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A map of the fractal structure of high-tech dynamics across EU regions

Ariel L. Wirkierman* Tommaso Ciarli† Maria Savona‡

Abstract

The paper provides a novel, theoretically driven map of EU regional asymmetries, based on the shares and dynamics of high-tech employment and wages, as well as the structure of inter-regional Input-Output relations at the EU NUTS-1 regional level. We use data from EUROSTAT and the EU-REGIO database to perform a trade-aware shift-share analysis coupled with a hierarchical clustering. We show that EU regions present a fractal structure of asymmetries, i.e. the emergence of core-periphery relations at progressively smaller scales, in relation to both spatial and trade dimensions. We identify regional clusters labelled 'consolidated core', 'declining core', 'emerging cities', 'declining peripheries' and 'CEE factories', and we show that there is a polarising dynamics between driving and follower clusters, drawing implications for EU cohesion policy.

JEL classification codes: R11, O30, C38

Keywords: Regional high-tech employment, Regional wage rate differentials, Cluster Analysis, European cohesion policy

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1 Introduction

European countries are facing unprecedented challenges in terms of post Covid-19 pandemic resilience and recovery. The double-dips of the post-financial and post-pandemic crises are slowing down employment, productivity and growth prospects, while exacerbating pre-existent inequalities (Evenhuis et al., 2021). Furthering inequalities is argued to engender social instability and political polarisation (Rodríguez-Pose, 2018).

Persistent and potentially increasing asymmetries in the employment structure of EU countries are also due to the reconfiguration of trade patterns within and outside the EU, and the intensity and (technological) quality of integration in Global Value Chains (GVCs) (Bontadini et al., 2019). These trends seem to have exacerbated the gap between core and non-core countries and favoured the emergence of new peripheries (Wirkierman et al., 2018).

In response to this, the new EU cohesion policy package is being approved at time of writing. It represents a — again unprecedented — set of cohesion instruments and funds for the period 2021-2027, that add to the traditional European Territorial Cooperation programmes ("Interreg"), European Regional Development Fund (ERDF) and the Cohesion Fund (CF), by launching the Just Transition Fund (JTF) as part of the EU Green New Deal.

The EU cohesion policy, at this particular historical moment, is a one-time opportunity to tackle not only the post-pandemic recovery, but also the root, structural causes of EU inequalities, across cities, regions and countries. Some scholars argue that it is important to devise instruments that are 'place-based sensitive' (Iammarino et al., 2020), and that are able to address the 'geography of discontent' (Rodríguez-Pose, 2018). It is therefore all the more important to understand old and new determinants of EU inequalities, particularly in terms of regional employment and wage asymmetries.

Some of these root causes have been imputed to the long-term trends of financialisation and financial globalisation, as well as to institutional factors such as the lessening in the incentives to unionise and the bargaining power of unions, in a context of more fragmented labour markets (Evenhuis et al., 2021). The fragmentation of labour markets is in turn the result of a complex and intertwined set of determinants, that have to do with sectoral structural changes, technological change, and agglomeration forces that concentrate high-tech activities and talents in urban areas.

A major role in the heightened inequality across EU regions has been played by changes in their industry mix (Cutrini, 2019), which has resulted in a few technology 'clubs', with high-income clubs characterised by a specialisation in manufacturing and highly productive services. It has been suggested that regions with high concentrations of manufacturing activities typically have lower levels of inequality, whereas regions with high concentrations of service activities, creative industries such as arts and entertainment, as well as knowledge-intensive business services, tend to have higher levels of inequality (Cutrini, 2019). This is also affected by the concentration of high-skilled services, creative industries and generally more complex activities in urban contexts and large cities (Balland et al., 2020).

An increase in employment in high-tech sectors (i.e. with a comparatively higher share of high-skill workers) has a multiplier effect on other sectors, and create jobs also in low-tech, non-tradeable sectors (Moretti and Thulin, 2013). However, because these jobs are relatively poorly paid, average wages fall as a consequence of increased high-tech employment, leading to an increase in inequality (Lee and Clarke, 2019). This seems to be the case, for instance, in the UK local labour markets (Travel-to-Work-Areas) where investments in Research and Development in some areas seem to be associated to an increase in routinised jobs (Ciarli et al., 2018).

More in general, innovation and high-tech activities tend to concentrate in a few countries, in a few regions within countries, and in a few cities within regions, in a structure that reproduces fractals. There seems to be a recursive dynamics between specialising in high-tech activities (which require sophisticated capabilities and high skills) and developing further complex activities, that concentrate in fewer and fewer urban areas (Balland et al., 2020).

For instance, focusing on the case of metropolitan areas in the US, Balland et al. (2020) find that the complexity of activities, variously measured, explains from 40% to 80% of the variance in urban concentration of occupations, industries and technologies. Such concentration is accompanied by an increased concentration in high skills and know-how (Gomez-Lievano and Patterson-Lomba, 2019). As a result, growing economic inequalities between regions within countries, are accompanied by rising inequalities at the intra-regional level and within cities (Evenhuis et al., 2021).

As argued above, the intertwined dynamics linked to: (i) changes in the sectoral composition of regions and countries; (ii) technological changes, that affect the complexification of production and increase requirements of high-tech inputs and advanced skills; (iii) agglomeration forces that lead to the concentration of such activities in a few countries, a few regions within countries and a few urban areas within regions, all contribute to make asymmetries persistent and increase EU inequality.

What could slow down and reverse such a polarising dynamics, possibly complement the efforts of any cohesion policy and allow 'left behind places' to catch up? One such opportunities is provided by inter-regional (technological and economic) inter-dependencies. These are claimed to be relevant for (peripheral) regions to learn technological capabilities from (core) regions (Balland and Boschma, 2021). In addition, regions are more likely to enter new technological and scientific fields (measured by patents) when they are 'connected' to regions that have complementary capabilities to their own (Balland and Boschma, 2021, p. 2). Hence, although peripheral regions diversify less, they might benefit from connections to complementary regions.

The ambition of this paper is to take into account the above-mentioned relevant dimensions and their relationships to characterise the differential trajectories leading to EU regional inequality, and map them in a meaningful and policy-relevant way. In addition to the contributions reviewed above, we also consider the very important dimension of inter-regional 'connectivity', which we proxy in terms of inter-regional trade in high-tech inputs. Mapping EU regions also on the basis of inter-regional trade allows us to explore whether this is a potential channel for catching up or, indeed, a further element of acceleration of EU regional inequalities.

To operationalise the objective above, we combine hierarchical clustering with a 'trade-aware' shift-share decomposition applied on a set of 67 NUTS-1 EU regions covering the period 2010-2017/19, to account for the following dimensions: the share and dynamics of employment in high-tech manufacturing and knowledge-intensive service activities; the associated regional wage share and high-tech wage rate dynamics; technological capabilities, in terms of regional intensity of granted patents; as well as inter-regional backward and forward trade linkages.

The further contribution of this paper is to map EU asymmetries in terms of the peculiar fractal structure of the dimensions above. We therefore identify a novel 'core-periphery' structure amongst EU regions, which results from the (long-term) polarising role of innovation, and that might have only been exacerbated by the double-dip shocks of the financial crisis and the Covid-19 pandemic.

Overall, the evidence shows a number of new elements that explain a peculiar, fine-grained core-periphery *fractal* structure, that is, a recursive emergence of core-periphery relations at progressively smaller scales, in relation to both the *spatial* and trade dimensions. This is in line with some of the above literature, but is based on an in-depth, exhaustive exploration of the role of inter-regional trade in rendering regional dynamics interdependent.

The remainder of the paper is structured as follows. Section 2 specifies the data intensive methods and empirical strategy adopted. Section 3 reports the results and offers a discussion of the fractal map of EU regional asymmetries. Finally, section 4 briefly concludes, and draws implications for EU cohesion policy.

2 Methods and Data

The aim of this section is to introduce the techniques, metrics, empirical strategy and data used to devise a map of EU regions clustered by similarity in terms of high-tech technological features, employment and wage rate dynamics.

2.1 Inter-regional Input-Output relations

To quantitatively characterise the innovativeness of a region, (per-capita) patent applications by region r — labelled PAT_r in what follows — is a key and widely used indicator.

However, patents measure innovative output which only *potentially* leads to technological change, i.e. 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.[1] This may be inferred by recalling the overlap between IPC (International Patent Classification) codes and 2-digit NACE Rev. 2 codes corresponding to high-tech industry types (see, e.g. Van Looy et al., 2015, pp. 8-11).

To operationalise the extent to which regions produce and trade in high-tech products we consider an inter-regional input-output (IRIO, hereinafter) system. In an IRIO scheme with m regions and n industries, of which n_h are

[1] According to EUROSTAT, high-tech industry and knowledge-intensive services comprise 2-digit codes 21, 26, 59 to 63 and 72 from the NACE Rev. 2 classification. See Table 2 below for details.

high-technology sectors, we may write:

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

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 inter-regional trade, so intra-regional transactions can be set to zero, i.e. $X_{rr}^{ij} = K_{rr}^{i} = 0$. Hence, T_{rs} in (1) 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 $(m \times m)$ inter-regional trade matrix in high-tech products measuring *gross* flows. To uncover the structural features of the trading regions, it is often useful to express the elements of $\boldsymbol{T}$ in *intensive* terms. In particular, we may write:

$$p_{sr} = a_{rs} = \frac{T_{rs}}{\sum_{r=1}^{m} T_{rs}} \tag{2}$$

i.e. 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 ($\sum_{r=1}^{m} p_{sr} = 1$), each *row* representing the regional distribution of payments by region s for the purchase of a (monetary) unit of high-tech inputs over regions $r = 1, \ldots, m$.

By superposing a *chance process* interpretation on $\boldsymbol{P}$ — through the device of a finite Markov chain (Grinstead and 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 ($\boldsymbol{p}^T_{(2)} = \boldsymbol{p}^T_{(1)}\boldsymbol{P} = \boldsymbol{p}^T_{(0)}\boldsymbol{P}^2$) until a fixed point is reached:[2]

$$\boldsymbol{\pi}^T \boldsymbol{P} = \boldsymbol{\pi}^T \tag{3}$$

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 expenditure in high-tech inputs circulating in the inter-regional system, 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 *producer* (and extra-regional exporter) of high-tech inputs in the inter-regional system.

If, instead, we focus on the delivery of products acting as a counterpart to monetary payments in (2), coefficient a_{rs} is a measure proxying a direct *backward* linkage effect, as it represents the induced high-tech input demand by region s to provider region r.

Correspondingly, we may also define d_{rs}:

$$d_{rs} = \frac{T_{rs}}{\sum_{s=1}^{m} T_{rs}} \tag{4}$$

proxying a direct *forward* linkage effect, as it represents the share of (extra-)regional sales of high-tech inputs from region r to region s. Hence, for example, the higher the value of d_{rs}, the higher the intensity with which a cost increase of high-tech industries in region r would be transmitted to region s.

In traditional Input-Output analysis, backward and forward linkage effects are interpreted from the perspective of the region *generating* the impulse, i.e. by activating input demand (backward) or by passing through input costs (forward), respectively. Hence, the aim is to understand how a given region *affects* others, rather than to assess how it is *affected by* others.

If, instead, we adopt this *latter* perspective, forward linkage coefficient d_{rs} quantifies how an increase in economic activity of region s induces higher activity in region r. From the viewpoint of region r, the higher its share of sales to region s, the higher its exposure to a change in economic activity in region s. Correspondingly, from the viewpoint of region s, backward linkage coefficient a_{rs} quantifies how a cost increase in region r will put a pressure on region s to raise its own costs, the higher its share of high-tech inputs imported from

[2] Formally, row vector $\boldsymbol{\pi}^T$ is the left eigenvector associated to 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 (3) is guaranteed by the Perron-Frobenius theorem (Meyer, 2000, p. 693).

region r.

2.2 Trade-aware shift-share decomposition

With this interpretation in mind, we use trade inter-dependencies to formulate a 'trade-aware' shift-share decomposition (Nazara and Hewings, 2004) of employment and wage rate dynamics in high-tech sectors.

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

$$C_r^h := \frac{\Delta L_r^h}{\sum_{r=1}^m \Delta L_r^h} = 1/m + (C_{rs}^h - 1/m) + (C_r^h - C_{rs}^h) \qquad (5)$$

where:

$$C_{rs}^h = \frac{\sum_{s=1}^m d_{rs} \Delta L_s^h}{\sum_{s=1}^m \Delta L_s^h} \qquad (6)$$

Note that C_r^h in (5) measures a growth contribution, i.e. a ratio between two absolute changes. Thus, it does not measure the *pace* of growth (as a rate of change would), but the *proportional* contribution of region r to the *absolute* change in aggregate employment.[3]

An interesting feature of indicator C_r^h is that it captures the regional *distribution* of absolute changes. As such, the uniform regional contribution is given by $1/m$, because if all m regions contributed equally, each would increase (or decrease) employment by $1/m$ times the absolute change in aggregate employment. And this represents the first addendum of the right-hand side of (5). The remaining two addenda will capture the regional *deviation* from the uniform contribution.

In particular, from the perspective of region r, in order to understand how changes in other regions affect its own employment, C_{rs}^h in (6) measures the

[3] 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.

growth contribution by all high-tech product *destinations* of region r. The change in employment in each purchasing region s is weighted by its importance for region r, by means of forward linkage coefficient d_{rs}. Hence, if the destinations of region r increase their employment, this would induce demand for region's r high-tech output, expanding its high-tech employment. Note that C^h_{rs} is region-*specific* (as regional trading partners will differ). Thus, the second addendum of the right-hand of (5) — $(C^h_{rs} - 1/m)$ — captures the extent to which growth contributions by region's r *trading partners* exceed (or fall short of) the uniform contribution; potentially driving employment growth in region r.

Instead, the third addendum of the right-hand side of (5) — $(C^h_r - C^h_{rs})$ — captures the extent to which region's r own growth contribution exceeds (or falls short of) that of its trading partners. That is, whether region r is over-performing (or under-performing) its closest 'neighbours', in terms of its proportional contribution to aggregate high-tech employment changes.

In this way, the three addenda in decomposition (5) allow to quantify respectively the uniform contribution to growth, the influence of the *context* in which a region is operating, and its over-performance within that context.

The fact that units of employment across regions are additive renders possible the use of the contribution to growth as an indicator of regional dynamics. However, when we want to apply the same decomposition for wage *rates*, these are no longer additive, as they are expressed *per unit of employment*. Therefore, wage rate dynamics will be analysed in terms of rates of change.

In a system with m regions, if w^h_r stands for the (nominal) wage rate in high-tech sectors within region r (with Δw^h_r indicating the absolute change between two time periods), the *rate of change* in region's r high-tech wage rate may be defined and decomposed as:

$$G^h_r := \frac{\Delta w^h_r}{w^h_r} = G^h + (G^h_{sr} - G^h) + (G^h_r - G^h_{sr}) \tag{7}$$

where:

$$G^h = \frac{\Delta w^h}{w^h} \quad \text{with} \quad w^h = \frac{\sum_{r=1}^m W^h_r}{\sum_{r=1}^m L^h_r}, \tag{8}$$

$$G^h_{sr} = \frac{\sum_{s=1}^m a_{sr} \Delta w^h_s}{\sum_{s=1}^m a_{sr} w^h_s} \tag{9}$$

Decomposition (7) follows a similar logic to (5), but works in terms of growth rates, rather than growth contributions. As may be seen from (8), the first addendum of the right-hand side of (7) corresponds to the growth rate of the cross-regional, aggregate high-tech wage rate G^h. Note that W_r^h in (8) stands for the total (monetary) labour compensation paid in high-tech sectors within region r. The remaining two addenda of (7) capture the regional *deviation* from the aggregate growth rate.

In particular, from the perspective of region r, in order to understand how changes in other regions affect its own wage rate, G_{sr}^h in (9) measures the wage rate growth of all *suppliers* of high-tech products to region r. The increase in labour costs in each supplier region is weighted by its importance as an input source for region r, by means of backward linkage coefficient a_{sr}. Hence, if regions from which r buys its high-tech inputs increase their wage rates, there will be a pressure on input users in region r to increase their wage rate as well. Note that G_{sr}^h is region-*specific* (as regional trading partners will differ). Thus, the second addendum of the right-hand of (7) — $(G_{sr}^h - G^h)$ — captures the extent to which the pace of high-tech wage rate expansion of region's r *trading partners* exceeds (or falls short of) aggregate high-tech wage rate dynamics.

Instead, the third addendum of the right-hand side of (7) — $(G_r^h - G_{sr}^h)$ — captures the extent to which region's r own growth rate exceeds (or falls short of) that of its trading partners. That is, whether region r is increasing labour costs proportionally more (or less) than its closest 'neighbours'.

In this way, the three addenda in decomposition (7) allow to quantify the cross-regional, aggregate high-tech wage rate growth, the influence of the *context* in which a region is operating, and its labour cost advantage (or disadvantage) within that context.

2.3 Empirical strategy: hierarchical clustering and appreciative theorising

On the basis of the indicators derived so far, our empirical strategy may be described as follows. Our starting point is a multivariate sample of observations across $m = 67$ EU NUTS-1 regions for the following variables in each region r:

$$(\mathrm{PAT}_r, \pi_r, C_r^h, G_r^h) \tag{10}$$

where PAT_r stands for (per-capita) patent applications to the European Patent Office (EPO), π_r — obtained from (3) — is an indicator of a region's high-tech trade centrality, C_r^h — defined in (5) — measures a region's contribution to the growth of aggregate high-tech employment, and G_r^h — defined in (7) — is the rate of change of a region's high-tech wage rate.

We aim to identify a set of mutually exclusive regional groups, i.e. clusters, based on (relatively) similar within-group values when considering all variables in (10) jointly. To do so, we apply a data-driven, agglomerative hierarchical clustering technique (Everitt and Hothorn, 2011, p. 166) to obtain a regional map of high-tech 'clubs' in the EU.

Intuitively, if we had only two dimensions by which to compare regions, e.g. patent applications (PAT_r) and high-tech trade centrality (π_r), the problem would be relatively straightforward to visualise: groups would be identified by drawing lines across a two-dimensional scatter-plot separating different 'clouds' of dots, each dot representing a region along those two dimensions.

However, considering $q = 4$ dimensions simultaneously requires to refine both the assessment of the relative distance between q-dimensional (data) points, as well as the procedure to merge regions into groups.

To compute the distance between region r and s across the q variables, we use the Euclidean distance. And given that the variables in (10) differ in their unit of measurement, we standarise each of them before computing bilateral regional distances:

$$\delta_{rs} = \left(\sum_{k=1}^{q} (z_{rk} - z_{sk})^2 \right)^{1/2}, \quad \text{with} \quad z_{rk} = \frac{x_{rk} - \bar{x}_k}{SD_k}, \quad z_{sk} = \frac{x_{sk} - \bar{x}_k}{SD_k} \tag{11}$$

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

As an outcome, the obtained symmetric bilateral distance matrix $\mathbf{\Gamma} = [\delta_{rs}]$ is used to merge regions into groups. Starting from a set of $m = 67$ clusters (each representing a different region), the agglomerative algorithm merges the nearest pair of distinct clusters into a new group, iteratively repeating the process until only one group (containing all regions) is obtained.

While the bilateral distance between two regions is given by (11), the distance between any two regional groups will be given by the distance between those two regions — one in each group — which are more *dissimilar* between them:

$$\delta_{AB} = \max_{r \in A, s \in B} (\delta_{rs}) \tag{12}$$

where A and B are regional groups. The clustering rule given by (12) is known as complete linkage (or farthest neighbour) clustering (Everitt and Hothorn, 2011, p. 167). Intuitively, regional groups will be merged in this case when the most distant pair of regions between two groups are still relatively closer than with respect to any other group.

Applying this iterative algorithm leads to a hierarchical structure known as *dendrogram*, in which regions have been successively merged into non-overlapping subsets.

After allocating regions into their respective clusters, we considered decompositions (5) and (7), together with additional contextual variables, in order to perform an exercise in 'appreciative theorising' (Nelson, 1998, p. 500): a theoretically-informed data interpretation exercise which remains close to empirical details. The full set of variables considered is reported in Table 1.

A relevant methodological point of our approach concerns the fact that the clustering algorithm has been applied on a subset of only four variables: PAT_r and π_r summarise technological features of innovation and revealed high-tech competitiveness, whereas C_r^h and G_r^h capture employment and labour cost dynamics. We *then* explain regional differences considering *all* indicators in Table 1, including region-specific components of decompositions (5) and (7). In this way, we uncover cluster-level features enriching the description of the map of uneven high-tech dynamics across EU regions.

Table 1: Full set of variables reported in empirical results

Column(s)	Meaning (Unit)	Period	Formula
[01]	Patent applications to EPO (number/mill. inhabitants)	2010-12	PAT_r in (10)
[02]	High-tech Trade Centrality (in %)	2010	π_r in (3)
[03]	Regional contribution to growth of aggregate employment across regions (in %)	2010-12/2017-19	$\frac{\sum_{i=1}^{n} \Delta L_r^i}{\sum_{r=1}^{m} \sum_{i=1}^{n} \Delta L_r^i}$
[04]-[07]	Regional contribution to growth of high-tech employment across regions and its decomposition (in %)	2010-12/2017-19	Expression (5)
[08]	Regional contribution to growth of high-tech manufacturing employment across regions (in %)	2010-12/2017-19	$\frac{\sum_{i=1}^{n_h^{man}} \Delta L_r^i}{\sum_{r=1}^{m} \sum_{i=1}^{n_h^{man}} \Delta L_r^i}$
[09]	Regional contribution to growth of high-tech knowledge-intensive service employment across regions (in %)	2010-12/2017-19	$\frac{\sum_{i=1}^{n_h^{kis}} \Delta L_r^i}{\sum_{r=1}^{m} \sum_{i=1}^{n_h^{kis}} \Delta L_r^i}$
[10]-[13]	Regional growth rate of the hourly wage rate in manufacturing and ICT services and its decomposition (in p.p.)	2010-12/2015-17	Expression (7)
[14]	Regional high-tech employment share (in %)	2010-12	$L_r^h / \sum_{i=1}^{n} L_r^i$
[15]	Regional wage share in Gross Value Added (in %)	2010-12	$\frac{\sum_{i=1}^{n} W_r^i}{\sum_{i=1}^{n} L_r^i}$
[16]	Regional hourly wage rate in manufacturing and ICT services (in EUR/hour)	2010-12	w_r^h in (7)
[17]-[19]	Absolute changes in variables [14]-[16]: 2010-12/2017-19 ([17]) and 2010-12/2015-17 ([18]-[19])		

Notes: Column numbers correspond to those reported in Tables 3 and 4 of Section 3; p.p. stands for percentage points; n corresponds to the total number of industries in a region; m stands for the number of regions; n_h^{man} stands for high-tech manufacturing sectors; n_h^{kis} stands for high-tech knowledge intensive services.

2.4 Data: High-tech employment, wage rates and inter-regional 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 previous paragraphs is a challenging task. Given the trade-off between coverage and granularity, we had to make some compromises.

Our two data sources are EUROSTAT and the EU-REGIO database (Thissen et al., 2018). We adopted the definition of high-tech industry and knowledge intensive services established by EUROSTAT, comprising a subset of 2-digit codes from the NACE Rev. 2 classification, as reported in Table 2.[4]

Table 2: High-tech industry and knowledge-intensive services

Aggregation by NACE Rev. 2

Code	Descriptor	*NACE Rev. 2. Codes - 2digit level*	
C_HTC	High-technology manufacturing industries	21	Manufacture of basic pharmaceutical products and pharmaceutical preparations;
		26	Manufacture of computer, electronic and optical products.
Code	**Descriptor**	***NACE Rev. 2. Codes - 2digit level***	
KIS_HTC	High-tech knowledge-intensive services	59 to 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: Own elaboration based on EUROSTAT.

Data on high-tech employment (in thousand persons) at the NUTS-1 regional level between 2010 and 2019 comes from the EU Labour force survey (LFS).[5] We have used this data source to obtain C_r^h in (5), computing the change between three-year averages (2017-2019 with respect to 2010-2012), with the aim of capturing more persistent trends.

In order to obtain G_r^h in (7), we used mutually consistent data on (current price) gross value added, compensation of employees and employment (in thousand hours worked) at the NUTS-1 level between 2010 and 2017 from EUROSTAT's regional economic accounts.[6] Also in this case, we computed

[4]For details on the classification of industries by technological intensity, see: `https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf`

[5]For details, see: `https://ec.europa.eu/eurostat/cache/metadata/en/htec_esms.htm`

[6]For details, see: `https://ec.europa.eu/eurostat/cache/metadata/en/reg_eco10_esms.htm`

the change between three-year averages (2015-2017 with respect to 2010-2012). However, we had to make two compromises. First, sectoral disaggregation is at the 1-digit, section level of the NACE Rev. 2 classification. Therefore, we *proxied* the coverage of industries from Table 2 by considering the combined wage rate of NACE Rev. 2 letters C and J, i.e. 'Manufacturing' and 'Information and Communication' sectors, respectively. Second, regional data points are based on the NUTS 2016 classification. Unfortunately, due to regional border redefinitions in the transition between NUTS 2013 and NUTS 2016, France and Poland only report regional accounts data from 2016 onwards. Hence, regions from these two countries had to be excluded from the analysis.

Moreover, note that w_r^h in (7) represents the nominal hourly wage rate (in €/hour). There is a twofold motivation behind this conscious choice. First, we are mostly concerned with the high-tech wage rate as a production *cost*, rather than as a source of aggregate demand. In the latter case, adjusting for the purchasing power of wages (using *national* consumer price indices) would have been more relevant. In fact, w_r^h represents a *sectoral* — rather than economy-wide — magnitude. Second, the *evolution* of the nominal wage rate aims to *proxy* a key component of *price* dynamics, in order to infer changes in sectoral cost competitiveness. This is also why nominal magnitudes have been expressed in € across regions (even for those with a different national currency).

Data from patent applications to the EPO per million inhabitants at the NUTS-1 regional level have been obtained from EUROSTAT.[7] Data is available up to the year 2012, so we considered the three-year average 2010-2012. Hence, variable PAT_r in (10) measures the 'initial condition' of regional innovation output.[8]

Finally, inter-regional intermediate and fixed capital input trade data to build accounting system (1) and all its derived magnitudes — including linkage coefficients a_{rs} and d_{rs} in (2) and (4), respectively — has been extracted and articulated from the EU-REGIO database. This database includes the first yearly time-series of inter-regional Input-Output tables with detail for European regions at the NUTS-2 level, covering the 2000-2010 period.[9] As with data coming from regional economic accounts, we had to make some compromises. First, the database sectoral disaggregation consists of 14 industries collating ac-

[7]For details, see: `https://ec.europa.eu/eurostat/cache/metadata/en/pat_esms.htm`

[8]Moreover, we translated regional data originally codified in the NUTS 2013 classification into the NUTS 2016 one.

[9]For details, see: `https://data.overheid.nl/en/dataset/d345b89c-d203-494a-a6d6-f95a3a62ada3`. The database may be accessed at: `https://dataportaal.pbl.nl/downloads/PBL_Euregio/`.

tivities from the ISIC Rev. 3 classification. Hence, we *proxied* the coverage of industries from Table 2 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).[10] Second, we aggregated NUTS-2-level transactions into a NUTS-1 scheme, under the NUTS 2016 classification.[11] Finally, given the time span covered by EU-REGIO, we used the latest available year (2010) to compute the high-tech trade centrality indicator π_r in (10), as well as linkage coefficients a_{rs} and d_{rs}. Thus, regional trade weights of shift-share decompositions (5) and (7) are *fixed* across time.

As an outcome, we articulated a dataset for $m = 67$ NUTS-1 European regions, reported in Table 5 of Appendix A. The argument for choosing the NUTS-1 level of analysis is twofold. First, it allows for a more comprehensive coverage of current EU member states. Data points for several region $\times$ 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 Results and Discussion

In this section we report and discuss our empirical results. First, we describe the clusters obtained through the empirical strategy specified in section 2, characterising and distinguishing each cluster by means of the expanded variable set of Table 1. Then, we discuss the results highlighting the *fractal* configuration of high-tech differences across EU regions.

3.1 Hierarchical clustering of European NUTS-1 regions

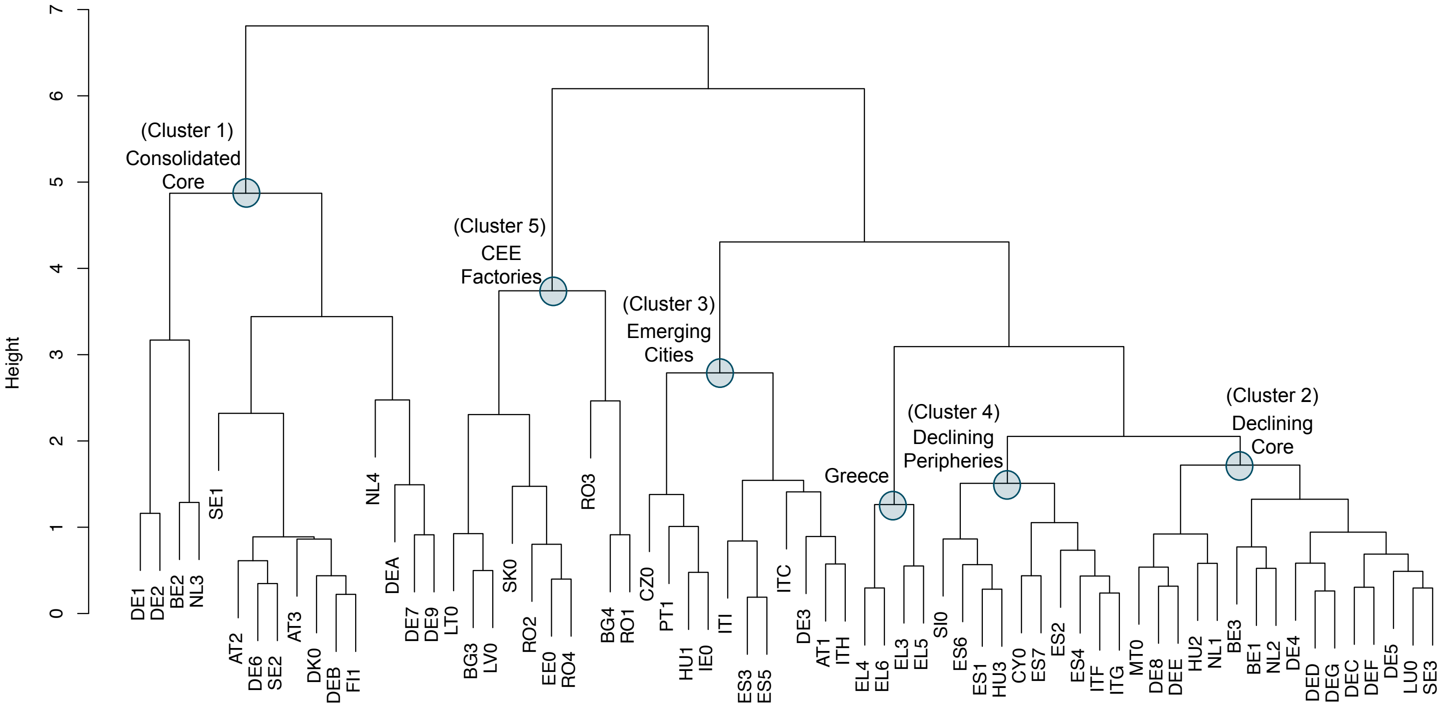
Figure 1 displays the dendrogram obtained from applying the hierarchical clustering algorithm on distance matrix $\mathbf{\Gamma} = [\delta_{rs}]$, computed according to (11).[12]

[10] Unfortunately, the 'Real estate, renting and business activities' sector of the EU-REGIO database merges knowledge-intensive services with sectors which notoriously distort inter-regional 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 inter-regional flows (1).

[11] Croatia has not been explicitly included in the EU-REGIO database, so we had to exclude it from the analysis. Moreover, transactions for Bulgarian and Romanian regions are only available at the national level, so we estimated inter-regional transactions for these two countries by distributing country-level values using regional shares in gross value added.

[12] Distance matrix $\mathbf{\Gamma} = [\delta_{rs}]$ is graphically represented in Appendix A, Figure 6.

Figure 1: Dendrogram of high-tech clusters across European NUTS-1 regions



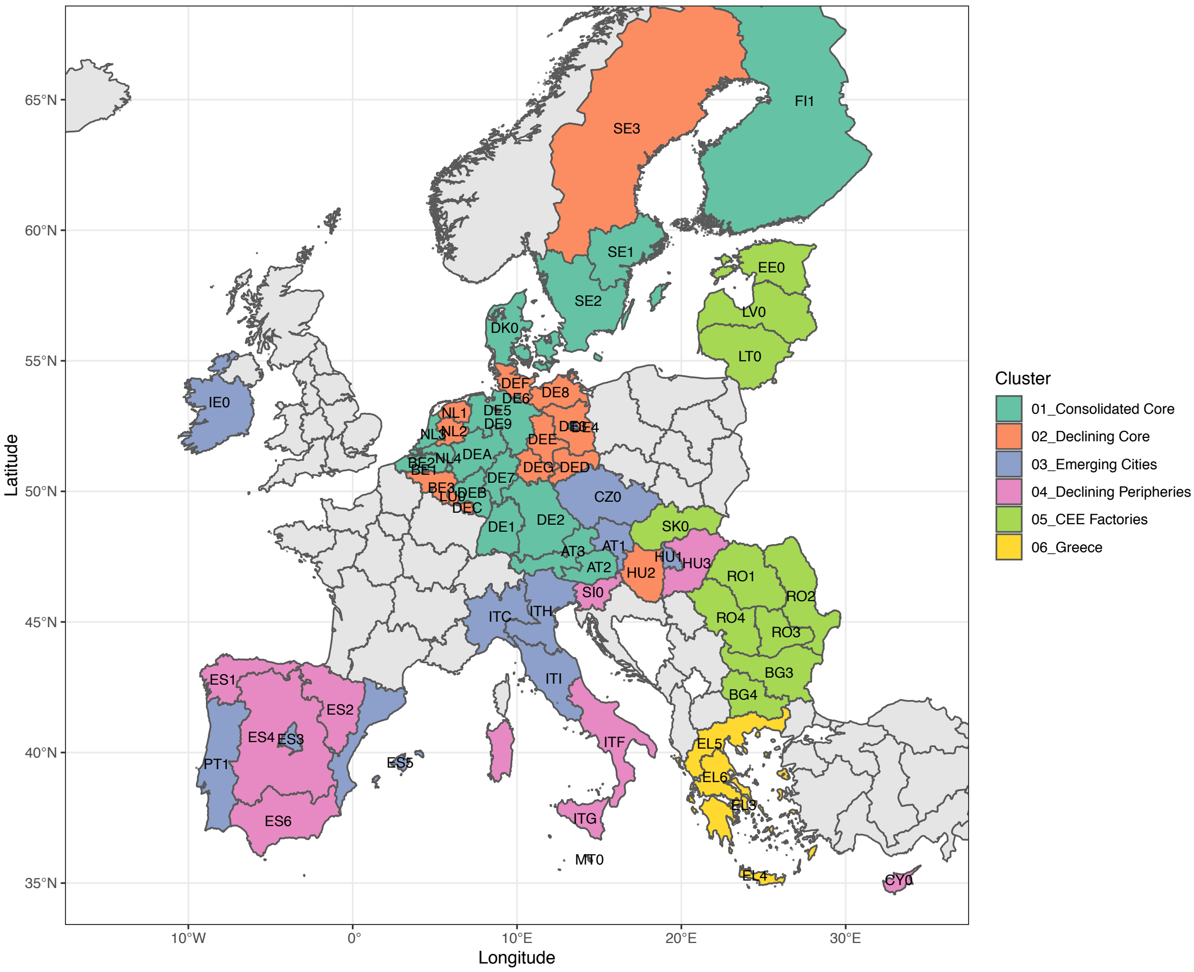
Source: Own elaboration based on EUROSTAT data and EU-REGIO database.

Notes: Regional NUTS-1 codes are described in Appendix A, Table 5.

Cluster labelling is based on the analysis reported below. Our main interest is on the 5 clusters encompassing regions from different EU countries, as Greek regions followed a sufficiently distinct dynamics to become a cluster of their own. Moreover, in order to grasp the spatial pattern of cluster composition, Figure 2 depicts the geographical layout of the identified clusters.

To characterise each cluster and its constituting regions, Tables 3 and 4 report the values of all variables specified in Table 1 by region and averaged by cluster. Columns `[01]`, `[02]`, `[04]` and `[10]` correspond to the variables in (10) used to compute the clusters of regions; columns `[04]-[07]` correspond to the shift-share decomposition of high-tech employment growth specified in (5), whereas columns `[10]-[13]` to the shift-share decomposition of wage rate growth in manufacturing and ICT services specified in (7).

Figure 2: Map of high-tech clusters across European NUTS-1 regions



Source: Own elaboration based on EUROSTAT data and EU-REGIO database.

Notes: Regional NUTS-1 codes are described in Appendix A, Table 5.

Table 3: High-tech employment and wage rate decompositions, high-tech trade centrality and patent applications

(Cluster-level averages and Clusters 1 and 2)

	NUTS-1	Regional Descriptor	Cluster	*Technological features* [01] Patent Applic. *(2010-12)* (per mill.)	[02] High-Tech. Centrality *(2010)* (in %)	*Employment dynamics* [03] Employ ment *(CtG)* (in %)	[04] Employment in high-tech. sectors *(CtG: 2010-12 to 2017-19)* Cr = (in %)	[05] C (in %)	[06] (Crs - C) (in %)	[07] (Cr - Crs) (in %)	[08] High-Tech. Empl. Manuf. *(CtG)* (in %)	[09] Services (in %)	*Wage rate dynamics* [10] Wage rates in Manuf. and ICT Services *(Growth rate; 2010-12 to 2015-17)* Gr = (in p.p.)	[11] G (in p.p.)	[12] (Gsr - G) (in p.p.)	[13] (Gr - Gsr) (in p.p.)	*Initial conditions* [14] High-Tech. Emp. share *(2010-12)* (in %)	[15] Wage share (in %)	[16] Wage rate (€/hour)	*Change from initial conditions* [17] High-Tech Emp. share *(Difference with 2010-12)* (in p.p.)	[18] Wage share (in p.p.)	[19] Wage rate (€/hour)
Cluster-level averages		Consolidated Core	1	527.54	3.67	2.88	1.44	1.49	0.35	-0.40	2.83	1.18	11.96	11.02	0.42	0.52	4.46	55.33	34.74	0.07	0.07	4.12
		Declining Core	2	186.94	0.88	0.53	0.06	1.49	0.37	-1.80	-0.17	0.10	13.44	11.02	0.45	1.97	3.74	55.61	27.50	-0.14	-0.06	3.42
		Emerging Cities	3	159.73	1.67	2.80	3.78	1.49	0.53	1.75	1.88	4.17	7.78	11.02	-0.99	-2.25	5.18	49.47	22.12	0.39	-1.53	1.92
		Declining Peripheries	4	40.99	0.65	0.91	0.80	1.49	0.93	-1.63	1.28	0.71	4.81	11.02	-2.81	-3.41	2.54	51.15	17.22	0.27	-2.15	0.76
		CEE Factories	5	12.19	0.21	0.80	2.42	1.49	0.65	0.28	2.08	2.44	41.68	11.02	0.27	30.38	2.69	41.80	4.72	0.87	3.23	1.86
Consolidated Core - Cluster 1	AT2	Sudosterreich	1	371.60	0.57	0.34	1.17	1.49	0.53	-0.86	1.94	1.02	14.62	11.02	1.26	2.34	3.10	54.04	28.57	0.82	0.71	4.18
	AT3	Westosterreich	1	554.96	1.12	1.10	1.42	1.49	0.75	-0.82	3.01	1.12	16.88	11.02	1.11	4.74	2.59	51.00	28.67	0.45	0.60	4.84
	BE2	Vlaams Gewest	1	328.87	7.56	1.69	1.95	1.49	0.07	0.39	-0.39	2.42	10.80	11.02	0.89	-1.11	4.55	55.87	38.71	0.23	-2.05	4.18
	DE1	Baden-Wurttemberg	1	930.39	8.68	6.87	3.89	1.49	0.35	2.05	13.60	2.03	13.57	11.02	-0.77	3.32	5.30	56.65	37.39	-0.09	1.58	5.07
	DE2	Bayern	1	795.77	9.06	7.23	2.18	1.49	0.46	0.22	21.29	-1.52	14.41	11.02	-0.71	4.10	5.15	55.45	36.59	-0.26	0.70	5.27
	DE6	Hamburg	1	413.65	0.96	1.29	1.59	1.49	0.78	-0.68	6.05	0.74	11.47	11.02	0.39	0.06	4.99	52.52	42.96	0.55	2.14	4.93
	DE7	Hessen	1	529.87	4.20	2.92	0.59	1.49	0.54	-1.44	1.91	0.34	10.80	11.02	-0.10	-0.12	5.36	56.69	37.11	-0.31	1.01	4.01
	DE9	Niedersachsen	1	351.03	3.57	3.46	1.05	1.49	0.40	-0.85	2.83	0.71	14.16	11.02	-0.28	3.41	2.61	54.52	32.61	-0.02	1.79	4.62
	DEA	Nordrhein-Westfalen	1	493.30	5.53	7.83	-0.62	1.49	0.70	-2.81	6.26	-1.96	10.89	11.02	-0.13	0.00	3.91	57.43	35.11	-0.36	1.83	3.82
	DEB	Rheinland-Pfalz	1	501.71	1.17	1.57	0.20	1.49	0.58	-1.87	5.66	-0.86	12.30	11.02	0.06	1.22	3.67	55.83	34.24	-0.18	0.45	4.21
	DK0	Danmark	1	425.74	1.22	2.01	0.61	1.49	0.59	-1.47	-1.13	0.95	9.87	11.02	1.11	-2.26	5.46	62.31	39.84	-0.20	-2.58	3.93
	FI1	Manner-Suomi	1	501.86	0.90	0.65	0.44	1.49	0.43	-1.48	-10.02	2.48	10.45	11.02	0.19	-0.76	5.86	56.46	32.24	-0.01	-1.56	3.37
	NL3	West-Nederland	1	220.74	8.41	3.13	3.91	1.49	0.03	2.39	0.15	4.66	8.31	11.02	1.11	-3.83	4.20	54.86	36.04	0.36	-1.66	2.99
	NL4	Zuid-Nederland	1	853.85	3.55	0.99	-0.78	1.49	0.19	-2.45	-7.01	0.43	9.87	11.02	1.10	-2.25	3.87	56.24	32.87	-0.47	-2.43	3.24
	SE1	Ostra Sverige	1	679.76	1.29	2.76	4.04	1.49	-0.48	3.02	0.86	4.68	12.36	11.02	0.71	0.63	6.78	50.50	34.40	0.54	1.04	4.25
	SE2	Sodra Sverige	1	487.47	0.87	2.22	1.43	1.49	-0.35	0.29	0.27	1.67	10.58	11.02	0.78	-1.23	4.00	54.92	28.48	0.09	-0.41	3.01
Declining Core - Cluster 2	BE1	Brussels-Capital Reg.	2	241.56	1.20	0.53	0.38	1.49	0.13	-1.24	-0.45	0.54	7.22	11.02	0.73	-4.53	6.83	59.61	48.31	-0.12	-3.06	3.49
	BE3	Region Wallonne	2	236.77	2.75	0.42	0.30	1.49	0.10	-1.30	3.13	-0.25	10.38	11.02	0.80	-1.44	4.30	59.45	38.53	0.03	-1.39	4.00
	DE4	Brandenburg	2	184.13	0.75	0.40	-0.85	1.49	0.62	-2.96	0.27	-1.08	16.92	11.02	0.30	5.60	3.30	54.26	23.34	-0.57	-0.10	3.95
	DE5	Bremen	2	200.29	0.56	0.37	0.25	1.49	0.37	-1.61	0.03	0.29	14.66	11.02	-0.10	3.74	3.43	56.94	37.97	0.18	2.13	5.57
	DE8	Mecklenb.-Vorpom.	2	93.80	0.39	-0.04	0.03	1.49	0.74	-2.20	0.03	0.03	15.16	11.02	0.46	3.68	1.96	57.59	21.18	0.04	1.15	3.21
	DEC	Saarland	2	310.70	0.63	0.31	-0.31	1.49	0.34	-2.14	0.48	-0.47	8.99	11.02	-0.38	-1.65	3.32	59.55	34.32	-0.64	0.93	3.09
	DED	Sachsen	2	209.43	1.48	0.90	-0.06	1.49	0.52	-2.07	2.80	-0.61	17.35	11.02	0.34	5.99	4.07	58.01	22.59	-0.19	0.72	3.92
	DEE	Sachsen-Anhalt	2	79.14	0.50	-0.41	-0.07	1.49	0.60	-2.16	-1.22	0.16	19.85	11.02	0.82	8.02	2.30	56.32	21.54	0.04	1.64	4.28
	DEF	Schleswig-Holstein	2	316.68	0.71	1.26	0.02	1.49	0.76	-2.24	-1.25	0.27	12.65	11.02	0.24	1.39	3.34	54.56	31.92	-0.25	0.93	4.04
	DEG	Thuringen	2	230.77	0.97	-0.35	-0.09	1.49	0.24	-1.82	3.25	-0.74	17.49	11.02	0.51	5.96	3.47	59.33	21.02	0.04	0.08	3.68
	HU2	Dunantul	2	19.41	0.81	2.00	-0.66	1.49	1.13	-3.28	-9.69	1.09	15.19	11.02	2.06	2.11	4.88	50.69	7.01	-0.98	-1.79	1.07
	LU0	Luxembourg	2	285.63	0.05	0.60	0.35	1.49	0.17	-1.31	-0.09	0.44	11.91	11.02	0.83	0.06	4.04	54.69	36.54	0.11	-1.50	4.35
	MT0	Malta	2	21.02	0.01	0.79	0.58	1.49	0.33	-1.24	0.66	0.57	18.82	11.02	-2.91	10.70	5.59	50.31	10.62	0.04	-3.51	2.00
	NL1	Noord-Nederland	2	109.58	0.98	0.22	-0.18	1.49	0.02	-1.69	-1.22	0.02	10.35	11.02	1.26	-1.93	2.82	47.51	28.73	-0.21	3.59	2.97
	NL2	Oost-Nederland	2	217.49	2.03	1.00	0.94	1.49	0.04	-0.59	0.95	0.94	8.17	11.02	1.27	-4.13	3.44	57.30	29.98	0.18	-1.84	2.45
	SE3	Norra Sverige	2	234.67	0.33	0.45	0.30	1.49	-0.23	-0.96	-0.33	0.43	9.89	11.02	0.96	-2.09	2.72	53.57	26.47	0.12	1.11	2.62

Source: Own computations based on Regional Accounts, Labour Force Survey (LFS) databases (EUROSTAT) and EU-EUREGIO database. *Notes*: CtG stands for 'Contribution to Growth'; p.p. stands for percentage points. See Table 1 for a detailed specification of columns [01]-[19]. Regional NUTS-1 codes are described in Appendix A, Table 5.

Table 4: High-tech employment and wage rate decompositions, high-tech trade centrality and patent applications

(Clusters 3, 4, 5 and Greece)

	NUTS-1	Regional Descriptor	Cluster	Technological features [01] Patent Applic. (2010-12) (per mill.)	[02] High-Tech. Centrality (2010) (in %)	Employment dynamics [03] Employ ment (CtG) (in %)	[04] Employment in high-tech. sectors (CtG: 2010-12 to 2017-19) Cr = (in %)	[05] C (in %)	[06] (Crs - C) (in %)	[07] (Cr - Crs) (in %)	[08] High-Tech. Empl. Manuf. (CtG) (in %)	[09] Services (in %)	Wage rate dynamics [10] Wage rates in Manuf. and ICT Services (Growth rate; 2010-12 to 2015-17) Gr = (in p.p.)	[11] G (in p.p.)	[12] (Gsr - G) (in p.p.)	[13] (Gr - Gsr) (in p.p.)	Initial conditions [14] High-Tech. Emp. share (2010-12) (in %)	[15] Wage share (in %)	[16] Wage rate (€/hour)	Change from initial conditions [17] High-Tech Emp. share (Difference with 2010-12) (in p.p.)	[18] Wage share (in p.p.)	[19] Wage rate (€/hour)
Emerging Cities - Cluster 3	AT1	Ostosterreich	3	273.22	1.09	1.46	2.51	1.49	0.64	0.37	3.61	2.31	13.88	11.02	1.30	1.56	4.66	53.47	31.20	0.63	0.81	4.33
	CZ0	Ceska Republika	3	36.94	3.12	4.35	5.67	1.49	0.51	3.67	3.88	6.06	8.58	11.02	1.85	-4.30	4.41	44.90	9.28	0.42	0.15	0.80
	DE3	Berlin	3	379.40	1.45	3.39	3.15	1.49	0.58	1.07	5.64	2.69	13.63	11.02	0.38	2.23	7.35	56.97	36.48	-0.02	2.09	4.97
	ES3	Comunidad Madrid	3	83.97	1.41	1.32	2.30	1.49	0.61	0.19	-4.08	3.55	4.07	11.02	-3.75	-3.20	8.02	56.27	26.96	0.21	-1.56	1.10
	ES5	Este	3	83.77	1.30	5.07	2.54	1.49	1.44	-0.40	0.66	2.92	2.21	11.02	-3.25	-5.56	3.60	51.74	21.15	0.02	-2.36	0.47
	HU1	Kozep-Magyarorszag	3	96.65	1.35	2.59	4.90	1.49	0.88	2.53	6.89	4.54	4.56	11.02	2.30	-8.76	7.40	52.20	8.86	1.17	-0.88	0.40
	IE0	Ireland	3	136.46	1.36	4.02	5.12	1.49	0.13	3.49	5.40	5.09	11.20	11.02	-0.37	0.55	7.87	44.60	28.11	0.33	-12.54	3.15
	ITC	Nord-Ovest	3	240.27	3.53	2.75	3.68	1.49	0.22	1.96	-1.25	4.65	7.70	11.02	-0.67	-2.65	4.22	43.73	25.23	0.22	0.00	1.94
	ITH	Nord-Est	3	286.50	1.80	1.72	1.87	1.49	0.48	-0.10	-0.60	2.36	9.47	11.02	-1.54	-0.01	2.83	44.31	23.12	0.17	-0.71	2.19
	ITI	Centro (It)	3	121.14	1.65	2.57	3.71	1.49	0.19	2.03	-0.92	4.64	6.01	11.02	-1.09	-3.92	4.43	43.40	22.81	0.31	0.33	1.37
	PT1	Continente	3	18.66	0.35	1.52	6.10	1.49	0.14	4.47	1.52	7.02	4.22	11.02	-6.07	-0.74	2.24	52.59	10.13	0.86	-2.21	0.43
Declining Peripheries - Cluster 4	CY0	Kypros	4	12.31	0.03	0.08	0.31	1.49	-0.04	-1.14	0.48	0.28	-4.19	11.02	-7.54	-7.68	2.55	54.13	14.45	0.50	-3.94	-0.61
	ES1	Noroeste	4	30.54	0.74	-0.13	1.46	1.49	0.69	-0.72	1.70	1.42	5.21	11.02	-3.52	-2.29	2.37	50.04	20.14	0.60	-2.30	1.05
	ES2	Noreste	4	136.44	1.53	0.19	-0.14	1.49	0.72	-2.36	0.24	-0.22	1.91	11.02	-2.78	-6.33	3.16	51.93	23.66	-0.08	-2.34	0.45
	ES4	Centro (Es)	4	17.25	0.54	0.50	0.12	1.49	1.32	-2.70	1.61	-0.17	3.71	11.02	-4.29	-3.02	2.08	49.18	19.31	-0.01	-2.40	0.72
	ES6	Sur	4	21.66	0.34	3.53	2.14	1.49	1.75	-1.11	-0.36	2.63	3.26	11.02	-4.00	-3.76	1.93	51.79	18.73	0.24	-2.85	0.61
	ES7	Canarias	4	8.55	0.08	1.41	0.82	1.49	1.86	-2.53	0.42	0.91	0.90	11.02	-4.09	-6.03	1.26	51.17	18.36	0.47	-1.36	0.17
	HU3	Alfold Es Eszak	4	24.94	0.66	3.26	1.49	1.49	1.07	-1.07	6.86	0.46	9.54	11.02	1.98	-3.46	3.43	53.39	6.85	0.02	-1.80	0.65
	ITF	Sud	4	37.05	1.11	0.72	0.13	1.49	0.29	-1.66	-2.53	0.64	8.57	11.02	-1.32	-1.13	1.97	44.94	17.91	-0.01	-1.04	1.53
	ITG	Isole	4	19.95	1.33	-0.82	0.35	1.49	0.68	-1.82	0.66	0.30	6.25	11.02	-0.48	-4.29	1.70	45.85	18.17	0.19	-1.15	1.14
	SI0	Slovenija	4	101.24	0.18	0.39	1.28	1.49	0.94	-1.15	3.73	0.82	12.90	11.02	-2.05	3.92	4.90	59.13	14.67	0.74	-2.35	1.89
CEE Factories - Cluster 5	BG3	Sev. I Yugoiztochna	5	2.76	0.03	0.64	0.09	1.49	1.08	-2.48	-1.19	0.34	45.94	11.02	-0.66	35.58	1.74	40.92	2.51	-0.02	4.58	1.15
	BG4	Yug. I Yuzhna Tsentr.	5	11.42	0.06	1.45	4.10	1.49	1.08	1.53	3.13	4.32	59.68	11.02	-0.66	49.32	4.33	42.11	3.50	1.34	7.84	2.09
	EE0	Eesti	5	39.47	0.06	0.78	2.15	1.49	0.15	0.51	-0.36	2.65	29.69	11.02	1.39	17.28	3.72	51.90	7.28	1.85	3.38	2.16
	LT0	Lietuva	5	13.39	0.23	1.19	1.69	1.49	0.13	0.07	1.46	1.74	43.62	11.02	1.47	31.13	2.19	44.10	6.00	0.69	3.92	2.62
	LV0	Latvija	5	18.68	0.03	0.48	0.90	1.49	0.30	-0.90	1.40	0.80	48.80	11.02	4.32	33.46	2.90	45.93	5.43	0.55	6.55	2.65
	RO1	Macroregiunea Unu	5	3.71	0.05	1.09	2.55	1.49	0.68	0.37	5.16	2.06	56.28	11.02	-0.65	45.91	1.74	37.54	2.97	0.75	2.31	1.67
	RO2	Macroregiunea Doi	5	1.73	0.05	0.36	0.87	1.49	0.68	-1.30	-0.42	1.13	28.44	11.02	-0.65	18.07	0.88	37.02	2.87	0.22	-0.72	0.82
	RO3	Macroregiunea Trei	5	11.48	0.08	0.75	6.67	1.49	0.68	4.49	1.76	7.66	44.33	11.02	-0.65	33.96	3.26	39.53	4.79	1.80	0.10	2.12
	RO4	Macroregiunea Patru	5	4.24	0.04	-1.47	2.05	1.49	0.68	-0.12	6.32	0.62	35.36	11.02	-0.65	24.99	2.19	38.53	3.37	1.08	0.92	1.19
	SK0	Slovensko	5	15.01	1.45	2.70	3.14	1.49	1.01	0.63	3.52	3.08	24.65	11.02	-0.53	14.16	3.95	40.44	8.50	0.48	3.44	2.09
	EL3	Attiki	6	23.54	0.09	-1.54	1.62	1.49	-0.74	0.86	1.88	1.57	-15.72	11.02	-3.81	-22.93	4.21	39.36	13.36	1.21	-2.33	-2.10
	EL4	Nisia Aigaiou, Kriti	6	12.27	0.01	0.06	-0.07	1.49	0.02	-1.58	-0.03	-0.08	-23.03	11.02	-13.43	-20.62	0.92	40.50	12.98	-0.12	-2.06	-2.99
	EL5	Voreia Ellada	6	7.22	0.04	-0.34	0.92	1.49	-0.33	-0.25	1.31	0.85	-21.56	11.02	-10.09	-22.50	1.19	42.28	11.89	0.64	-2.92	-2.56
	EL6	Kentriki Ellada	6	3.53	0.03	-0.57	-0.15	1.49	-0.35	-1.30	-0.09	-0.17	-27.55	11.02	-9.26	-29.31	0.80	39.68	17.90	-0.08	-2.86	-4.93
		Total			100.00	100.00	100.00	100.00	31.61	-31.61	100.00	100.00										
		Average		2.83									12.97	11.02	-0.88	2.83	3.70	50.90	22.61	0.24	-0.24	2.32

Source: Own computations based on Regional Accounts, Labour Force Survey (LFS) databases (EUROSTAT) and EU-EUREGIO database. *Notes*: CtG stands for 'Contribution to Growth'; p.p. stands for percentage points. See Table 1 for a detailed specification of columns [01]-[19]. Regional NUTS-1 codes are described in Appendix A, Table 5.

The first cluster (Figure 2 and Table 3) is composed of EU regions that are part of the '*consolidated core*' of the European innovation system (cluster 1). These regions include some of the most innovative European cities with a strong tradition in manufacturing such as Munich, Hamburg, Copenhagen, Amsterdam and Stockholm, plus some highly innovative regions in Austria, Belgium, Germany (Baden-Wurttemberg), Sweden (Sodra Sverige) and Finland. Taken together, these 16 regions (24% of the total) account for 61% of (per capita) patent applications in 2010-12 across all regions (column `[01]`).[13] Beyond inventions, these regions are also main suppliers of high-tech inputs to all other regions, producing 59% of high-tech inter-regional trade (3.67% per region, on average, which is 2.3 times greater than the second highest cluster) (column `[02]`). This is an impressive concentration of productive and technological capabilities, if we also consider that a consistent share of high-tech products exported by these regions is consumed within the cluster.[14]

These leading European regions include some of the "large cities" that have been attracting most innovation and developing the most complex technologies (Balland et al., 2020). They are also the cities that generate the high-tech jobs with highest wages. While the initial average hourly wage rate was already 1.54 times above the cross-regional average (column `[16]`), it has also experienced the highest *absolute* growth (column `[19]`).

Despite starting from a relatively high share of employment in high-tech industries (4.46% on average, column `[14]`), regions in cluster 1 have a relative contribution to the absolute change in EU high-tech employment in line with a uniform value (1.44% in column `[04]` with respect to 1.49% in column `[05]`, respectively). This increase in high-tech employment is accompanied by the highest average contribution to total employment growth across regions (2.9% per region, on average, in column `[03]`). That is, they attract employment in high-tech industries as well as in the rest of the regional economy (Moretti and Thulin, 2013).

Being composed of traditionally strong manufacturing regions, the cluster's impressive high-tech trade centrality (column `[02]`) is matched by contributing to over 45% of EU-wide high-tech manufacturing employment increase (column `[08]`). Notably, two regions alone — Baden-Wurttemberg (DE1) and Bayern

[13] All column numbers refer to Tables 3 and 4.

[14] The intensity of inter-regional trade relations in high-tech products may be quantified by direct forward (d_{rs}) and backward (a_{rs}) linkage coefficients, computed according to (4) and (2), respectively. Tables 7 and 8 in Appendix A report the most relevant direct linkage coefficients.

(DE2) — account for almost 35% of the EU-wide increase.[15]

Not only is the cluster's high-tech employment growth contribution close to a uniform cross-regional value, but also its wage rate dynamics is closest to the average EU-wide growth rate (11.96 p.p. in column `[10]` with respect to 11.02 p.p. in column `[11]`, respectively). This is coupled with a cluster average wage share which is second to highest and increasing (columns `[16]` and `[18]`, respectively).

In sum, the regions in the 'consolidated core' are characterised by a pattern of virtuous accumulation of technological capabilities, high-tech productive centrality, attracting highly remunerated high-tech employment, with a fairer region-wide distribution of the fruits of technical progress.

The performance of cluster 1 partially leads the dynamics of three other clusters, either negatively ('declining core', cluster 2) or positively ('emerging cities', cluster 3 and 'CEE factories', cluster 5, though for different reasons). Instead, cluster 4 ('declining peripheries') is weakly connected with the 'consolidated core' (and with most other clusters) in terms of high-tech input trade linkages (see Tables 7 and 8 in Appendix A). We discuss them in turn.

The second cluster (Figure 2 and Table 3) is composed of 16 regions that are peripheral to the 'consolidated core', and which we label '*declining core*' (cluster 2). Its 16 regions are also innovative: while representing only 24% of the total, they account for over 20% of (per capita) patent applications in 2010-12. However, beyond inventions, these regions account for only 14% of high-tech inter-regional input trade (0.88% per region, on average, in column `[02]`). The 'declining core' includes all Belgian, Dutch, German, and Swedish regions not included in cluster 1.[16]

These regions are the main *extra*-cluster suppliers to the 'consolidated core' and, to some extent, also main buyers from it (see Tables 7 and 8 in Appendix A). However, with only a few exceptions, their share of high-tech employment decreased between 2010-12 and 2017-19 (column `[17]`). It is the cluster with the lowest proportional contribution to EU-wide high-tech employment increase (column `[04]`), and has the sharpest negative differential with respect to the contribution of their main trading destinations, which are from cluster 1 (column `[07]`). Regions from cluster 2 also have the lowest contribution to total

[15]The sharply negative growth contributions by Manner-Suomi (FI1) and Zuid-Nederland (NL4) could represent either a potential long-run decline *or* an outsourcing strategy of manufacturing output. For example, from Table 8 in Appendix A, it emerges that Eesti (EE0) and Latvija (LV0) source 27.1% and 24.5%, respectively, of their high-tech input requirements from Manner-Suomi (FI1).

[16]The cluster also includes Luxembourg and two other peripheral regions from Hungary and Malta.

employment growth, led by a negligible increase in high-tech services and a decline in high-tech manufacturing (columns [08]-[09]). This declining trend might predate the period considered, given the relatively low regional high-tech employment share already present in 2010-12, in contrast to their innovative performance.

Despite the negative employment performance, high-tech sector wages in these regions grew, on average, faster than in the 'consolidated core' — their main input suppliers — explaining the positive wage growth differential (column [13]). Hence, the fast pace of wage rate growth seems to benefit cluster 2 regions from the geographical closeness to the 'consolidated core', despite losing jobs to them.

Cluster 3 (Figure 2 and Table 4) is composed of regions scattered across the four cardinal points of the EU. Similarly to the first cluster of 'consolidated core' regions, some of these are large cities (Berlin, Budapest, Madrid); some are small countries/regions centred around a capital (or main) city (Ireland, Portugal, Estonia, Czech Republic, Vienna, Northern Italy and Central Italy). With an heterogeneous patenting activity within the cluster, taken together these regions accounted for 13% of (per capita) patent applications in 2010-12 (column [1]). This inventive activity is accompanied by the second highest trade centrality (column [02]), jointly accounting for over 18% of the production of high-tech inter-regional input trade.

Despite a substantially lower starting point, these *'emerging cities'* have the highest average contribution to EU-wide absolute change in high-tech employment (3.8% per region, on average, in column [04]). This increase in high-tech employment is significantly over-performing its trading destinations (column [07]), and is accompanied by a notorious contribution to EU-wide increase in total employment (2.8% per region, on average, in column [03]). This performance suggests that the 'emerging cities' represent an attraction force for employment in the neighbouring regions (mainly the 'declining peripheries' in cluster 4).

Beyond the underlying innovative and productive capabilities, these regions differ substantially from those in the 'consolidated core' on several accounts. First, the cluster of 'emerging cities' accounts for almost 46% of EU-wide increase in high-tech knowledge-intensive services, with an average regional contribution of 4.2% (column [09]). Instead, the cluster's contribution to high-tech manufacturing employment growth is — though still considerable — less than half of its contribution to service employment growth (column [08]).

Second, wage rates do not follow the same virtuous dynamics as they do in the 'consolidated core': the initial average hourly high-tech wage rate is substantially lower (column [16]) and its increase in absolute terms is less than half of that in cluster 1 (column [19]). Its growth rate (column [10]) is below average, and substantially less than that of the cluster's high-tech input suppliers (consisting mostly of intra-cluster regions, the 'consolidated core', and 'declining peripheries'). Finally, the regional wage share is below 50% (column [15]) and decreasing (column [18]), suggesting an increase in within-region inequality.

Highly connected to all other regions through high-tech input trade, the dynamics of some of the 'emerging cities' may contain elements of 'spurious' growth in high-tech employment, being mostly in service sectors requiring a degree of innovation capabilities, but which do not attract particularly high paying jobs, if not from the 'declining peripheries'.

The two remaining clusters are very different in relation to both innovation and wages. Altogether, these 20 regions (30% of the total) account for 4% of (per capita) patenting activity in 2010-12, with only two regions — Noreste in Spain (ES2) and Slovenija (SI0) — being responsible for almost half of these patents. The two clusters differ substantially between them but are both trade peripheries, especially of the 'emerging cities'.

The fourth cluster (Figure 2 and Table 4) is composed of peripheral regions in Southern and Central Europe. These are the 'declining peripheries' (cluster 4). Beyond their low patenting activity, these regions account for only 6.5% of the production of high-tech inter-regional input trade (0.65% per region, on average, in column [02]).

Similarly to the relation between the 'consolidated' and 'declining' core, 'declining peripheries' are located around 'emerging cities', and their inter-regional high-tech input trade is precisely concentrated around them, as well as around other intra-cluster regions (see Tables 7 and 8 in Appendix A).

Cluster 4 regions seem to be losing ground in all respects. Their contained contribution to employment growth is observed both economy-wide (0.91% on average, in column [03]) and specifically in high-tech sectors (0.80% on average, in column [04]). Within the latter, their low dynamism is evinced by the negative differential with respect to the cluster's high-tech input destinations (column [07]). This is similar to what happens between the 'declining core' and the 'consolidated core', with the substantial difference that the hourly high-tech wage rate of 'declining peripheries' has been relatively stagnant (columns [10] and [19]) — particularly in relation to their main high-trade input suppliers (column [13]) — and the average regional wage share has declined sharply (column [18]). Instead, the 'declining core' experiences the fastest pace of wage rate expansion, faster than that of their high-tech input suppliers.

Hence, while peripheries evince a similar pattern of stagnant high-tech employment in relation to their respective core, they show an opposite trajectory in terms of high-tech wage growth, suggesting further income polarisation.

Cluster 5 (Figure 2 and Table 4) includes regions in Central-Eastern Europe (CEE) that in 2010-12 had almost no contribution to EU-wide innovation outputs (less than 1% of per capita patent applications and 2% of high-tech inter-regional trade, columns [01]-[02]) and had a relatively low initial share of employment in high-tech sectors (2.54% per region, on average, in column [14]). These *'CEE factories'* compete mainly on the basis of unit labour costs.

At first sight, these regions may be seen as a relative success story of European integration. Their contribution to EU-wide absolute change in high-tech employment is second only to the 'emerging cities' (2.4% per region, on average, in column [04]) and over-performing their high-tech input destinations (column [07]). Notably, the contribution to high-tech employment has been the most balanced across all clusters when considering the distinction between high-tech manufacturing and knowledge-intensive services (columns [08]-[09]).

However, the growth of high-tech employment did not go hand in hand with overall regional employment growth. The relative contribution of the cluster to EU-wide total employment has been considerably smaller (0.8% per region, on average, in column [03]) than its contribution to high-tech employment. While this might suggest a process of relative *specialisation*, such growth differential actually alerts on a process of net *migration* of the CEE labour force (Astrov et al., 2019).

In terms of the high-tech wage rate, a 'convergence-type' dynamics may be observed: starting from the lowest hourly average wage rate (column [16]), regions from cluster 5 experienced the fastest proportional growth in wages (41.7 p.p. per region, on average, in column [10]), and an *absolute* increase which is very close to that of the 'emerging cities' (column [19]). In fact, the cluster has had a high-tech wage rate increase 30.4 p.p. above that of its high-tech input providers (column [13]).

While, on the one hand, such a high increase in high-tech wage rates *vis-à-vis* the rest of the regional economy is likely to increase inequality between sectors, on the other hand, high-tech wage dynamics was accompanied by a sizeable increase in the regional aggregate wage share (3.23 p.p. per region, on average, in column [18]).

However, regions from Cluster 5 highly depend on high-tech input provision from 'emerging cities' and 'declining peripheries', possibly due to their outsourcing strategies (see Table 8 in Appendix A). This raises questions on how strong and persistent high-tech employment growth in 'CEE factories' may be, particularly if they do not develop endogenous innovative capabilities.

Finally, the case of Greece evinces the risks of increasing regional polarisation within the EU. Figure 1 suggests that Greek regions would have been clustered with declining areas of Europe. But their trajectory is worryingly unique. The positive contribution of (only) two of its regions to high-tech employment growth (column [04]) is coupled with country-wide, sharp deflationary high-tech wage dynamics (column [10]), negative contribution to total employment growth (column [03]) and decreasing regional wage share (column [18]). Greek regions are also weakly integrated with the rest of Europe, being mostly mutually dependent and, to a lesser extent, relying on high-tech input provision from some of the 'emerging cities' (see Tables 7 and 8 in Appendix A).

3.2 Discussion: the fractal structure of regional high-tech dynamics

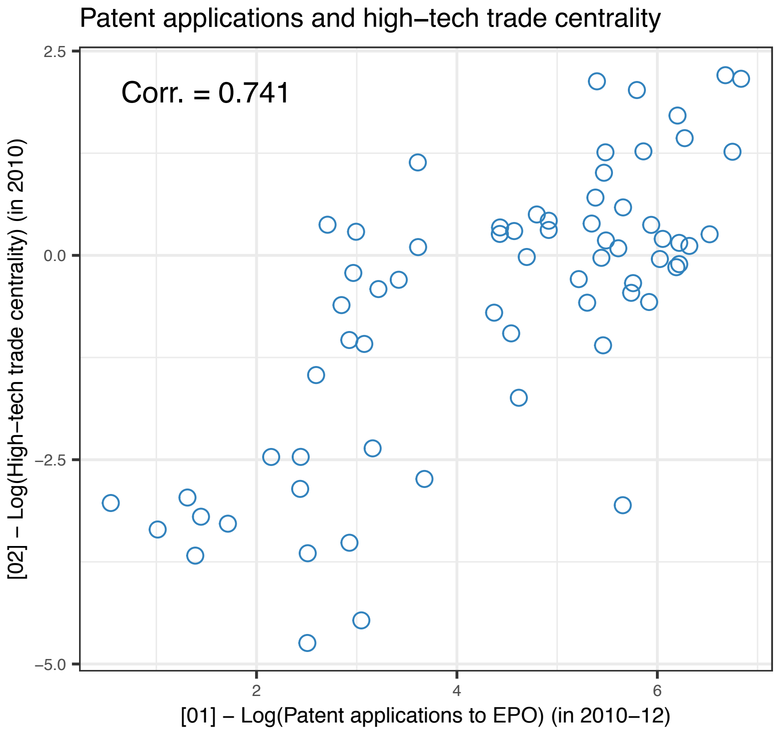
Overall, the results confirm the well-known core-periphery structure among EU regions, but the evidence shows a number of new elements to *explain* this structure, and possibly offers a potential handle to reduce such inequalities, based on the analysis of the interactions between these regions.

The results suggest a fractal structure of European regions, characterised by the presence of similar patterns recurring at a progressively smaller scale: a recursive emergence of core-periphery relations at different scales, in relation to both the *spatial* and trade dimensions.

The first core-periphery relation is the standard one between the highly innovative regions in the two 'core' clusters (1 and 2) and the low/non-innovative peripheries (with a few exceptions) in the other three clusters (3, 4 and 5). This first asymmetry — determined by innovation outputs — is further deepened by the role of knowledge in developing high-tech productive potential *across* regions, as evinced by the strong, positive correlation between (per-capita) patent applications and high-tech trade centrality, depicted in Figure 3.

Within each of these groups, we observe a second core-periphery layer. The 'consolidated core' keeps growing at a fast rate, attracts high skilled workers

Figure 3: Innovation outputs and high-tech productive potential



Source: Own elaboration based on EUROSTAT data and EU-REGIO database. *Notes*: variable numbers correspond to those specified in Table 1. The Pearson correlation coefficient is included.

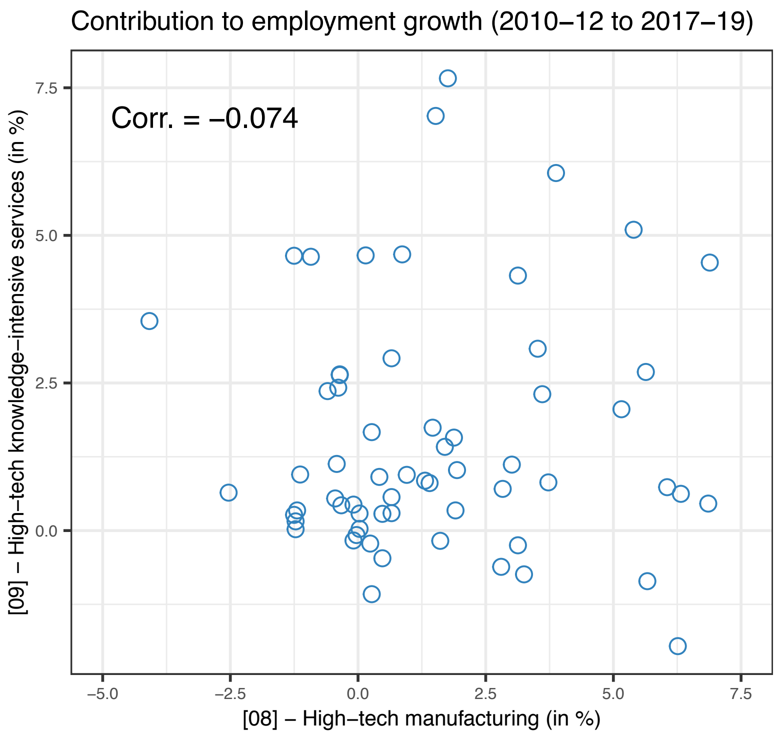
in high-tech industries, keeps innovating, with the two 'core' clusters trading with each other. The regions across the two clusters are strongly connected by input-output relations, as well as by geographical proximity. Despite the stagnant employment dynamics of the 'declining core', its regions are an important source of labour and high-tech inputs for the 'consolidated core'.

Similarly, the second group of clusters is led by the 'emerging cities', which the remaining two clusters depend on, albeit in different ways. The cluster of 'declining peripheries' provides 'emerging cities' with both labour force — as suggested by its stagnant *local* employment — and high-tech inputs produced at low unit labour costs, as these regions themselves experience a decline in wage shares and sluggish high-tech wages rates. The 'CEE factories' provide low unit labour cost inputs to the 'emerging cities', and in turn depend on the latter — *and* on the 'consolidated core' — for their own inputs, evincing a dense process of offshoring. At the same time, the 'emerging cities' depend on both the 'declining peripheries' *and* the 'consolidated core' as their main source of low cost employment and high-tech inputs, respectively, articulating a *multi-layered* core-periphery structure.

It is not clear whether this arrangement will constitute a virtuous dynamics, or if these three clusters (3, 4 and 5) may risk to decline, depending on the extent to which regions in the 'emerging cities' innovate, compete and maintain the current driving role for the peripheries of Europe through their high-tech expansion.

In this regard, it is noticeable the geographical divide *within* 'emerging cities' when comparing the asymmetry in employment growth contribution by type of high-tech sector. Most cluster regions from Central/Northern Europe contribute relatively more to high-tech manufacturing (`AT1`, `DE3`, `IE0`, `HU1`), whereas Southern European regions contribute relatively more (or even only to) to high-tech knowledge intensive services (`ES3`, `ES5`, `ITC`, `ITH`, `ITI`, `PT1`). This is particularly relevant because regional contributions to high-tech employment growth by industry type are, essentially, uncorrelated, as depicted in Figure 4. Hence, strong complementarities between high-tech manufacturing and service sectors are the exception, rather than the rule, so path-dependency in regional specialisation patterns may be expected.

Figure 4: High-tech manufacturing and knowledge-intensive services

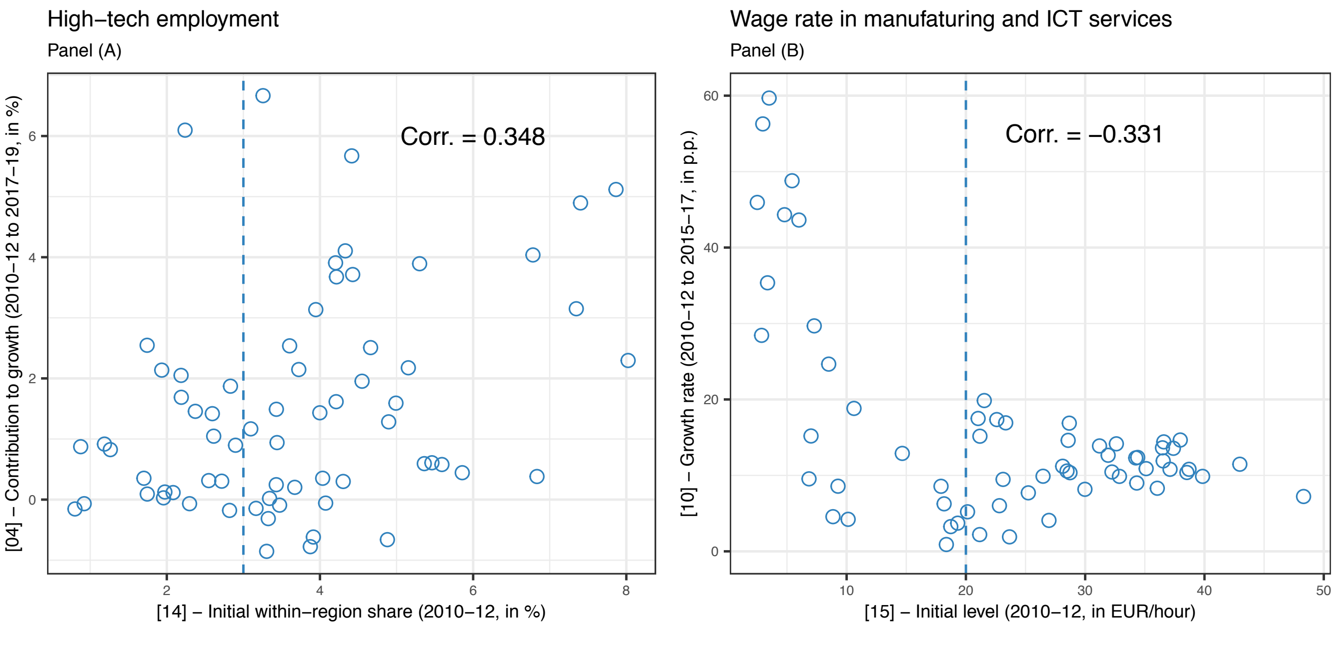


Source: Own elaboration based on EUROSTAT data and EU-REGIO database. *Notes*: variable numbers correspond to those specified in Table 1. The Pearson correlation coefficient is included.

Although both play a centripetal role with respect to their neighbouring clusters, the 'consolidated core' and the 'emerging cities' seem to follow different strategies to grow, attract and generate high-tech employment. Regions in the 'consolidated core' also increase high-tech wages and the regional wage share, whereas regions in the 'emerging cities' do not sufficiently catch-up in terms of wage rate growth with the 'core', reduce their wage share, and attract employment from regions with relatively low unit labour costs.

We observe inequalities emerging within regions in the 'emerging cities', 'declining peripheries' and 'CEE factories', in connection to their higher contribution to high-tech employment growth. Starting from relatively low wage shares and rates, most regions in these clusters experience a decline in the wage share (except the 'CEE factories' that cannot go any lower) and a relatively low increase in high-tech sector wages with respect to the European average and with respect to their trading partners. Within the 'CEE factories', where high-tech sector wages increase rapidly, inequality is likely created with respect to the wages in other sectors.

Figure 5: Convergence versus Cumulative Dynamics



Source: Own elaboration based on EUROSTAT data and EU-REGIO database. *Notes*: variable numbers correspond to those specified in Table 1. The Pearson correlation coefficient is included.

In this regard, the catch-up process with leading regions suggests the combination of two mechanisms at work. As depicted in Panel (A) of Figure 5, for initial high-tech employment shares *below* 3%, a convergence-type of mechanism seems to be operating but, above this threshold, a Kaldorian mechanism of cumulative dynamics seems more plausible, where initial shares are positively correlated with growth contributions. Notably, Panel (B) of Figure 5 suggests a similar configuration for high-tech wage rates: regions with an initial hourly wage rate *below* €20/hour have a faster rate of wage growth, whereas for those with a higher initial wage rate, a positive relationship between the initial wage level and its growth rate is observed.

Therefore, for both high-tech employment quantities and costs, convergence mechanisms operate up to a threshold, from where path-dependent, cumulative dynamics take hold. If this is the case, the possibility of European regions catching up — on the basis of high-tech sectoral upgrading — risks to remain an unfulfilled aim.

4 Concluding Remarks

The paper has investigated high-tech employment and wage rate dynamics across 67 European NUTS-1 regions during the 2010-19 period, i.e. between the aftermath of the Global Financial Crisis (2007-09) and before the unleashing of the Covid-19 pandemic (2020). Combining hierarchical clustering with a 'trade-aware' shift-share decomposition, the paper has offered a novel angle to identify and map European regional inequalities. A fractal structure emerges, that entails differences in concentration of high-tech sectors, highly skilled jobs and innovation performance.

Our empirical strategy led to the identification of 5 inter-country regional clusters: 'consolidated core', 'declining core', 'emerging cities', 'declining peripheries' and 'CEE factories'.

Most importantly, though — as the cluster labelling suggests — a multi-layered core-periphery structure emerges by considering the inter-regional high-tech input trade network. First, while the stagnant employment dynamics in the 'declining core' suggests that it loses jobs to the 'consolidated core', the latter pulls the former by absorbing its high-tech inputs. Second, a further core-periphery layer is represented by the trade links between the 'emerging cities' and both the 'declining peripheries' and 'CEE factories'. The former similarly pulls the two latter, in terms of attracting labour force ('declining peripheries') and sustaining high-tech input demand ('CEE factories').

In the first case, though, inter-regional trade between clusters at the innovative 'core' of the EU is able to leverage on the leading regions of the 'consolidated core' to support regions within the 'declining core'. In the second case, inter-regional trade does not (yet) seem to represent a learning or catching up opportunity for neither the 'declining peripheries' nor the 'CEE factories'.

Hence, so far, the dynamics between 'emerging cities' and their peripheries represents a different, less sustainable model. The limited extent of convergence-type dynamics in high-tech wage rates — coupled with regional wage share decline — suggests that 'emerging cities' offer less prospects for wage progression to its trade partners, but also to some of its own regions.

This poses a challenge to EU cohesion policies. Not only should they address the well known (and largely explored) EU North-South and West-East divides, but also the more complex layers of inequalities within each of these blocks, that our findings identify, and that might require a more complex, indeed 'place sensitive' (Iammarino et al., 2020) strategy.

Indeed, the challenges for implementing the new EU Cohesion policy legislative package 2021-27 are not only due to the aftermath of the Covid-19 pandemic and its risks for social cohesion. Rather, we argue, because of the structural, ingrained nature of EU regional asymmetries, which innovation seems in some cases to exacerbate, the challenges to 'fill [cohesion policy] with content and prioritise the investments'[17] are linked to the risks of (trade-specialisation) traps. Re-balancing the multiple layers of asymmetries that emerge from our analysis would require also inter-regional 'trade-sensitive' industrial and innovation policies.

In summary, we trust that the exhaustive, fine-grained picture of EU regional recurring asymmetries identified here helps addressing not only the relatively well known North-South and East-West imbalances, but also the most hidden ones, i.e. the persistence of relatively weak regions within strong areas. This supports the narrative underpinning the need of supporting 'left behind' places, and, we argue, with instruments that are sensitive to the intertwined dynamics between regional innovation and trade-specialisation.

Disclosure statement

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

[17] As stated by the Commissioner for Cohesion and Reforms, Elisa Ferreira, in welcoming the political agreement over the new EU Cohesion policy legislative package 2021-2027. For details, see https://ec.europa.eu/newsroom/regio/items/697648.

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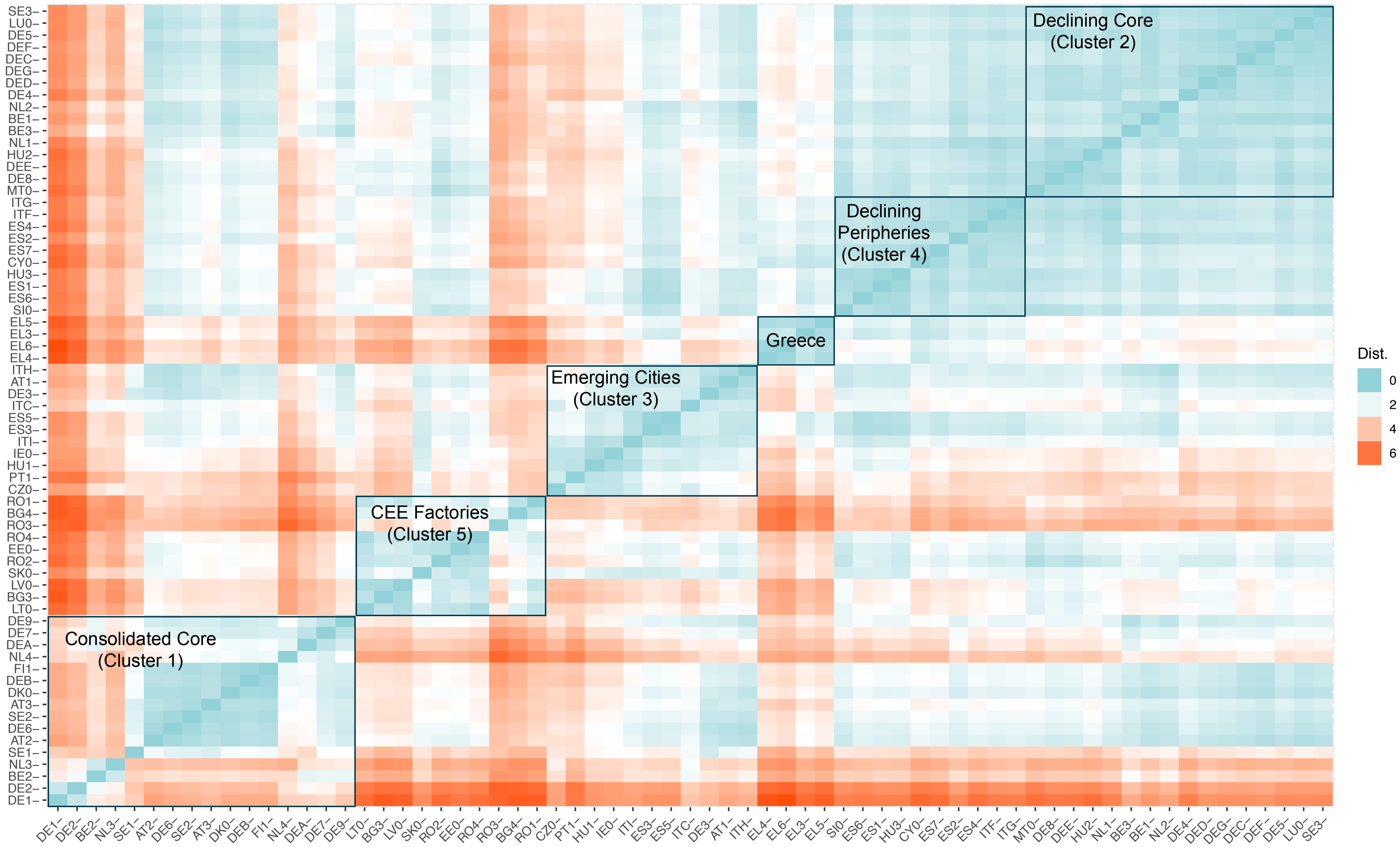
A Additional tables and figures

Table 5: Regional NUTS-1 Codes

NUTS-1 Code	Country	Regional Descriptor
AT1	Austria	Ostosterreich
AT2	Austria	Sudosterreich
AT3	Austria	Westosterreich
BE1	Belgium	Brussels-Capital Region
BE2	Belgium	Vlaams Gewest
BE3	Belgium	Region Wallonne
BG3	Bulgaria	Severna I Yugoiztochna
BG4	Bulgaria	Yugozapadna I Yuzhna Tsentralna
CY0	Cyprus	Kypros
CZ0	Czechia	Ceska Republika
DE1	Germany	Baden-Wurttemberg
DE2	Germany	Bayern
DE3	Germany	Berlin
DE4	Germany	Brandenburg
DE5	Germany	Bremen
DE6	Germany	Hamburg
DE7	Germany	Hessen
DE8	Germany	Mecklenburg-Vorpommern
DE9	Germany	Niedersachsen
DEA	Germany	Nordrhein-Westfalen
DEB	Germany	Rheinland-Pfalz
DEC	Germany	Saarland
DED	Germany	Sachsen
DEE	Germany	Sachsen-Anhalt
DEF	Germany	Schleswig-Holstein
DEG	Germany	Thuringen
DK0	Denmark	Danmark
EE0	Estonia	Eesti
EL3	Greece	Attiki
EL4	Greece	Nisia Aigaiou, Kriti
EL5	Greece	Voreia Ellada
EL6	Greece	Kentriki Ellada
ES1	Spain	Noroeste
ES2	Spain	Noreste
ES3	Spain	Comunidad De Madrid
ES4	Spain	Centro (Es)
ES5	Spain	Este
ES6	Spain	Sur
ES7	Spain	Canarias
FI1	Finland	Manner-Suomi
HU1	Hungary	Kozep-Magyarorszag
HU2	Hungary	Dunantul
HU3	Hungary	Alfold Es Eszak
IE0	Ireland	Ireland
ITC	Italy	Nord-Ovest
ITF	Italy	Sud
ITG	Italy	Isole
ITH	Italy	Nord-Est
ITI	Italy	Centro (It)
LT0	Lithuania	Lietuva
LU0	Luxembourg	Luxembourg
LV0	Latvia	Latvija
MT0	Malta	Malta
NL1	Netherlands	Noord-Nederland
NL2	Netherlands	Oost-Nederland
NL3	Netherlands	West-Nederland
NL4	Netherlands	Zuid-Nederland
PT1	Portugal	Continente
RO1	Romania	Macroregiunea Unu
RO2	Romania	Macroregiunea Doi
RO3	Romania	Macroregiunea Trei
RO4	Romania	Macroregiunea Patru
SE1	Sweden	Ostra Sverige
SE2	Sweden	Sodra Sverige
SE3	Sweden	Norra Sverige
SI0	Slovenia	Slovenija
SK0	Slovakia	Slovensko

Source: Own elaboration based on EUROSTAT

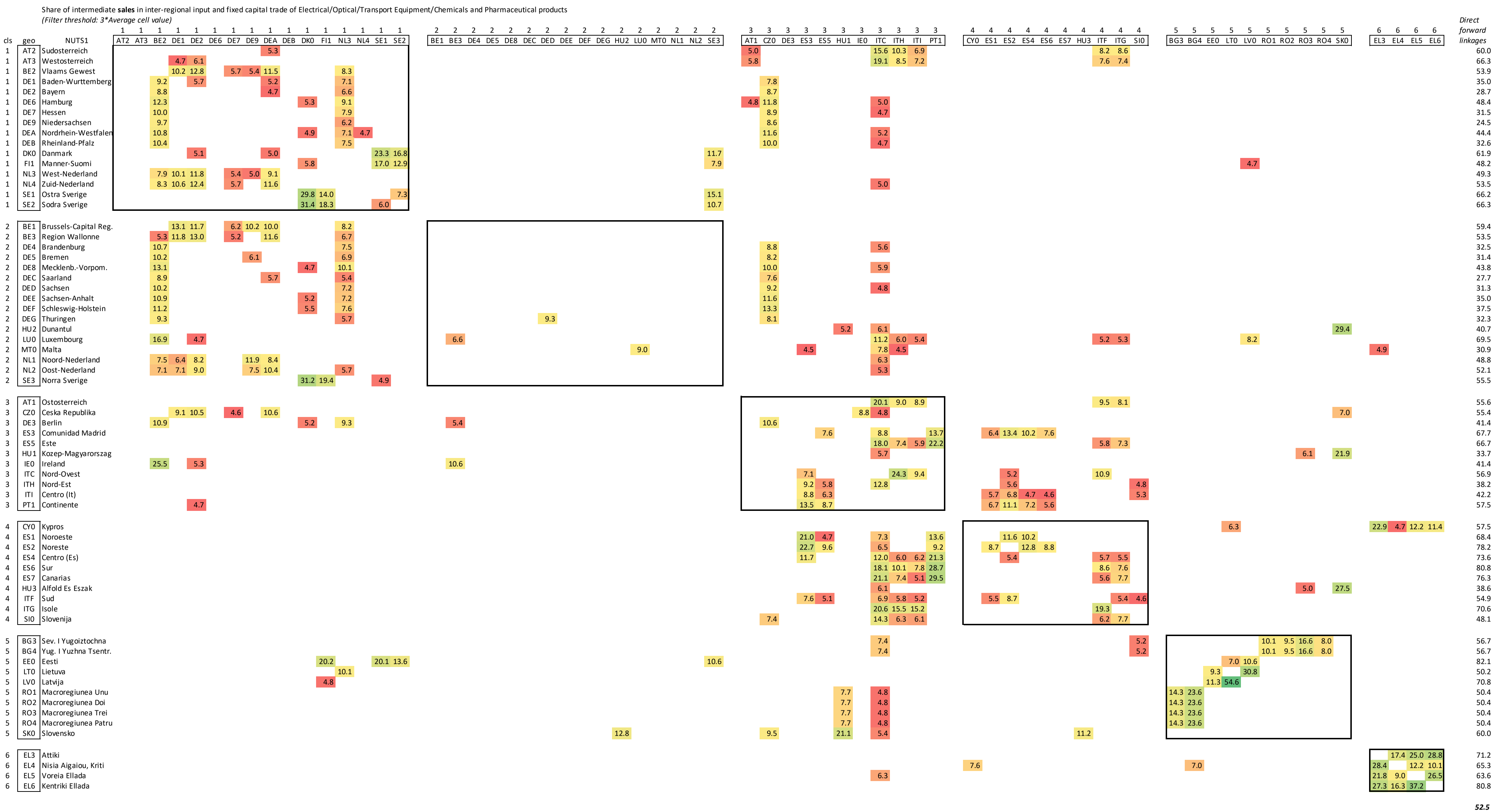
Figure 6: Distance matrix $\mathbf{\Gamma} = [\delta_{rs}]$ between European NUTS-1 regions



Source: Own elaboration based on EUROSTAT data and EU-REGIO database.
Notes: Regional NUTS-1 codes are described in Appendix A, Table 5.

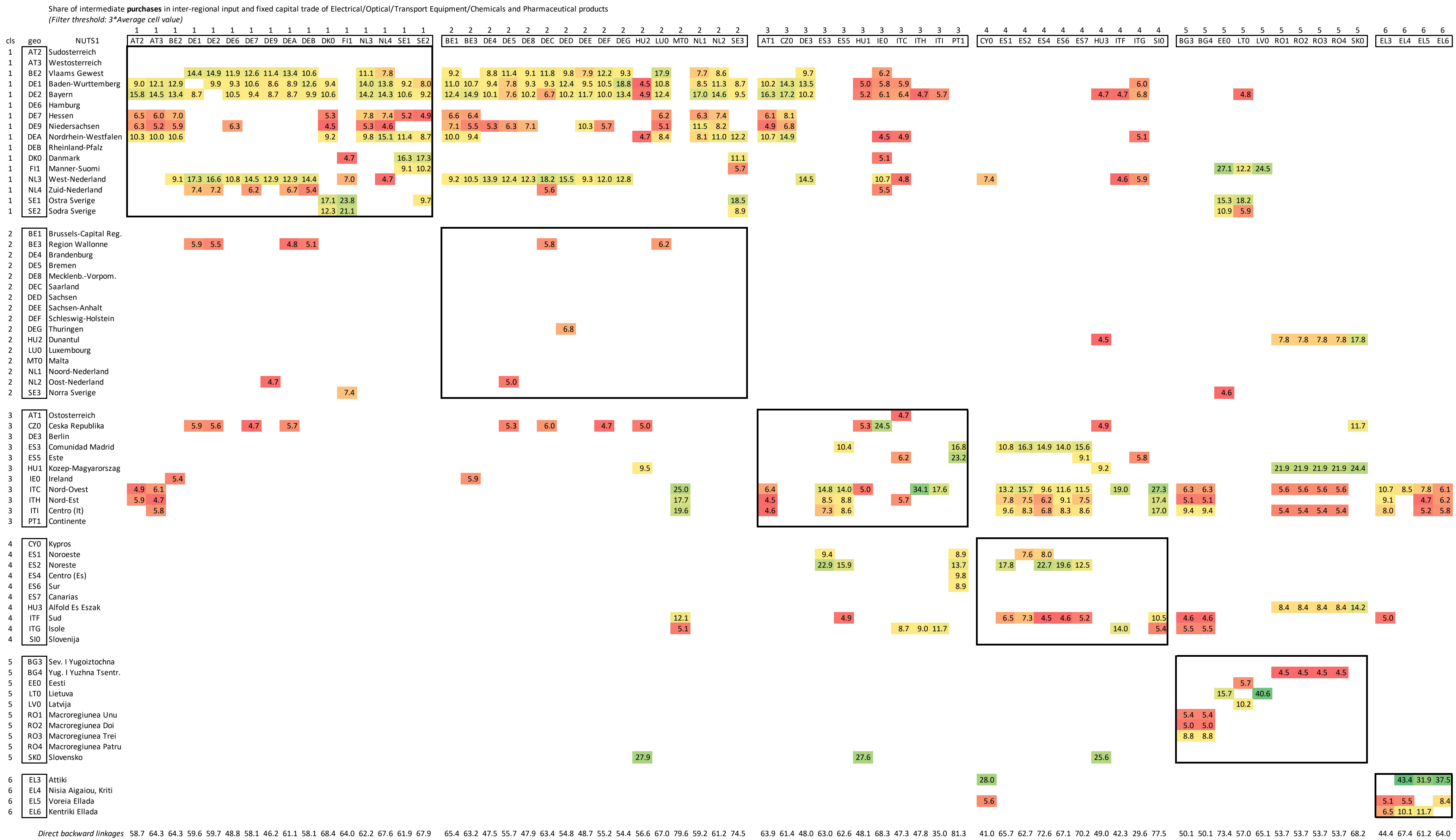
The colour intensity of each cell represents the regional bilateral distance δ_{rs}, computed according to (11).

Figure 7: Direct Forward Linkage Coefficients (d_{rs})



Source: Own elaboration based on EUROSTAT data and EU-REGIO database. Notes: Regional NUTS-1 codes are described in Appendix A, Table 5. Direct forward linkage coefficients d_{rs} have been computed according to (4). Only those coefficients higher than $3 \times \text{mean}(d_{rs})$ are displayed.

Figure 8: Direct Backward Linkage Coefficients (a_{rs})



Source: Own elaboration based on EUROSTAT data and EU-REGIO database. Notes: Regional NUTS-1 codes are described in Appendix A, Table 5. Direct backward linkage coefficients a_{rs} have been computed according to (2). Only those coefficients higher than $3 \times \text{mean}(a_{rs})$ are displayed.

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