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Knowledge, Jobs, and Unemployment in Regions

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Abstract

This study explores the connection between regional labor markets, knowledge spillovers, and technological diversification in 272 European regions for 2011-2021. We find that innovation – measured as the number of patents – has a strong, positive correlation with employment. We find that innovation – measured as the number of patents – has a strong, positive correlation with employment. We find that innovation – measured as the number of patents – has a strong, positive correlation with employment. Furthermore, regions where innovation is more connected to other research via forward and backward citations tend to experience greater employment. Finally, when a region's research is concentrated in a small number of technological fields and/or unevenly distributed across those fields, it tends towards lower employment. Finally, granular analysis finds that the effects are strongest in manufacturing, for STEM workers and highly educated workers more broadly. Thus, the most effective development strategy will likely involve not just the promotion of R&D but also greater connections with global knowledge networks and a more diverse set of technical fields.

Keywords: Knowledge Spillovers, Employment, Innovation, Technological Diversification.

JEL codes: J21; J24; O31; O33.

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1 Introduction

This paper analyses the impact of technological innovation on employment across European regions during the decade from 2011 to 2021. The nexus between technological progress, particularly in fields such as automation and artificial intelligence (AI), and labor market dynamics has been subject to intense economic debate.[1] Many suggest that technologies like automation and AI may result in job displacement (Frey and Osborne (2017),Brynjolfsson and McAfee (2014)).[2] Others suggest that new technology can create jobs directly linked to it and make firms more efficient, increasing labor demand (e.g., Acemoglu and Restrepo (2018, 2019); Autor et al. (2020)).[3] Policy initiatives like the European 2020 Strategy often promote innovation, assuming it will generate more and better employment opportunities than it displaces. The paper aims to empirically test this assumption by analyzing the innovation-employment relationship across European regions.

Examining this relationship at the regional level offers distinct benefits. Primarily, it enables exploring region-specific economic activities that national-level data may not fully capture. This approach addresses a gap in the existing literature, which has largely focused on the innovation-employment nexus within a single country or industry, often considering data from earlier periods.[4] The impact of innovation on employment, be it positive or negative, is likely dependent on critical economic factors specific to each region, which consequently affect the emergence and evolution of spatial disparities. Second, this approach provides detailed insights into how different sectors and categories of workers are impacted by innovation within these regions. The need for such disaggregation is highlighted by Calvino and Virgillito (2018) to reconcile occasionally conflicting results. Finally, understanding these regional dynamics is essential for developing targeted economic policies, as it accounts for the unique economic, cultural, and infrastructural characteristics of each area.

While most studies typically concentrate on a singular aspect of innovation,

[1] Refer to Calvino and Virgillito (2018) for a comprehensive review of this subject.

[2] For a detailed examination of how artificial intelligence affects labor markets, see Duch-Brown et al. (2022).

[3] Moreover, new technologies can raise the marginal product of labor and capital, resulting in higher wages and returns to capital. These two effects contribute to a rise in real income. If demand is sufficiently elastic and positively responds to increases in income and decreases in prices, technologies may lead to demand-induced raise in output and employment (Bessen (2019)).

[4] Notable exceptions are Fagerberg (2000) or Rocchetta et al. (2022).

such as patent counts or R&D expenditure levels, our methodologie include several measures of a region's patenting activity, including the count of patents, the number of forward citations, spillovers arising from backward citations, and measures examining the concentration of its research efforts across technological fields. Taken together, this provides a picture of the employment-innovation link that is broader in geographic scope, more contemporary in time, and more nuanced in terms of its consideration of heterogeneous effects and the different ways one might consider a region's innovative activity.

We consider four measures of innovation activity. First, following numerous studies, we use the count of patents in a region to control for its level of innovation. Second, we use the forward and backward citations of a region's patents. This has two interpretations, one based on quality and one on linkages. One might expect that patents receiving more forward citations are higher quality patents and therefore have greater employment effects.[5] More backward citations, on the other hand, might be indicative of less original ideas which therefore have lower employment impacts. Alternatively, these can be thought of as measures of a region's links to knowledge across the globe. Just as work in international trade tends to find that firms involved in global value chains have greater productivity, the employment enhancement effects of regional innovation may be greater when it stems from a greater involvement with global technological changes as embodied by more forward and backward citations.

While these measures have been standard in the literature for some time, more recent developments, particularly in the economic geography literature, finds that it is not just the amount of innovation taking place but how it is distributed across the various technological fields. We borrow from these and construct a Theil (1967) index for technological concentration.[6] In particular, this allows us to decompose concentration into a between measure (capturing how many fields a region is active in) and a within measure (capturing the intensity of activity in those fields).

Such concentration can cut both ways in terms of its employment effects. On the one hand, concentration in a narrow area can lead to absorptive capacity, something that is essential for understanding and applying new knowledge.[7] Regions with robust absorptive capacity can effectively leverage knowledge to stimulate job

[5]See Ernst et al. (2014) for discussion on forward citations as a quality measure.

[6]Rocchetta et al. (2022) do the same for a sample of 15 EU countries from 2004 to 2011.

[7]According to Cohen and Levinthal (1990), absorptive capacity refers to the "ability of a firm to recognize the value of new, external information, assimilate it, and apply it to commercial ends". Although most related empirical evidence is at the firm level, the notion of absorptive capacity has also been effectively applied to more aggregate contexts, such as at the level of regions (see e.g., Miguélez and Moreno (2015)).

growth, suggesting a positive effect of concentration on employment. On the other hand, focusing on one area tends to silo thinking, impeding the creative thought needed to make significant jumps in technology. Furthermore, such focus leaves a region vulnerable to market changes and technology-specific shocks.[8] Indeed, much of the economic geography research on innovation and employment has specifically focused on the resilience of the regional labour market.[9,10]

We find that regions that innovate more tend to have higher employment. This result is strongly consistent with that found elsewhere, showing that the lesson learned from studies using one or just a few countries is more broadly applicable. Likewise, regions that have more forward citations and stronger backward spillovers tend to have higher employment. This too is consistent with the bulk of those studies with a smaller geographic coverage. Turning to the concentration measures, we find that regions with more concentrated technological innovations have lower employment. This then supports the "diversity creates resilience" results from the economic geography literature and again shows that such findings hold more broadly.

Finally, unlike most existing studies, we examine how these effects vary between different sectors and workers. Beginning with a comparison of manufacturing and services employment, we find that the quantity and quality of innovation matters for manufacturing but not services. This may speak to either a greater role for patenting in manufacturing overall or that the types of innovations (labour productivity enhancing versus labour replacing) may differ across them. Turning to heterogeneous effects across workers, we find that the impacts are greatest among "techies" (workers in STEM fields) and highly-educated (and highly-paid) workers overall. Thus, even as employment overall can rise following innovation, so too may inequality.

As an additional set of results, we also provide evidence on the effect of innovation on the unemployment rate. Given its construction as the ratio of employed over total active population, this index offers a complementary perspective to our results on employment by also addressing changes in the demographic composition of regions. Findings are largely aligned to baseline results: we find that better innovation outcomes reduce the unemployment rate while knowledge concentration

[8] Mewes and Broekel (2022) make this point in their analysis of technological complexity and income growth in Europe.

[9] See, for example, Kim et al. (2023), Toth et al. (2022), or Rocchetta et al. (2022).

[10] Recent advances in economic geography, such as Kim et al. (2023), attempt to relate the diverse technological fields by their cognitive proximity. The notion here, following Nooteboom (2000), is that even when region's fields differ, if they are related they "speak the same language" and thus the region can reap the benefits of both absorptive capacity and diversification.

increases it.

All together, these results make two points for the strategic use of innovation policy. First, on an EU level, smaller and peripheral economies tend to have less innovation, weaker connections via citations, and more concentration. Thus, from an EU cohesion perspective, there may be value in promoting innovation in lagging areas. Furthermore, a push to use innovation policy as a mechanism may need to be matched with either redistribution or education efforts to ensure that the gains from innovation are widely felt.

This paper is related to a strand of the literature that has examined the impact of innovation, spillovers, and employment effects at the local level. A range of studies have explored the relationship between innovation, spillovers, and employment in regions. Capello and Lenzi (2012) found that the impact of innovation on employment growth is influenced by regional characteristics, with product innovation having a positive effect in regions with a larger presence of production functions. Monchuk and Miranowski (2010) and Bottazzi and Peri (2002) both found a positive association between local innovation and employment growth, with Bottazzi and Peri (2002) also identifying the existence of spillovers within a 300 km range. However, the size of these spillovers is relatively small. Hou et al. (2018) and Cabrer-Borrás and Serrano-Domingo (2007) both found that product innovation stimulates employment, with Cabrer-Borrás and Serrano-Domingo (2007) highlighting the role of regional development in enhancing the effectiveness of R&D policies. Audretsch et al. (2011) further emphasized the importance of regional competitiveness and university spillovers in fostering innovation activity.

This paper is also relevant to the literature examining how innovation impacts different industries and worker categories within a single country. In the context of Finland, Aldieri et al. (2021) and in China, Zhu et al. (2021) both report adverse effects on low-skilled workers, with the latter study also noting a positive influence on more educated workers. Moreover, Lee and Clarke (2019) observes favorable outcomes for low-skilled workers due to the expansion of high-tech industries.

The remainder of the paper is structured as follows: Section 2 outlines the data sources and presents essential stylized facts on employment and innovation. Section 3 details our analytical strategy, followed by Section 4, which discusses the empirical findings. The paper concludes in Section 6, offering a summary of our results and their implications for economic policy and future research directions.

2 Data and Facts

2.1 Data

Our goal is to consider the impact of innovation, knowledge spillovers and knowledge concentration on employment levels and unemployment rates in European regions. With this in mind, we operate at the regional NUTS 2-digit level, resulting in 272 regions across 33 countries for the period 2011 to 2021. Table A2 in the Appendix lists the countries and regions covered in our analysis. To do so, we draw from three primary data sources, one for regional labor outcomes and controls and two for patents. In this section we describe these data and lay out several stylized facts regarding employment and patenting.

Employment and other region-specific data. For the regional data, we rely on the Eurostat regional database. This dataset provides rich information concerning employment and unemployment rates as well as additional economic statistics such as the level of education, GDP, and population. Although Eurostat provides some information even at a finer level of disaggregation, we use the NUTS2 administrative level for three reasons. First, some data in Eurostat are only available at that high level of aggregation. Second, as discussed further below, patenting is not a common activity. As such, working at a very disaggregated level will yield a large number of zero patenting regions. Finally, the NUTS2 level is also the framework generally used by Member States and the EU Structural Funds to apply regional policies: therefore it looks as the appropriate administrative dimension to study innovation and labour market outcomes.

For our analysis, we use data on total regional employment as well as employment levels disaggregated by industry (NACE 1-digit) or education level.[11] In addition, we specifically consider "techies", that is scientists and engineers. As shown by Harrigan et al. (2021, 2023), this group is especially exposed to technology as they directly adopt, manage, and diffuse technological innovations. Because of this, there may be a particular link between innovation and employment for these workers.

In addition, as control variables, we extract information on regional GDP, population, and population growth. Finally, as a robustness check, we use the unemployment rate rather than employment.[12] Note that our use of (logged) employment

[11]We categorize workers into low (ISCED 0-2), middle (ISCED 3-4), and high (ISCED 5-8) skill groups using the International Standard Classification of Education.

[12]Although one would expect these to be equal but opposite, this is not precisely true as the unemployment rate is measured as the number of employed relative to the number of job holders and seekers.

differs from those studies that use employment growth (e.g. Kim et al. (2023) and Rocchetta et al. (2022)). We do so in part because regions with low employment can have more volatile changes in employment growth, potentially clouding the linkages between employment and innovation.

One challenge in the Eurostat database is that, even at the NUTS2 level, data coverage can vary across countries and time. Furthermore, some countries changed their NUTS2 classification during our sample period, for example when a larger region is divided into multiple smaller ones. To address these challenges, we harmonize the NUTS2 classification from 2011 to 2021. This period and process both extends the coverage of our analysis and helps mitigate potential issues arising from missing data and measurement errors. Detailed information on this harmonization process can be found in Appendix A.

Innovation. Turning to innovation, there are four aspects of it we wish to capture: the level of innovation, its quality, knowledge spillovers through citations between regions, and knowledge concentration. Here, we discuss each of these in turn, including the data used in their construction.

Level of Innovation. To measure the level of innovation, we utilize the number of patent publications. In doing so, we acknowledge that this is only a proxy for a particular type of innovative activity.[13] Not all innovations are even eligible for patent protection and of those that are, not all innovators will seek such protection due to the cost and uncertain nature of patenting (see Davies et al. (2020) for discussion). Further, patents represent the outcome of a successful research attempt and not all such efforts are fruitful. Nevertheless, measuring innovation as patents is advantageous because of patent data availability over time and locations. Thus, while we acknowledge the limitations of this measure as innovation, we follow a large literature that nevertheless does so.[14]

In our analysis, we operate at the level of a patent family. In practice, a single invention can result in multiple patent actions, potentially including multiple applications (due to reapplication following rejection and/or submission to multiple patent offices) and publications (issuance of the accepted application by a given patent office). These are then grouped together into a family which represents the invention on which they are all based. Using patent families thus avoids double

If people quit looking, the unemployment rate can fall even as the number of jobs does not change.

[13]Buerger et al. (2012) find a greater effect of patents than R&D spending on German employment.

[14]Seminal studies using patents include Jaffe (1986) and Jaffe et al. (1993). Recent contributes include Aghion et al. (2022) and Berkes et al. (2022).

counting. To assign a patent to a year, we use the publication date of the earliest application within the family.[15] Finally, note that we use all patent, not just granted patents. We do so for two reasons. First, since only about 50 percent of patents are granted (Davies et al. (2020)), using only granted patents would exacerbate the misalignment between patent numbers and innovation. Second, as discussed by Davies et al. (2020), there is a long and variable time lag between application and granting (over five years on average for applications to the European Patent Office). Thus, were we to use granted patents only, this would force us to end our sample earlier because of the truncation in the number of granted patents this would cause.

For our patent information, we use two sources. First, we use the PATSTAT database.[16] This database is attractive due to its comprehensive global coverage and detail on each patent. In particular, we utilize three pieces of information. First, as noted above, we use the timing of a patent. Second, we make use of the backward citations of a patent which can then be reversed to calculate its forward citations. This is then used to construct measures of quality and spillovers as discussed below. Third, we use the International Patent Classification (IPC) which categorizes patents into 35 technological fields.

In addition to PATSTAT, we employ the Bureau Van Dijk's Orbis IP database to assign patents to regions. Although PATSTAT does provide location data, these are often incomplete, particularly in terms of sub-national location. In contrast, Orbis IP provides detailed location information for all patents, albeit only for those owned by the firms it covers. Nevertheless, using Orbis IP provides us with roughly ten times more patents with NUTS2 information than PATSTAT does. Although Orbis IP is not a random sample but tends to cover larger firms, because patenting is concentrated in large firms – Davies et al. (2020) find that the top five percent of innovators make up nearly 75 percent of European patents – we believe that the benefit from better location information is worth this sacrifice. Note that by using Orbis IP, we are using assignees (owners) to link patents to regions. Finally, as is standard, we use fractional apportionment, that is, when x percent of assignees on a patent family are in region r, we assign this share of the patent (and its citations) to region r. This then is merged with the PATSTAT information using the unique family identifier.

With this in hand, we construct the stock of patents in region r in year t as

[15] By using the publishing date rather than the filing date, this arguably makes the timing closer to the public availability of the information contained in the patent, something important when considering spillovers.

[16] Specifically, we use the Spring 2022 version. See https://inspire.wipo.int/patstat-online.

the number of patents arising from it from 2000 until year t. We use this stock as one of our variables of interest. Note that by starting the stock construction in 2000 – a decade before our employment data being – this allows us to control for historical dependencies that may shape both current innovation and employment patterns as well as to focus on the stock of more recent knowledge.

Innovation Quality. As discussed above, we can link the patents in our data to others using the citation information available via PATSTAT.[17] Thus, for a patent we can count the total number of forward citations it receives (again using fractional apportionment for citations). Then summing across patents in region r's stock in year t we have the total forward citations received by rt's patent stock. Finally, dividing this by the patent stock results in a measure of the average quality of patents by region-year. Note that these citations are not limited to those received from European patents and this is therefore a measure of the global importance, not merely European influence. As a last point, as these citations can come from patents outside of the region, this measure can serve as a forward spillover measure.

Knowledge spillovers. In addition to measuring a region innovation outcomes in terms of total patenting and patent quality, we can use backward citations given by a region to previously produced knowledge to measure a spillover from that knowledge to local innovation outcomes and thus local employment effects.

Accounting for the impact of these knowledge spillovers is paramount as it takes into account the externality on employment outcomes due to knowledge diffusion. To measure these backward spillovers we use information available in PATSTAT on backward citations given by a region r when producing knowledge in t. Let us use r' to refer to cited regions and s to the year of the cited inventions; note that r' can be equal to r and $s \leq t$. We define a backward knowledge spillover as $Spillover_{rt}$ and calculate it as the weighted average of cited regions' forward citations stock[18]:

$$Spillover_{rt} = \sum_{r'}^{R} \sum_{s=0}^{t} w_{rr'ts} * C^{f}_{r's} \tag{1}$$

$C^{f}_{r's}$ is the forward citations stock of region r' at year s. The forward citations stock measures the total knowledge generated by r' up to s and absorbed by other

[17]Note that for citation counts, we use all citations in PATSTAT, not only those which also appear in Orbis IP.

[18]While forward citations may not provide a flawless measure of knowledge stock, they serve as a practical and quantifiable reference point that allows us take into account both the number and the quality of the innovation stock produced by cited region r' up to time s.

regions citing those inventions. R is the set of all regions cited in year t by region r and s is the year of the cited inventions of region r'. To account for citations to patents out of Europe, the set R includes a "rest of the world" region. $w_{rr'ts}$ is the weight attached to $C^f_{r's}$ and it is build as:

$$w_{rr'ts} = \frac{c^b_{rr'ts}}{c^b_{rt}} \tag{2}$$

c^b_{rrts} is the number of (backward) citations given up to year t by r to inventions of region r' up to year s and $c^b_{rt} = \sum_{r'}^{R} \sum_{s=0}^{t} c_{rr'ts}$ is the sum of all (backward) citations given up to year t by r to all inventions in any year s to any r', including r itself.

Knowledge Concentration. Beyond the amount of innovation outcomes and spillovers, another potentially important feature of the innovation landscape for employment is the concentration of innovation. When a region's innovative activity is focused in a narrow research field, this might generate synergies that lead to greater employment. On the other hand, this concentration can make a region vulnerable to the vagaries of market shocks, perhaps impeding the creation of new jobs. Equally, if exploiting new technologies requires specialized skills, then a concentrated innovation sector can begin to bump against labour market constraints that weaken its employment effects.

With these in mind, we combine PATSTAT's information on the technological fields of patents with that on forward citations. Within PATSTAT, each patent is allocated a weight across the 35 IPC technological fields (where the weights sum to one). We use this to then fractionally allocate that patent's forward citations across fields. Summing these up across the patents in region r's patent stock in year t, we then have the stock of forward citations within a region-technology-year rjt. This can be used to construct two concentration measures.

The first is the Herfindahl index, calculated as follows:

$$HHI_{rt} = \sum_{j=1}^{35} \left(\frac{C^f_{rjt}}{C^f_{rt}} \right)^2 \tag{3}$$

where C^f_{rt} is the total number of forward citations in region r as of time t. Note that the 35 comes from the 35 technological classes in PATSTAT.

The second measure, the Theil index, is calculated as:

$$T_i = \frac{1}{35}\sum_{j=1}^{35}\frac{C^f_{rjt}}{\mu_{rt}} ln\left(\frac{C^f_{rjt}}{\mu_{rt}}\right) \qquad with \qquad \mu_{rt} = \frac{1}{35}\sum_{j=1}^{35} C^f_{rjt} \tag{4}$$

Where μ_{rt} denotes the average of citations received across all technological fields for region r in year t.

One attractive feature of the Theil index is that it can be decomposed into two components. The between component (T^B) speaks to the number of currently active technological fields. Specifically, this component is:

$$T^B_{rt} = ln\left(\frac{35}{\mathcal{J}^a_{rt}}\right) \tag{5}$$

where $\mathcal{J}^a_i$ is the number of technological fields with a positive knowledge stock in region r as of t. If a region has a positive knowledge stock in all fields, the index is zero, i.e. such a region would have a low level of technological concentration as measured by its between component.

The within component (T^W) provides information on the distribution of citations across active technological fields. It is computed as follows:

$$T^W_{rt} = \frac{1}{\mathcal{J}^a_{rt}}\sum_{j=1}^{\mathcal{J}^a_{rt}}\frac{C^f_{rjt}}{\mu^a_{rt}} ln\left(\frac{C^f_{rjt}}{\mu^a_{rt}}\right) \qquad with \qquad \mu^a_{rt} = \frac{1}{\mathcal{J}^a_{rt}}\sum_{1}^{\mathcal{J}^a_{rt}} C^f_{rjt} \tag{6}$$

where $\mathcal{J}^a_{rt}$ is again the number of fields with positive knowledge stock, and μ^a_{rt} is the average of citations received only by those technological fields.[19] If a region has the same knowledge stock in all fields, the index is zero and the region displays a low level of technological concentration as measured by its within component.

2.2 Facts

With our data laid out, we next identify four stylized facts on the relationship between employment and innovation in a regional context. Although there are several studies looking at employment and innovation at a sub-national level, these tend to use data within a single country (e.g. Jaffe et al. (1993) and Murata et al. (2014) in the United States).

Fact 1. Innovation is positively associated with employment. In Figure 1, we show the correlation between regional innovation and the ratio of employment to population in 2021. We use an adjusted measure of employment

[19] T^W_{rt} corresponds to the Theil index computed on positive support of knowledge stock.

to control for the mechanical relationship that would arise when considering total employment and total innovation due to the size of a region. In this figure, the size of the circle is proportional to the region's share of European GDP.

In Panel (a), we compare adjusted employment to the number of patents in a region. As is shown, there is a clear positive correlation. Likewise, in Panel (b), we find that those regions with higher patent quality (which again is measured as citations per patent) tend towards higher employment. Together, these suggest that more innovative regions – and in particular those with more influential innovations – will have more employment relative to the size of their population.

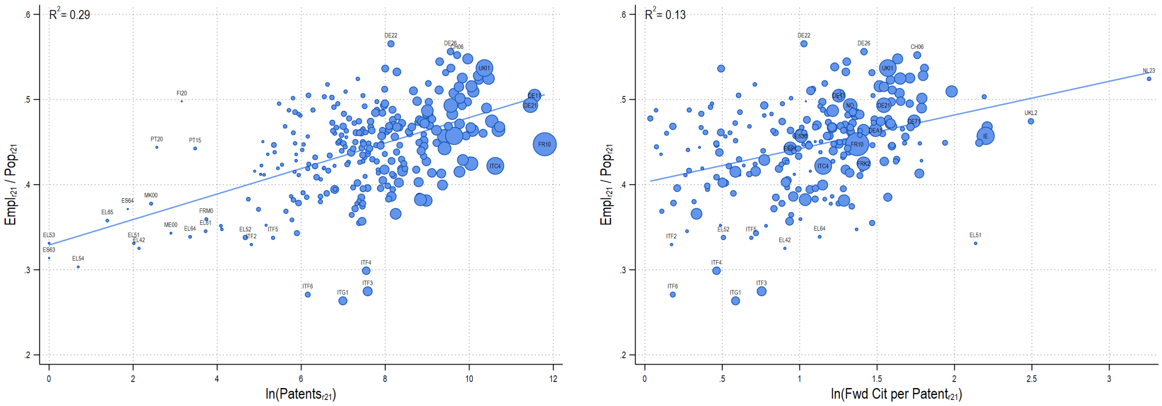
The importance of both quantity *and* quality of innovations is especially well illustrated by the four Italian regions which in Panel (a), which, despite having an average number of patents, have noticeably low employment. This is in part explained by the low number of citations their innovations generate as shown in Panel (b). However, these two factors alone cannot explain the low employment performance of these regions. This then leaves room for other factors – including the backward spillovers and concentration of innovation – to play an important role in the employment-innovation relationship.

A second feature of the data Figure 1 reveals is that innovation is a concentrated activity that is dominated by a few regions in terms of quantity and quality. Île de France (FR10), Stuttgart (DE11) and Oberbayern (DE21) are responsible for a substantial share of innovation (more than 18% measured by total patents). Overall, over 50% of the European patents in our data originate from just 22 regions.[20] Likewise, a small group of regions excel in terms of innovation quality. Notably, the overlap between these leading innovation regions is far from complete. For example, regions from Greece, Ireland, and the Netherlands rank highly in terms of citations per patent even though they produce only a moderate number patents. A particular feature of these latter two is that they are tax havens and specifically havens that have patent boxes that provide for especially low tax rates on income earned via patents. This may therefore be the result of the strategic choice of where to location especially innovative (and thus lucrative) innovation for tax purposes.[21] Finally, those regions located on the periphery of Europe tend towards weaker employment, less innovation, and lower quality innovation. Thus, geography, including proximity to markets, is undoubtedly an important feature

[20]These regions include Île de France, Stuttgart, Oberbayern, Etelä-Suomi, Düsseldorf, Lombardia, Darmstadt, Noord-Holland, Karlsruhe, Inner London, Tübingen, Mittelfranken, Nordwestschweiz, Noord-Brabant, Zuid-Holland, Köln, Stockholm, Rhône-Alpes, Arnsberg, Zürich, Freiburg and Detmold.

[21]For more on the role of patent boxes on the location of innovation, see Dischinger and Riedel (2011), Alstadsaeter et al. (2018), Davies et al. (2020), and Schwab and Todtenhaupt (2021).

in innovative capacity and overall economic performance.



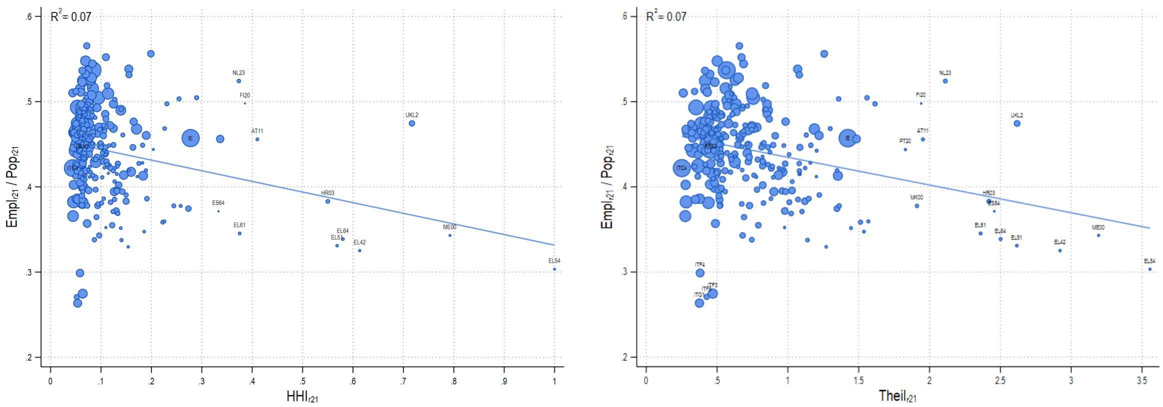
(a) Innovation

(b) Innovation Quality

Figure 1: Innovation and employment

Notes: The figure shows the correlation between employment divided by population in 2021 and total innovation (Panel(a)) and innovation quality (Panel (b)). The size of the circle is proportional to the region's share of European GDP.

Fact 2. Knowledge concentration is negatively associated with employment levels. Evidence provided in Fact 1 suggests that, although the quantity and quality of innovation are likely linked to employment, some regions still suffer from lower employment levels than their performance on those dimensions would suggest. We therefore next turn to the technological concentration of a region and its correlation to employment. With this in mind, Figure 2 presents the correlations between adjusted employment in 2021 and the Herfindahl (Panel (a)) and the Theil index (Panel (b)). As before, the size of each circle is proportional to region's share in European GDP.



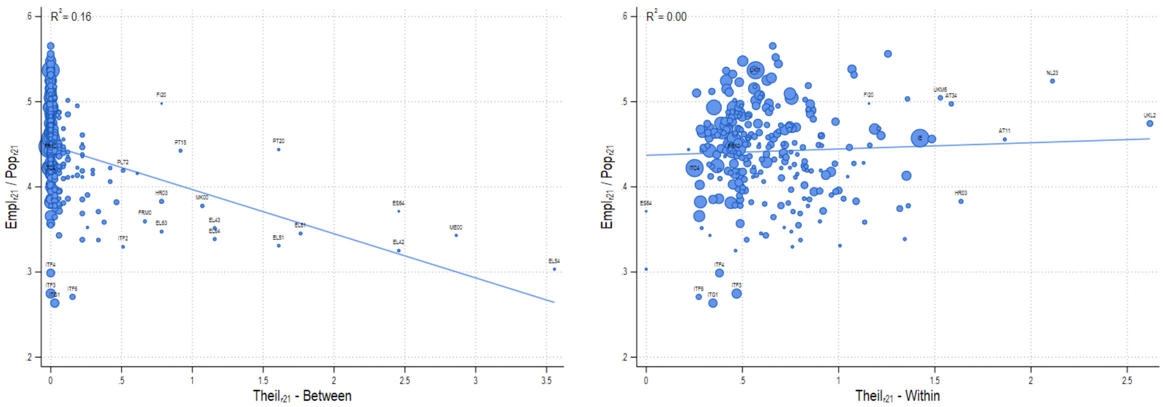
(a) HHI (b) Theil index

Figure 2: Knowledge concentration and employment levels

Notes: The figure displays the correlation between the regional HHI (Panel (a)) and Theil (Panel (b)) indexes and the employment to population ratio in 2021. The HHI is computed as: $HHI_i = \sum_1^{\mathcal{J}} \left(\frac{C^f_{ij}}{C^f_i}\right)^2$. The Theil index is computed as: $T_i = \frac{1}{\mathcal{J}} \sum_{j=1}^{\mathcal{J}} \frac{C^f_{ij}}{\mu_i} ln\left(\frac{C^f_{ij}}{\mu_i}\right)$ with $\mu_i = \frac{1}{\mathcal{J}} \sum_1^{\mathcal{J}} C^f_{ij}$. The size of the circle is proportional to the region's share of European GDP.

Figure 2 reveals two key patterns that mirror those in Figure 1. First, there is a clear negative correlation between technological concentration, regardless of how it is measured, and employment. Thus, more concentrated regions tend to have weaker employment outcomes. This finding is in line with Jacob's externalities theory (Jacobs (1969)), which suggests that a more diverse industrial composition contributes to economic growth. Second, there is more concentration in small and peripheral regions. This is perhaps not surprising since those regions tend to have fewer patents. Together, this suggests a scale effect akin to the work of (Jacobs (1969) and Glaeser et al. (1992)) who highlight the role of cross-fertilization for the development of local knowledge bases. If small and peripheral regions are unable to support sufficiently vibrant innovation sectors, then these synergies may not manifest, resulting in small, narrowly focused R&D activities that do not contribute much to employment.

Digging deeper, Figure 3 decomposes the Theil index into its between (Panel (a)) and within (Panel (b)) components and compares them to employment relative to population. This reveals a negative correlation between employment and the between component of the Theil measure but not with its within component. Looking first to the between measure in Panel (a), we see that having a positive knowledge stock in a larger number of active technological fields (a lower between measure) tends towards higher employment. Although the data suggest that most regions are relatively similar in the between component, those that are more concentrated tend towards weaker employment outcomes. In comparison, Panel (b)'s presentation of the within component (the distribution of innovation across these active technological fields) finds no significant correlation. This does not, however, mean that there is no effect – recall that this figure controls for no other features of regions. Together, these suggest that a diverse innovative landscape may be important to developing externalities that lead from knowledge creation to job creation but that more nuanced consideration is required.



(a) Theil - Between

(b) Theil - Within

Figure 3: Theil index decomposition

Notes: The figure displays the correlation between employment relative to population in 2021 and the between (Panel (a)) and within (Panel 9b)) component of the Theil index. The between component of the Theil is computed as: $T_i^B = ln\left(\frac{\mathcal{J}}{\mathcal{J}_i^a}\right)$. The within component of the Theil is computed as: $T_i^W = \frac{1}{\mathcal{J}_i^a}\sum_1^{\mathcal{J}_i^a} \frac{C_{ij}^f}{\mu_i^a} ln\left(\frac{C_{ij}^f}{\mu_i^a}\right)$ with $\mu_i^a = \frac{1}{\mathcal{J}_i^a}\sum_1^{\mathcal{J}_i^a} C_{ij}^f$. The size of the circle is proportional to the region's share of European GDP.

Fact 3. Growing technological fields are localized in a few regions. While the above suggests that expanding the scope of innovation (both in terms of number of fields and promoting even growth across them) can boost employment, it does not speak to *which* fields appear to be expanding and which are stagnating. Understanding that may be a key factor in developing employment-enhancing policy. With this in mind, Table 1 provides an overview of forward citations and patenting activities within the top 5 and bottom 5 technological fields, based on the growth of forward citations between 2011 and 2021.[22, 23] The table also provides the regional concentration (*Reg. Conc.*) index of each field across European regions.[24] Note that this measure captures the concentration of technological fields across regions, not the geographic proximity of those regions.

The first lesson to be learned from Table 1 is that the European innovation landscape has experienced tremendous change during the decade of our sample. Some fields, especially Micro-structural and Nano-technology (Field 22) and Electrical machinery, apparatus and energy (19) have experienced dramatic growth in terms of both forward citations and the number of patents. Others, including Pharmaceuticals (16) and Telecommunications (3) have seen a significant contraction.

Second, there is no clear-cut relationship between a field's regional concentration and the growth in either the number of forward citations or patents. In the fastest growing fields, Digital Communications (4) is the most concentrated, yet is only in fourth place in terms of the growth rate of citations and the number of patents. Micro-structural and nano-technology, however, is by far the fastest growing field while displaying a moderate extent of concentration. Examination of the shrinking sectors likewise yields no obvious relationship between regional concentration and field growth.

In Figure 4 and 5, we expand on this by examining which regions contribute most to the forward citation growth rates of the fastest expanding and contracting fields.[25] Regions with the highest growth rates are shaded in dark blue, while those experiencing the most significant declines are shaded in yellow.

Inspection of these suggest that some regions, such as Île de France (FR10),

[22]In the calculation of Table 1 are included the countries in our sample, along with Albania, Liechtenstein and Turkey. For the latter countries we can indeed retrieve data on innovations but not for employment.

[23]For detailed results, please refer to Table C1 in Appendix C. Additionally, the Appendix table provides insights into the regions that have the most significant impacts on the growth and decline of citations in each technological field, information used in the below figures.

[24]This index is calculated as a Theil index, and the formula is: $T_j = \frac{1}{\mathcal{R}} \sum_{r=1}^{\mathcal{R}} \frac{C^f_{rj}}{\mu_j} ln \left(\frac{C^f_{rj}}{\mu_j} \right)$ with $\mu_j = \frac{1}{\mathcal{R}} \sum_1^{\mathcal{R}} C^f_{rj}$; $\mathcal{R}$ is the number of total NUTS2 for which data on innovations are available.

[25]See Appendix C for further details.

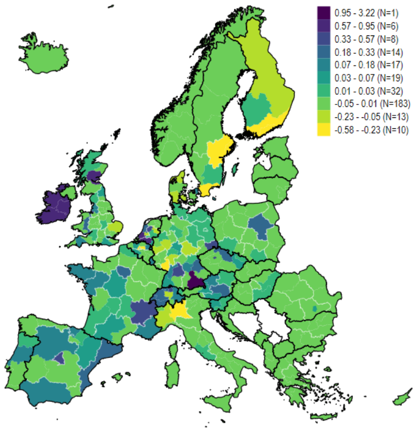
Table 1: Innovation growth and knowledge spillovers across technological fields

Technological Field	Reg. Conc.	% Cit_{j21}	% Δ Cit_{j21-11}	% Pat_{j21}	% Δ Pat_{j21-11}
Micro-structural and nano-technology (22)	2.03	0.13	12.54	0.13	32.64
Electrical machinery, apparatus, energy (1)	1.50	5.75	7.89	6.68	15.51
Surface technology, coating (21)	1.61	1.62	4.60	1.50	-1.59
Digital communication (4)	2.78	5.42	4.40	3.00	5.09
Other consumer goods (34)	1.84	1.86	3.96	2.35	8.41
...	...	...	...	...	...
Analysis of biological materials (11)	1.40	0.41	-5.16	0.57	-7.72
Textile and paper machines (28)	1.69	1.70	-8.46	2.28	-22.24
Organic fine chemistry (14)	2.36	2.93	-8.74	2.75	-17.33
Telecommunications (3)	2.41	3.32	-9.26	1.96	-21.93
Pharmaceuticals (16)	1.56	2.32	-10.35	2.63	-14.33

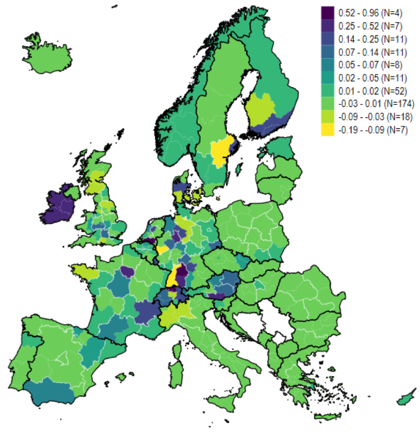
Notes: The table reports the top growing and the top declining technological fields (j) in terms of the growth rate of citations in the period 2021-2012. %Δ Cit_{j21-11}. %Δ Cit_{j21-11} is computed as the growth rate of citations shares: $(\%Cit_{j21} - \%Cit_{j11})/\%Cit_{j11}$, with $\%Cit_{jt} = \frac{Cit_j}{\sum_1^{\mathcal{J}} Cit_j}$. Spatial concentration is measured through the Theil index which provides the concentration in the citation stock of each field across NUTS2 regions. The index is calculated as: $T_j = \frac{1}{\mathcal{I}} \sum_{i=1}^{\mathcal{I}} \frac{C_{ij}}{\mu_j} ln \left(\frac{C_{ij}}{\mu_j} \right)$ with $\mu_j = \frac{1}{\mathcal{I}} \sum_1^{\mathcal{I}} C_{ij}$; $\mathcal{I}$ is the number of total NUTS2 for which data on innovations are available.

Ireland, and Oberbayern (DE21) have consistently been leaders in multiple technological fields including Digital Communication, and Micro-structural and Nano-Technology. This potentially supports the cross-fertilization story of Jacobs (1969) and Glaeser et al. (1992). At the same time, however, major leaders such as Île de France (FR10) and Düsseldorf (DE12) also contribute highly to the decline of fields such as Organic Fine Chemistry or Textile and Paper Machines. Thus, a key part of being a leading innovation region may be the ability to pivot from one field to another as the market evolves. Returning to the link between employment and innovation, this agility may be an important part when linking knowledge generation to high employment levels.

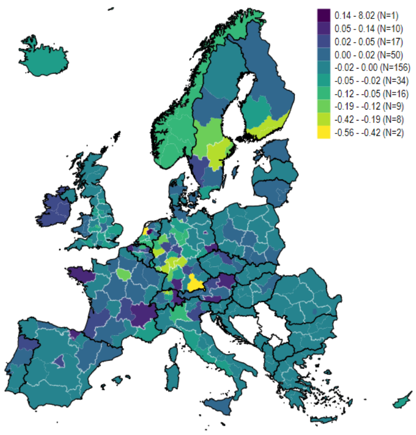
Finally, some regions, notably Ireland and Noord-Brabant (NL41) are interesting cases as they contribute significantly to the growth of highly concentrated fields like Digital Communication and Micro-structural and Nano-Technology while also playing a role in dampening the decline of sectors such as Organic Fine Chemistry and Telecommunications. As noted above, these regions are tax havens with patent boxes, suggesting that multinationals may be strategically locating valuable intellectual property across many fields in such countries for tax-minimizing purposes.



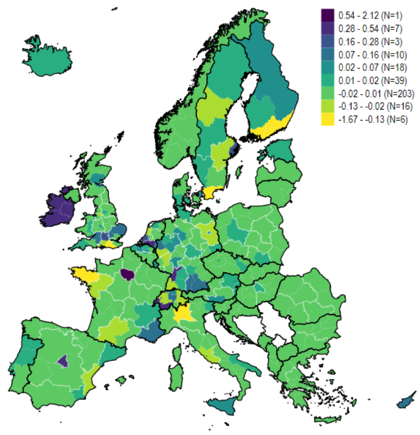
(a) Micro-structural and nano-technology



(b) Electrical machinery, apparatus, energy



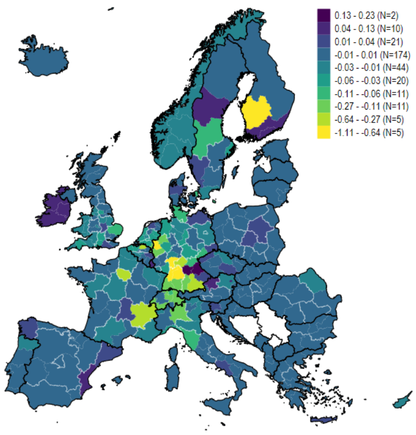
(c) Surface technology, coating



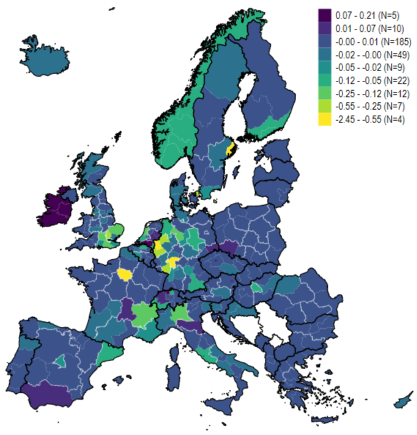
(d) Digital Communication

Figure 4: NUTS2 decomposition of aggregate tech fields growth rate - Top growing fields

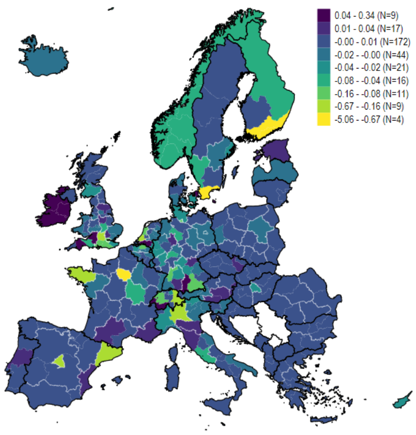
Notes: These maps illustrate the growth rate of citations reported in Table 1 across NUTS2 regions for the top 4 growing fields. Regions with the highest growth rates of citation in technological fields are shaded in dark blue, while regions experiencing the most significant declines are shaded in yellow.



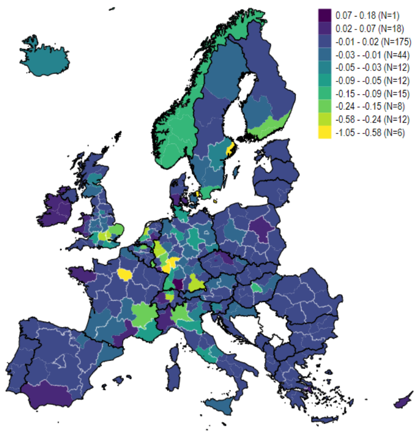
(a) Textile and paper machine



(b) Organic fine chemistry



(c) Telecommunications



(d) Pharmaceutical

Figure 5: NUTS2 decomposition of aggregate tech fields growth rate - Top declining fields

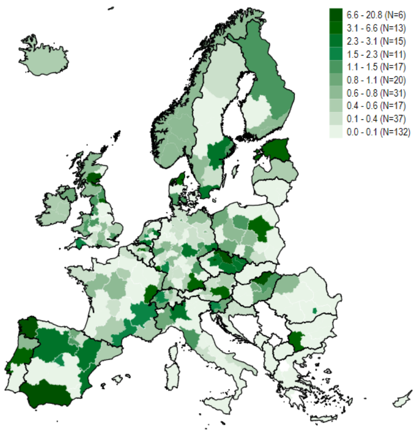
Notes: These maps illustrate the decomposition of aggregate growth rate of citations reported in Table 1 across NUTS2 regions for the top 4 declining fields. Regions with the highest growth rates of citation in technological fields are shaded in dark blue, while regions experiencing the most significant declines are shaded in yellow.

Fact 4. Regional technological advantages. We complete our initial foray into the data by examining how the presence of top-growing and declining technological fields is linked to a region's technological specialization. For this purpose, we use the Regional Technological Advantage (RTA) index, which builds from Belassa (1965). For a given technological field j, this measure is computed as $\left(\frac{C^f_{rj}}{\sum_j C^f_{rj}}\right) / \left(\frac{\sum_r C^f_{rj}}{\sum_r \sum_j C^f_{rj}}\right)$, where C^f_{rj} are forward citations received by region r in field j.[26] When a region's RTA is above one for field j, this means that

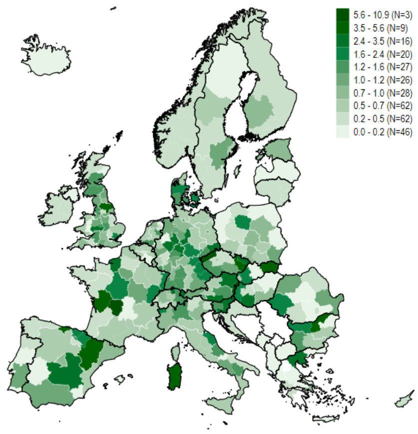
[26]As above, this is done only for those regions with NUTS2 information plus Albania, Liechtenstein and Turkey.

compared to the European average, a greater share of its forward citations are in this technological field, i.e. that it specializes in j.

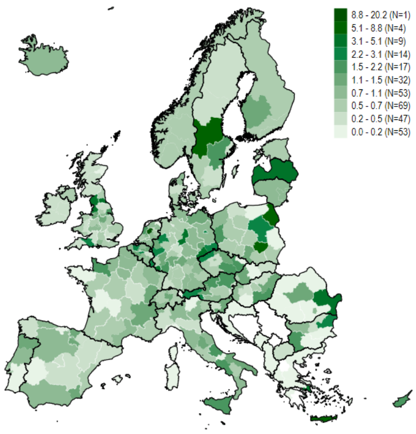
Figure 6 illustrates how the RTA is distributed across regions in 2021 for the four leading technological fields as indicated in Table 1. We report the distribution of the declining technological fields in Figure 7. In both, a deeper shade of green indicates a more pronounced specialization in the respective technological field.



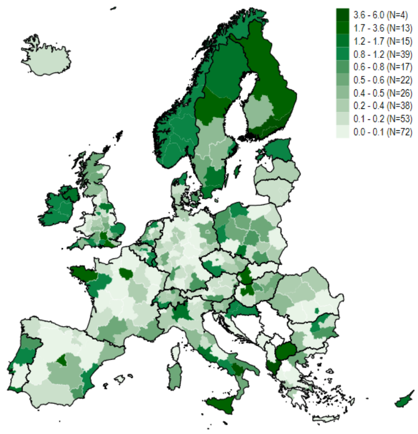
(a) Micro-structural and nano-technology



(b) Electrical machinery, apparatus, energy



(c) Surface technology, coating



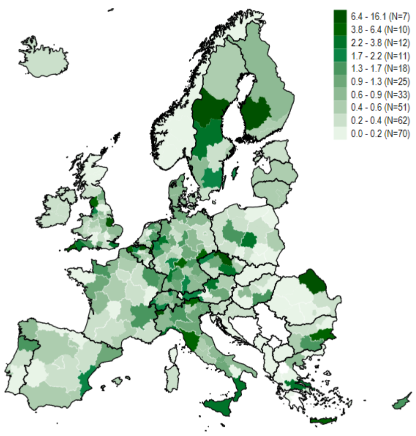
(d) Digital Communication

Figure 6: Revealed Technological Advantages across regions - Top growing fields

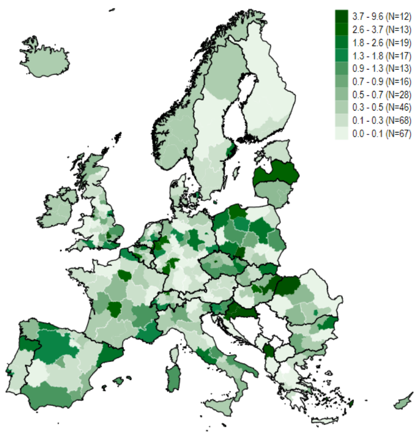
Notes: The maps illustrate the Regional Technological Advantage (RTA) index for each NUTS2 region within distinct technological fields in 2021, focusing on the top-growing fields. A darker shade of green signifies a higher degree of specialization in the particular technological field.

Our analysis reveals significant regional specialization and disparities in technological fields across European regions. For instance, Severovýchod and Praha (Czech Republic), Eastern Scotland, Galicia and Andalucia (Spain), Észak-Magyarország

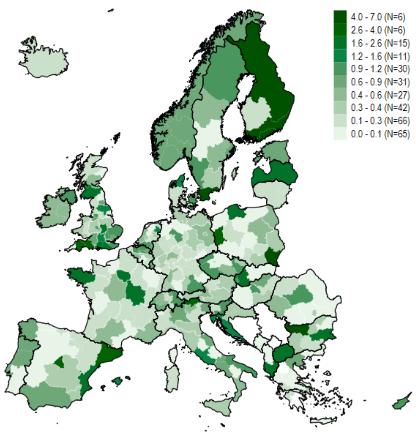
(Hungary) and Vlaams-Brabant (Belgium) are highly specialized in micro-structural and nano-technology. Likewise, Burgenland (Austria), Limousin and Poitou-Charentes (France), Severozápad (Czech Republic) and Severen tsentralen (Bulgaria) exhibit strong specialization in electrical machinery and apparatus. While it is tempting to suggest that such specialization in these fast growing technological fields has the potential to generate job creation and regional development, the above negative relationship between concentration and employment argues against this.



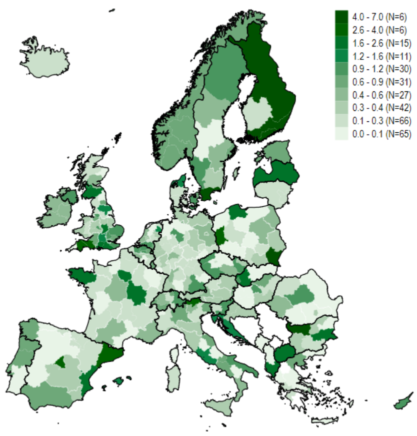
(a) Textile and paper machine



(b) Organic fine chemistry



(c) Telecommunications



(d) Pharmaceutical

Figure 7: Revealed Technological Advantages of regions - Top declining fields

Notes: The maps illustrate the Regional Technological Advantage (RTA) index for each NUTS2 region within distinct technological fields in 2021, focusing on the top-declining fields. A deeper shade of green indicates a more pronounced specialization in the respective technological field.

Turning to the declining fields in Figure 7, we find that specialization in the declining industries tends towards the European periphery. For example, Notio

Aigaio (Greece), Ciudad de Melilla (Spain), Molise (Italy) and Kontinentalna Hrvatska (Croatia) all specialize in Pharmaceuticals while Telecommunications is a specialty in Eastern Europe (Severozapaden (Bulgaria) and Podkarpackie (Poland)) and Scandinavia (Pohjois- ja Itä-Suomi and Etelä-Suomi (Finalnd) and Sydsverige (Sweden)). As Facts 1 and 2 found that such regions tended to lag behind in both employment, this again suggests that concentration of innovation may limit employment growth. That said, Île de France (France), Darmstadt (Germany) and Outer London (UK) all specialize in Organic Fine Chemistry yet are able to maintain employment. This, however, may again be due to agility as they also specialize in growing fields. Thus, specialization in and of itself may not be detrimental to employment, so long as a region has the capability to rapidly respond to market changes.

3 Regression Analysis

Although our stylized facts show clear relationships between the level of innovation, its quality, and its concentration, the patterns suggest that all three may be important along with other regional factors. We therefore turn to regression analysis to gain a clearer insight into these patterns.

To do so, we use the Poisson Maximum Likelihood (PPML) estimator introduced by Silva and Tenreyro (2006) . This has two advantages over a log-linear OLS model. First, it allows for heteroskedasticity, something likely to feature in our data if the precision of employment data varies with population size. Second, it is unlikely that employment levels are normally distributed due to differences in regional size. The PPML estimator accounts for both of these issues.[27] The estimated model for employment in region r in year t can be expressed as follows:

$$\begin{aligned} Employment_{rt} = \exp[&\delta_1 Innovation_{rt} + \delta_2 Innov.Quality_{rt} + \delta_3 Spillovers_{rt} + \\ &\delta_4 Concentration_{rt} + \mathbf{X}_{rt}^{'}\alpha + \gamma_r + \gamma_t] \times u_{rt}. \end{aligned} \tag{7}$$

In this, we have up to four innovation measures, depending on the specification. This includes the number of patents, $Innovation_{rt}$, and the number of forward citations per patents, $Innov.Quality_{rt}$. $Spillovers_{rt}$ captures the degree to which a region's innovation draws from existing knowledge. $Concentration_{rt}$ is the Theil index of concentration in region r which, depending on the specification, is further

[27]Note that the PPML estimation procedure uses levels of the dependent variable but logs of the explanatory variables. Thus, with the exception of the concentration measures, all explanatory variables are logged. Spillovers, which can have a value of zero, instead uses the inverse hyperbolic sine.

decomposed into the between and within components. The vector X_{rt} controls for regional GDP, population, and population growth, thus accounting for regional size effects. Population growth in particular accounts for inter-regional migration. We include two sets of fixed effects, γ_r and γ_t, to account for region-specific differences in employment levels as well as common, time-varying shocks. Finally, the error term is denoted as u_{rjt}. Throughout our empirical analysis, we cluster the standard errors at the NUTS2 level to account for potential correlations within regions over time.

4 Estimation Results

Effects on employment. Table 2 builds our regression specification to our preferred one by considering different measures of innovative activity before combining them in our baseline specification. In columns 1 to 5, we use total regional employment. Columns 6 and 7, meanwhile, consider employment in manufacturing and services separately. All specifications include region and year fixed effects.

Beginning with the control variables, unsurprisingly, both GDP and population are positively correlated with the level of employment with robust significance (excepting population for manufacturing). Conversely, population growth is significant only for services employment.

Turning to the innovation variables, column 1 shows that regions with more innovation have significantly higher employment with an elasticity of approximately 0.07. Although quality of innovation is also positively related to employment, this effect is less precisely measured. One potential reason for this is that different technologies tend to have different average levels of citations per patent. As such, it may be that differential field specializations across regions add noise clouding the precise estimation of the role of innovation quality (more on this when we separate manufacturing and services).

Column 2 replaces these measures with the spillover variable capturing the reliance on prior research via backward citations. We find a positive and significant coefficient suggesting that stronger connections to previous knowledge positively affect employment outcomes.

Columns 3 and 4 instead use the Theil concentration index, either the overall concentration (column 3) or its two components (column 4). In each case, we find that more concentration is correlated with lower employment. In particular, column 4 shows that both the within and between components are negatively related to employment, suggesting that the differences found in Figure 3 were due to a failure to control for both aspects of concentration at once.

Column 5 includes all of our innovation measures at once (with concentration again broken into its components). As can be seen, each measure's coefficient is largely what was found in the preceding columns. Further, each remains significant (although the innovation quantity and spillover coefficients are somewhat less significant, likely due to the correlation). These estimates then suggest that regions with more innovations have higher growth with the elasticity around 0.06. Given the same amount of innovations, higher quality of patents further increases employment with an elasticity of 0.065. In addition, regions that are able to draw on prior innovations to support their own tend to have higher employment, although this effect is an order of magnitude smaller than the direct effect from their own innovation. Finally, more concentrated regions, in terms of either their number of active research areas as well as how activity is spread across their active fields tend to have lower employment. The elasticity from the two Theil components are statistically equal and are slightly larger than those for innovation quantity and quality.

Together, these estimates suggest that more innovation, innovation of a greater quality and innovation that draws from a larger base of knowledge can drive employment. This strategy, however, works best when it is evenly spread across a larger number of fields, perhaps because this permits the agility needed to respond to changing market conditions.

Finally, columns 6 and 7 consider employment in two broad industries – manufacturing and services.[28] This decomposition very quickly shows to quite different responses to innovation. In terms of the quantity of innovation, quality and spillover, only manufacturing employment appears responsive. Indeed, the point estimates and significance levels for these are markedly higher than in the total employment results of column 5. Likewise the point estimate for the within component of the Theil index nearly doubles in size, suggesting that manufacturing employment suffers greatly when innovation is concentrated in a few active fields. No significant relationship, however, is found for the between measure, i.e. the number of active fields has no significant correlation with employment. Turning to services, only the two Theil components are significant. Thus, services employment seems related to the concentration of innovation, not necessarily its level. This may reflect the relative importance of patenting as a method of protecting

[28]Unfortunately, greater disaggregation by industry is unavailable in Eurostat. Eurostat classifies manufacturing as manufacturing industries (NACE C), mining and quarrying (NACE B), electricity, gas, steam, and air conditioning supply (NACE D), as well as water supply, sewerage, waste management, Melilla in Spain (ES64) drives the difference in observations across regressions.

proprietary knowledge in manufacturing as compared to services. Alternatively, at least for citations, this difference in significance may result from the idea that focusing specifically on manufacturing employment provides a better fit between field of specialization and citation patterns across technologies.

Table 2: Impact of innovation, spillovers and concentration on employment

	Dep. Variable: Employment						
Sample			Whole			Manuf.	Services
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Innovation	0.073***				0.059**	0.128***	0.027
	(0.026)				(0.026)	(0.039)	(0.029)
Innov. quality	0.065*				0.065*	0.163***	0.055
	(0.035)				(0.034)	(0.050)	(0.035)
Spillovers		0.005***			0.005**	0.009***	0.003
		(0.001)			(0.002)	(0.004)	(0.003)
Concentration:							
– Overall			-0.120***				
			(0.030)				
– Within				-0.111**	-0.113***	-0.216***	-0.139***
				(0.043)	(0.042)	(0.076)	(0.048)
– Between				-0.126***	-0.089***	-0.090	-0.203***
				(0.031)	(0.034)	(0.069)	(0.053)
(log) GDP	0.120***	0.127***	0.110***	0.110***	0.104***	0.126***	0.179***
	(0.019)	(0.019)	(0.018)	(0.018)	(0.018)	(0.040)	(0.020)
(log) Pop	0.675***	0.645***	0.749***	0.752***	0.759***	0.147	0.615***
	(0.064)	(0.065)	(0.070)	(0.070)	(0.068)	(0.131)	(0.089)
Pop. Growth	0.256	0.235	0.235	0.232	0.265	0.347	0.691***
	(0.158)	(0.159)	(0.175)	(0.176)	(0.173)	(0.243)	(0.178)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# Regions	272	272	272	272	272	271	272
Obs.	2,884	2,884	2,884	2,884	2,884	2,872	2,884
Pseudo R^2	0.980	0.980	0.980	0.980	0.980	0.930	0.977

Sample years: 2011-2021. The dependent variable is employment in a NUTS2 region. Manufacturing includes NACE C plus industries such as mining and quarrying (NACE B), electricity, gas, steam and air conditioning supply (NACE D), as well as water supply, sewerage, waste management, and remediation activities (NACE E). There is a lack of manufacturing employment data for Melilla in Spain (ES64). Consequently, this data gap has led to discrepancies in the number of observations when compared to the baseline regressions. PPML estimates with robust standard errors clustered at NUTS 2-digit level in parentheses. ***, **, and * significantly different from 0 at the 1%, 5%, and 10% confidence levels, respectively.

Longer lags. In the above results, we estimated the contemporaneous relationship between innovation and employment. Longer run effects, however, can also be possible as innovation permeates the labour market. On the other hand, the effects may be fairly short lived for two reasons. First, in order to patent an innovation, an application must generally be submitted shortly after its first use. For the European Patent Office, this window is six months.[29] Thus, the effect from

[29] See https://www.epo.org/en/legal/guidelines-epc/2023/b_vi_5_5.html.

patenting – our measure of innovation – may be rather quick. Furthermore, in the innovation race between firms, a given invention's usefulness may be swiftly superceded by subsequent technological development.

With these potentially conflicting possibilities in mind, Table 3, instead uses three and five year lags of our innovation variables. Note that this brings the added benefit of mitigating potential endogeneity concerns. In this table, columns 1 and 2 use total employment for the three- and five-year lags respectively; columns 3 and 4 do the same for manufacturing while the last two columns do so for services.

Looking at the results for total employment, we find point estimates in line with the prior results, however, the significance of nearly all of the innovation measures evaporates. This is not the case, however, for manufacturing. The three-year lag estimates (column 3) are broadly the same as what was found before with one exception – the between component of concentration is now also negatively related with employment. When using five-year lags, we find a similar set of estimates, albeit significance is again lower for the quantity and quality of innovation. This suggests that the impacts of innovation are at least somewhat persistent over time.

In services, however, we again find significance only for the concentration measures and even there, the point estimates are half as large as previously found. This suggests a rapid decay in the role of innovation concentration in services. As this sector is anecdotally perceived as a rapidly evolving one, it may be that its related technologies rapidly become obsolete.

Thus, at least when focusing on specific sectors, our results are robust to lagged measures of innovation, a feature which helps to reassure us that the patterns we observe are not driven by endogeneity.

Heterogeneous effects across worker categories. The above results suggest a differential effect on employment in manufacturing and services. Here, we explore another dimension of heterogeneity by using the Eurostat data that provides employment by three educational categories as well as "techies" (scientists and engineers). The estimates from these subsamples are presented in Table 4 which includes each of these four groups and results from using the contemporaneous innovation variables, their three-year lags, and their five-year lags.

The first six columns present results for the techies and all high-skill workers. As can be seen, the results broadly match those from before, i.e. more innovation and less concentration boosts employment. Although the innovation quality measure retains the sign of their prior coefficient, it is only occasionally significant. The primary difference found between the STEM-oriented techies and all highly educated workers is that techies do not feel the negative effect of concentration

Table 3: Impact of lagged innovation, spillovers and concentration on employment

	Dep. Variable: Employment					
Sample	Total		Manuf.		Services	
Lag	3^{rd}	5^{th}	3^{rd}	5^{th}	3^{rd}	5^{th}
	(1)	(2)	(3)	(4)	(5)	(6)
Innovation	0.029	0.016	0.057**	0.033	-0.002	-0.010
	(0.019)	(0.018)	(0.026)	(0.024)	(0.022)	(0.020)
Innov. quality	0.034	0.023	0.074**	0.043	0.013	-0.005
	(0.021)	(0.016)	(0.033)	(0.028)	(0.022)	(0.017)
Spillovers	0.004**	0.004**	0.006***	0.007***	0.003	0.002
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Concentration:						
– Within	-0.042	-0.050**	-0.116**	-0.094**	-0.071**	-0.052**
	(0.032)	(0.021)	(0.054)	(0.039)	(0.035)	(0.024)
– Between	-0.030	-0.018	-0.088**	-0.056*	-0.140***	-0.117***
	(0.030)	(0.026)	(0.042)	(0.031)	(0.032)	(0.022)
(log) GDP	0.116***	0.120***	0.128***	0.141***	0.184***	0.186***
	(0.018)	(0.018)	(0.040)	(0.040)	(0.018)	(0.019)
(log) Pop	0.721***	0.717***	0.174	0.147	0.635***	0.656***
	(0.073)	(0.076)	(0.137)	(0.138)	(0.089)	(0.091)
Pop. Growth	0.234	0.246	0.247	0.263	0.640***	0.659***
	(0.159)	(0.157)	(0.242)	(0.243)	(0.176)	(0.170)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
# Regions	272	271	271	270	272	271
Obs.	2,879	2,869	2,868	2,860	2,879	2,869
Pseudo R^2	0.980	0.980	0.930	0.930	0.977	0.977

Sample years: 2011-2021. The dependent variable is employment in a NUTS2 region. Manufacturing includes NACE C plus industries such as mining and quarrying (NACE B), electricity, gas, steam and air conditioning supply (NACE D), as well as water supply, sewerage, waste management, and remediation activities (NACE E). There is a lack of manufacturing employment data for Melilla in Spain (ES64). Consequently, this data gap has led to discrepancies in the number of observations when compared to the baseline regressions. PPML estimates with robust standard errors clustered at NUTS 2-digit level in parentheses. ***, **, and * significantly different from 0 at the 1%, 5%, and 10% confidence levels, respectively.

until five years later, a result perhaps suggesting that in the industries in which they feature most strongly (including manufacturing industries), technology has a longer shelf life.

In contrast, medium-skill workers have relatively little in the way of a significant relationship between innovation and employment and low-skill workers have essentially no relationship between their employment and innovation.

Together, these estimates suggest that innovation as measured by patents is likely a skill-biased technological process that works to the benefit of workers with the ability to exploit the opportunities new technologies present.

Table 4: Effects on employment across worker categories

	Dep. Variable: Employment											
				Skill-level								
Sample	Techies			High			Middle			Low		
Lag	–	3^{rd}	5^{th}	–	3^{rd}	5^{th}	–	3^{rd}	5^{th}	–	3^{rd}	5^{th}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Innovation	0.241***	0.141***	0.099*	0.196***	0.119***	0.084***	0.019	0.009	0.026	-0.174*	-0.133	-0.098
	(0.072)	(0.051)	(0.051)	(0.047)	(0.031)	(0.029)	(0.040)	(0.030)	(0.029)	(0.097)	(0.083)	(0.071)
Innov. Quality	0.096	0.069	0.070*	0.064	0.014	-0.015	0.051	0.029	-0.009	0.100	0.041	0.066
	(0.084)	(0.060)	(0.042)	(0.059)	(0.040)	(0.032)	(0.042)	(0.030)	(0.025)	(0.111)	(0.070)	(0.059)
Spillovers	0.008	0.010**	0.000	0.004	0.006**	0.003	0.005	0.006***	0.006**	0.007	0.001	0.005
	(0.007)	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.006)	(0.004)	(0.003)
Concentration												
– Between	-0.054	-0.095	-0.128**	-0.133	-0.133***	-0.100***	-0.144**	-0.006	-0.004	0.028	0.062	-0.044
	(0.126)	(0.078)	(0.060)	(0.087)	(0.049)	(0.038)	(0.061)	(0.050)	(0.040)	(0.099)	(0.117)	(0.103)
– Within	-0.135	-0.063	-0.140**	-0.236***	-0.111**	-0.127***	-0.065	-0.063	-0.055*	0.048	0.095	0.140
	(0.116)	(0.085)	(0.064)	(0.077)	(0.056)	(0.041)	(0.066)	(0.043)	(0.032)	(0.155)	(0.090)	(0.086)
(log) GDP	0.076	0.087	0.088	-0.001	0.014	0.025	0.046	0.050	0.045	0.178*	0.172**	0.167**
	(0.057)	(0.057)	(0.055)	(0.029)	(0.027)	(0.027)	(0.035)	(0.035)	(0.037)	(0.092)	(0.084)	(0.078)
(log) Pop	1.207***	1.268***	1.396***	1.063***	1.132***	1.171***	-0.028	-0.065	-0.044	0.884***	0.687***	0.607**
	(0.226)	(0.238)	(0.235)	(0.142)	(0.147)	(0.150)	(0.130)	(0.135)	(0.129)	(0.277)	(0.259)	(0.267)
Pop. Growth	-0.164	-0.322	-0.341	-0.762***	-0.940***	-0.959***	0.672***	0.657***	0.677***	0.606*	0.811**	0.783**
	(0.354)	(0.351)	(0.354)	(0.243)	(0.250)	(0.249)	(0.254)	(0.238)	(0.230)	(0.357)	(0.369)	(0.360)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# Regions	271	271	270	272	272	271	272	272	271	272	272	271
Obs.	2,867	2,862	2,852	2,884	2,879	2,869	2,884	2,879	2,869	2,884	2,879	2,869
Pseudo R^2	0.886	0.885	0.885	0.962	0.962	0.962	0.960	0.960	0.959	0.947	0.947	0.947

Sample years: 2011-2021. The dependent variable is employment in a NUTS2 region. Low-Skilled are workers with ISCED levels 0-2; Middle-Skilled are workers with ISCED levels 3-4; High-Skilled are workers with ISCED levels 5-8; Techies are scientists and engineers. PPML estimates with robust standard errors clustered at NUTS 2-digit level in parentheses. ***, **, and * significantly different from 0 at the 1%, 5%, and 10% confidence levels, respectively.

5 Effects on unemployment

In the above results, our dependent variable was the employment level (or, since we control for population, the employment rate). We used that labour market outcome for two reasons. First, unlike the unemployment rate which can vary as the unemployed quit their job search (such as if they return to education to retrain in the face of advancing technology), the employment rate does not. Second, and more pragmatically, Eurostat provides employment data for manufacturing and services but does not provide data on the unemployment rate. Nevertheless, in Table 5 we present estimates comparable to Table 4 but use the unemployment rate as our dependent variable. Based on the above results, we expect that regions with better innovation outcomes will have lower unemployment rates. Similarly, we anticipate that more concentrated regions have higher unemployment rates.

As can be seen, these expectations are largely borne out. The most striking difference is that, in contrast to the employment results of Table 4, here we find significant coefficients even for the middle- and low-skill workers. Since there was no estimated impact on the number of employed in these categories yet their unemployment rate falls, this could be due to exits from the labour search market in search of upskilling opportunities. This possibility, however, is best addressed by alternative datasets with more granular information, e.g. analysis within a single country as opposed to our cross-country study.

Table 5: Effects on unemployment across worker categories

	Dep. Variable: Unemployment Rate											
							Skill-level					
Sample		All			High			Middle			Low	
Lag	–	3^{rd}	5^{th}	–	3^{rd}	5^{th}	–	3^{rd}	5^{th}	–	3^{rd}	5^{th}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Innovation	-0.316***	-0.177**	-0.040	-0.415***	-0.202***	-0.019	-0.270***	-0.092	0.040	-0.292**	-0.123	0.017
	(0.097)	(0.072)	(0.064)	(0.095)	(0.075)	(0.076)	(0.101)	(0.077)	(0.068)	(0.117)	(0.094)	(0.082)
Innov. Quality	-0.253***	-0.094*	-0.101*	-0.356***	-0.036	-0.008	-0.261***	-0.068	-0.065	-0.317***	-0.199**	-0.197**
	(0.095)	(0.052)	(0.056)	(0.095)	(0.074)	(0.053)	(0.101)	(0.054)	(0.061)	(0.098)	(0.082)	(0.085)
Spillovers	-0.011	0.008	-0.001	-0.013**	0.005	-0.001	-0.002	0.009*	0.000	-0.018**	-0.000	-0.002
	(0.007)	(0.005)	(0.004)	(0.006)	(0.005)	(0.005)	(0.008)	(0.005)	(0.004)	(0.008)	(0.007)	(0.005)
Concentration												
– Within	0.791***	0.328***	0.358***	0.873***	0.308**	0.392***	0.677***	0.241*	0.268***	0.704***	0.410***	0.424***
	(0.153)	(0.114)	(0.083)	(0.166)	(0.126)	(0.095)	(0.181)	(0.138)	(0.092)	(0.183)	(0.134)	(0.101)
– Between	0.343***	0.284**	0.233**	0.363***	0.239**	0.292***	0.472***	0.327**	0.240**	0.277*	0.208	0.219*
	(0.129)	(0.120)	(0.094)	(0.141)	(0.108)	(0.070)	(0.175)	(0.142)	(0.096)	(0.142)	(0.142)	(0.115)
(log) GDP	-1.059***	-1.201***	-1.225***	-0.732***	-0.920***	-0.959***	-1.082***	-1.226***	-1.246***	-0.825***	-0.901***	-0.917***
	(0.119)	(0.127)	(0.124)	(0.129)	(0.132)	(0.124)	(0.119)	(0.126)	(0.122)	(0.165)	(0.168)	(0.162)
Pop. Growth	-3.326***	-2.748***	-2.750***	-1.329*	-0.975	-1.302*	-3.976***	-3.572***	-3.265***	-3.260***	-2.923***	-3.058***
	(0.913)	(0.855)	(0.898)	(0.803)	(0.760)	(0.738)	(1.158)	(1.106)	(1.069)	(0.873)	(0.851)	(0.936)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# Regions	272	272	271	246	246	245	269	269	268	267	267	266
Obs.	2,869	2,864	2,854	2,288	2,284	2,274	2,777	2,772	2,762	2,640	2,635	2,625
Pseudo R^2	0.438	0.437	0.433	0.411	0.410	0.407	0.458	0.457	0.454	0.413	0.412	0.410

Sample years: 2011-2021. The dependent variable is unemployment in a NUTS2 region. Low-Skilled are workers with ISCED levels 0-2; Middle-Skilled are workers with ISCED levels 3-4; High-Skilled are workers with ISCED levels 5-8. PPML estimates with robust standard errors clustered at NUTS 2-digit level in parentheses. ***, **, and * significantly different from 0 at the 1%, 5%, and 10% confidence levels, respectively.

6 Conclusion and Policy Implications

While as a general concept there has been little doubt that innovation can serve as a driver of job creation, the specifics of this relationship has been unclear. Questions such as which aspects of innovation – its level, quality, relationship to prior work, and concentration – as well as which jobs – manufacturing versus services or which skill levels – remain. Understanding these nuances is critical if one is seeking to make policy recommendations that will achieve their intended goals.

In this paper, we contribute by using data from Orbis IP to examine the relationship between innovation, measured by patenting activity, and employment across 272 European regions for 2011-2021. Relative to the existing literature, we present three major innovations. First, our use of patents from Orbis IP allow us to match nearly ten times as many patents to regions as using PATSTAT, the dominant source of patent information, would. Second, while the concentration of innovation has been considered elsewhere, we introduce the Theil index, a measure that allows us to separately consider the number of active technological fields in a region (between) as well as the distribution of activity across those fields (within). Third, our employment data allows us to consider heterogeneous impacts across industries and worker skill-level.

We find that innovation, both in terms of quantity (number of patents) and quality (forward citations per patent), is linked with higher employment. Furthermore, when local innovation draws more from the existing research (backward spillover), employment tends to be higher. Thus, more and more connected research appears to promote job creation. Conversely, regions whose innovation is more concentrated – and in particular those where research activity is distributed unequally across technological fields – tend towards weaker employment outcomes. This may indicate the risk of "putting all of the eggs in one basket", that is, having a diverse research landscape may allow a region to respond more swiftly to market changes and thus retain jobs.

Digging deeper, our granular analysis finds that these effects are more robust in manufacturing than services, both in the immediate and longer runs. This suggests both that patenting as a measure of innovation may be more applicable to manufacturing and that services is a more dynamic sector where new technologies become outdated very quickly. Finally, we find that the employment effects of diverse, active, and interconnected innovation are primarily found for high-skill workers.

Together, these results suggest that although a general approach towards encouraging innovation may increase jobs via, for example, R&D subsidies, tax incentives, or patent boxes, the impact may be unevenly felt across the labour market.[30] Furthermore, the most successful policies may be those specifically designed to encourage expansion into new technological areas. This then may provide credence to the so-called "smart specialization strategies" that prioritize particular technological areas for development when such strategies promote diversification.[31] In addition, by promoting a region's position in global value chains of knowledge production, thereby increasing both forward and backward spillovers, policy makers may be able to make the most out of the labour market effects of its research.

Furthermore, our analysis suggests that since peripheral and small European countries tend to have less innovation overall, and that what innovation they have tends to be isolated and concentrated, then it may be useful to promote regional development of innovative capacity so as to ensure more even job creation across Europe. At a point in time where there is growing doubt in the European project, understanding such approaches may be a necessary component for maintaining European cohesion.

[30] Akcigit et al. (2018) provide further discussion on taxes and innovation.

[31] Lo Conte et al. (2023) provide a recent discussion on smart specialization strategies and estimate their impact on regional productivity.

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A Data coverage and harmonization of NUTS-2 digit classification

In this section, we outline the coverage and data sources for our study, particularly focusing on employment outcomes and regional controls from the Eurostat database. Several limitations and missing data points are pertinent to our analysis:

Countries and year coverage. Data on employment outcomes and regional controls are sourced from Eurostat. The Eurostat database has limited coverage for NUTS 2-digit level data across years and countries. The following limitations are relevant for our study.

Data on aggregate employment are missing for UK for the years 2020 and 2021, for Macedonia and Montenegro for the year 2021 and for the Poland NUTS2 PL12 for 2012 and 2011.

For the same country-years also data on unemployment are missing. For this variable these additional NUTS2-have missing values: German NUTS2 DE22, DE23, DE24, DE26, DE50, DE73, DEB1, DEC0, DED4 for 2021 and DEB2 for years 2019 to 2021; Poland region PL43 for years 2020 and 2021; UKM6 for year 2019. Unemployment is also missing for FI20 for all years: national statistics data are used for replacement of this region.

To address missing data for GDP, we complement Eurostat information with national and international official statistics. Data for GDP for UK and for Switzerland comes from national official institutes, while data for Iceland comes from World Bank. The missing value for Norway GDP for 2021 is ipolated using available data.

Low skill employment corresponds to ISCED levels 0-2, "Less than primary, primary and lower secondary education"; middle skill to ISCED levels 3-4 "Upper secondary and post-secondary non-tertiary education"; high skill to ISCED levels 5-8 "Tertiary education".

Employment in "Manufacturing" includes NACE C plus industries such as mining and quarrying (NACE B), electricity, gas, steam and air conditioning supply (NACE D), as well as water supply, sewerage, waste management, and remediation activities (NACE E). Employment in "Services" includes NACE E to U.

When building facts 1 and 2, missing data for 2021 have been replaced with the most recent available year. As data on innovation from PATSTAT and ORBIS IP allows us to have broader coverage over NUTS2 regions, data facts 3 and 4 exploit this information using also data for Albania, Lichtenstein, and Turkey. The latter is not reported in the maps in facts 3 and 4 for graphical reasons. Note that its contribution to innovation and knowledge flows is marginal.

NUTS 2-digit harmonization. The NUTS 2-digit classification has undergone changes through the period under scrutiny. While many countries have faced re-coding of NUTS2 with small or zero changes in regional boundaries (such as France), other countries have undergone profound changes. Particularly relevant for our study are changes that substantially affected the borders of some regions, or changes that implied the division of larger NUTS2 into new smaller NUTS2. Two examples are useful to illustrate the relevance of these changes. As concerns substantial changes of regional borders, Ireland has undergone a major reclassification of NUTS2 between the 2013 and the 2016 NUTS classification. The two NUTS2 composing the country in the 2013 classification (IE01 and IE02) have been replaced in the 2016 classification by three NUTS2 (IE04, IE05 and IE06) that span over different borders with respect to previous regions. In practice, there is no way to compare the regions before and after the re-classification. A similar change occurred for Norway. To avoid dropping these countries from our sample we aggregated data at the national level. As concerns examples of the division of larger NUTS2 into new smaller NUTS2, the classification of the city of London has changed between the 2010 and the 2013 NUTS classification. Each of the two NUTS2 composing the city (UKI1 and UKI2) have been split into new smaller NUTS2 (UKI1 into UKI3 and UKI4, and UKI2 into UKI5, UKI6 and UKI7). To retain information for NUTS2 interested by these types of division, we aggregated our data to the largest NUTS2 throughout our period: e.g. in the case of London we aggregated all information at the UKI1 and UKI2 level.

The unemployment variable for aggregated regions is built as the average across sub-components.

Table A1 lists the changes addressed in the harmonization procedure.

Table A1: NUTS 2-digit re-classification

Aggregate NUTS2	Sub-component NUTS2	Change between classifications
Pohjois- ja Itä-Suomi (FI1D)	Itä-Suomi (FI13), Pohjois-Suomi (FI1A)	NUTS2006-NUTS2010
Etelä-Suomi (FI18)	Helsinki-Uusimaa (FI1B), Etelä-Suomi (FI1C)	NUTS2006-NUTS2010
Inner London (UKI1)	Inner London - West (UKI3), Inner London - East (UKI4)	NUTS2010-NUTS2013
Outer London (UKI2)	Outer London - East and North East (UKI5), Outer London - South (UKI6), Outer London - West and North West (UKI7)	NUTS2010-NUTS2013
South Western Scotland (UKM3)	West Central Scotland (UKM8), Southern Scotland (UKM9)	NUTS2013-NUTS2016
Lietuva (LT00)	Sostinės regionas (LT01), Vidurio ir vakarų Lietuvos regionas (LT02)	NUTS2013-NUTS2016
Közép-Magyarország (HU10)	Budapest (HU11), Pest (HU12)	NUTS2013-NUTS2016
Mazowieckie (PL12)	Warszawski stołeczny (PL91), Mazowiecki regionalny (PL92)	NUTS2013-NUTS2016
Kontinentalna Hrvatska (HR04)	Panonska Hrvatska (HR02), Grad Zagreb (HR05), Sjeverna Hrvatska (HR06)	NUTS2016-NUTS2021
Ireland (IE)	all NUTS2	NUTS2013-NUTS2016
Norway (NO)	all NUTS2	NUTS2016-NUTS2021

Notes:

Below we provide the full list of regions included in the regression sample.

Table A2: List of Region in the Sample

Country	Region
Austria	Burgenland (AT), Kärnten, Niederösterreich, Oberösterreich, Salzburg, Steiermark, Tirol, Vorarlberg, Wien
Belgium	Prov. Antwerpen, Prov. Brabant wallon, Prov. Hainaut, Prov. Limburg (BE), Prov. Liège, Prov. Luxembourg (BE), Prov. Namur, Prov. Oost-Vlaanderen, Prov. Vlaams-Brabant, Prov. West-Vlaanderen, Région de Bruxelles-Capitale/Brussels Hoofdstedelijk Gewest
Bulgaria	Severen tsentralen, Severoiztochen, Severozapaden, Yugoiztochen, Yugozapaden, Yuzhen tsentralen
Switzerland	Espace Mittelland, Nordwestschweiz, Ostschweiz, Région lémanique, Ticino, Zentralschweiz, Zürich
Cyprus	Kypros
Czech Republic	Jihovýchod, Jihozápad, Moravskoslezsko, Praha, Severovýchod, Severozápad, Strední Cechy, Strední Morava
Germany	Arnsberg, Berlin, Brandenburg, Braunschweig, Bremen, Chemnitz, Darmstadt, Detmold, Dresden, Düsseldorf, Freiburg, Gießen, Hamburg, Hannover, Karlsruhe, Kassel, Koblenz, Köln, Leipzig, Lüneburg, Mecklenburg-Vorpommern, Mittelfranken, Münster, Niederbayern, Oberbayern, Oberfranken, Oberpfalz, Rheinhessen-Pfalz, Saarland, Sachsen-Anhalt, Schleswig-Holstein, Schwaben, Stuttgart, Thüringen, Trier, Tübingen, Unterfranken, Weser-Ems
Denmark	Hovedstaden, Midtjylland, Nordjylland, Sjælland, Syddanmark
Estonia	Eesti
Greece	Anatoliki Makedonia - Thraki, Attiki, Dytiki Ellada, Ipeiros, Kentriki Makedonia, Kriti, Notio Aigaio, Sterea Ellada, Thessalia
Spain	Andalucía, Aragón, Canarias, Cantabria, Castilla y León, Castilla-la Mancha, Cataluña, Ciudad de Melilla, Comunidad Foral de Navarra, Comunidad de Madrid, Comunitat Valenciana, Extremadura, Galicia, Illes Balears, La Rioja, País Vasco, Principado de Asturias, Región de Murcia
Finland	Etelä-Suomi, Länsi-Suomi, Pohjois- ja Itä-Suomi, Åland
France	Alsace, Aquitaine, Auvergne, Basse-Normandie, Bourgogne, Bretagne, Centre - Val de Loire, Champagne-Ardenne, Corse, Franche-Comté, Haute-Normandie, Languedoc-Roussillon, Limousin, Lorraine, Midi-Pyrénées, Nord-Pas-de-Calais, Pays-de-la Loire, Picardie, Poitou-Charentes, Provence-Alpes-Côte d'Azur, Rhône-Alpes, Île de France
Croatia	Jadranska Hrvatska, Kontinentalna Hrvatska (NUTS 2016)
Hungary	Dél-Alföld, Dél-Dunántúl, Közép-Dunántúl, Közép-Magyarország (NUTS 2013), Nyugat-Dunántúl, Észak-Alföld, Észak-Magyarország
Ireland	Ireland - Full country
Iceland	Ísland
Italy	Abruzzo, Basilicata, Calabria, Campania, Emilia-Romagna, Friuli-Venezia Giulia, Lazio, Liguria, Lombardia, Marche, Molise, Piemonte, Provincia Autonoma di Bolzano/Bozen, Provincia Autonoma di Trento, Puglia, Sardegna, Sicilia, Toscana, Umbria, Valle d'Aosta/Vallée d'Aoste, Veneto
Lithuania	Lietuva (NUTS 2013)
Luxembourg	Luxembourg
Latvia	Latvija
Macedonia	Severna Makedonija
Malta	Malta
Montenegro	Crna Gora
Netherlands	Drenthe, Flevoland, Friesland (NL), Gelderland, Groningen, Limburg (NL), Noord-Brabant, Noord-Holland, Overijssel, Utrecht, Zeeland, Zuid-Holland
Norway	Norway - Full country

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Table A2 – continued from previous page

Country	Region
Poland	Dolnoslaskie, Kujawsko-Pomorskie, Lubelskie, Lubuskie, Lódzkie, Malopolskie, Mazowieckie, Opolskie, Podkarpackie, Podlaskie, Pomorskie, Slaskie, Swietokrzyskie, Warminsko-Mazurskie, Wielkopolskie, Zachodniopomorskie
Portugal	Alentejo, Algarve, Centro (PT), Norte, Região Autónoma da Madeira (PT), Região Autónoma dos Açores (PT), Área Metropolitana de Lisboa
Romania	Bucuresti - Ilfov, Centru, Nord-Est, Nord-Vest, Sud - Muntenia, Sud-Est, Sud-Vest Oltenia, Vest
Sweden	Mellersta Norrland, Norra Mellansverige, Småland med öarna, Stockholm, Sydsverige, Västsverige, Östra Mellansverige, Övre Norrland
Slovenia	Vzhodna Slovenija (NUTS 2010), Zahodna Slovenija (NUTS 2010)
Slovakia	Bratislavský kraj, Stredné Slovensko, Východné Slovensko, Západné Slovensko
United Kingdom	Bedfordshire and Hertfordshire, Berkshire, Buckinghamshire and Oxfordshire, Cheshire, Cornwall and Isles of Scilly, Cumbria, Derbyshire and Nottinghamshire, Devon, Dorset and Somerset, East Anglia, East Wales, East Yorkshire and Northern Lincolnshire, Eastern Scotland (NUTS 2013), Essex, Gloucestershire, Wiltshire and Bristol/Bath area, Greater Manchester, Hampshire and Isle of Wight, Herefordshire, Worcestershire and Warwickshire, Highlands and Islands, Inner London (NUTS 2010), Kent, Lancashire, Leicestershire, Rutland and Northamptonshire, Lincolnshire, Merseyside, North Eastern Scotland, North Yorkshire, Northern Ireland (UK), Northumberland and Tyne and Wear, Outer London (NUTS 2010), Shropshire and Staffordshire, South Western Scotland (NUTS 2013), South Yorkshire, Surrey, East and West Sussex, Tees Valley and Durham, West Midlands, West Wales and The Valleys, West Yorkshire

B Descriptive Statistics

Table B1: Descriptive statistics

	N	Mean	SD	p25	Median	p75
Employment:						
– Aggregate	2884	827.355	668.267	405.4	645.8	1036.25
– Manufacturing	2872	145.548	129.701	62.2	115.9	181.75
– Services	2884	642.716	555.458	303.3	489.2	803.1
– Low-Skilled	2884	147.836	177.394	53.05	91.7	164.55
– Middle-Skilled	2884	396.629	293.821	188.6	332.1	527
– High-Skilled	2884	280.747	286.306	114	200.7	342.5
– Techies	2867	66.959	65.018	24.3	48.1	85
Innovation	2884	7.207	1.840	6.156	7.317	8.474
Innovation quality	2884	1.114	0.799	.762	1.261	1.647
Spillovers	2884	16.719	0.583	16.487	16.751	16.995
Conc. (Overall)	2884	0.804	0.511	0.482	0.647	0.959
Conc. (Between)	2884	0.149	0.438	0	0	0.059
Conc. (Within)	2884	0.655	0.319	0.456	0.571	0.791
(log) GDP	2884	10.501	1.006	9.847	10.564	11.187
(log) Pop.	2884	14.179	0.806	13.787	14.219	14.671
Pop. Growth	2884	.002	.008	-.002	.002	.006
Unemployment rate:						
– Aggregate	2869	8.203	5.657	4.3	6.7	9.8
– Low-Skilled	2640	14.77	7.983	8.9	13	18.5
– Middle-Skilled	2777	8.392	5.959	4.2	6.8	10.3
– High-Skilled	2288	5.631	4.304	2.9	4.3	6.3

Descriptive statistics for the baseline estimation sample (Table 2), which comprises 272 NUTS 2-digit regions and covers the years from 2011 to 2021. descriptive statistics for unemployment are computed on the estimation sample of Table **??**.

C Fact 3. Tech fields and localization in regions (Full Table).

Table C1: Innovation growth by technological field and regional specialization

Field	Spatial Conc.	% Cit_{21}	% Δ Cit_{21-11}	% Pat_{21}	% Δ Pat_{21-11}	Top growing NUTS2	Top declining NUTS2
Micro-structural and nano-technology (22)	2.03	0.13	12.54	0.13	32.64	1) Oberbayern (DE21) 2) Eastern Scotland (NUTS 2013) (UKM2) 3) Ireland - Full country (IE)	1) Sydsverige (SE22) 2) Lombardia (ITC4) 3) Inner London (NUTS 2010) (UKI1)
Electrical machinery, apparatus, energy (1)	1.50	5.75	7.89	6.68	15.51	1) Noord-Brabant (NL41) 2) Stuttgart (DE11) 3) Zürich (CH04)	1) Freiburg (DE13) 2) Hamburg (DE60) 3) Köln (DEA2)
Surface technology, coating (21)	1.61	1.62	4.60	1.50	-1.59	1) Flevoland (NL23) 2) Tübingen (DE14) 3) Berlin (DE30)	1) Oberbayern (DE21) 2) Noord-Holland (NL32) 3) Darmstadt (DE71)
Digital communication (4)	2.78	5.42	4.40	3.00	5.09	1) Île de France (FR10) 2) Noord-Brabant (NL41) 3) Région lémanique (CH01)	1) Etelä-Suomi (FI18) 2) Lombardia (ITC4) 3) Sydsverige (SE22)
Other consumer goods (34)	1.84	1.86	3.96	2.35	8.41	1) Espace Mittelland (CH02) 2) Inner London (NUTS 2010) (UKI1) 3) Mittelfranken (DE25)	1) Rhône-Alpes (FRK2) 2) Île de France (FR10) 3) Veneto (ITH3)
Computer technology (6)	1.97	8.22	3.94	4.63	4.24	1) Ireland - Full country (IE) 2) Noord-Brabant (NL41) 3) East Anglia (UKH1)	1) Oberbayern (DE21) 2) Etelä-Suomi (FI18) 3) Lombardia (ITC4)
Transport (32)	1.92	7.25	3.77	8.84	9.98	1) Île de France (FR10) 2) West Midlands (UKG3) 3) Västsverige (SE23)	1) Unterfranken (DE26) 2) Lüneburg (DE93) 3) Weser-Ems (DE94)
Semiconductors (8)	2.31	3.41	3.54	2.03	-6.25	1) Flevoland (NL23) 2) Kärnten (AT21) 3) Ireland - Full country (IE)	1) Oberbayern (DE21) 2) Noord-Brabant (NL41) 3) Inner London (NUTS 2010) (UKI1)
Engines, pumps, turbines (27)	1.80	3.34	3.35	3.84	13.95	1) Midtjylland (DK04) 2) Mittelfranken (DE25) 3) Hannover (DE92)	1) Stuttgart (DE11) 2) Lüneburg (DE93) 3) Köln (DEA2)
Control (12)	1.53	1.91	3.33	1.83	3.62	1) Noord-Brabant (NL41) 2) Stockholm (SE11) 3) Västsverige (SE23)	1) Noord-Holland (NL32) 2) Etelä-Suomi (FI18) 3) Karlsruhe (DE12)
Measurement (10)	1.57	5.37	3.15	5.43	10.41	1) Noord-Brabant (NL41) 2) Île de France (FR10) 3) Espace Mittelland (CH02)	1) Zuid-Holland (NL33) 2) Etelä-Suomi (FI18) 3) Hampshire and Isle of Wight (UKJ3)
IT methods for management (7)	1.86	1.21	2.76	0.91	14.43	1) Noord-Brabant (NL41)	1) Ostschweiz (CH05)

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Table C1 – continued from previous page

Field	Spatial Conc.	% Cit_{21}	% Δ Cit_{21-11}	% Pat_{21}	% Δ Pat_{21-11}	Top growing NUTS2	Top declining NUTS2
						2) Île de France (FR10) 3) Ireland - Full country (IE)	2) Noord-Holland (NL32) 3) Karlsruhe (DE12)
Materials, metallurgy (20)	1.82	1.65	1.93	1.91	-2.74	1) Oberbayern (DE21) 2) Västsverige (SE23) 3) País Vasco (ES21)	1) Noord-Holland (NL32) 2) Köln (DEA2) 3) Düsseldorf (DEA1)
Other special machines (29)	1.24	2.65	1.62	3.91	1.41	1) Noord-Brabant (NL41) 2) Oberpfalz (DE23) 3) Weser-Ems (DE94)	1) Lombardia (ITC4) 2) Darmstadt (DE71) 3) Zentralschweiz (CH06)
Handling (25)	1.33	2.89	1.27	4.17	-2.73	1) Oberpfalz (DE23) 2) Schwaben (DE27) 3) Norway - Full country (NO)	1) Karlsruhe (DE12) 2) Emilia-Romagna (ITH5) 3) Zentralschweiz (CH06)
Mechanical elements (31)	1.85	4.21	1.04	5.90	7.21	1) Mittelfranken (DE25) 2) Picardie (FRE2) 3) Steiermark (AT22)	1) Karlsruhe (DE12) 2) Arnsberg (DEA5) 3) Unterfranken (DE26)
Thermal processes and apparatus (30)	1.49	1.30	0.93	2.16	4.75	1) Stuttgart (DE11) 2) Outer London (NUTS 2010) (UKI2) 3) Île de France (FR10)	1) Lüneburg (DE93) 2) Espace Mittelland (CH02) 3) Noord-Holland (NL32)
Environmental technology (24)	1.68	1.09	-0.28	1.57	0.30	1) Inner London (NUTS 2010) (UKI1) 2) Saarland (DEC0) 3) Nordwestschweiz (CH03)	1) Stuttgart (DE11) 2) Oberbayern (DE21) 3) Köln (DEA2)
Furniture, games (33)	1.52	1.74	-0.68	2.54	-1.26	1) Etelä-Suomi (FI18) 2) Detmold (DEA4) 3) Düsseldorf (DEA1)	1) Darmstadt (DE71) 2) Noord-Holland (NL32) 3) Lombardia (ITC4)
Medical technology (13)	1.58	7.69	-2.14	4.24	6.74	1) Ireland - Full country (IE) 2) Zentralschweiz (CH06) 3) Darmstadt (DE71)	1) East Wales (UKL2) 2) Freiburg (DE13) 3) West Yorkshire (UKE4)
Machine tools (26)	1.65	2.46	-2.64	3.34	-5.99	1) Ireland - Full country (IE) 2) Schwaben (DE27) 3) Île de France (FR10)	1) Liechtenstein (LI00) 2) Stuttgart (DE11) 3) Düsseldorf (DEA1)
Audio-visual technology (2)	2.00	3.32	-2.90	2.35	-16.04	1) Hovedstaden (DK01) 2) Oberbayern (DE21) 3) Eastern Scotland (NUTS 2013) (UKM2)	1) Noord-Holland (NL32) 2) Bretagne (FRH0) 3) Mittelfranken (DE25)
Civil engineering (35)	1.63	3.38	-3.40	5.31	-3.80	1) Norway - Full country (NO) 2) Koblenz (DEB1) 3) Hovedstaden (DK01)	1) Zuid-Holland (NL33) 2) Sydsverige (SE22) 3) Arnsberg (DEA5)
Basic communication processes (5)	2.41	0.96	-3.72	0.78	-13.40	1) Région lémanique (CH01) 2) Kärnten (AT21) 3) Noord-Brabant (NL41)	1) Oberbayern (DE21) 2) Etelä-Suomi (FI18) 3) Île de France (FR10)
Macromolecular chemistry, polymers (17)	2.03	1.76	-3.88	1.34	-2.72	1) Wien (AT13) 2) Noord-Brabant (NL41) 3) Auvergne (FRK1)	1) Etelä-Suomi (FI18) 2) Darmstadt (DE71) 3) Oberbayern (DE21)

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Table C1 – continued from previous page

Field	Spatial Conc.	% Cit_{21}	% Δ Cit_{21-11}	% Pat_{21}	% Δ Pat_{21-11}	Top growing NUTS2	Top declining NUTS2
Chemical engineering (23)	1.38	2.03	-3.89	2.50	-4.08	1) Flevoland (NL23) 2) Inner London (NUTS 2010) (UKI1) 3) Noord-Brabant (NL41)	1) Oberbayern (DE21) 2) Düsseldorf (DEA1) 3) Noord-Holland (NL32)
Optics (9)	2.04	2.46	-4.17	1.89	-10.61	1) Noord-Holland (NL32) 2) Prov. Vlaams-Brabant (BE24) 3) Luxembourg (LU00)	1) Noord-Brabant (NL41) 2) Oberbayern (DE21) 3) Stuttgart (DE11)
Basic materials chemistry (19)	2.02	2.22	-4.35	1.96	-4.45	1) Noord-Brabant (NL41) 2) Schleswig-Holstein (DEF0) 3) Nordwestschweiz (CH03)	1) Düsseldorf (DEA1) 2) Zuid-Holland (NL33) 3) Hamburg (DE60)
Biotechnology (15)	1.65	1.34	-4.57	1.66	-8.71	1) Tübingen (DE14) 2) Cataluña (ES51) 3) Koblenz (DEB1)	1) Hovedstaden (DK01) 2) Düsseldorf (DEA1) 3) Darmstadt (DE71)
Food chemistry (18)	1.75	0.66	-4.70	1.09	0.76	1) Noord-Holland (NL32) 2) Limburg (NL) (NL42) 3) Zuid-Holland (NL33)	1) Région lémanique (CH01) 2) Hovedstaden (DK01) 3) Düsseldorf (DEA1)
Analysis of biological materials (11)	1.40	0.41	-5.16	0.57	-7.72	1) Zürich (CH04) 2) Darmstadt (DE71) 3) Nordwestschweiz (CH03)	1) Zentralschweiz (CH06) 2) Hovedstaden (DK01) 3) Oberbayern (DE21)
Textile and paper machines (28)	1.69	1.70	-8.46	2.28	-22.24	1) Oberpfalz (DE23) 2) Mittelfranken (DE25) 3) Oberösterreich (AT31)	1) Darmstadt (DE71) 2) Stuttgart (DE11) 3) Karlsruhe (DE12)
Organic fine chemistry (14)	2.36	2.93	-8.74	2.75	-17.33	1) Ireland - Full country (IE) 2) Nordwestschweiz (CH03) 3) Noord-Brabant (NL41)	1) Île de France (FR10) 2) Darmstadt (DE71) 3) Stockholm (SE11)
Telecommunications (3)	2.41	3.32	-9.26	1.96	-21.93	1) Noord-Brabant (NL41) 2) Ireland - Full country (IE) 3) Devon (UKK4)	1) Etelä-Suomi (FI18) 2) Sydsverige (SE22) 3) Île de France (FR10)
Pharmaceuticals (16)	1.56	2.32	-10.35	2.63	-14.33	1) Tübingen (DE14) 2) Istanbul (TR10) 3) Praha (CZ01)	1) Stockholm (SE11) 2) Île de France (FR10) 3) Rheinhessen-Pfalz (DEB3)

Notes: The table reports technological fields (j) sorted by the growth rate of citations in the period 2021-2012. %Δ Cit_{j21-12}. %Δ Cit_{j21-12} is computed as the growth rate of citations shares: $(\%Cit_{j21} - \%Cit_{j12})/\%Cit_{j12}$, with $\%Cit_{jt} = \frac{Cit_j}{\sum_1^{\mathcal{J}} Cit_j}$. Theil_j provides the concentration in the citation stock of each field across NUTS2 regions. 'Top growing NUTS2' provides the top 3 NUTS-2 with the most positive weighted contribution to the aggregate results; 'Top declining NUTS2' those with the most negative weighted contribution.

rethink GSC

ABOUT RETHINK-GSC

The project ‚Rethinking Global Supply Chains: Measurement, Impact and Policy' (RETHINK-GSC) captures the impact of knowledge flows and service inputs in Global Supply Chains (GSCs). Researchers from 11 institutes are applying their broad expertise in a multidisciplinary approach, developing new methodologies and using innovative techniques to analyse, measure and quantify the increasing importance of intangibles in global supply chains and to provide new insights into current and expected changes in global production processes.

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