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Employment imbalances in EU regions: technological dependence or high-tech trade centrality?

Ariel L. Wirkierman[a], Tommaso Ciarli[b,c] and Maria Savona[c,d]

ABSTRACT
We analyse the role of technological dependence and interregional trade centrality in explaining a region's employment performance. We first identify the core–periphery technological structure of European Union (EU) regions, clustering them based on their high-tech trade relations (trade blocks) and technological and economic indicators (place-based regional groups). We show that EU regions have a fractal structure: blocks at the core and periphery of the high-tech trade network are divided into core and peripheral subgroups, which differ significantly in terms of innovation and employment performance. Next, the econometric analysis shows that buyer centrality is the main component of employment growth (especially in services), but within trade blocks it has to be combined with low technological dependence on more innovative regions (especially in manufacturing). Cohesion policies should pay attention to the fractal structure of regional inequalities, and Smart Specialisation strategies should consider that unrelated diversification towards activities intensive in the use of high-tech inputs may be more conducive to employment growth.

KEYWORDS
regional high-tech employment; input trade networks; cluster analysis; European Cohesion Policy

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1. INTRODUCTION

The double-dips of the post-financial and post-pandemic crises are slowing down productivity and growth prospects, while exacerbating pre-existent inequalities between regions in Europe (Evenhuis et al., 2021). Furthering inequalities is argued to engender social instability and political polarisation (Rodriguez-Pose, 2018; Rodriguez-Pose et al., 2021).

Asymmetries in the employment structure of EU countries represent an important determinant of such inequalities. EU employment imbalances have been associated with technological imbalances (Feldman et al., 2021; Iammarino et al., 2019; Lee & Rodriguez-Pose, 2012), the reconfiguration of trade within and outside the European Union (EU) (Thissen et al., 2016), and the intensity and (technological) quality of integration in global value chains (GVCs) (Bontadini et al., 2019, 2024). These trends seem to have exacerbated the technological gaps and employment growth differences between core and non-core countries and favoured the emergence of new peripheries, across and within countries (Wirkierman et al., 2018).

This paper contributes to the understanding of European regional employment imbalances, as measured by total and high-tech regional contribution to EU-wide employment growth. Bathelt et al. (2024) distinguish between three main sources of (inter)regional inequality: urban scale, technical change (including skills and education) and interregional connectivity. Here we focus on the latter two. As knowledge benefits from local spillovers (Delgado et al., 2016; Jaffe et al., 1993), it concentrates in space, while regions grow unequal (Andrews & Whalley, 2022; Audretsch & Feldman, 1996). This applies also to cities within regions (Balland et al., 2020), and individuals within cities (Lee, 2016), following a fractal structure. Global connectivity contributes to this inequality, as technologically advanced regions benefit more from international businesses (Cantwell & Iammarino, 2001).

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Regional trade linkages might mitigate interregional inequalities by facilitating knowledge spillovers across regions (Balland & Boschma, 2021). But do they actually do it? Lack of convergence among EU regions suggests that a few core regions (Fagerberg et al., 1997; Verspagen, 2010; Wirkierman et al., 2018) work as international knowledge hubs (Ho & Verspagen, 2006), reproducing the core–periphery technological dependence observed in international development (Cimoli & Porcile, 2009, 2011). If a similar core–periphery structure of technological dependence is observed among regions, it might lead Smart Specialisation policies, based on supporting innovation in *related* industries, to actually increase inequality among regions (Pinheiro et al., 2022; Rigby et al., 2022). Smart Specialisation would then need to be accompanied by active policies to support technological capabilities through *unrelated* diversification in peripheral regions.

In this paper we build on theories of technological dependence and core–periphery relations to study the combined role of trade and technological relations between regions. To the best of our knowledge, the literature on regional collaborations has rarely incorporated interregional trade links, with the exception of Thissen et al. (2016) and Cortinovis and Van Oort (2019). We contribute to filling this gap in the literature by combining trade interactions with technological differences in a novel way, in order to study the role of interregional linkages in influencing regional employment disparities.

Specifically, we address the following research question: What is the role of high-tech (buyer and supplier) trade centrality and technological dependence in explaining employment imbalances across EU regions?

We operationalise it as follows. We first build indicators of interregional high-tech trade centrality and regional technological and employment (relative) performance. We then empirically identify EU regional trade blocks – based on regions' high-tech trade linkages – and place-based regional groups – based on technological and employment performance. We define as 'core' those regions with high innovative performance and/or a central role within the high-tech input trade network. We next estimate the roles of technological dependence (based on *relative* technological performance) and high-tech trade centrality in relation to the regional contribution to EU-wide (total and high-tech) employment growth.

We find that by classifying regions belonging to each trade block according to their place-based performance, a *fractal* structure of regional inequalities clearly emerges: the large technological differences between trade blocks hide similarly large (when not larger) differences across regions within trade blocks. On average, core regions (within trade blocks) contribute between five and six times more to total and high-tech employment than peripheral regions (within trade blocks).

Next, our econometric analysis shows that technological dependence is negatively related to the contribution to employment growth, whereas trade centrality is positively related. Buyer centrality seems to drive the latter result, although also high-tech supplier centrality is relevant. In other words, regions that are more likely to be central buyers of high-tech inputs have a higher contribution to EU-wide employment growth. Second, within trade blocks, we find that being at the core of high-tech input trade is not enough, it has to be combined with a high regional innovative capacity. Third, when contributing to EU-wide high-tech employment, there is a substantial difference between services and manufacturing: trade centrality is positively related to a region's contribution to high-tech employment in knowledge-intensive services, whereas technological dependence is negatively related to a region contribution to high-tech employment in manufacturing.

In sum, we show that European regional employment imbalances can be explained by core–periphery technological relations, as measured by interregional high-tech trade linkages, and technological dependency. These findings suggest that there is a dark side to uneven innovation trajectories, as innovation tends to increase inequalities between regions. We further show that these inequalities can contribute to unequal trade relations, with a selected number of regions at the core of the trade network benefiting more than peripheral ones, thus increasing the wedge between them. As indicated in previous literature, Smart Specialisation policies alone may increase inequality among regions (Rigby et al., 2022). The dark side effect of innovation in creating regional inequalities (Pinheiro et al., 2022) can be mitigated by EU policies that balance capabilities across regions and level the playing field. We thus suggest that the 'place-based' policies underpinning Smart Specialisation strategies at the EU level (Di Cataldo et al., 2022) need to be complemented by industrial and innovation policies that increase capabilities in peripheral regions. Importantly, these policies should consider the interregional trade connections of peripheral regions, that are based on their current diverse specialisation (Cortinovis & Van Oort, 2019; Thissen et al., 2018).

The remainder of the paper is structured as follows. Section 2 briefly reviews the streams of literature to which we contribute. Section 3 describes the data-intensive methods and empirical strategy adopted, unveiling the cluster structure of EU regions. Section 4 reports the empirical results, discussing the fractal structure of EU regional asymmetries and assessing the roles of high-tech trade centrality and technological dependence. Finally, section 5 concludes.

2. INNOVATION, CONNECTIVITY AND REGIONAL INEQUALITY: A CORE–PERIPHERY VIEW

2.1. Innovation and inequality between regions: a fractal structure

Knowledge concentrates in space and over time, and so does the production of science, technologies and innovations that use and contribute to that knowledge. A large corpus of scholarly work since Audretsch and

Feldman (1996) has demonstrated that innovation and production cluster spatially. As a consequence of this spatial cumulative process, regions grow unequal: regions that have an initial advantage in participating in knowledge production are likely to attract more innovative activity over time. This cumulative mechanism, underpinning regional advantage, has been documented across countries (Kaldor, 1981) and regions (Andrews & Whalley, 2022) for some time. Delgado et al. (2016) show that such advantage is related to concentration of knowledge flows and benefits from spillovers, the demand and supply of related skills, and the availability of inputs. For instance, Jaffe et al. (1993) have shown that US patents tend to cite more frequently patents from the same metropolitan area, suggesting that spillovers increase with proximity and inventions concentrate in the same location over time. The same applies to cities: science, innovation and production have followed a long-term tendency to cluster in a few large cities (e.g., see the recent evidence from the United States by Balland et al., 2020).[1]

Inequality also grows *within* regions and cities, and more so within innovative regions (Lee, 2011, 2016, 2019; Lee & Rodriguez-Pose, 2012). This suggests a fractal nature of the relation between the concentration of innovation and inequality, between countries, regions within countries, cities within regions, and firms and individuals within cities.

Over time, radical technological breakthroughs, among other factors, might disrupt such cumulative processes. As technological paradigms change, so could the fortune of regions and cities. Does this lead to catch-up and leapfrogging of regions that are initially less innovative? Only to a limited extent. Jaffe et al. (1993) had already shown that the localisation of knowledge production takes time to change. More recent evidence by Gagliardi et al. (2023) shows that, among the traditional manufacturing city hubs, those with a higher proportion of high-skilled workers successfully managed the transition from manufacturing to services and regained the lead in terms of employment generation, even after the drop in the value-added manufacturing share. Hence, inequality between regions with different initial levels of innovative activities tends to persist over time and is hard to mitigate.

2.2. Connectivity and inequality between regions: technological dependence and core–periphery relations

If technological breakthroughs rarely reduce inequality between regions, can technological and trade relations facilitate convergence?

The literature has shown that regions benefit from connecting to international business, to access knowledge, market and innovation opportunities (Cantwell & Zaman, 2018; Iammarino & McCann, 2013; Johanson & Vahlne, 2009; Li & Bathelt, 2018). For instance, with regard to European regions, Cantwell and Iammarino (2001) show that multinational companies contribute to shaping the industrial and technological trajectories of regions: only for some of them, though, the trajectory moves towards high-tech industries.

Besides global connectivity (Bathelt & Buchholz, 2024; Benoit & Belderbos, 2024), regional linkages can also generate knowledge spillovers and benefit regional technological change and growth. For instance, Balland and Boschma (2021) show that interregional linkages formed through collaborations on patented inventions benefit the regional diversification, especially of peripheral regions. Ho and Verspagen (2006) study whether there is a higher order regional innovation system (Cantwell & Iammarino, 2001; Cantwell & Janne, 1999) connecting European regions, and document a less promising role of interregional technology relations. They find that only a handful of regions work as international knowledge hubs, but that the knowledge flows between those core and the other regions (based on patent citations) are limited.

There is less work studying the role of regional trade connectivity on regional income (Bathelt & Buchholz, 2024; Liang et al., 2024) and even less on interregional inequality.

Technological dependence and core–periphery trade relationships are well established concepts in the literature on economic development and structural change (Cimoli et al., 2009). According to core–periphery theories related to technological change, the lack of opportunities to develop own technological capabilities lead peripheral areas to acquire/import technologies from core areas. If this process does not entail, albeit gradual, technological learning and spillovers, peripheries might remain technology-dependent and stuck in underdevelopment traps (Hartmann et al., 2020).

Core–periphery theories have also been employed to understand regional peripheries in high income countries (Scott & Storper, 1992).[2] The literature has extensively analysed processes of convergence and divergence among EU regions. Limited convergence was observed between EU-12 countries between 1997 and 2010 (Cappelen et al., 2013). Fagerberg et al. (1997) show that EU regional convergence has come to a halt since the 1980s, with regions divided into different growth clubs experiencing different performance in economic and employment growth (Fagerberg & Verspagen, 1996). More recently, Verspagen (2010) clusters EU regions based on their innovation/economic performance and spatial proximity. He finds four clusters of regions, which exhibit different growth and innovation performance: South Europe, East Europe, and two groups in West and North Europe. A major role in these differences among EU regions has been played by changes in their industry mix (Cutrini, 2019), which has favoured the emergence of a few technology 'clubs' (Wirkierman et al., 2018), characterised by a specialisation in manufacturing and highly productive knowledge-intensive services.

Going beyond mapping core–periphery relations, to our knowledge there is scarce evidence on the role of interregional trade networks to explain regional growth differences, with few exceptions (Cortinovis & Van Oort, 2019;

Thissen et al., 2016). Thissen et al. (2016) study regional (trade) network membership and find that revealed competition plays a dominant role with respect to sectoral and geographical characteristics in explaining regional growth. Closer to our work is Cortinovis and Van Oort (2019), who find that trade network-mediated spillovers, alongside traditional geographical proximity and co-patenting, matter the most to explain productivity asymmetries. In particular, they find that knowledge spillovers directed from highly innovative regions towards laggard ones are only effective when imported. Here the view is that Smart Specialisation strategies, centred around supporting own innovation performance based on the idiosyncratic sectoral structure of peripheral regions, might not be fully effective and trade-specific links across regions should also be considered.

However, Fagerberg et al. (1997) show that the lack of convergence between EU regions can be explained by the differences in science and technology efforts, but also the limited capabilities of backward regions to absorb knowledge and technologies from other regions. Further, Boschma and Iammarino (2009) show that specialisation in related industries is important for regions to benefit from technological spillovers from other regions.

Taken together, this evidence suggests that interregional interactions alone may not help to reduce inequalities between regions, especially if the lack of technological capabilities do not allow them to take advantage of such interactions.

2.3. The dark side of Smart Specialisation strategies: Can they also reduce interregional inequalities?

If inequalities between regions with different initial levels of innovative activities persist over time, and are entrenched in core–periphery trade and technological interactions among regions, do Smart Specialisation policies contribute to levelling up?

In essence, Smart Specialisation strategies suggest that regions should leverage their own specific capabilities – associated with sectoral and knowledge competitive advantages – to shift the structure of output and employment towards new productive specialisations (Boschma, 2021; Foresight, 2011; Fort et al., 2018). Building on the evidence above, regions with advanced technological capabilities and specialised in more sophisticated products are likely to benefit more from trade and diversification into even more sophisticated products than regions that are specialised in less sophisticated products (Rigby et al., 2022). As a result, Smart Specialisation may deepen inequality between regions (Pinheiro et al., 2022). For instance, looking at structural funds, Cappelen et al. (2003) show that, while EU structural policies did help in the convergence among EU regions, they have been more effective in regions that have developed comparatively more innovative capabilities.

What could reverse such a polarising dynamics and complement cohesion policies that aim at making 'left behind places' to catch up and mitigating the 'geography of discontent' (Rodriguez-Pose, 2018)?

Some scholars argue that it is important to devise instruments that are 'place-based sensitive' (Iammarino et al., 2020) as part of the EU 'Smart Specialisation' framework (Di Cataldo et al., 2022). Arguably, peripheral regions might lack the technological and innovative capabilities to build 'their own' competitive advantage (Bosma et al., 2009; Di Cataldo et al., 2022), which limits the effect of Smart Specialisation policies (Balland et al., 2019).

Against this backdrop, in addition to Smart Specialisation strategies, opportunities for technological learning could be provided through interregional (technological and economic) exchanges between technologically 'peripheral' and 'core' regions (Balland & Boschma, 2021). Regions are more likely to shift to new technological and scientific fields when they are 'connected' to regions that have capabilities complementary with their own (Balland & Boschma, 2021, p. 2). Although 'peripheral' regions may have less opportunities to diversify, they can benefit from connections to 'core' regions.

We take the argument of 'interregional connectivity' further in this paper, by analysing the role of interregional high-tech input trade on regional contributions to EU-wide employment growth. We contribute by explicitly operationalising core–periphery relations in terms of technological dependence and high-tech trade centrality. Importantly, in this study we use a combination of patent data, data on regional trade networks in high-tech products and employment dynamics.

3. METHODS, DATA AND CLUSTERING

We first introduce the techniques, metrics, empirical strategy and data used to uncover the structure of employment imbalances across EU regions and the role of innovative performance and high-tech trade centrality in conditioning these imbalances.[3] Our research question intends to relate the structure of regional employment imbalances to local innovative performance and the regional position within the high-tech interregional EU input trade network. We start by providing the set of indicators employed in our empirical strategy.

3.1. Three indicators of regional performance: employment, innovation and high-tech specialisation

We use employment dynamics as indicator of inclusive growth of a region. Within the EU, that is, in a context of free labour mobility, achieving local employment growth *across* regions may be challenging, given the cross-regional competition for labour inputs. Uneven employment dynamics sustained through time may give rise to employment imbalances, where geographically close regions see sharply opposite patterns of employment creation/destruction.

To quantify the extent of these imbalances, we measure a region's contribution to EU-wide employment growth.

In a system with m regions, n sectors and n_h high-tech sectors, we define L_r^i as the level of employment in sector i of region r during time t (time index suppressed). Hence, $L_r = \sum_{i=1}^{n} L_r^i$ represents total employment in region r and $L_r^h = \sum_{i=1}^{n_h} L_r^i$ stands for high-tech employment in region r (with ΔL_r and ΔL_r^h indicating the absolute change between two time periods). A region's r *contribution to growth* of EU-wide total and high-tech employment, CtG_r and CtG_r^h, may then be defined, respectively, as:

$$CtG_r := \frac{\Delta L_r}{\sum_{r=1}^{m} \Delta L_r} \tag{1}$$

$$CtG_r^h := \frac{\Delta L_r^h}{\sum_{r=1}^{m} \Delta L_r^h} \tag{2}$$

Note that CtG_r in (1) and CtG_r^h in (2) measure a growth contribution, that is, a ratio between two absolute changes. Thus, they do not measure the *pace* of growth (as a rate of change would), but the *proportional* contribution of region r to the *absolute* change in EU-wide total and high-tech employment, respectively.[4]

An interesting feature of indicators (1) and (2) is that they capture the regional *distribution* of absolute changes. The fact that units of employment across regions are additive makes it possible to use (1) and (2) as indicators of regional employment imbalances.

To quantitatively characterise regional innovative performance, we use (per-capita) patent applications by region r, labelled PAT_r in what follows. Patent counts normalised by local population size capture the comparative evolution of the regional productive knowledge base (Acs et al., 2002). As such, this is a first dimension which we aim to relate to local employment dynamics.

However, patents measure innovative output which only *potentially* leads to technological change, that is, adoption and diffusion of new productive opportunities. To capitalise gains from patenting activity, regions that successfully codify the knowledge contained in patents would be expected to engage in production and trade of high-tech products. This may be inferred by recalling the overlap between International Patent Classification (IPC) codes and two-digit NACE Rev. 2 codes corresponding to high-tech industry types (e.g., Van Looy et al., 2015, pp. 8–11).

To operationalise the extent to which regions trade in high-tech products we first consider an interregional input–output (IRIO) system, from which we derive an interregional high-tech input trade network. In an IRIO scheme with m regions and n industries, of which n_h are high-technology sectors, we may write:

$$T_{rs} = \sum_{i=1}^{n_h} \sum_{j=1}^{n} X_{rs}^{ij} + K_{rs}^i \tag{3}$$

where X_{rs}^{ij} represents intermediate input sales from high-tech sector i in region r to purchasing industry j in region s, whereas K_{rs}^i are fixed capital sales from high-tech sector i in region r to (final demand in) region s.

With a focus on revealed regional *competitiveness*, we consider only interregional trade, so intra-regional transactions can be set to zero, that is, $X_{rr}^{ij} = K_{rr}^i = 0$. Hence, T_{rs} in (3) is the value of deliveries of intermediate and fixed capital high-tech inputs by region r to *all* purchasing industries in region s.

Matrix $\boldsymbol{T} = [T_{rs}]$ is a square $(m \times m)$ interregional trade matrix in high-tech products measuring *gross* flows. Note that our aggregation scheme renders rows and columns of matrix $\boldsymbol{T}$ asymmetric: products of origin (rows) come exclusively from high-tech industries, whereas the destination industry for these products (columns) may be any sector in the economy (including final demand, for fixed capital inputs). Had we not proceeded this way, we would not have been able to build a high-tech trade network where each cell of interregional exchanges considers *both* circulating and fixed capital inputs.

3.2. Data: high-tech employment, patent applications and interregional input trade in European NUTS-1 regions

Collating and articulating comparable data at a regional level across EU countries on high-tech sectors for all dimensions covered in the analysis is a challenging task. Given the trade-off between coverage and granularity, we had to make some compromises.

Our three data sources are EUROSTAT, the OECD-REGPAT (Maraut et al., 2008) and the EU-REGIO (Thissen et al., 2018) databases. We adopted the definition of high-tech industry and knowledge-intensive services established by EUROSTAT, comprising a subset of two-digit codes from the NACE Rev. 2 classification (Table 1).[5]

Data on high-tech employment (in thousands of persons) at the NUTS-1 regional level between 1999 and 2019 comes from the EU's Labour force survey (LFS).[6] We have used this data source to obtain CtG_r in (1) and CtG_r^h in (2), computing the change between five-year averages (2015–19 with respect to 1999–2003), with the aim of capturing more persistent trends.

Data for patent applications to the European Patent Office (EPO) per 1 million inhabitants at the NUTS-1 regional level have been obtained from OECD-REGPAT, Aug-2022 Edition. Comparable data are available up to 2018, so we considered the time average throughout the 1999–2018 period. Hence, variable PAT_r measures the average performance of regional innovation output.

Finally, interregional intermediate and fixed capital input trade data to build accounting system (3) and all its derived magnitudes has been extracted and articulated from the EU-REGIO database. This database includes the first yearly time-series of IRIO tables with detail for European regions at the NUTS-2 level, covering the 2000–10 period.[7] To render data sources compatible, we had to make some compromises. First, the sectoral disaggregation of EU-REGIO consists of 14 industries collating activities from the International Standard Industrial Classification (ISIC) Rev. 3 classification. Hence, we

Table 1. High-tech industry and knowledge-intensive services.

Code	Descriptor	Aggregation by NACE Rev. 2	
		NACE Rev. 2 codes: two-digit level	
C_HTC	High-technology manufacturing industries	21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
		26	Manufacture of computer, electronic and optical products
KIS_HTC	High-tech knowledge-intensive services	59–63	Motion picture, video and television programme production, sound recording and music publish activities; Programming and broadcasting activities; Telecommunications; computer programming, consultancy and related activities; Information service activities
		72	Scientific research and development

Source: Authors' own elaboration based on EUROSTAT.

proxied the coverage of industries from Table 1 by considering sectors 'Coke, refined petroleum, nuclear fuel and chemicals' (which includes pharmaceutical products) and 'Electrical, optical and transport equipment' (which includes the manufacturing of computer, electronic and optical products).[8] Second, we aggregated NUTS-2-level transactions into a NUTS-1 scheme, under the NUTS 2016 classification.[9] Finally, given the time span covered by EU-REGIO, we used the latest available year (2010).

As an outcome, we articulated a dataset for $m = 98$ NUTS-1 European regions, reported in Table A1 of Appendix A in the supplemental data online. The argument for choosing the NUTS-1 level of analysis is twofold. First, it allows for a more comprehensive coverage of EU member states during the period analysed. Data points for several region × year combinations at the NUTS-2 level are missing for some of the variables considered. Second, the NUTS-1 level allows for a more *parsimonious* description of results. As a drawback, for relatively smaller countries, some of the regions included correspond to their entire country.

3.3. Trade- and place-based clustering

Our aim is to obtain a structure of technological dependence which conditions regional inclusive growth by intertwining the trade-based positioning of regions with their place-based performance. To make it explicit, we exploit, on the one hand, the network structure of high-tech input trade transactions and, on the other, create a network structure of place-based performance, based on the cross-regional similarity of performance indicators (innovative activity and the contribution to EU-wide – total and high-tech – employment growth).

First, consider high-tech input trade. We take matrix $\boldsymbol{T} = [T_{rs}]$ in (3) and turn it into an undirected, weighted graph, whose adjacency matrix $\boldsymbol{W}$ is given by:[10]

$$\boldsymbol{W} = \frac{1/2 \cdot (\boldsymbol{T} + \boldsymbol{T}^T)}{\boldsymbol{1}^T \boldsymbol{T} \boldsymbol{1}} \tag{4}$$

that is, each element w_{rs} of $\boldsymbol{W}$ is a network link which captures the high-tech input trade intensity between regions r and s.

By applying the Louvain modularity maximisation algorithm (Menczer et al., 2020, p. 168), we partition network $\boldsymbol{W}$ into a set of 'trade blocks', where each region is allocated to a specific community with which it has relatively stronger high-tech input trade ties.[11]

We found four trade blocks ('Nordic', 'West', 'South' and 'East'), which configure a geographically cohesive picture. Relatively stronger high-tech trade ties for NUTS-1 regions are localised. Agglomeration forces within each block make nearby regions dependent on each other. Figure 1 displays the trade blocks found.[12]

Second, consider place-based performance. We aim to identify a set of mutually exclusive regional groups, based on (relatively) similar within-group values when considering jointly the following indicators of technological and employment regional performance:

$$(CtG_r,\ CtG_r^h,\ PAT_r) \quad \text{for each region } r \tag{5}$$

To do so, we compute the distance between region r and s – in terms of the $q = 3$ variables in (5) – using the Euclidean distance. Given that variables in (5) differ in their unit of measurement, we standardise each of them before computing bilateral regional distances:

$$\delta_{rs} = \left(\sum_{k=1}^{q} (z_{rk} - z_{sk})^2 \right)^{1/2}, \quad \text{with} \\ z_{rk} = \frac{x_{rk} - \bar{x}_k}{SD_k}, \quad z_{sk} = \frac{x_{sk} - \bar{x}_k}{SD_k} \tag{6}$$

where $\bar{x}_k$ and SD_k are the cross-regional sample average and standard deviation, respectively, for variable $k = 1, \ldots, q$.

The bilateral *distance* metric δ_{rs} is turned into a *similarity* metric by computing:

$$\gamma_{rs} = \frac{1}{1 + \delta_{rs}}.$$

As an outcome, the symmetric bilateral similarity matrix $\boldsymbol{\Gamma} = [\gamma_{rs}]$ contains a network structure which we use to merge regions into groups, according to the similarity of their place-based performance. To maintain consistency, also in this case we apply the Louvain modularity

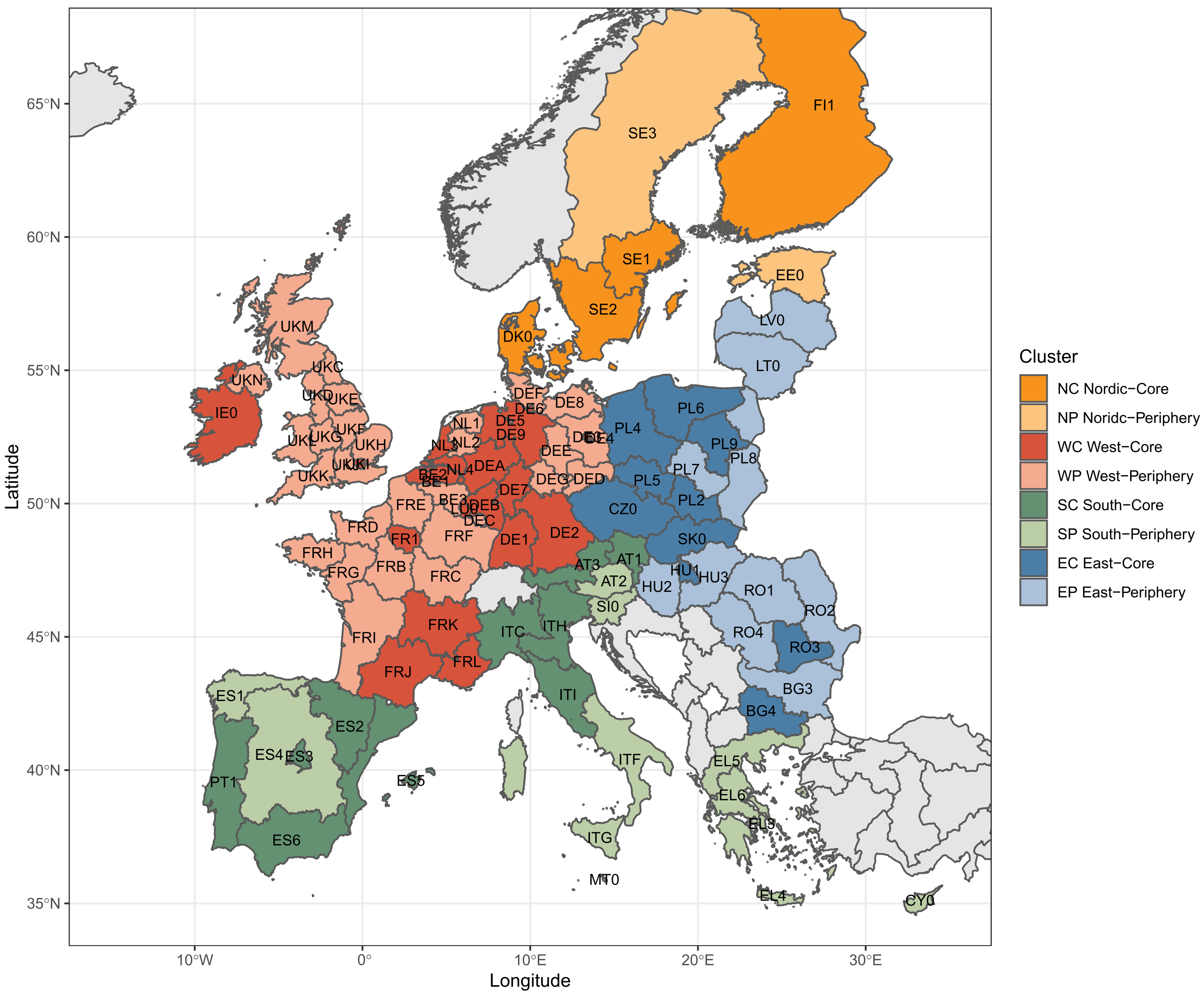

Figure 1. Map of trade blocks × place-based regional groups across European NUTS-1 regions.
Note: Regional NUTS-1 codes are described in Table A1 in Appendix A in the supplemental data online; detailed group composition is reported in Table A2 online.
Source: Authors' own elaboration based on EUROSTAT, OECD-REGPAT and EU-REGIO databases.

maximisation algorithm to obtain a network partition of performance groups.

This place-based clustering results in the bisection of regions into two groups, which may be labelled 'core' and 'periphery'. Its core–periphery nature is due to finding high- and low-performing regions which are *mutually dependent* in terms of high-tech trade links. Core regions are highly performant, whereas peripheral ones show stagnant (or even declining) employment and/or innovative dynamics. The crucial point, though, is that this latter partition *cuts across* trade blocks, that is, within each trade block we find some regions which belong to the core and others to the periphery of the place-based partition. Hence, overlapping trade-based blocks with place-based regional groups configures a partition of EU regions which may be interpreted as a fractal map (Figure 1).[13]

Its fractal nature can be explained as follows: at a higher level, the West trade block as a whole represents a core set of regions on which the other three blocks depend, especially in terms of high-tech inputs (as will be seen below, West regions accumulate almost 80% of high-tech supplier centrality). Yet, at a more granular level, *within* each trade block, there is a new layer of core–periphery relations. This creates a *fractal* core–periphery structure, which reproduces itself when increasing the level of granularity.

3.4. Econometric specification: employment dynamics, high-tech centrality and technological dependence

We have shown the fractal structure of regions in relation to their high-tech trade position and employment-*cum*-innovative performance. We now analyse the role of technological dependence and high-tech centrality on employment growth, within this core–periphery technological structure. First, we build relevant indicators to capture these dimensions and proceed to formulate a linear regression model.

To uncover the structural features of the trading regions, it is often useful to express the elements of high-tech input trade matrix $\boldsymbol{T} = [T_{rs}]$ in (3) in *intensive* terms. In particular, we may write:

$$p_{sr} = a_{rs} = \frac{T_{rs}}{\sum_{r=1}^{m} T_{rs}} \tag{7}$$

that is, p_{sr} is the payment by region s to region r for the purchase of high-tech inputs, per unit of total high-tech input purchases by region s.

Matrix $\boldsymbol{P} = [p_{sr}]$ is non-negative ($p_{sr} \geq 0$) and row-stochastic $\left(\sum_{r=1}^{m} p_{sr} = 1\right)$, each *row* representing the regional distribution of payments by region s for the purchase of a (monetary) unit of high-tech inputs from regions $r = 1, \ldots, m$.

By superposing a *chance process* interpretation on $\boldsymbol{P}$ – through the device of a finite Markov chain (Grinstead & Snell, 1997, p. 405) – we may describe the emerging connectivity patterns between regions. Each non-negative element p_{sr} can be interpreted as the probability of transitioning from region s (row s in $\boldsymbol{P}$) to region r (column r in $\boldsymbol{P}$) in the upcoming iteration of the chance process: €1 spent on high-tech inputs by region s has a probability p_{sr} of going to region r. If region r receives that payment, it will produce high-tech output generating income, inducing further spending, according to the probabilities in its row r of matrix $\boldsymbol{P}$.

As we iterate *step-wise* over this chance process, the probabilities of €1 being spent on each region as the process unfolds (say, from $t = 0$ to $t = 1$) are given by $\boldsymbol{p}_{(1)}^T = \boldsymbol{p}_{(0)}^T \boldsymbol{P}$, where $\boldsymbol{p}$ is a probability vector. This iteration process continues $(\boldsymbol{p}_{(2)}^T = \boldsymbol{p}_{(1)}^T \boldsymbol{P} = \boldsymbol{p}_{(0)}^T \boldsymbol{P}^2)$ until a fixed point is reached:[14]

$$\boldsymbol{\pi}^T \boldsymbol{P} = \boldsymbol{\pi}^T \tag{8}$$

where, adopting the normalisation $\sum_{r=1}^{m} \pi_r = 1$, $\boldsymbol{\pi}^T$ specifies the vector of *stationary* probabilities. Intuitively, if we had €1 of income, vector $\boldsymbol{\pi}^T$ indicates how it would be proportionally distributed across regions in the long run. Hence, each element of $\boldsymbol{\pi}^T = [\pi_r]$ captures the importance of region r as a *supplier* (and extra-regional exporter) of high-tech inputs in the interregional system.

If, instead, we are interested in capturing the importance of region s as a *buyer* (and extra-regional importer) of high-tech inputs, we need to consider the proportional *row* structure of transaction matrix $\boldsymbol{T}$, by defining:

$$q_{sr} = d_{rs} = \frac{T_{rs}}{\sum_{s=1}^{m} T_{rs}} \tag{9}$$

that is, q_{sr} is the payment by region s to region r for the purchase of high-tech inputs, per unit of total high-tech input sales by region r.

Matrix $\boldsymbol{Q} = [q_{sr}]$ is non-negative ($q_{sr} \geq 0$) and column-stochastic $\left(\sum_{s=1}^{m} q_{sr} = 1\right)$, each *column* representing the regional distribution of receipts by region r for the sale of a (monetary) unit of high-tech inputs to regions $s = 1, \ldots, m$.

Also in this case we superpose a chance process interpretation on $\boldsymbol{Q}$. Each non-negative element q_{sr} can be interpreted as the probability of transitioning from region s (row s in $\boldsymbol{Q}$) to region r (column r in $\boldsymbol{Q}$) in the upcoming iteration of the chance process: €1 sold of high-tech inputs by region r has a probability q_{sr} of having been spent by region s. If region s made that payment, it should have sold output to obtain purchasing power to spend, according to the probabilities in its column s of matrix $\boldsymbol{Q}$. We may iterate this process to obtain fixed point:

$$\boldsymbol{Q\rho} = \boldsymbol{\rho} \tag{10}$$

where, adopting the normalisation $\sum_{s=1}^{m} \rho_s = 1$, $\boldsymbol{\rho}$ specifies the vector of *stationary* probabilities. Intuitively, if we had €1 of expenditure, vector $\boldsymbol{\rho}$ indicates how it would be proportionally distributed across regions in the long run. Hence, each element of $\boldsymbol{\rho} = [\rho_s]$ captures the importance of region s as a *buyer* (and extra-regional importer) of high-tech inputs in the interregional system.

Intuitively, q_{sr} quantifies how much income of r comes from s. Hence, it measures the importance of s as a *buyer*. Instead, p_{sr} quantifies how much expenditure of s goes to r. Hence, it measures the importance of r as a *seller* or *supplier*.

By giving a chance process interpretation to the network we focused on money flows, rather than product flows. If, instead, we focused on product flows – as traditional input–output (I-O) does – we would have that $\boldsymbol{P} = \boldsymbol{A}^T$ and $\boldsymbol{Q} = \boldsymbol{D}^T$, where $\boldsymbol{A}$ is an input coefficient matrix of a *closed* I-O model and $\boldsymbol{D}$ is a matrix of output proportions for a *closed* I-O model, respectively.[15]

Coefficients π_r and ρ_s are indicators of high-tech extra-regional supplier and buyer centrality for regions r and s, respectively. They summarise the systemic importance of each region within the high-tech input trade network for each role.

We next measure regional technological *dependence* by computing the ratio of 'imported' to locally-produced patent applications, using high-tech trade weights at the cluster level to obtain a measure of 'imported' patents, that is, a *dependency ratio* defined as:

$$TecDep_r = \frac{\sum_{c \neq c_r} \left(\sum_{s=1}^{m_c} a_{sr}\right) \cdot (1/m_c)\left(\sum_{s=1}^{m_c} PAT_s\right)}{PAT_r} \tag{11}$$

where index c sums across all regional groups but c_r, that is, the group including region r, and m_c is the number of regions in a regional group c.

Intuitively, the numerator of $TecDep_r$ represents a weighted (by direct trade backward linkages) sum of average patenting intensity of all regional groups with which region r has trade connections. Instead, the denominator measures regional patenting intensity. Hence, innovation output is measured in *relative* terms: relative to the innovative activity of each region's high-tech input suppliers.

Finally, we study the extent to which buyer and supplier trade centrality, and technological dependence, predict the inclusive growth of a region r with the following linear regression:

$$Y_r = \beta_0 + \beta_1 \cdot \ln(TecDep_r) + \beta_2 \cdot HTec\_ctg_r + \beta_3 \cdot HTechShare_r + \beta_4 \cdot \ln(BuyerCent_r) + \beta_5 \cdot \ln(SuppCent_r) + \epsilon_r \quad (12)$$

where the role of Y_r may be taken by $CtGEmp_r$, $CtGHTech_r$, $CtGHTechMan_{rc}$ or $CtGHTechKIS_{rc}$.[16] All variable descriptions are summarised in Table 2.

Equation (12) allows to estimate total ($CtGEmp_r$) and high-tech ($CtGHTech_r$) regional contribution to EU-wide employment growth as a function of technological dependence ($TecDep_r$) and high-tech input trade centralities ($BuyerCent_r$ and $SuppCent_r$), controlling for the (within-region) contribution of high-tech employment to total employment growth ($HTec\_ctg_r$) and the initial share of high-tech employment ($HTechShare_r$).

Besides our baseline specification, we estimate a linear regression with trade block fixed effects (λ_c), in order to capture the statistical relationship between variables *within* each trade community. In this case, for each region r in trade cluster c we have:

$$Y_{rc} = \beta_0 + \beta_1 \cdot \ln(TecDep_{rc}) + \beta_2 \cdot HTecg\_ctg_{rc} + \beta_3 \cdot HTechShare_{rc} + \beta_4 \cdot \ln(BuyerCent_{rc}) + \beta_5 \cdot \ln(SuppCent_{rc}) + \lambda_c + \epsilon_{rc} \quad (13)$$

where the role of Y_{rc} may be taken by $CtGEmp_{rc}$, $CtGHTech_{rc}$, $CtGHTechMan_{rc}$ or $CtGHTechKIS_{rc}$.

4. RESULTS AND DISCUSSION

4.1. The fractal structure: EU trade blocks embedding core and peripheral regions

In section 3.3 we identified four EU regional trade blocks on the basis of interregional high-tech input trade: North, West, South and East (Figure 1). Figures 2 and 3 report cluster averages and total values for each variable in Table 2 over the regions composing each block.

The West block includes 49 regions from Western Europe, which, on average, have experienced the highest contribution to total employment growth between 1999 and 2019 (Figure 2, column 2). These are also the regions that constitute the core of the supply network of European high-tech input trade (Figure 2, column 10), and which have the second highest average buyer centrality (Figure 2, column 11).[17] Because regions in the Western block also generate a large number of patents per capita (Figure 2, column 1), they are the least dependent on 'foreign' technology (Figure 2, column 7). Despite their leading innovative performance, their average contribution to EU-wide *high-tech* employment growth between 1999 and 2019 is relative lower vis-à-vis most other blocks (Figure 2, column 3), especially in manufacturing (Figure 2, column 4). This is partly due to their high-tech employment share being already high at the end of the 1990s.[18]

The Nordic trade block is the smallest, including six regions from Northern Europe. These regions are highly innovative (Figure 2, column 1), technologically

Table 2. Full set of variables reported in empirical results.

Column	Meaning (unit)	Period	Formula	Econometric label
[01]	Patent applications to the European Patent Office (EPO) (n/1 million inhabitants)	1999–2018	PAT_r in (5)	
[02]	Regional contribution to EU-wide total employment growth (%)	1999–2003, 2015–19	CtG_r in (1)	*CtGEmp*
[03]	Regional contribution to EU-wide high-tech employment growth (%)	1999–2003, 2015–19	CtG^h_r in (2)	*CtGHTech*
[04]	Regional contribution to EU-wide high-tech manufacturing employment growth (%)	1999–2003, 2015–19	$\frac{\sum_{i=1}^{n_h^{man}} \Delta L_r^i}{\sum_{r=1}^{m} \sum_{i=1}^{n_h^{man}} \Delta L_r^i}$	*CtGHTechMan*
[05]	Regional contribution to EU-wide high-tech knowledge-intensive service employment growth (%)	1999–2003, 2015–19	$\frac{\sum_{i=1}^{n_h^{kis}} \Delta L_r^i}{\sum_{r=1}^{m} \sum_{i=1}^{n_h^{kis}} \Delta L_r^i}$	*CtGHTechKIS*
[06]	Contribution of high-tech to total *within*-region employment growth (%)	1999–2003, 2015–19	$\frac{\sum_{i=1}^{n_h} \Delta L_r^i}{\sum_{i=1}^{n} \Delta L_r^i}$	*HTech_ctg*
[07]	Technological dependence	1999–2018	$TecDep_r$ in (11)	*TecDep*
[08]	Regional high-tech employment share (%)	1999–2003	$L_r^h / \sum_{i=1}^{n} L_r^i$	*HTechShare*
[09]	Absolute change in [08] (percentage points)	1999–2003, 2015–19		
[10]	High-tech trade supplier centrality (%)	2010	π_r in (8)	*SuppCent*
[11]	High-tech trade buyer centrality (%)	2010	ρ_s in (10)	*BuyerCent*

Note: Column numbers correspond to those reported in Figure 2.
n, Number of industries in a region; m, number of regions; n_h^{man}, number of high-tech manufacturing sectors; n_h^{kis}, number of high-tech knowledge-intensive service industries.

Group *Averages*			Innovation	Employment dynamics						HTech. Empl. Share		Input Trade	
			[01]	[02]	[03]	[04]	[05]	[06]	[07]	[08]	[09]	[10]	[11]
			Patent App. EPO	Employ ment	Employment in HTech. *Total*	Manuf.	Services	*HTech to Total*	*Tech. Dep.*	Initial Cond.	*(99-03) (15-19)*	HTech. Centrality Supplier	Buyer
			(99-18)	*(CtG)*	*(CtG: 1999-2003 to 2015-2019)*					*(99-03)*		*(2010)*	*(2010)*
# Reg.	Regional Descriptor	Group	(per mill.)	(in %)	(in %)	(in %)	(in %)	(in %)	*(ratio)*	(in %)	(%-points)	(in %)	(in %)
High-Tech Trade blocks													
6	Nordic	N	244.48	0.78	0.52	-5.17	0.90	5.49	2.89	4.97	0.10	0.46	0.85
49	West	W	146.76	1.33	0.63	-3.13	0.83	1.74	2.45	4.15	-0.10	1.62	1.06
23	South	S	52.45	0.88	1.38	0.16	1.25	7.54	8.94	2.88	0.49	0.45	1.43
20	East	E	5.45	0.51	1.73	4.04	1.26	4.38	41.13	2.62	0.93	0.38	0.51
Place-based performance groups													
43	Core	C	178.67	1.85	1.93	0.48	1.74	4.75	4.89	4.32	0.41	1.65	1.53
55	Periphery	P	41.64	0.37	0.31	-2.19	0.46	3.18	17.37	3.02	0.14	0.53	0.62
High-Tech Trade x Performance groups													
4	Nordic-Core	NC	335.36	1.04	0.55	-7.59	1.13	3.14	0.44	5.81	-0.25	0.63	1.06
2	Nordic-Periphery	NP	62.72	0.25	0.44	-0.34	0.43	10.19	7.79	3.29	0.80	0.11	0.44
19	West-Core	WC	286.92	2.20	1.43	-0.53	1.36	3.44	0.16	4.98	0.03	2.86	1.73
30	West-Periphery	WP	57.99	0.77	0.12	-4.78	0.50	0.66	3.90	3.63	-0.19	0.83	0.63
10	South-Core	SC	81.40	1.83	2.50	-0.52	2.34	5.72	3.00	3.56	0.50	0.78	2.16
13	South-Periphery	SP	30.18	0.15	0.52	0.69	0.42	8.95	13.51	2.35	0.49	0.20	0.87
10	East-Core	EC	7.58	1.52	2.87	6.61	2.10	6.92	17.53	3.22	1.31	0.61	0.73
10	East-Periphery	EP	3.31	-0.51	0.58	1.46	0.41	1.84	64.74	2.01	0.55	0.14	0.29

Figure 2. Innovative performance, employment dynamics and high-tech trade input centralities at the regional group level.
Note: All variables, organised by column number, are described in Table 2. Group composition is reported in Table A2 in Appendix A in the supplemental data online.
Source: Authors' own elaboration based on EUROSTAT, OECD-REGPAT and EU-REGIO databases.

Group *Totals*			Employment dynamics				Input Trade		
			[02]	[03]	[04]	[05]	[10]	[11]	
			Employ ment	Employment in HTech. *Total*	Manuf.	Services	HTech. Centrality Supplier	Buyer	
			(CtG)	*(CtG: 1999-2003 to 2015-2019)*			*(2010)*	*(2010)*	
# Reg.	Regional Descriptor	Group	(in %)	(in %)	(in %)	(in %)	(in %)	(in %)	
High-Tech Trade blocks									
6	Nordic	N	4.67	3.10	-31.05	5.38	2.74	5.11	
49	West	W	64.93	30.66	-153.51	40.68	79.29	51.79	
23	South	S	20.25	31.73	3.77	28.84	10.40	32.89	
20	East	E	10.15	34.51	80.79	25.11	7.57	10.21	
Place-based Performance groups			100.00	100.00	-100.00	100.00	100.00	100.00	*Total*
43	Core	C	79.54	83.06	20.50	74.62	70.84	65.85	
55	Periphery	P	20.46	16.94	-120.50	25.38	29.16	34.15	
High-Tech Trade x Performance groups			100.00	100.00	-100.00	100.00	100.00	100.00	*Total*
4	Nordic-Core	NC	4.18	2.21	-30.36	4.51	2.52	4.23	
2	Nordic-Periphery	NP	0.49	0.89	-0.68	0.87	0.22	0.88	
19	West-Core	WC	41.80	27.16	-10.06	25.77	54.36	32.78	
30	West-Periphery	WP	23.13	3.50	-143.45	14.91	24.93	19.01	
10	South-Core	SC	18.34	25.00	-5.22	23.38	7.82	21.58	
13	South-Periphery	SP	1.91	6.74	8.99	5.45	2.58	11.32	
10	East-Core	EC	15.21	28.69	66.14	20.96	6.14	7.26	
10	East-Periphery	EP	-5.06	5.81	14.65	4.15	1.43	2.94	
			100.00	100.00	-100.00	100.00	100.00	100.00	*Total*

Figure 3. Employment dynamics and high-tech trade input centralities at the regional group level.
Note: All variables, organised by column number, are described in Table 2. Group composition is reported in Table A2 in Appendix A in the supplemental data online.
Source: Authors' own elaboration based on EUROSTAT, OECD-REGPAT and EU-REGIO databases.

independent from the rest of Europe, but rather peripheral as regards high-tech input trade (Figure 2, columns 10 and 11). Their contribution to total and high-tech employment growth is, on average, relatively low (Figure 2, columns 2 and 3), especially in manufacturing (Figure 2, column 4). This suggests a process of structural transformation, with a sharply declining share of high-tech manufacturing in output.

The Southern block is composed of 23 regions, which, on average, patent three times less than the Western block

(Figure 2, column 1), and purchase large amounts of high-tech inputs from other regions, being at the core of the buyer network (Figure 2, column 11). In terms of innovative output, these regions are, on average, peripheral with respect to the Western (and Nordic) blocks, being highly dependent on their technologies. Their average contribution to total employment growth is relatively low (Figure 2, column 2), but the contribution to high-tech employment growth is higher than in Western regions, both in manufacturing and in services (Figure 2, columns 4 and 5). This is partly due to a substantially lower initial share of high-tech employment (Figure 2, column 8), which may reflect the growth of business services in selected urban peripheral areas across internationally fragmented production processes (Scott & Storper, 1992; Timmer et al., 2019).

The regions that, on average, have seen the strongest contribution to high-tech employment growth (Figure 2, column 3) and the largest catching-up (Figure 2, columns 8 and 9) are the 20 regions in the Eastern block. This is despite a low average inventive activity (Figure 2, column 1), marginal insertion in the European high-tech input trade network (Figure 2, columns 10 and 11), and highest technological dependence on other EU regions (Figure 2, column 7). Besides the catching-up in high-tech employment, the contribution to EU-wide growth in total employment staggers behind all other trade blocks (Figure 2, column 2), suggesting a process of migration towards other EU regions, which may reflect the move of unskilled workers towards core regions (Scott & Storper, 1992). Hence, the Eastern block experiences a process of well-known absorption of high-tech manufacturing employment (and to a lesser extent, services), in line with intra-EU offshoring practices taking place during the period analysed.

The large differences between trade blocks hide similarly large (when not larger) differences across regions *within* trade blocks. Let us take the Western trade block for example – at the core of the high-tech input trade network – which has contributed the most to European employment growth and produces the second largest (per-capita) count of patented inventions. Within the Western trade block, there are large differences between the ‘core’ and the ‘periphery’. Regions in the Western core have patented five times more inventions than those in the Western periphery (Figure 2, column 1). As a result, Western core regions are net sellers of inventions (the dependency ratio is, on average, 0.16), whereas Western peripheral regions are net buyers of inventions (the dependency ratio is, on average, 3.9) (Figure 2, column 7). The average contribution to EU employment growth of core regions is almost three times as large as that of peripheral regions (Figure 2, column 2), and their contribution to employment growth in high-tech industries is almost 12 times as large (Figure 2, column 3).

This large gap between core and peripheral regions within trade blocks is observed across all of them. On average, regions in the core contribute between five and six times more to total and high-tech employment than regions in the periphery (Figure 2, columns 2 and 3). That is, the catching-up in high-tech employment occurs between core regions of different trade blocks, but not between periphery and core regions within trade blocks.

The other property of the fractal structure is that core regions in peripheral trade blocks may experience higher relative employment growth than peripheral regions in core trade blocks. For instance, this is the case of Southern core regions when compared to the Western periphery, even though the Western trade block has a higher innovative performance than the Southern one. Southern core regions are, though, central high-tech input buyers, suggesting that their contribution to high-tech employment growth is linked to their trade centrality rather than to their innovative performance.

While we do not aim to propose a new taxonomy for European regions, it is interesting to briefly compare our regional groups with other typologies in the club convergence and innovation literature. For instance, Verspagen (2010) devises a spatial hierarchy of innovation and growth dynamics in the EU. Based on spatial correlation and principal component analysis (for education levels, employment shares and sectoral patenting) his results (Verspagen, 2010, p. 124, map 2) depict a neat geographical pattern (South, East and two groups in West and North of Europe), with patent intensity and urban development as key drivers. His conjecture on Southern and Eastern urban centres as being unable to generate and use spillovers from their neighbouring regions could be related to our results on high-tech input trade centrality: it is this productive aspect of interregional relations that facilitated the emergence of the spatial ‘corridors’ which Verspagen alludes to, both with regard to processes of catch-up (for core regions in the South and East) and decline (for peripheral regions in the West and North). A second interesting example concerns the territorial taxonomy reflecting different phases of innovative processes proposed by Capello and Lenzi (2013). Based on a series of knowledge and innovation indicators, the authors obtain five clusters which represent innovation ‘patterns’. Their results (Capello & Lenzi, 2013, p. 145, fig. 4) may also be interpreted as displaying a marked core–periphery structure (in terms of knowledge generation and acquisition), even if focusing on a partially different set of metrics. The high intensity and broad scope of patenting for their clusters 1 and 2 (composed of core regions) contrasts with the high product innovation and potential for commercial applications of cluster 3 (partially overlapping with our South and East cores) and with under-performing clusters 4 and 5 (partially overlapping with our South and East peripheries).

The novelty in our results is that we complement innovative performance, a dimension present in existing typologies, with interregional high-tech input trade data, a dimension not explicitly considered by previous typologies, to obtain our core–periphery fractal structure. This, we believe, allows considering a policy relevant dimension, which we discuss in our conclusions.

4.2. The contribution of technological dependence and trade centrality to regional employment growth

We now go back to our central question on the extent to which the (fractal) technological core–periphery structure of EU regions is related to their inclusive growth. Is the relative capacity of a region to contribute to EU-wide (total and high-tech) employment growth related to their relative dependence on technologies produced by trade partners?

Table 3 reports the estimates of the specification described in equation (12). Column (1) shows that technological dependence is negatively related to a region's contribution to employment growth. The relation is statistically significant, the magnitude is high, and alone, our measure of technological dependence explains a substantial share of the cross regional variation in the contribution to employment growth ($R^2 = 0.27$). Regions that are twice as dependent than average on importing technologies contributed 35% less to EU total employment growth between 1999 and 2019. The initial share of high-tech employment of a region (column 3), and the contribution of high-tech employment to total employment within the region (columns 2 and 3) also explain part of that correlation, and reduce the estimated regression coefficient for the dependency ratio to 25%.

As expected, when we introduce the measures of trade centrality (supplier and buyer), the estimated coefficient for the dependency ratio is reduced (columns 4-6). Regions that are (buyer or supplier) central within the high-tech input trade network experience a substantially larger contribution to EU total employment growth, especially when they are buyer-central. However, the association with technological dependence is still significantly negative, suggesting that, while importing high-tech inputs is beneficial to create employment, it is less beneficial if the region only relies on imports of most of its technologies.

Finally, when we include all controls and both measures of trade centrality, the dependency ratio is no longer statistically significant (column 9). The main predictor of the regional contribution to EU-wide total employment growth is buyer centrality. That is, regions that are more centrally located as buyers of high-tech inputs – independently of their *relative* inventive capacity (i.e., indirectly imported vis-à-vis local patenting intensity) – contribute the most to EU-wide total employment. As will be shown below (Table 4), this result is driven by the high share of knowledge-intensive services in the industry mix of high-tech products, whereas for high-tech manufacturing, the dependency ratio still plays a statistically significant role.

At any rate, what should be clear is that absorptive capacity is *not* independent from the extent to which regions can exploit trade linkages. High-tech inputs embed and codify knowledge. Such knowledge requires local capabilities for a region to become a hub in this interregional high-tech input trade network. Hence, trade linkages cannot be beneficial to regions who lack regional absorptive capacity. This is in line and complements the view by Balland and Boschma (2021, p. 1067): weak own regional capabilities cannot be compensated by merely being connected to extra-regional complementary capabilities.

In terms of the different roles within the interregional high-tech input trade network, while seller centrality is also significant, buyer centrality seems to dominate. This may be related to the secular servitisation of economies. Most employment creation in the past two decades has been in the service sector, which generates limited amount of high-tech inputs, but needs them to produce. This suggests the importance of *backward* high-tech trade linkages for local employment demand in using industries. Industries producing high-tech inputs are also more likely to be more capital intensive, so they account for a smaller share of local jobs per unit of output.

So far, results compare regions across both trade blocks and place-based regional groups. As we have noticed, the EU regional dependence is fractal: between and within trade blocks.

To study if technological dependence is relevant within trade blocks, we control for trade block fixed effects in equation (13). Results in column 10 show that, within trade blocks, more dependent regions are likely to experience a lower contribution to EU-wide employment growth, even when we control for everything else. The role of buyer centrality is even stronger. That is, for peripheral regions within trade blocks (with lower patenting activity in relation to their suppliers of high-tech inputs) it is crucial to have a central position in the buyer network (i.e., rely substantially on the purchase of high-tech inputs) but at the same time generate some absorptive capacity (measured by the number of inventions).

Table 4 reports results for the regional contribution to EU-wide *high-tech* employment growth. Column (1) shows that, across all regions (not controlling for trade block fixed effects) technological dependence is not statistically significant. The relation with buyer centrality is even stronger in comparison to total employment (Table 3, column 9). However, when we study differences within trade blocks (controlling for trade block fixed effects), we find that, for given levels of buyer centrality, regions that are more dependent on others to access technology (i.e., produce relatively fewer inventions than they purchase) have a lower contribution to high-tech employment growth (although the relation is statistically weaker than in the case of total employment).

Next, we distinguish between the contribution to high-tech employment growth in manufacturing (column 3) and services (column 4). Results are radically different. First, as expected, the average results (column 2) are dominated by what happens in services, where most of the jobs are created across regions.

Second, to contribute to EU-wide employment growth in high-tech manufacturing, trade centrality is not relevant, but the technology dependency ratio is. That is, regions that create high-tech employment in manufacturing do not purchase high-tech inputs from other regions more than average, but are relatively more independent in patenting inventions (the estimated regression coefficient is large).

Table 3. Contribution to European Union-wide total employment growth (*CtGEmp*).

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ln(*TecDep*)	−0.35***	−0.35***	−0.25***	−0.20***	−0.16**	−0.15**	−0.13**	−0.10	−0.09	−0.16**
	(0.08)	(0.08)	(0.09)	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)	(0.06)	(0.07)
HTech_ctg		0.02**	0.02**				0.01**	0.02*	0.01**	0.01*
		(0.01)	(0.01)				(0.01)	(0.01)	(0.01)	(0.01)
HTechShare			0.19**				0.16**	0.14*	0.14**	0.14**
			(0.08)				(0.07)	(0.07)	(0.07)	(0.07)
ln(*BuyerCent*)				0.77***		0.56***	0.73***		0.55***	0.63**
				(0.15)		(0.21)	(0.15)		(0.19)	(0.28)
ln(*SuppCent*)					0.40***	0.20*		0.37***	0.17*	0.12
					(0.07)	(0.10)		(0.07)	(0.09)	(0.16)
Constant	1.36***	1.30***	0.53	1.46***	1.51***	1.50***	0.75**	0.86**	0.85**	0.84**
	(0.15)	(0.15)	(0.38)	(0.13)	(0.13)	(0.12)	(0.32)	(0.36)	(0.33)	(0.32)
Observations	98	98	98	98	98	98	98	98	98	98
R^2	0.27	0.30	0.34	0.45	0.41	0.47	0.50	0.46	0.51	0.54
Trade block FE	No	No	No	No	No	No	No	No	No	Yes

Note: Reported are the results from the linear regression models specified in (12) and (13). The outcome variable is $CtGEmp_r$, that is, the regional contribution to EU-wide employment growth (Table 2). *TecDep* is the technology dependence ratio as measured by (11); *HTech_ctg* is the regional contribution of high tech employment to total employment growth within the region; *HTechShare* is the regional high-tech employment share (%) in the period 1999–2003; *BuyerCent* and *SuppCent* measure high-tech input trade centralities for backward and forward trade linkages, respectively. All variables are described in Table 2. Columns 1–9 do not include trade block fixed effects and differ with respect to the controls included in the estimation. Column 10 includes trade block fixed effects. Robust standard errors are shown in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 4. Contribution to European Union-wide high-tech employment growth.

Variables	(1) All High-tech (*CtGHTech*)	(2) All High-tech (*CtGHTech*)	(3) Manufacturing (*CtGHTechMan*)	(4) Services (*CtGHTechKIS*)
ln(*TecDep*)	0.09	−0.15*	−1.58*	−0.00
	(0.09)	(0.09)	(0.84)	(0.05)
HTech_ctg	0.02**	0.02**	0.17***	0.01
	(0.01)	(0.01)	(0.06)	(0.01)
HTechShare	−0.01	−0.04	−2.48***	0.16*
	(0.11)	(0.12)	(0.69)	(0.09)
ln(*BuyerCent*)	0.94***	0.95***	2.11	0.70***
	(0.23)	(0.35)	(2.27)	(0.27)
ln(*SuppCent*)	−0.14	−0.10	−0.47	−0.06
	(0.12)	(0.20)	(0.92)	(0.16)
Constant	1.06**	0.98**	7.29**	0.31
	(0.42)	(0.40)	(3.47)	(0.30)
Observations	98	98	98	98
R^2	0.25	0.40	0.35	0.39
Trade block FE	No	Yes	Yes	Yes

Note: Reported are the results from the linear regression models specified in (12) and (13). The outcome variables are $CtHTech_r$, $CtGHTechMan_r$ and $CtGHTechKIS_r$, that is, the regional contribution to EU-wide high-tech (columns 1 and 2), high-tech manufacturing (column 3) and knowledge-intensive service (column 4) employment growth, respectively (Table 2). *TecDep* is the technology dependence ratio as measured by (11); *HTech_ctg* is the regional contribution of high tech employment to total employment growth within the region; *HTechShare* is the regional high-tech employment share (%) in the period 1999–2003; *BuyerCent* and *SuppCent* measure high-tech input trade centralities for backward and forward trade linkages, respectively. All variables are described in Table 2. Column 1 does not include trade block fixed effects. Columns 2–4 include trade block fixed effects. Robust standard errors are shown in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

To better explain these results, let us focus on the main group of regions that contributes to employment growth in high-tech manufacturing: Eastern core regions, especially those in Poland and the Czech Republic (see Table A2 in Appendix A in the supplemental data online). These regions have been catching up over the 20-year period of our analysis, as shown by the high negative coefficient for the initial share of high-tech employment (column 3). They have been strengthening high-tech sectors in manufacturing, but only when innovating and becoming less dependent on the purchase of foreign inventions. This is not the case for highly dependent regions in the periphery of the Eastern trade block.

Third, in knowledge-intensive service industries, instead, we do not observe a catching-up process (column 4): the coefficient for the initial share of high-tech employment is small, weakly significant and, if at all, positive. Regional employment contribution to knowledge-intensive services increases only in regions that also have a high buyer centrality, that is, that buy technologies incorporated in inputs. Technology dependence is not at all correlated. This confirms the central role of buying high-tech inputs for increasing employment in knowledge-intensive services.

5. CONCLUSIONS

In this paper we analyse the role of technological dependence and trade centrality in explaining a region's contribution to EU-wide total and high-tech employment growth.

We first analyse the technological core–periphery structure of EU regions, by clustering them based on their high-tech input trade relations (trade blocks) and performance (place-based regional groups). The EU core–periphery structure is due to finding high- and low-performing regions which are *mutually dependent* in terms of high-tech trade links. We show that core–periphery relations between EU regions have a fractal structure: regions at the core of the high-tech input trade network are clearly divided in two clusters that differ significantly with respect to their innovation and employment growth performance. We find a similar within-block core–periphery structure across all peripheral trade blocks.

We then econometrically analyse the correlation of a region's technological dependence and high-tech trade centrality with its contribution to total and high-tech employment growth in Europe, as conditioned by the trade blocks identified.

We find three main results. First, across and within trade blocks, buyer centrality is relevant to both total and high-tech employment growth. Regions that generate more total and high-tech employment than average are also more central than average in the high-tech input trade network.

Second, within trade blocks, being at the core of high-tech input trade is not enough, it has to be combined with a low relative dependence from 'foreign' innovation, that is with a high regional innovative capacity (measured by patenting).[19]

Third, when analysing the contribution to high-tech employment growth these results hold only in the case of services. Regions create employment in knowledge-intensive services mainly by importing high-tech inputs. The few regions that contribute to high-tech employment growth in manufacturing, do not benefit from high buyer centrality in the high-tech input trade network but from a low technological dependency ratio (i.e., relatively high within-region innovation). These are mainly regions that are catching-up, that is, which had a low share of high-tech employment at the end of the 1990s.

Our results suggest several interpretations about the nuanced connections between technological dependence, high-tech trade centrality and employment imbalances.

On the one hand, while Southern and Eastern core regions catch up in terms of high-tech employment with respect to the West and North, benefiting from trade centrality, their peripheral regions do not, because of their higher technological dependence.

On the other hand, Western peripheral regions suffer from a substantial shrink of high-tech manufacturing employment compared to other peripheral trade blocks, and this is linked not so much to their innovative performance, but to their peripheral role as buyers within the high-tech input trade network.[20] This is even more evident in the case of the Nordic core, with a striking innovative performance, not supported by high-tech trade centrality. This means that being at the periphery of trade flows might void the potentially positive effect of innovation-driven growth. Hence, innovation is a necessary but not sufficient condition, whereas high-tech trade centrality may be a necessary *and* – in the case of knowledge-intensive services – sufficient condition to spur (high-tech) employment growth, as observed in the Southern core regions. This does not mean that local capabilities are not relevant, but that it is the backward linkage effect of high-tech input sourcing which drives employment creation in knowledge-intensive services, rather than their degree of innovative autonomy with respect to foreign trade partners. Naturally, absorptive capacity to thrive in such interregional high-tech input trade network remains crucial.

Our results point to several policy implications. We highlight two. First, cohesion policies need to pay attention to the fractal structure of EU inequalities across regions. As is well known, a few regions in the west of Europe are at the core of EU innovation, production and trade. These are also the regions that manage to grow while generating most employment. However, within the Western trade block there are also peripheral regions, with a much lower contribution to EU-wide employment growth. This core–periphery divide is also observed across peripheral trade blocks. Hence, EU policies may need to complement place-based approaches (technological capabilities) with an awareness of the high-tech trade centrality of a region to generate inclusive growth.

Second, it has been recognised that interregional connectivity has not been successfully accounted for in EU's Smart Specialisation Strategy (S3) and that interregional knowledge ties have an impact on regional processes of related diversification (Balland & Boschma, 2021, p. 1059). The relevant connections are those that allow to take advantage of *complementary* capabilities present in other regions. A way to embed and codify this flow of complementary knowledge is through high-tech input flows. Hence, the important role of buyer centrality in our results for (relative) employment growth confirms this. The policy implication of this is that supporting absorptive capacities to successfully integrate into the interregional high-tech input trade network may be conducive to achieving the *unrelated* diversification that laggard regions need, in order to regain regional competitiveness and create jobs across Europe.

Overall, this paper represents a step towards understanding the core–periphery, fractal structure of the EU, emphasising the role of interregional production, trade and knowledge linkages in its configuration. However, additional work needs to be undertaken.

First, to consider additional indicators of regional performance (such as labour productivity, wage rates and regional income inequalities) to obtain a more nuanced picture about the different dimensions of the core–periphery structure: Are core regions in the East – which have been catching-up in employment terms – doing so also in terms of wage rates? How has income distribution changed in peripheral regions of the West and core regions of the North, which have markedly lost high-tech manufacturing employment?

Second, to apply a richer set of network metrics to understand the different roles of regions in the high-tech (and other) input trade network(s) in Europe. Our measures of buyer and supplier centrality are 'circular': a region will be more central the more it is connected to central others. But, given current geopolitical developments, it would be equally relevant to quantify local vulnerabilities, that is, the extent to which a disruption to a region's production and trade of (high-tech) inputs may result in sizeable systemic effects, for example along the lines of Wirkierman et al. (2022).

Third, to consider explicitly the global (or regional) value chain dimension of interregional linkages. Rather than consolidating inter-industry relations by destination industry and focusing only on high-tech products by industry of origin, it would be interesting to relate our core–periphery structure to the degree of (backward/forward) integration and positioning of EU regions within interregional (and inter-country) value chains, possibly exploiting the full EU-REGIO database used in this paper.

Finally, the paper has a number of limitations that could be addressed if better data were available. First, our analysis is cross-sectional, mainly because the information to build interregional trade networks is restricted to few years. Future research may invest in extending this type of data. Second, our analysis is relevant at the

NUTS-1 regional level. In future research, when data became available, it would be important to explore if the results hold also at more granular levels, extending the fractal nature of the core–periphery technological structure. Third, regions may differ in terms of their functional specialisation *within* a high-tech industry (Timmer et al., 2019). When data on trade in value added for recent years – combined with compatible data on employment by industry and occupation – become available at a regional level, future research may dig deeper into how trade centrality relates to the positioning of regions in an inter-country value chain and the set of tasks performed.

DISCLOSURE STATEMENT

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

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NOTES

1. Fritsch and Wyrwich (2021) note that the United States is among the countries with the highest concentration in cities.
2. For a recent review, see Cesaroni et al. (2019).
3. According to EUROSTAT, high-tech industry and knowledge-intensive services comprise two-digit codes 21, 26, 59–63 and 72 from the NACE Rev. 2 classification (see Table 1 for details).
4. The contribution to aggregate growth of variable X by region r is defined as:

$$\frac{\Delta X_r}{\Delta X},$$

where:

$$X = \sum_{r=1}^{m} X_r.$$

Note that:

$$\frac{\Delta X_r}{\Delta X} = \left(\frac{\Delta X_r}{X_r}\right) / \left(\frac{\Delta X}{X}\right) \cdot \frac{X_r}{X} = \frac{G_r}{G} \cdot \frac{X_r}{X},$$

where G_r and G are the growth rates of variable X for region r and the aggregate, respectively. That is, the contribution to growth measures the *combined effect* of a growth rate differential (between r and the aggregate) coupled with the initial share of r in the total.
5. For details about the classification of industries by technological intensity, see https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf/.
6. For details, see https://ec.europa.eu/eurostat/cache/metadata/en/htec_esms.htm/.
7. For details, see https://data.overheid.nl/en/dataset/d345b89c-d203-494a-a6d6-f95a3a62ada3/. For the database, see https://dataportaal.pbl.nl/downloads/PBL_Euregio/.
8. Unfortunately, the 'Real estate, renting and business activities' sector of the EU-REGIO database merges knowledge-intensive services with sectors which notoriously distort interregional trade of high-tech products. Hence, we have not included this EU-REGIO industry aggregate amongst the set of high-tech products used to articulate the system of interregional flows (3).
9. Croatia has not been explicitly included in the EU-REGIO database, so it was excluded from the analysis. Moreover, transactions for Bulgarian and Romanian regions are only available at the national level, so we estimated interregional transactions for these two countries by distributing country-level values using regional shares in gross value added.
10. Vector $\boldsymbol{1}$ is a vector of ones, that is, a sum vector, of adequate dimensions.
11. The notion of *modularity* of a partition of nodes in a network was introduced by Newman and Girvan (2004, sect. IV). Intuitively, random networks are not supposed to have a community structure. The metric of modularity quantifies how 'community-like' subnetworks of a partition are by comparing *actual* with *expected* link density in a (degree-preserving) random network. If the value of within-community links is greater than the expected random value, it is unlikely that the within-community link structure is a random result, so modularity will be high. The Louvain algorithm (Blondel et al., 2008) is the most widely used hierarchical agglomerative method for modularity maximisation.
12. As will be shown below, within each trade block there is a core and peripheral place-based regional group.
13. Moreover, whilst trade blocks configure mainly a picture of *national* aggregates, when overlapped with the place-based clustering, resulting regional groups divide countries.
14. Formally, row vector $\boldsymbol{\pi}^T$ is the left eigenvector associated with the leading (unitary) eigenvalue of matrix $\boldsymbol{P}$. Assuming that matrix $\boldsymbol{P}$ is irreducible (i.e. $\boldsymbol{P}^k$ has only positive entries for some k), the existence, uniqueness and non-negativity of the solution to eigensystem (8) is guaranteed by the Perron-Frobenius theorem (Meyer, 2000, p. 693).
15. In this case, the corresponding eigensystems would be: $\boldsymbol{A\pi} = \boldsymbol{\pi}$ and $\boldsymbol{\rho}^T\boldsymbol{D} = \boldsymbol{\rho}^T$, respectively.
16. We can split manufacturing ($CtGHTechMan_{rc}$) and knowledge-intensive services ($CtGHTechKIS_{rc}$) only in the case of high-tech employment.
17. When we consider the accumulated trade block total, instead of the average, the centrality of this block is even more pronounced (Figure 3, columns 10 and 11).

18. High-tech employment in trade blocks with lower initial high-tech employment share has been catching up.
19. These findings are in line with Thissen et al. (2016) and Cortinovis and Van Oort (2019) who find that trade relations multiply the benefits on productivity only in importing regions that have enough own technological capabilities.
20. These regions mainly comprise parts of north and east of Germany and the Netherlands, south of Belgium, France (except Ile-De-France and the south) and the UK (except London). Interestingly, with the exception of Nordrhein-Westfalen (DEA), 'old industrial regions' in Western Europe are comprised here (Birch et al., 2010, tab.1, p. 40). In most cases, these territories have core regions as close neighbours, who concentrate production and/or use of high-tech inputs. While their high-tech input supplier centrality is, on average, still relatively high (despite the pervasive loss of associated high-tech manufacturing employment), there is a much weaker average performance of buyer centrality, on which knowledge-intensive services mostly depend. Hence, this suggests that the transition from a manufacturing to a service-intensive high-tech specialisation is slow in comparison to the speed of loss of manufacturing jobs. The asymmetry between (average) buyer and supplier centrality for Western peripheral regions is probably reflecting this incomplete transition.

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