unconventionality, technological coherence (as a measure of technological relatedness), 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

Figure 4: Impulse response: Regions in and outside EU15 and Norway.

(a) Regions in EU15 and Norway.



(b) European regions not in EU15 and Norway.



Notes: IRF shows the effect of a standard deviation shock 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 1,000 draws.

More and less innovative regions As a second heterogeneity test, we split regions according to their total number of patents and identify the most and least innovative regions. The most innovative regions are those with more than 76 patents (average total number of patents across regions) on average over the period 1980-2014.

Table 4 reports the PVAR results and Figure 5 shows the corresponding impulse response functions. From Table 4a and Figure 5a, we can confirm the statistically significant (and positive) effects of technological diversification on employment and GDP growth in the most innovative regions, both in the short and long run. It is worth noticing that in this case the effect of technological relatedness is also positive on GDP growth. For what concerns the less innovative regions (Table 4b and Figure 5b), instead, there is no effect of shocks in technological unconventionality. Although these regions are relatively less technically advanced, we can still observe an effect of technological relatedness on employment growth.

Table 4: Effects of technological diversification in the most and less innovative regions.

(a) The most innovative regions.

	(1) Tech_Unconv$_t$	(2) Tech_Coherence$_t$	(3) Emp_Growth$_t$	(4) GDP_Growth$_t$
Tech_Unconv$_{t-1}$	0.354***	4.936***	0.0274*	0.296***
	(0.0360)	(0.327)	(0.0151)	(0.0256)
Tech_Coherence$_{t-1}$	-0.0253***	1.119***	0.00421***	0.0129***
	(0.00217)	(0.0207)	(0.000912)	(0.00147)
Emp_Growth$_{t-1}$	-0.239***	3.585***	0.175***	-0.0846*
	(0.0289)	(0.382)	(0.0312)	(0.0489)
GDP_Growth$_{t-1}$	0.207***	-1.750***	0.139***	0.213***
	(0.0207)	(0.194)	(0.0132)	(0.0475)
Observations	4,175	4,175	4,175	4,175

Notes: 1-lag PVAR estimations of the following reduced form model on the most innovative 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 coherence (as a measure of 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

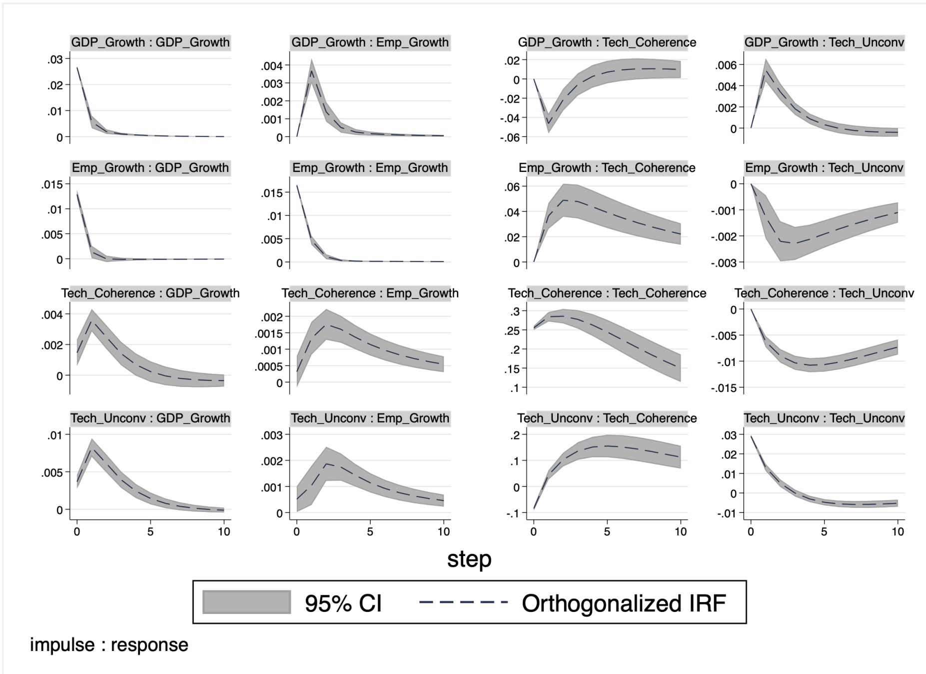
(b) The less innovative regions.

	(1) Tech_Unconv$_t$	(2) Tech_Coherence$_t$	(3) Emp_Growth$_t$	(4) GDP_Growth$_t$
Tech_Unconv$_{t-1}$	0.0971**	-1.248*	0.00318	0.0222
	(0.0455)	(0.686)	(0.0107)	(0.0164)
Tech_Coherence$_{t-1}$	-0.00907***	0.192***	0.00125*	2.94e-05
	(0.00281)	(0.0439)	(0.000637)	(0.000851)
Emp_Growth$_{t-1}$	0.283***	6.376***	0.205***	-0.0863***
	(0.0770)	(1.173)	(0.0668)	(0.0335)
GDP_Growth$_{t-1}$	-0.506***	-10.93***	0.184***	0.655***
	(0.0910)	(1.348)	(0.0238)	(0.0396)
Observations	2,619	2,619	2,619	2,619

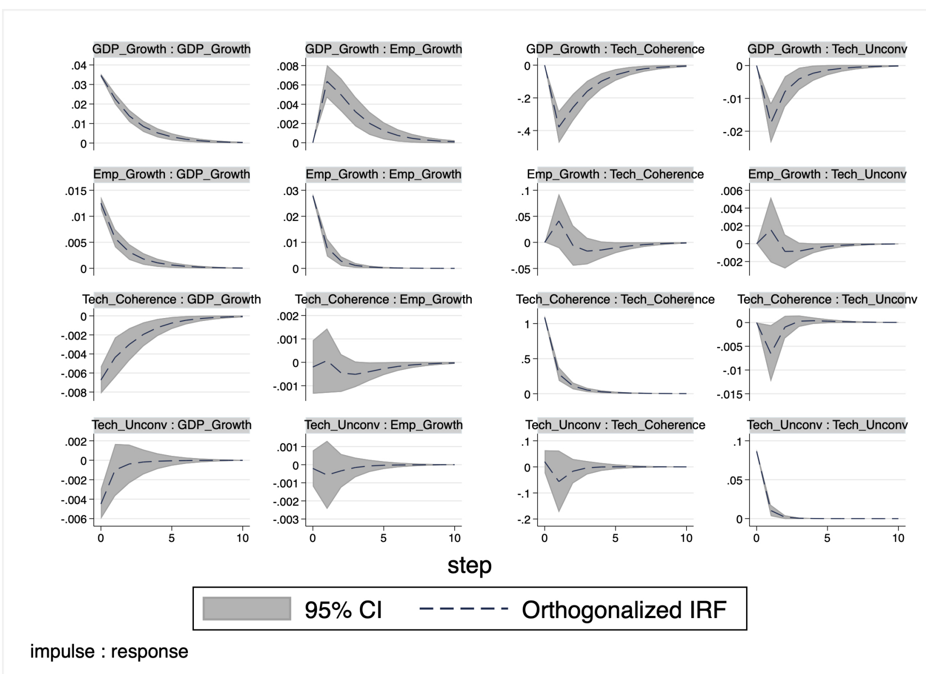
Notes: 1-lag PVAR estimations of the following reduced form model on less innovative regions: $X_{rt} = \alpha + \sum_{i=1}^{p} \beta_i X_{r,t-i} + \phi_r + \epsilon_{rt}$. The main variables are technological unconventionality, technological coherence (as a measure of technological relatedness), employment 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 1,000 draws. *** p<0.01, ** p<0.05, * p<0.1

Figure 5: Impulse response: The most and less innovative regions

(a) The most innovative regions.



(b) The less innovative regions.



Notes: IRF shows the effect of a standard deviation shock 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 1,000 draws.

5.2 Robustness checks

We test the robustness of our results by adding exogenous controls (population level) at the regional level in Table A1 and Figure A1. In Table A2 and Figure A2, instead, we examine whether our results are driven 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 A3 and Figure A3. Finally, we show in Table A4 and Figure A4 and Table A5 and Figure A5 our estimations using two alternative Cholesky decomposition orderings.

All these additional results and figures, presented in Appendix A, confirm that technological relatedness has a short-term effect on employment growth and a negative effect on GDP growth. Technological unconventionality, instead, has 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 output 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 configurations 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 recombinations help regions to move towards new technological frontiers.

An increase in technological relatedness induce a positive effect on employment in the short run and negative effects in the long run. Conversely, an increase in technological unconventionality positively affects output growth in the long run.

In addition to its novel empirical findings, the paper also makes theoretical and methodological contributions. We elaborated on the direction and the short- vs. long-term effects of different forms of technological diversification on regions' economic performance. We adopted a methodological framework that allowed for the identification of causal effects of technological diversification, thus addressing in a novel way the pervasive endogeneity problems that make causal claims very difficult in the existing innovation and economic geography literature. Thirdly, and differently from the prior art 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.

These 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, however, diversification strategies have different, and more or less persistent, effects on GDP and employment. The identification of technological capabilities is essential to devise the most appropriate incentive schemes. If a region has to improve its employment growth performance, it can design innovation policies that promote the recombination of related pieces of knowledge. The exploitation of related knowledge components through recombinant search allows local economies to create new technological 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 a region targets GDP growth, it may promote the recombination of knowledge that is more distant from existing technological capabilities. The exploration of unconventional recombinations 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. Exploiting already existing local technological knowledge is important to maintain satisfactory performance in the job market, but it is also fundamental 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 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, in association with growing income inequalities.

References

Abbasiharofteh, M., D. F. Kogler, and B. Lengyel (2023). "Atypical Combinations of Technologies in Regional Co-Inventor Networks". *Research Policy* 52(10), 104886.

Abrigo, M. R. and I. Love (2016). "Estimation of Panel Vector Autoregression in Stata". *The Stata Journal* 16(3), 778–804.

Aharonson, B. S. and M. A. Schilling (2016). "Mapping the technological landscape: Measuring technology distance, technological footprints, and technology evolution". *Research Policy* 45(1), 81–96.

Amoroso, S. et al. (2022). "Technological Relatedness and Industrial Transformation: Introduction to the Special Issue". *The Journal of Technology Transfer*, 1–7.

Andrews, D. W. and B. Lu (2001). "Consistent Model and Moment Selection Procedures for GMM Estimation with Application to Dynamic Panel Data Models". *Journal of econometrics* 101(1), 123–164.

Antonelli, C., F. Crespi, and F. Quatraro (2022). "Knowledge complexity and the mechanisms of knowledge generation and exploitation: The European evidence". *Research Policy* 51(8), 104081.

Antonelli, C., J.-L. Gaffard, and M. Quéré (2003). "Interactive Learning and Technological Knowledge: The Localised Character of Innovation Processes". In: *Cognitive Developments in Economics*. London: Routledge, 280–291.

Arrow, K. (1962). "Economic Welfare and the Allocation of Resources for Invention". In: *The Rate and Direction of Inventive Activity: Economic and Social Factors*. Ed. by R. R. Nelson. Princeton, NJ: Princeton University Press, 609–626.

Arthur, W. B. (1994). *Increasing Returns and Path Dependence in the Economy*. Ann Arbor, MI: University of Michigan Press.

— (2021). "Foundations of Complexity Economics". *Nature Reviews Physics* 3(2), 136–145.

Balland, P.-A., D. Rigby, and R. Boschma (2015). "The Technological Resilience of US Cities". *Cambridge Journal of Regions, Economy and Society* 8(2), 167–184.

Balland, P.-A. et al. (2019). "Smart specialization policy in the European Union: relatedness, knowledge complexity and regional diversification". *Regional studies* 53(9), 1252–1268.

Balland, P.-A. et al. (2022). "Reprint of The New Paradigm of Economic Complexity". *Research Policy* 51(8), 104568.

Bathelt, H. and M. Storper (2022). "Related Variety and Regional Development". *Papers in Evolutionary Economic Geography* 22.14.

Beaudry, C. and A. Schiffauerova (2009). "Who's Right, Marshall or Jacobs? The Localization Versus Urbanization Debate". *Research Policy* 38(2), 318–337.

Berkes, E. and R. Gaetani (2021). "The Geography of Unconventional Innovation". *The Economic Journal* 131(636), 1466–1514.

Boschma, R. (2017). "Relatedness as Driver of Regional Diversification: A Research Agenda". *Regional Studies* 51(3), 351–364.

Boschma, R. and G. Capone (2015). "Institutions and Diversification: Related Versus Unrelated Diversification in a Varieties of Capitalism Framework". *Research Policy* 44(10), 1902–1914.

Boschma, R. and K. Frenken (2010). "Technological Relatedness and Regional Branching". In: *Beyond Territory: Dynamic Geographies of Knowledge Creation, Diffusion and Innovation*. Ed. by H. Bathelt, M. Feldman, and D. F. Kogler. Routledge, 64–81.

Boschma, R. and R. Martin (2010). "The Aims and Scope of Evolutionary Economic Geography". In: *The Handbook of Evolutionary Economic Geography*. Ed. by R. Boschma and R. Martin. Cheltenham: Edward Elgar Publishing, 3–39.

Brezis, E. S., P. R. Krugman, and D. Tsiddon (1993). "Leapfrogging in International Competition: A Theory of Cycles in National Technological Leadership". *The American Economic Review* 83(5), 1211–1219.

Caragliu, A. and P. Nijkamp (2016). “Space and Knowledge Spillovers in European Regions: The Impact of Different Forms of Proximity on Spatial Knowledge Diffusion”. *Journal of Economic Geography* 16(3), 749–774.

Castaldi, C., K. Frenken, and B. Los (2015). “Related Variety, Unrelated Variety and Technological Breakthroughs: An Analysis of US State-Level Patenting”. *Regional Studies* 49(5), 767–781.

Cohen, W. M., D. A. Levinthal, et al. (1990). “Absorptive Capacity: A New Perspective on Learning and Innovation”. *Administrative Science Quarterly* 35(1), 128–152.

Content, J. and K. Frenken (2016). “Related Variety and Economic Development: A Literature Review”. *European Planning Studies* 24(12), 2097–2112.

Cortinovis, N., R. Crescenzi, and F. Van Oort (2020). “Multinational Enterprises, Industrial Relatedness and Employment in European Regions”. *Journal of Economic Geography* 20(5), 1165–1205.

Diodato, D. and A. B. Weterings (2015). “The Resilience of Regional Labour Markets to Economic Shocks: Exploring the Role of Interactions Among Firms and Workers”. *Journal of Economic Geography* 15(4), 723–742.

Dosi, G. (1982). “Technological Paradigms and Technological Trajectories: A Suggested Interpretation of the Determinants and Directions of Technical Change”. *Research Policy* 11(3), 147–162.

Fleming, L. (2001). “Recombinant Uncertainty in Technological Search”. *Management Science* 47(1), 117–132.

Fontana, M. et al. (2020). “New and Atypical Combinations: An Assessment of Novelty and Interdisciplinarity”. *Research Policy* 49(7), 104063.

Freeman, C., J. Clark, and L. Soete (1982). *Unemployment and Technical Innovation: A Study of Long Waves and Economic Development*. 50. London: Frances Pinter.

Frenken, K. and R. A. Boschma (2007). “A Theoretical Framework for Evolutionary Economic Geography: Industrial Dynamics and Urban Growth as a Branching Process”. *Journal of Economic Geography* 7(5), 635–649.

Frenken, K., F. Van Oort, and T. Verburg (2007). “Related Variety, Unrelated Variety and Regional Economic Growth”. *Regional Studies* 41(5), 685–697.

Glaeser, E. L. (2005). “Reinventing Boston: 1630–2003”. *Journal of Economic Geography* 5(2), 119–153.

Grabher, G. (1993). "The Weakness of Strong Ties: The Lock-In of Regional Development in Ruhr Area". In: *The Embedded Firm: On the Socioeconomics of Industrial Networks*. Ed. by G. Grabher. London: Routledge, 255–277.

Griliches, Z. (1990). "Patent Statistics as Economic Indicators: A Survey". *Journal of Economic Literature* 28(4), 1661–1707.

Grossman, G. M. and E. Helpman (1993). *Innovation and Growth in the Global Economy*. Cambridge, MA: MIT Press.

Hall, B. H., A. B. Jaffe, and M. Trajtenberg (2001). *The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools*. Working Paper 8498. National Bureau of Economic Research.

Hausmann, R. et al. (2014). *The Atlas of Economic Complexity: Mapping Paths to Prosperity*. Boston: MIT Press.

Hidalgo, C. A. et al. (2007). "The Product Space Conditions the Development of Nations". *Science* 317(5837), 482–487.

Holm, J. R. and C. R. Østergaard (2015). "Regional Employment Growth, Shocks and Regional Industrial Resilience: A Quantitative Analysis of the Danish ICT Sector". *Regional Studies* 49(1), 95–112.

Holtz-Eakin, D., W. Newey, and H. S. Rosen (1988). "Estimating Vector Autoregressions with Panel Data". *Econometrica: Journal of the Econometric Society* 56(6), 1371–1395.

Jacobs, J. (1970). *The Economy of Cities*. New York: Vintage Books.

Jones, B. F. (2009). "The Burden of Knowledge and The "Death of the Renaissance Man": Is Innovation Getting Harder?" *The Review of Economic Studies* 76(1), 283–317.

Kim, D. et al. (2016). "Technological Novelty Profile and Invention's Future Impact". *EPJ Data Science* 5(1), 1–15.

Kogler, D. F., J. Essletzbichler, and D. L. Rigby (2017). "The Evolution of Specialization in the EU15 Knowledge Space". *Journal of Economic Geography* 17(2), 345–373.

Kogler, D. F., D. L. Rigby, and I. Tucker (2013). "Mapping Knowledge Space and Technological Relatedness in US Cities". *European Planning Studies* 21(9), 1374–1391.

Lee, K. (2013). *Schumpeterian Analysis of Economic Catch-Up: Knowledge, Path-Creation, and the Middle-Income Trap*. Cambridge: Cambridge University Press.

Lee, K. and C. Lim (2001). "Technological Regimes, Catching-Up and Leapfrogging: Findings From the Korean Industries". *Research policy* 30(3), 459–483.

Lee, K. and F. Malerba (2017). “Catch-Up Cycles and Changes in Industrial Leadership: Windows of Opportunity and Responses of Firms and Countries in the Evolution of Sectoral Systems”. *Research Policy* 46(2), 338–351.

Li, Y. and F. Neffke (2022). “Relatedness in Regional Development: In Search of the Right Specification”. *Papers in Evolutionary Economic Geography* 2208.

Marshall, A. (1890). *Principles of Economics*. London: Palgrave Macmillan.

Martin, R. (2012). “Regional Economic Resilience, Hysteresis and Recessionary Shocks”. *Journal of Economic Geography* 12(1), 1–32.

Martin, R. and P. Sunley (2006). “Path Dependence and Regional Economic Evolution”. *Journal of Economic Geography* 6(4), 395–437.

McCann, P. (2013). *Modern Urban and Regional Economics*. Oxford: Oxford University Press.

Muller, E. and A. Zenker (2001). “Business Services as Actors of Knowledge Transformation: The Role of KIBS in Regional and National Innovation Systems”. *Research Policy* 30(9), 1501–1516.

Neffke, F., M. Henning, and R. Boschma (2011). “How Do Regions Diversify Over Time? Industry Relatedness and the Development of New Growth Paths in Regions”. *Economic Geography* 87(3), 237–265.

Nelson, R. R. (1959). “The Simple Economics of Basic Scientific Research”. *Journal of Political Economy* 67(3), 297–306.

Nesta, L. and P. P. Saviotti (2005). “Coherence of the Knowledge Base and the Firm’s Innovative Performance: Evidence from the US Pharmaceutical Industry”. *The Journal of Industrial Economics* 53(1), 123–142.

Nesta, L. and P.-P. Saviotti (2006). “Firm Knowledge and Market Value in Biotechnology”. *Industrial and Corporate Change* 15(4), 625–652.

Nickell, S. (1981). “Biases in Dynamic Models with Fixed Effects”. *Econometrica: Journal of the Econometric Society* 49(6), 1417–1426.

Nomaler, Ö. and B. Verspagen (2022). “Complexity Research in Economics: Past, Present and Future”. *MERIT Working Papers* 2022-023.

Nooteboom, B. (2000). *Learning and Innovation in Organizations and Economies*. Oxford: Oxford University Press.

Petralia, S., P.-A. Balland, and A. Morrison (2017). “Climbing the Ladder of Technological Development”. *Research Policy* 46(5), 956–969.

Pinheiro, F. L. et al. (2022). "The Time and Frequency of Unrelated Diversification". *Research Policy* 51(8), 104323.

Rocchetta, S. and A. Mina (2019). "Technological Coherence and the Adaptive Resilience of Regional Economies". *Regional Studies* 53(10), 1421–1434.

Rocchetta, S. et al. (2022). "Technological Knowledge Spaces and the Resilience of European Regions". *Journal of Economic Geography* 22(1), 27–51.

Rosenberg, N. (1998). "Uncertainty and Technological Change". In: *The Economic Impact of Knowledge*. Ed. by T. Siesfeld, J. Cefola, and D. Neef. London: Routledge, 17–34.

Schumpeter, J. A. et al. (1939). *Business Cycles*. Vol. 1. New York: McGraw-Hill.

Scotchmer, S. (1991). "Standing on the Shoulders of Giants: Cumulative Research and the Patent Law". *Journal of Economic Perspectives* 5(1), 29–41.

Simon, H. A. (1990). "Bounded Rationality". In: *Utility and Probability*. Ed. by J. Eatwell, M. Milgate, and P. Newman. London: Palgrave Macmillan, 15–18.

Soete, L. (1985). "International Diffusion of Technology, Industrial Development and Technological Leapfrogging". *World Development* 13(3), 409–422.

Tanner, A. N. (2016). "The Emergence of New Technology-Based Industries: The Case of Fuel Cells and Its Technological Relatedness to Regional Knowledge Bases". *Journal of Economic Geography* 16(3), 611–635.

Teece, D. J. et al. (1994). "Understanding Corporate Coherence: Theory and Evidence". *Journal of Economic Behavior & Organization* 23(1), 1–30.

Uzzi, B. et al. (2013). "Atypical Combinations and Scientific Impact". *Science* 342(6157), 468–472.

Wang, J., R. Veugelers, and P. Stephan (2017). "Bias Against Novelty in Science: A Cautionary Tale for Users of Bibliometric Indicators". *Research Policy* 46(8), 1416–1436.

Weitzman, M. L. (1998). "Recombinant Growth". *Quarterly Journal of Economics* 113(2), 331–360.

Wuchty, S., B. F. Jones, and B. Uzzi (2007). "The Increasing Dominance of Teams in the Production of Knowledge". *Science* 316, 1036–1039.

Xiao, J., R. Boschma, and M. Andersson (2018). "Resilience in the European Union: The Effect of the 2008 Crisis On the Ability of Regions in Europe to Develop New Industrial Specializations". *Industrial and Corporate Change* 27(1), 15–47.

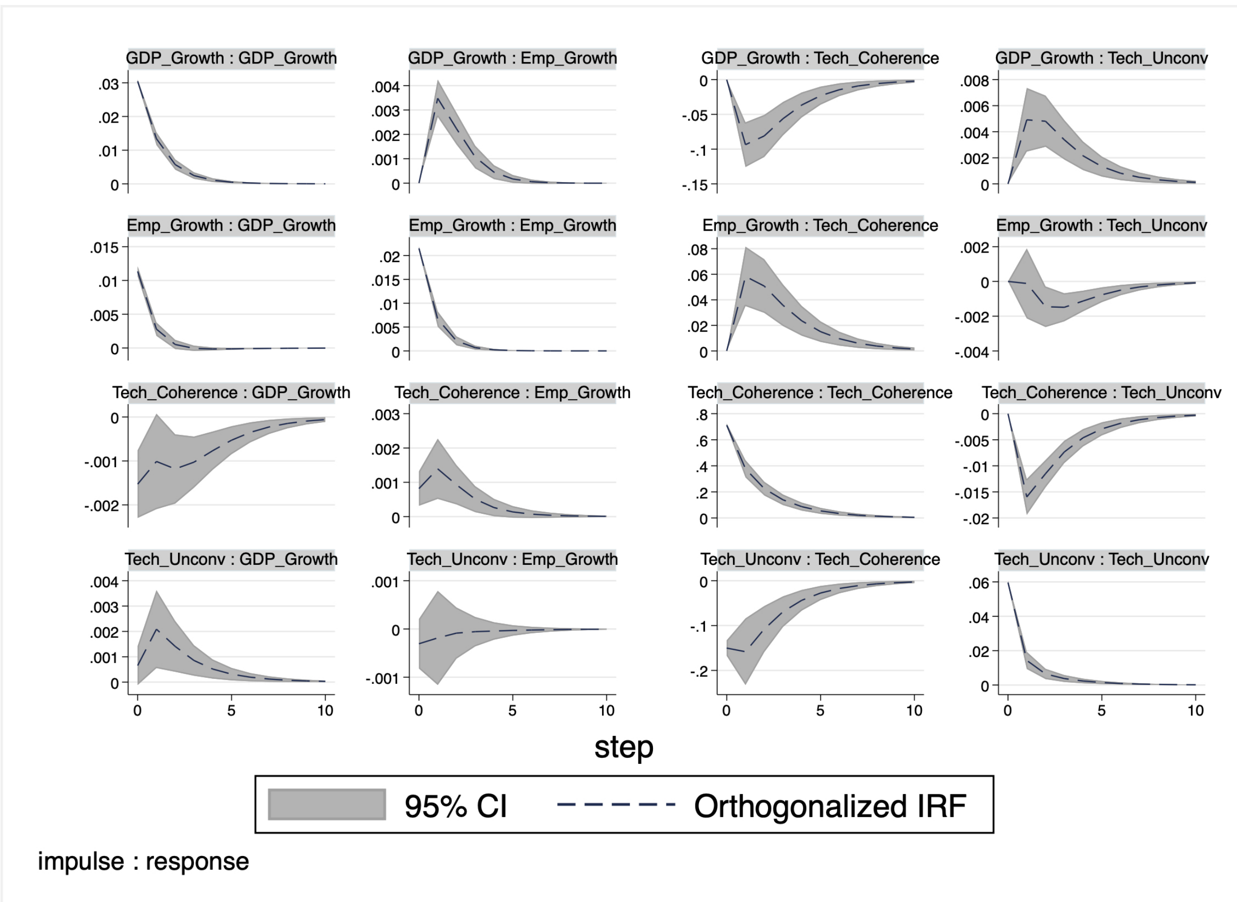
A Additional results

Table A1: Main results with additional controls.

	(1) $Tech\_Unconv_t$	(2) $Tech\_Coherence_t$	(3) Emp_Growth_t	(4) GDP_Growth_t
$Tech\_Unconv_{t-1}$	0.183***	-1.293*	0.00173	0.0288**
	(0.0461)	(0.736)	(0.00942)	(0.0135)
$Tech\_Coherence_{t-1}$	-0.0220***	0.518***	0.00191***	-0.000356
	(0.00253)	(0.0474)	(0.000611)	(0.000760)
Emp_Growth_{t-1}	-0.0906*	4.335***	0.250***	-0.103***
	(0.0540)	(0.674)	(0.0393)	(0.0264)
GDP_Growth_{t-1}	0.162***	-3.074***	0.114***	0.441***
	(0.0404)	(0.549)	(0.0131)	(0.0319)
Population	4.50e-06	-3.37e-05	-2.86e-06	-2.00e-05***
	(1.16e-05)	(9.25e-05)	(2.91e-06)	(4.94e-06)
Observations	6,794	6,794	6,794	6,794

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 coherence (as a measure of technological relatedness), employment growth and GDP growth at time t in region r. All regressions include region-fixed effects and control variables (population level). Standard errors are clustered at the regional level. *** p<0.01, ** p<0.05, * p<0.1

Figure A1: Impulse response: Main results with additional controls.



Notes: IRF shows the effect of a standard deviation shock 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 1,000 draws.

Table A2: Main results with three lags as instruments.

	(1) Tech_Unconv_t	(2) Tech_Coherence_t	(3) Emp_Growth_t	(4) GDP_Growth_t
Tech_Unconv_{t-1}	0.211***	-2.290***	0.00660	0.0598***
	(0.0453)	(0.717)	(0.00974)	(0.0146)
$\text{Tech\_Coherence}_{t-1}$	-0.0215***	0.359***	0.00150***	0.000327
	(0.00243)	(0.0439)	(0.000572)	(0.000782)
Emp_Growth_{t-1}	-0.0835*	20.52***	0.295***	-0.162***
	(0.0453)	(1.920)	(0.0446)	(0.0299)
GDP_Growth_{t-1}	0.143***	-15.19***	0.0949***	0.555***
	(0.0381)	(1.241)	(0.0131)	(0.0312)
Observations	6,794	6,794	6,794	6,794

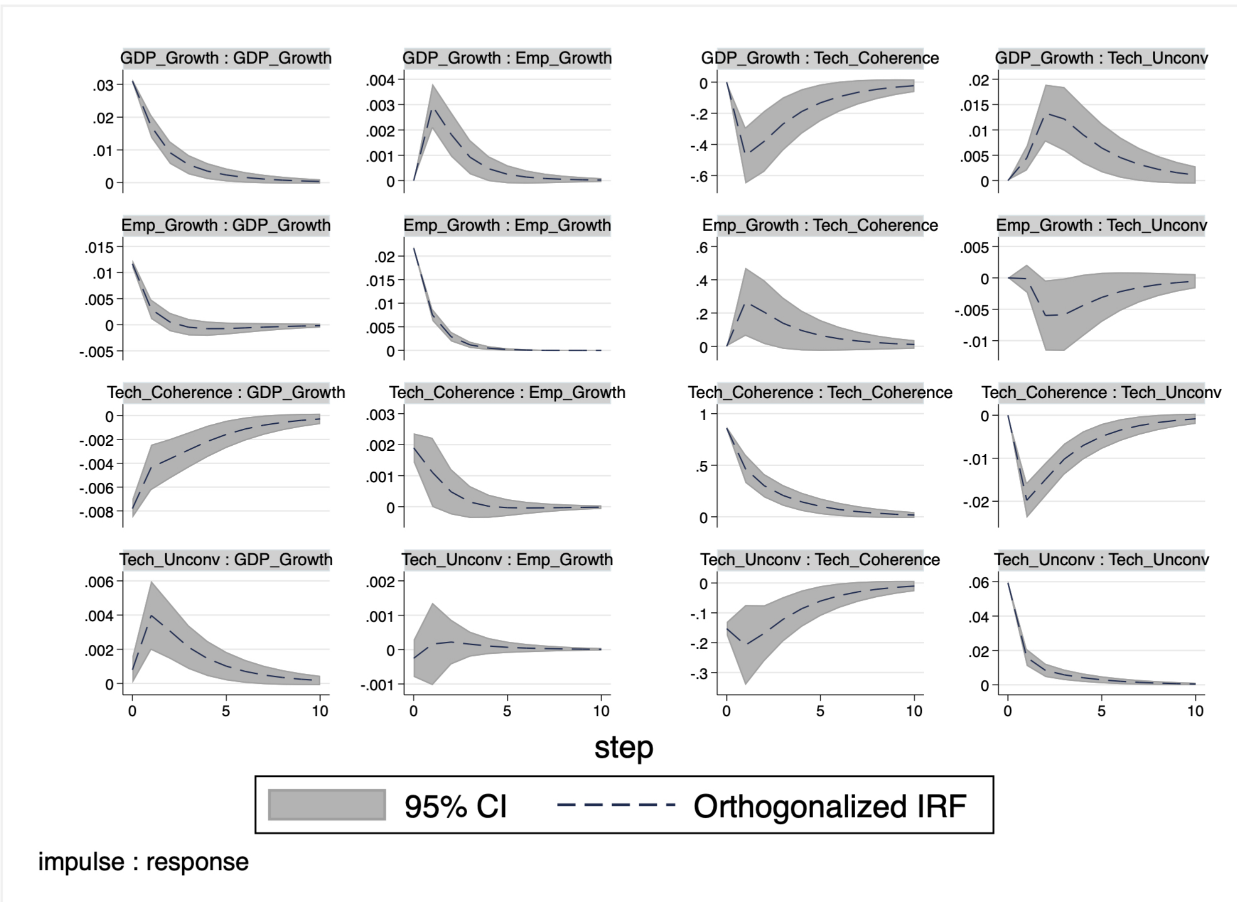
Notes: 1-lag PVAR estimations of the following reduced form model: $X_{rt} = \alpha + \sum_{i=1}^{p} \beta_i X_{r,t-i} + \phi_r + \epsilon_{rt}$. The main variables are technological unconventionality, technological coherence (as a measure of technological relatedness), employment growth and GDP growth 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 1,000 draws. *** p<0.01, ** p<0.05, * p<0.1

Table A3: Main results with second order VAR.

	(1) Tech_Unconv_t	(2) Tech_Coherence_t	(3) Emp_Growth_t	(4) GDP_Growth_t
Tech_Unconv_{t-1}	0.0443	0.241	0.000667	0.0414**
	(0.0527)	(0.872)	(0.0121)	(0.0171)
Tech_Unconv_{t-2}	0.0263	-0.565	0.00381	0.0320***
	(0.0376)	(0.617)	(0.00990)	(0.0105)
$\text{Tech\_Coherence}_{t-1}$	-0.0200***	0.400***	0.00174**	0.00242**
	(0.00424)	(0.0635)	(0.000782)	(0.00113)
$\text{Tech\_Coherence}_{t-2}$	-0.0139***	0.239***	-0.000272	-0.00305***
	(0.00197)	(0.0443)	(0.000570)	(0.000625)
Emp_Growth_{t-1}	0.128**	0.232	0.183***	-0.0674**
	(0.0508)	(0.792)	(0.0619)	(0.0283)
Emp_Growth_{t-2}	-0.0264	2.843***	0.0315	-0.0886***
	(0.0461)	(0.779)	(0.0339)	(0.0277)
GDP_Growth_{t-1}	-0.0481	-0.683	0.138***	0.256***
	(0.0399)	(0.471)	(0.0171)	(0.0277)
GDP_Growth_{t-2}	0.0226	-0.530	0.0491***	0.268***
	(0.0317)	(0.367)	(0.0153)	(0.0320)
Observations	6,510	6,510	6,510	6,510

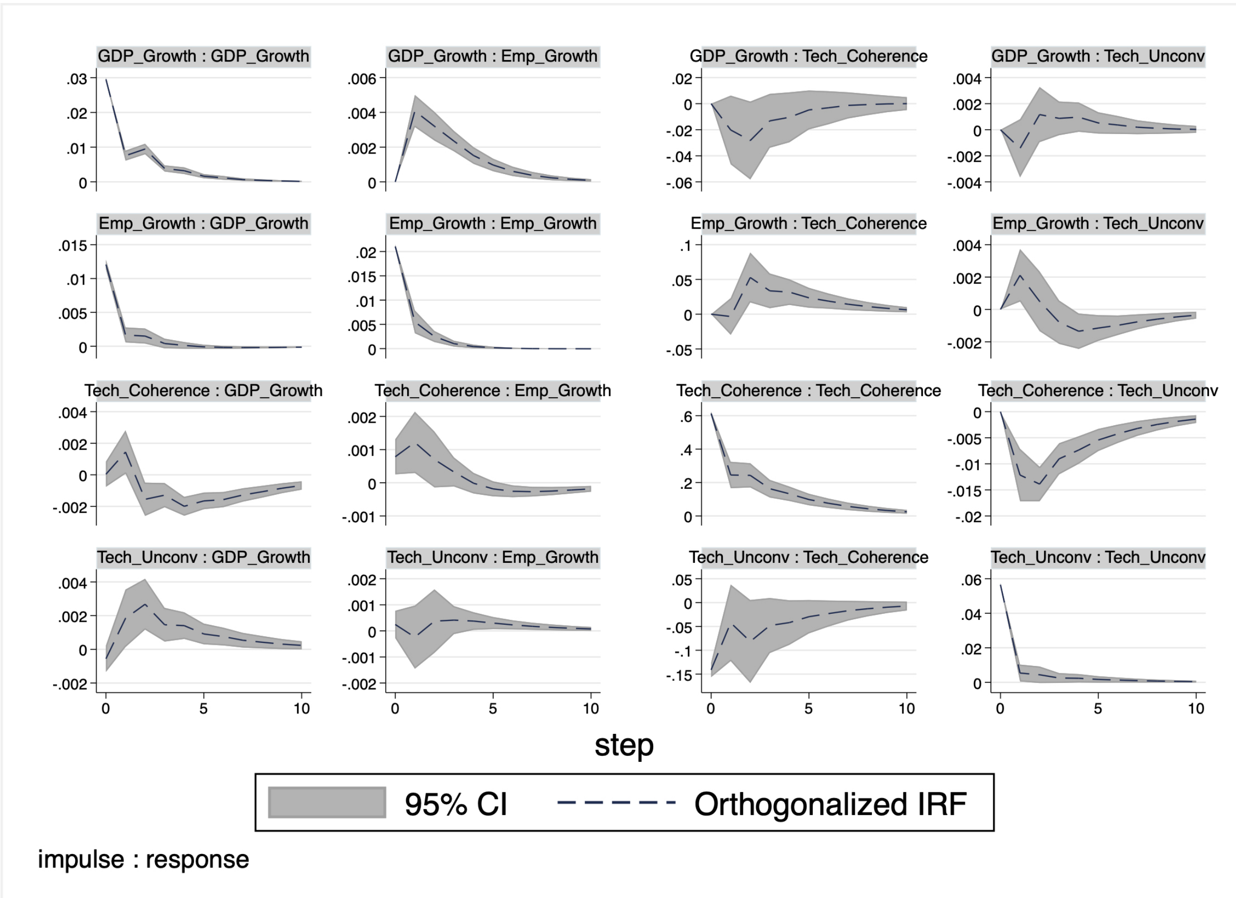
Notes: 1-lag PVAR estimations of the following reduced form model: $X_{rt} = \alpha + \sum_{i=1}^{p} \beta_i X_{r,t-i} + \phi_r + \epsilon_{rt}$. The main variables are technological unconventionality, technological coherence (as a measure of technological relatedness), employment growth and GDP growth 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

Figure A2: Impulse response: Main results with three lags as instruments.



Notes: IRF shows the effect of a standard deviation shock 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 1,000 draws.

Figure A3: Impulse response: Main results with second-order VAR.



Notes: IRF shows the effect of a standard deviation shock 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 1,000 draws.

Table A4: Main results with an alternative Cholesky decomposition (1).

	(1) Tech_Coherence$_t$	(2) Tech_Unconv$_t$	(3) Emp_Growth$_t$	(4) GDP_Growth$_t$
Tech_Coherence$_{t-1}$	0.515***	-0.0234***	0.00175***	-0.00165**
	(0.0425)	(0.00250)	(0.000585)	(0.000735)
Tech_Unconv$_{t-1}$	-0.992	0.159***	0.000570	0.0303**
	(0.754)	(0.0450)	(0.00931)	(0.0140)
Emp_Growth$_{t-1}$	5.471***	-0.0730	0.239***	-0.110***
	(0.671)	(0.0493)	(0.0388)	(0.0261)
GDP_Growth$_{t-1}$	-4.955***	0.165***	0.134***	0.515***
	(0.591)	(0.0401)	(0.0132)	(0.0300)
Observations	6,794	6,794	6,794	6,794

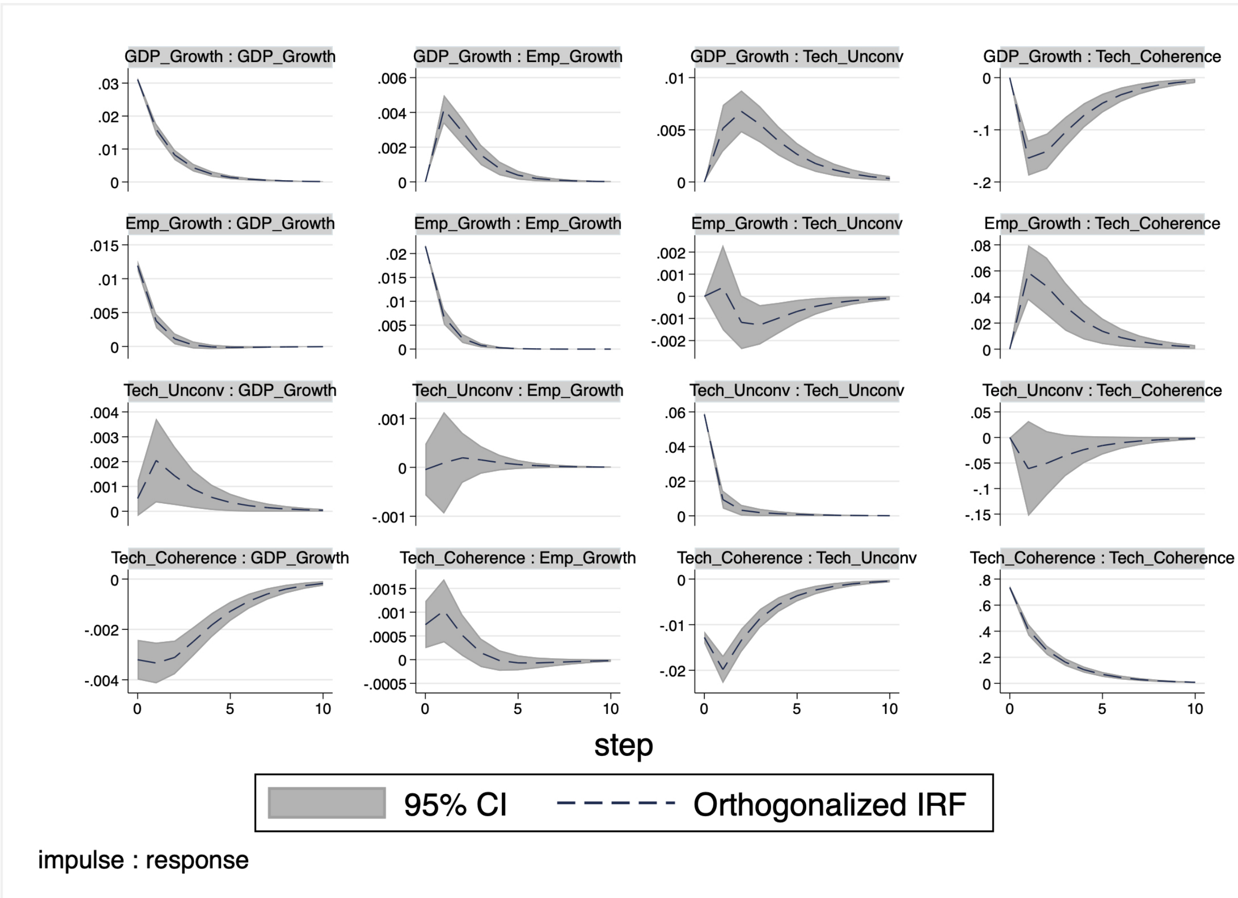
Notes: 1-lag PVAR estimations of the following reduced form model: $X_{rt} = \alpha + \sum_{i=1}^{p} \beta_i X_{r,t-i} + \phi_r + \epsilon_{rt}$. Main variables are technological coherence (as a measure of technological relatedness), technological unconventionality, employment growth and GDP growth at 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 A5: Main results with an alternative Cholesky decomposition (2).

	(1) Tech_Unconv$_t$	(2) Tech_Coherence$_t$	(3) GDP_Growth$_t$	(4) Emp_Growth$_t$
Tech_Unconv$_{t-1}$	0.159***	-0.992	0.0303**	0.000570
	(0.0450)	(0.754)	(0.0140)	(0.00931)
Tech_Coherence$_{t-1}$	-0.0234***	0.515***	-0.00165**	0.00175***
	(0.00250)	(0.0425)	(0.000735)	(0.000585)
GDP_Growth$_{t-1}$	0.165***	-4.955***	0.515***	0.134***
	(0.0401)	(0.591)	(0.0300)	(0.0132)
Emp_Growth$_{t-1}$	-0.0730	5.471***	-0.110***	0.239***
	(0.0493)	(0.671)	(0.0261)	(0.0388)
Observations	6,794	6,794	6,794	6,794

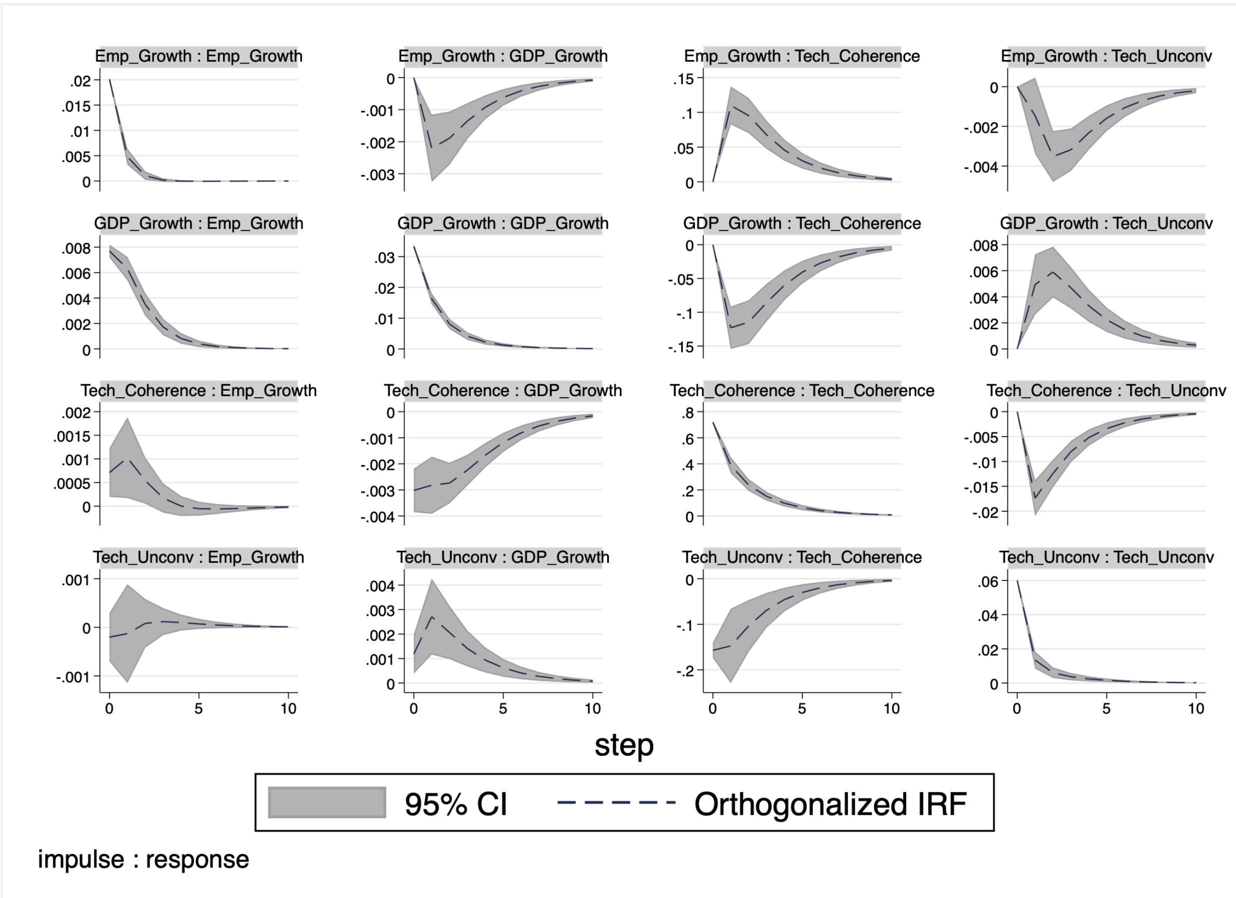
Notes: 1-lag PVAR estimations of the following reduced form model: $X_{rt} = \alpha + \sum_{i=1}^{p} \beta_i X_{r,t-i} + \phi_r + \epsilon_{rt}$. The main variables are technological unconventionality, technological coherence (as a measure of technological relatedness), GDP growth and employment growth 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

Figure A4: Impulse response: Main results with an alternative Cholesky decomposition (1).



Notes: IRF shows the effect of a standard deviation shock 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 1,000 draws.

Figure A5: Impulse response: Main results with an alternative Cholesky decomposition (2).



Notes: IRF showing the effect of a standard deviation shock of the impulse variable on one unit of the response variable over 10 years. Error bars (in gray) are generated by Monte Carlo simulations using 1,000 draws.