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Abstract

This paper studies the role of complementary interregional value chain linkages in functional upgrading and downgrading in global value chains in EU regions. It adopts an evolutionary approach to assess functional upgrading and downgrading using relatedness and economic complexity metrics. The empirical analysis of 199 EU regions between the years 2000-2010 shows that, while local capabilities remain crucial, complementary interregional value chain linkages increase (decrease) the likelihood of functional upgrading (downgrading) in GVCs. Regions engaged in GVCs in which partner regions offer complementary capabilities are more likely to specialise in more complex functions and to retain such specialisations over time. By doing so, this paper proposes a new theoretical-analytical framework to identify partner regions that can offer complementary capabilities in GVCs.

JEL classifications: F14, F63, O19, R11, R12

Keywords: Global value chains, upgrading/downgrading, interregional linkages, complementary capabilities, EU regions

1.- INTRODUCTION

The spatial fragmentation of production processes has fostered the rise of global value chains (GVCs) and functional specialisation in trade of countries and regions (Gereffi, 1999; Los et al., 2015; Timmer et al., 2015, 2019; Antràs, 2020). Regions differ in the production functions they develop in GVCs: while some regions concentrate on headquarters and R&D facilities, other regions have become locations of factories and logistic hubs (Gereffi et al., 2005; Crescenzi et al., 2014; Blažek, 2016). Since different production functions are associated with different levels of value added, a crucial challenge for regions is to functionally upgrade in GVCs, and to avoid downgrading (Humphrey & Schmitz, 2002; Giuliani et al., 2005; Pietrobelli & Rabellotti, 2007, 2011; Morrison et al., 2008; Iammarino & McCann, 2013; Timmer & Pahl, 2021).

To climb the ladder of functions in GVCs, regions can leverage on their own local capabilities. There is strong evidence in Evolutionary Economic Geography (EEG) that highlights the importance of local capabilities for regional diversification (Frenken et al., 2007; Hidalgo et al., 2007, 2018; Neffke et al., 2011; Rigby, 2015; Boschma, 2017; Petralia et al., 2017; Balland et al., 2019). However, regions can also exploit non-local sources of knowledge through the inflow of MNEs (Cantwell & Iammarino, 2000, 2005; Crescenzi et al., 2015, 2022; Neffke et al. 2018; Elekes et al., 2019), FDI (Crescenzi & Iammarino, 2017; Iammarino, 2018; Gagliardi et al., 2021) and high-skilled migrants (Breschi & Lissoni, 2009; Breschi et al., 2017, 2020; Miguelez and Moreno, 2018; Diodato et al., 2022; Morrison, 2023), among other mechanisms.

These non-local capabilities are particularly relevant in GVCs (Crescenzi & Harman, 2023). Regions are not isolated islands of production but they are rather connected through input-output linkages from which regions can learn (Storper, 1993; Gereffi, 1994, 1999; Pietrobelli & Rabellotti, 2007, 2011; De Marchi et al., 2018). Flows of intermediate products, services, and value added within and across value chains can act as knowledge pipelines, bringing new capabilities to regions (Bathelt et al., 2004; Maskell et al., 2006; Saliola & Zanfei, 2009; Morrison et al., 2013; Fusillo et al., 2024a, 2024b). Regions can benefit from participating in GVCs by learning from partner regions providing new capabilities (Frenken et al., 2023).

This paper highlights that GVCs act as a key source of non-local capabilities that may contribute to functional upgrading but may also prevent processes of functional downgrading in regions. However, we argue that value chain linkages *per se* might not matter, but rather value chain linkages with regions that offer complementary capabilities (Boschma and Iammarino, 2009; Balland and Boschma, 2021). That is, we suggest that linkages with regions with the same or unrelated functions in GVCs do not provide relevant capabilities from which regions can learn. Instead, we argue that linkages with regions that provide access to functions in GVCs that are related but missing in the region can effectively trigger the building of new capabilities, and foster functional upgrading and prevent functional downgrading to take place (Boschma, 2024; Sebestyén et al., 2024).

This paper presents an empirical analysis of the role of complementary interregional linkages on functional upgrading and downgrading in GVCs in 199 EU regions between the years 2000-2010. Results show indeed that complementary interregional value chain linkages are associated with a higher likelihood of functional upgrading in GVCs. Regions participating in GVCs in which partner regions offer complementary capabilities are more likely to specialise in more complex functions. On the other hand, complementary interregional value chain linkages are associated with a lower likelihood of functional downgrading in GVCs. Regions participating in GVCs in which partner regions offer complementary capabilities are less likely to lose their specialisation in complex functions. Furthermore, results highlight that local capabilities are also crucial for both promoting functional upgrading and avoiding functional downgrading. The effect of local capabilities turns out to be stronger than the one of inter-regional complementary linkages. What is more, the importance of non-local complementary capabilities decreases when regions already have strong local capabilities, pointing towards a substitution effect between the two.

These findings respond to a need echoed lately by scholars to integrate more tightly the EEG and GVCs literatures (Rodríguez-Pose, 2021; Yeung, 2021, 2024; Boschma, 2022, 2024; Lee, 2024). This paper highlights how local and non-local complementary capabilities are crucial to better understand the evolution of GVCs, such as functional upgrading and downgrading (De Propris, 2024; Poon, 2024). Furthermore, it underlines the role of interregional linkages in regional diversification and new path development dynamics, which has been understudied until recently (Boschma, 2017; Trippl et al., 2018; Whittle et al., 2020; Balland & Boschma, 2021). Finally, this paper provides a framework for identifying EU partners regions providing complementary capabilities in GVCs. Such a framework can identify untapped learning opportunities for regions involved in GVCs (Radosevic & Stankova, 2015; Giustolisi et al., 2023). This can contribute to enhancing interregional collaboration in the EU, which still remains underexploited (Bachtrögler-Unger et al., 2023).

The rest of this paper is structured as follows. Section 2 includes an overview of the relevant literature. Section 3 explains the dataset and the main variables used. Section 4 describes the empirical framework. Section 5 discusses the results. Section 6 concludes, outlines some potential public policy implications, and suggests venues for future research.

2.- INTERREGIONAL LINKAGES AND (DOWN-) UPGRADING IN GVCs

Around 70% of international trade worldwide involves global value chains (OECD, 2023). Regions engage in GVCs by specialising in certain functions along production processes, rather than producing products and services from its conception to its delivery to final consumers (Gereffi, 1999; Los et al., 2015; Timmer et al., 2015, 2019; Antràs, 2020; Coveri & Zanfei, 2023). Different functions produce different levels of value added: R&D and management activities are associated with higher value added than assembling or packaging (Gereffi et al., 2005; Crescenzi et al., 2014; Blažek, 2016). A key challenge for regions in GVCs is to move up towards high value added functions and to retain them over time (Humphrey & Schmitz, 2002; Giuliani et al., 2005; Pietrobelli & Rabellotti, 2007, 2011; Morrison et al., 2008; Iammarino & McCann, 2013; Plank & Staritz, 2015; Blažek, 2016; Pipkin & Fuentes, 2017; Kano et al., 2020; Timmer & Pahl, 2021).

Recent contributions on GVCs have started to apply the regional diversification framework (Hidalgo et al. 2007; Neffke et al. 2011; Boschma 2017; Hidalgo et al. 2018) to GVC upgrading and downgrading dynamics (Koch, 2021; Boschma 2022, 2024; Hernández-Rodríguez et al., 2023; Sebestyén et al., 2024). These studies highlight that local related capabilities are crucial to understand the evolution of GVCs.[1] They also have introduced revealed economic complexity metrics to identify upgrading and downgrading in GVCs (Hernández-Rodríguez et al. 2023), instead of using predefined functions in GVCs, as done in the smiling curve literature (Mudambi, 2008; Shin et al., 2012; Stöllinger, 2021; Capello & Dellisanti, 2024). Using a relatedness/complexity framework on GVC (Boschma, 2022, 2024), Hernández-Rodríguez et al. (2023) found that local capabilities enhance the chances of functional upgrading and lower the chances of functional downgrading in regions.

However, much less is known about the role of interregional linkages in regional diversification (Fold, 2014; Boschma, 2017; Trippl et al., 2018; Whittle et al., 2020; Balland and Boschma, 2021).These interregional linkages can take several forms through the participation of MNEs (Cantwell & Iammarino, 2000, 2005; Crescenzi et al., 2015, 2022; Elekes et al., 2019), FDI (Crescenzi & Iammarino, 2017; Iammarino, 2018; Gagliardi et al., 2021) and inflow of high-skilled migrants (Breschi & Lissoni, 2009; Breschi et al., 2017, 2020; Miguelez and Moreno, 2018; Diodato et al., 2022; Morrison, 2023), among others. The GVC and international trade literatures have shown how input-output relationships through value added exchanges in production processes can act as global knowledge pipelines (Dollar et al., 1988; Grossman and Helpman, 1991, 1993; Gereffi, 1994, 1999; Kaplinsky, 2000; Gereffi and Kaplinsky, 2001; Humphrey and Schmitz, 2002; Keller, 2004; Altenburg, 2006; Pietrobelli and Rabellotti, 2007, 2011; Morrison et al., 2013). For example, Ivarsson & Alvstam (2011) showed how IKEA's suppliers use IKEA's technological support to upgrade their operational, duplicative, adaptive, and innovative capabilities. Caliari et al. (2023) explored the link between a country's position in the aerospace global value chain and the strength of its innovation system, underlying differences depending on which functions countries are specialised in. Delera et al. (2022) found that firm's participation in GVCs is positively associated with the adoption of Industry 4.0 technologies in developing countries.

In this vein, Morrison et al. (2008) proposed a framework to approach learning and innovation in global value chains based on the notion of technological capabilities. Taking an evolutionary approach, and following Lall (1992), they distinguish three different kinds of technological capabilities: investment, production, and linkage capabilities. While production capabilities can be understood as local capabilities, linkage capabilities mainly refer to the ability of being connected and absorb external knowledge from interregional linkages (Cohen & Levinthal, 1990). Hence, regions participating in GVCs can access non-local knowledge and trigger functional upgrading by learning from partner regions (Boschma, 2022, 2024; Frenken et al., 2023).

However, previous studies on interregional linkages have underlined that connectivity is not *per se* a sufficient condition for triggering regional diversification (Boschma & Iammarino, 2009; Balland & Boschma, 2021; Corrocher et al., 2024). These studies have rather underlined the importance of complementary interregional linkages: being connected to external sources of knowledge is not *per se* sufficient to acquire new capabilities. Regions might only benefit from interregional linkages when these linkages are complementary to existing capabilities already present in the region (Boschma & Iammarino, 2009; Balland & Boschma, 2021).

A similar point has been made by the GVC literature. Regional participation in global value chains will not be automatically translated into a transfer and acquisition of new capabilities (Giuliani et al., 2005; Pietrobelli and Rabellotti, 2007, 2011; Morrison et al., 2008, 2013). Participation in GVCs in which partner regions can offer complementary capabilities may have an impact. In this context, Mäkitie et al. (2022) have theorized complementarity formation mechanisms within and across technology value chains.

Following this logic, we formulate the following hypotheses.

Hypothesis 1a: Regions participating in GVCs in which partner regions offer complementary capabilities are more likely to specialise in new functions.

Hypothesis 1b: Regions participating in GVCs in which partner regions offer complementary capabilities are more likely to specialise in complex functions.

Hypothesis 2a: Regions participating in GVCs in which partner regions offer complementary capabilities are more likely to preserve their specialisation in functions.

Hypothesis 2b: Regions participating in GVCs in which partner regions offer complementary capabilities are more likely to preserve their specialisation in complex functions.

3.- DATA AND VARIABLES

3.1.- DATA AND FUNCTIONS IN GVCs

This paper studies the role of complementary interregional value chain linkages in functional upgrading and downgrading in EU regions. For such purpose, we proxy functions in GVCs using occupation-industry pairs. Examples of functions are 'office clerks in manufacturing and mining', 'drivers and mobile-plant operators in manufacturing and mining', and 'office clerks in financial intermediation'. While there are alternative views on how functions (and/or tasks) should be identified, similar approaches have been used in many contributions (Goos and Manning, 2007; Henning and Eriksson, 2021; Henning and Kekezi, 2023; Deegan et al., 2024).

We consider the exports of functions in GVCs as the exports of domestic value added generated by each function (occupation-industry pair). This computation roughly takes two steps, following Timmer et al. (2019) and Hernández-Rodríguez et al. (2023). First, input-output tables are used to map the gross export of goods and services from a region to the domestic value added generated by each industry. Subsequently, this value added is distributed across functions based on occupational and wage data. It is also important to highlight that functions' exports are not only from an exporting industry itself, but rather all domestic functions along the value chains. This is particularly important for functions in services, since most of their exported value added is rather embedded in the exports of goods.

The recently developed interregional input-output tables (e.g. Thissen et al., 2018; Huang & Koutroumpis, 2023) provide valuable sources to trace domestic value added in regional exports. This paper uses EUREGIO (Thissen et al., 2018) which contains information on input-output relationships for 249 regions from 24 European countries, 16 non-EU countries, a rest of the world section, and 14 industries for the period 2000-2010. While EUREGIO allows to compute the domestic value added content of gross exports and the bilateral value added flows across EU regions, uncovering functional specialisation requires labour data. For this purpose, we use Eurostat's microdata on occupations and wages from the European Union Labour Force Survey (EULFS) and the European Union Structure of Earnings Survey (EUSES). These two databases allow to compute the income share of each function across EU regions. First, we use EULFS to know how workers are distributed across occupations within each regional industry. Second, we use the median wage of each occupation in each regional industry derived from EUSES and multiply it with the number of workers taken from EULFS to compute the income shares across functions. Subsequently, using the income share of each function, the domestic value added content of gross exports is distributed across functions. This allows to trace the value added produced by each function (occupation-industry pair) in each region and time period.

However, it is important to highlight there are some incompatibilities between the datasets (EUREGIO, EULFS and EUSES). First, the matching between regions is not always possible between the three databases, leading to the loss of a small number of regions. Second, EUREGIO and EULFS are at NUTS-2 level, while EUSES is at NUTS-1. We assumed wages are homogeneous across NUTS-2 within NUTS-1 when computing occupational income shares. Third, due to changes in the categorisation of occupation (from ISCO-88 to ISCO-08) in EUSES, only data for the years 2002 and 2006 is used, assuming linear interpolation between these years and keeping fixed the values for the years before 2002 and after 2006. Considering that the EULFS only uses ISCO-88, and that there is not a perfect match between ISCO-88 and ISCO-08, only 2 digits ISCO-88 is used. Fourth, the industrial classification of EUREGIO was followed since it is more aggregated than in EULFS and EUSES. Finally, to overcome some missing values in EUSES, and to ensure that the functions have a minimum threshold of relevance in the economies of regions, we follow the same criteria as in Hernández-Rodríguez et al. (2023).[2]

The final database consists of a panel on domestic value added content of gross exports and interregional value added flows for 199 EU NUTS-2 regions and 77 functions (occupation-industry pairs) for the period 2000-2010.[3] It is completed with a set of control variables: GDP per capita, population density, patent applications, and an indicator for total GVC participation. All control variables are retrieved from Eurostat with the exception of the total GVC participation, which was taken from EUREGIO. Finally, to smooth out yearly fluctuations the data is divided into average matrices for 4 non-overlapping time windows (t = 2000-2001, 2002-2004, 2005-2007, 2008-2010).

3.2.- FUNCTIONAL SPECIALISATION, LOCAL CAPABILITIES AND COMPLEMENTARY INTERREGIONAL CAPABILITIES

Following Timmer et al. (2019), a Functional Specialisation Index (*FSI*) for each region *r*, function *s* and time *t* is computed as follows:

$$FSI_{rst} = \begin{cases} 1 & \text{if } \dfrac{f_{rt}^{s}/\sum_s f_{rt}^{s}}{\sum_r f_{rt}^{s}/\sum_r \sum_s f_{rt}^{s}} \geq 1 \\ 0 & \text{otherwise} \end{cases} \quad (1),$$

where f_{rt}^{s} represents the exports of functions in GVCs as defined in Section 3.1. The *FSI* is a binary variable measuring revealed comparative advantages, as in Balassa (1965) but based on functions in GVCs.

Regions move towards new functions in GVCs and exit from existing ones. As explained before, this evolution is unlikely to be random but rather path dependent in relation with local related capabilities and complementary interregional capabilities (Hidalgo et al., 2007; Neffke et al., 2011; Rigby, 2015; Balland et al., 2019). The first step is to compute the degree of relatedness between the 77 considered functions in GVCs, following Hidalgo et al. (2007):

$$\phi_{s_i,s_j,t} = \min\left\{P\left(FSI_{s_i,t} = 1 \middle| FSI_{s_j,t} = 1\right), P\left(FSI_{s_j,t} = 1 \middle| FSI_{s_i,t} = 1\right)\right\}, \quad (2)$$

The degree of relatedness (ϕ) between two functions (s_i, s_j) is computed by the minimum value of the pairwise conditional probability of a region being specialised (*FSI*=1) in a function given that it is also specialised in another one in period *t*, where the conditional probabilities are derived from the observational co-occurrence of the two functions in each region.

The second step it to regionalize these data and measure a relatedness density measure, after Hidalgo et al. (2007). The local relatedness density (LRD) for each region *r* and a particular function s_i at time *t* is obtained by adding all the relatedness values of the other functions that are related to s_i, and in which region *r* is specialized in (i.e. the dummy *FSI* equals to 1):

$$\text{Local Relatedness Density}_{r,s_i,t} = \frac{\sum_s FSI_{rst}\phi_{s,s_i,t}}{\sum_s \phi_{s,s_i,t}}. \quad (3)$$

Second, we measure the role of complementary interregional linkages for functional upgrading and downgrading. As previously discussed, complementary interregional linkages can complement existing local capabilities to move up and climb the ladder of functions in GVCs. Following a similar logic proposed by Balland and Boschma (2021) who used co-inventor linkages to measure complementary linkages, we use value added flows instead. We propose a new measure of complementary relatedness density for functions in GVCs. We compute a bilateral complementarity relatedness density (BCRD) that a region *r* can obtain from a trade partner *p* for a particular function s_i, which can be formulated as follows:

$$BCRD_{r,p,s_i,t} = \frac{\sum_{s \neq s_i} FSI_{p,s,t}\left(1 - FSI_{r,s,t}\right)\phi_{s,s_i,t}}{\sum_s \phi_{s,s_i,t}}. \quad (4)$$

BCRD is derived from functions in which the partner region p has a comparative advantage ($FSI_{pst} = 1$) in which region r is not specialised ($FSI_{rst} = 0$). This is the potential complementary effect that region *r* may obtain from its trade partner p. BCRD will be high if the partner region p is specialised in many functions s that are closely related with s_i, in which region r does not have a specialisation. BCRD will be zero when regions r and p have an identical pattern of functional specialisation, meaning there is no complementarity.

Since regions are differently connected to their partners in terms of input-output linkages, it is necessary to weight BCRD by the strength of such linkages. We weigh the BCRD by bilateral value added trade flows (VAT), such that the complementarity relatedness density for a function s_i that region *r* derives from all its trade partners is given by:

$$\text{Complementary relatedness density}_{r,s_i,t} = \sum_{p \neq r} \frac{VAT_{prt}}{\sum_{p \neq r} VAT_{prt}} BCRD_{r,p,s_i,t} \quad (5)$$

Value-added trade is more relevant than gross exports because we want to capture the knowledge a region can learn from trade-related value-adding activities conducted by its trade partner. To be specific, we measure value added trade by the domestic value added contributed by the partner region p that is embedded in its gross export to region *r*. Our measure is in analogy with the concept of a country's domestic value added in gross export (see Koopman et al., 2014, Timmer et al., 2019), but in a bilateral setting. With EUREGIO data, we use a standard input-output approach to derive bilateral value added trade flows between regions:

$$VAT_{prt} = \boldsymbol{v}'_{pt}\left(I - \boldsymbol{A}_{pt}\right)^{-1}\boldsymbol{E}_{prt}, \quad (6)$$

Assuming there are in total G industries. $\boldsymbol{E}_{prt}$ is a G-element vector denoting gross export of each kind of goods and services from region p to r in year t. $\boldsymbol{A}_{pt}$ is the domestic input-output table of region p with a dimension of G x G, such that $\left(I - \boldsymbol{A}_{pt}\right)^{-1}$ is the Leontief-inverse which maps the gross export flows to required domestic gross output production in each industry. $\boldsymbol{v}_{pt}$ is a G-element vector for the value added to gross output ratio in each industry.

It should be noticed that, preferably, the complementarity relatedness density for a region should be computed from all its potential trade partners in the entire world. We only have functional data for 199 NUTS regions in the EU (see appendix I). As a result, we miss out part of the complementarity related density, and the indices will be underestimated if a region has strong linkages with non-EU countries and EU regions for which data is not available. We will mitigate this issue by including region and function fixed effects in the regressions. We believe that the underestimation is consistent for each region and can be alleviated by the fixed effects, since the composition of regions' trade partners is largely stable over time.

3.3.- UPGRADING, DOWNGRADING AND ECONOMIC COMPLEXITY

Our aim is to investigate the influence of the local relatedness density and the complementary relatedness density on the evolution of functional specialisations of regions. We will perform regression analyses (in Section 4) on the dependent variables that captures regions' entrance/exits from functions, as well as the regions' functional upgrading and downgrading.

Functional diversification refers to the entry of new functions in general. Formally, a region enters into a new comparative advantage which it did not possess in the previous time window:

$$\text{Diversification}_{rst} = \begin{cases} 1 & \text{if } FSI_{rst} = 1 \text{ and } FSI_{rs,t-1} = 0 \\ 0 & \text{if } FSI_{rst} = 0 \text{ and } FSI_{rs,t-1} = 0 \end{cases} \quad (7)$$

In a similar vein, functional exit is defined as a loss of a specialization in a function, in which the region was specialised in the previous time window.

$$\text{Exit}_{rst} = \begin{cases} 1 & \text{if } FSI_{rst} = 0 \text{ and } FSI_{rs,t-1} = 1 \\ 0 & \text{if } FSI_{rst} = 1 \text{ and } FSI_{rs,t-1} = 1 \end{cases} \quad (8)$$

We also analyse a refined subset to capture the upgrading and downgrading of GVC functions in each region. For this purpose, we employ economic complexity metrics. Economic complexity has been shown to positively correlate with economic growth of countries and regions (Hidalgo & Hausmann, 2009; Pintar & Scherngell, 2020; Mewes & Broekel, 2022; Rigby et al., 2022). Moving into more (less) complex functions can then be understood as functional upgrading (downgrading) in GVCs.

Such economic complexity indicators are computed by the method of reflections (Hidalgo and Hausmann, 2009). We compute a set of FSI_{rs} based on the average f_{rt}^{s} between the years 2000-2010, to construct an *R* x *S* matrix (*R* is the number of regions and *S* functions), ***M***, indicating whether a region on average have a comparative advantage in a function over the period. We compute the number of functions in which each region has a comparative advantage (diversity), and how common are functional specialisations across regions (ubiquity):

$$\text{Diversity}_r = K_{r0} = \sum_s M_{rs} \quad (9)$$

$$\text{Ubiquity}_s = K_{s0} = \sum_r M_{rs} \quad (10)$$

Then, the economic complexity of both regions (FCI_r) and functions (FCI_s) can be obtained using the following iteration of *n* rounds.

$$FCI_r = K_{rn} = \frac{1}{K_{r0}} \sum_s M_{rs} K_{s,n-1} \quad (11)$$

$$FCI_s = K_{sn} = \frac{1}{K_{s0}} \sum_r M_{rs} K_{r,n-1} \quad (12)$$

We exploit the differences in the economic complexity of functions (FCI_s) to empirically define upgrading and downgrading in GVCs. Functional upgrading means a region enters into a new function *s* with a higher complexity than the previous national average. To be more precise, $FCI_s > \overline{FCI}_{r,t-1}$, where $\overline{FCI}_{r,t-1} = \sum_s (FCI_s \times FSI_{rs,t-1}) / \sum_s FSI_{rs,t-1}$ is the average of the FCI_s in which the region was specialised in in the previous period. Therefore, in the regression analyses we are interested in the probability for a region to upgrade to the new functions s in the set of $FSI_{rs,t-1} = 0$ and $FCI_s > \overline{FCI}_{r,t-1}$, formally defined as:

$$\text{Upgrading}_{rst} = \begin{cases} 1 & if\ FSI_{rst} = 1, FSI_{rs,t-1} = 0, and\ FCI_s > \overline{FCI}_{r,t-1} \\ 0 & if\ FSI_{rst} = 0, FSI_{rs,t-1} = 0, and\ FCI_s > \overline{FCI}_{r,t-1} \end{cases} \quad (13)$$

Similarly, we will also test the probability of downgrading, i.e. the loss of a specialization in a function with a higher-than-average complexity:

$$\text{Downgrading}_{rst} = \begin{cases} 1 & if\ FSI_{rst} = 0, FSI_{rs,t-1} = 1, and\ FCI_s > \overline{FCI}_{r,t-1} \\ 0 & if\ FSI_{rst} = 1, FSI_{rs,t-1} = 1, and\ FCI_s > \overline{FCI}_{r,t-1} \end{cases} \quad (14)$$

3.4.- AN ILLUSTRATIVE EXAMPLE OF COMPLEMENTARITY RELATEDNESS DENSITY IN THE ITALIAN REGION OF FRIULI-VENEZIA-GIULIA

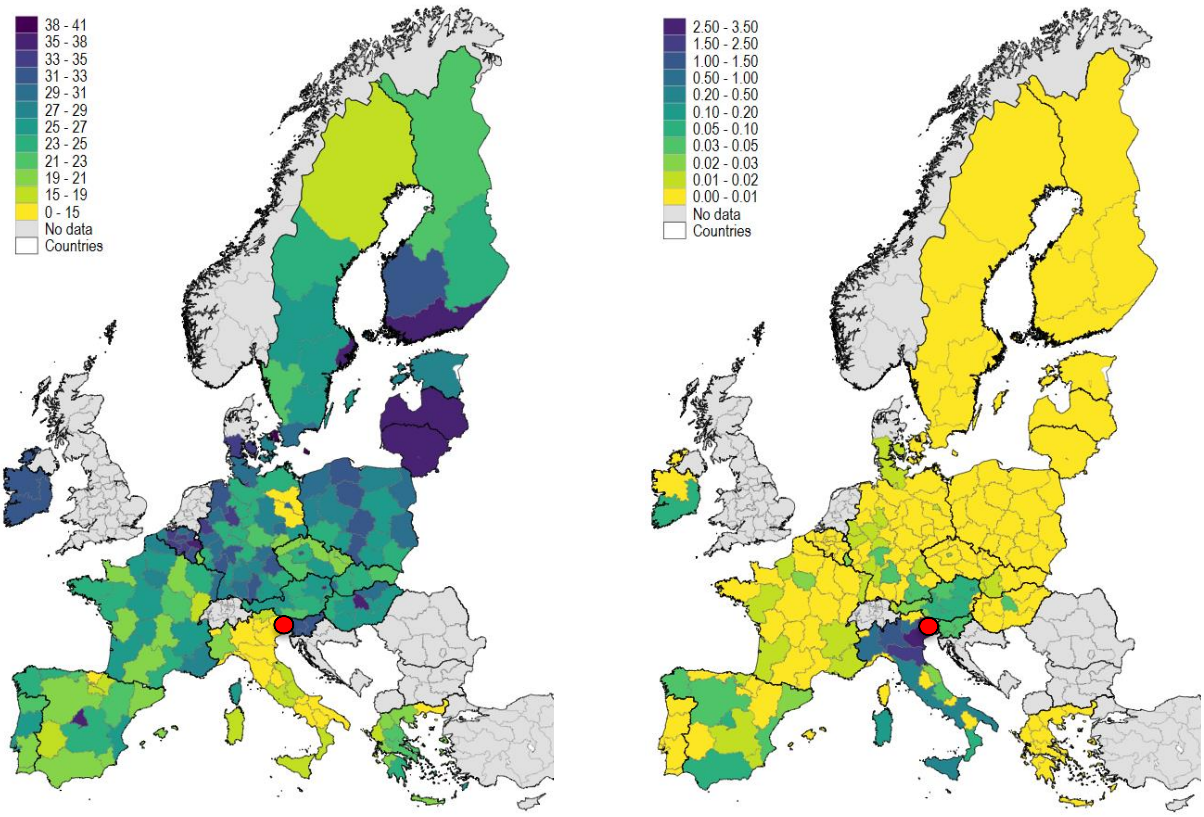
We illustrate the concept of complementary relatedness density in GVCs by presenting a particular example of the Italian region of Friuli-Venezia Giulia. The logistics industry is crucial in the region since Trieste has the biggest port of Italy in terms of annual cargo tonnage. However, the region is primarily specialised in low complex functions in the logistics industry, such as customer services clerks, sales and services elementary occupations, and drivers and mobile-plant operators. In this vein, a more preferable functional specialisation in the logistics industry could be physical, mathematical and engineering science professionals, which is the most complex function inside the logistics industry.

To move from more manufacturing-alike functions towards more science-related functions, the region could leverage on their own local capabilities, but also on complementary capabilities in partner regions in GVCs. In the map on the left hand-side of Figure 1, the bilateral complementarity relatedness density (BCRD) is shown, meaning the potential complementary relatedness density that could be offered by all EU regions. It represents the functions that are related to physical, mathematical and engineering science professionals in logistics in which Friuli-Venezia Giulia is not specialised but in which EU regions are specialized to a greater or lesser extent. The higher its value, the higher the level of complementary capabilities in EU regions that are missing in Friuli-Venezia Giulia. BCRDs are generally low for Italian regions. The highest complementarities can be found in regions such as Antwerp, Jutland, Slovenia, Helsinki and the Baltic countries which are also important regions in maritime logistics.

While these regions are in the position to potentially offer the highest complementary capabilities, the extent to which Friuli-Venezia Giulia could benefit from them depends on the strength of GVC linkages. As it happens in trade, national borders and geographical proximity matter: Friuli-Venezia Giulia tends to trade more inside Italy and with its neighbouring regions. This is depicted in the map on the right-hand side of Figure 1, which shows the complementary relatedness densities once weighted by the share of value added imported from each region (inside the summation in equation 5). It can be observed that, compared to the left map, other Italian and Austrian regions are playing a more prominent role in providing complementary capabilities, once considering the existing real GVC linkages. While some Irish, Danish and

Spanish regions remain important, others like Antwerp, Latvia, and Lithuania fade, due to their low value added trade with Friuli-Venezia Giulia.

Figure 1.- BCRD (left) and the real contribution to the complementary relatedness density (right) for physical, mathematical and engineering science professionals in logistics for Friuli-Venezia Giulia in the period 2008-2010



This framework for mapping complementary capabilities through the concept of complementary relatedness density can be developed for every region and every function in GVCs. This complementary relatedness density measure can provide an illustration of what potential EU partner regions can leverage complementary capabilities to foster functional upgrading in regions, and to avoid functional downgrading in global value chains.

3.5.- DESCRIPTIVE STATISTICS

Table 1 displays the main descriptive statistics of the variables. The number of observations for upgrading, diversification, downgrading, and exit, is lower than for the rest of variables, since if a region is already (-un)specialised in a function, it cannot become (-un)specialised again in the subsequent period. Furthermore, it is important to highlight that upgrading and downgrading consists of a subset of diversification and exit, respectively. Therefore, the number of observations is notably lower in the case of upgrading and downgrading than for diversification and exit, respectively.[4] Finally, some observations are missing for the control variable on population density since the data was not available for some regions in some years.

Table 1.- Descriptive statistics

Variables	N	Mean	SD	Min	Max
FSI	60,368	0.404	0.491	0	1
FCI_s	60,368	0.228	2.255	-3.8	5.313
Local rel. dens.	60,368	0.416	0.078	0	0.686
Compl. rel. dens.	60,368	0.14	0.032	0.031	0.315
Upgrading	15,238	0.141	0.348	0	1
Diversification	26,960	0.148	0.355	0	1
Downgrading	8,833	0.229	0.421	0	1
Exit	18,239	0.216	0.411	0	1
GDP per capita	60,368	22,322.961	8,896.779	6,533.932	68,114.922
Population dens.	56,133	286.387	679.43	3.3	6,744.633
GVC participation	60,368	0.636	0.088	0.341	0.838
Patents	60,368	684.168	1,242.329	0	9,324.06

4.- EMPIRICAL FRAMEWORK

We use fixed effect linear probability models (LPMs), because all the dependent variables are dummy variables.[5] These models have the following general specification:

$$Func\ Upg_{rst} = \alpha + \beta_1\ Local\ Rel\ Den_{rs,t-1} + \beta_2\ Compl\ Rel\ Den_{rs,t-1} + \gamma\ X_{r,t-1} + \varphi_r + \mu_s + \theta_t + \varepsilon_{rst} \quad (15)$$

As stated before, four dependent variables are used: functional upgrading, diversification, downgrading, and exit. The two main variables of interest are the local relatedness density (LRD) and the complementary relatedness density (CRD) for each region (r) and each function (s) in the previous time period (t-1). While the LRD captures the existence of local related capabilities, the CRD captures complementary non-local capabilities through global value chains. The models also add an interaction term between the two variables to test whether both local relatedness density and the complementary relatedness density have a positive (negative) effect on the likelihood of functional upgrading (downgrading) in GVCs.

The models also include a vector of control variables at the regional level ($X_{r,t-1}$), and region, function and time fixed effects ($\varphi_r, \mu_s, \theta_t$). The control variables include: (1) GDP per capita, as a proxy for the level of regional development; (2) population density, measured as population by square kilometer, as a proxy for agglomeration externalities; (3) number of patent applications, as a proxy for technological absorptive capacity; and (4) GVC participation, as a proxy for the ability of regions to participate in GVCs. These control variables are all in logarithm to control for excess kurtosis. To account for the presence of heteroskedasticity, standard errors are clustered at the regional level in all regressions. All independent variables are lagged by one period and mean centred. The time periods (t) refer to four time windows, namely 2000-2001, 2002-2004, 2005-2007, 2008-2010. $\varepsilon_{r,s,t}$ stands for the regression residual.

5.- RESULTS

Table 2 shows the results for the role of complementary interregional value chain linkages in the functional diversification and upgrading of EU regions in GVCs. Complementary relatedness density (CRD) is positively and significantly associated with higher chances of experiencing both functional diversification (models 1-3) and upgrading (models 4-6) in value chains. Particularly, the coefficients from the full models (2 and 5) suggest that one standard deviation increase in the CRD leads to a 6.7 and 5 percentage points increase in the likelihood of functional diversification and upgrading, respectively.[6] This leads to validate hypotheses 1a and 1b. The effects are large in magnitude, in view that the unconditional probability of diversification is only around 15%, and 14% for upgrading, as shown in Table 1. Thus, regions can leverage on complementary capabilities from value chain partners to diversify and upgrade in more complex functions in value chains.

Consistent with previous research, the local relatedness density (LRD) is also positively and significantly associated with the likelihood of functional diversification and upgrading. One standard deviation increase in the LRD leads to a 12.2 and 9.6 percentage points increase in the likelihood of functional diversification and upgrading, respectively. These effects are about the double in magnitude compared to those of the CRD a region obtains from its trade partners. While complementary non-local capabilities can help regions to diversify and upgrade in functions across GVCs, local capabilities remain crucial and have a more sizeable effect on functionally diversification and upgrading in value chains in EU regions.

Table 2.- Complementary interregional value chain linkages and functional diversification and upgrading.

	LPMs					
	Diversification			Upgrading		
	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	Full Model	Interaction	Baseline	Full Model	Interaction
Related. dens.	0.899***	1.609***	1.635***	0.953***	1.310***	1.340***
	(0.0683)	(0.0956)	(0.0934)	(0.0863)	(0.125)	(0.125)
Compl. rel. dens.	0.919***	2.028***	1.651***	0.920***	1.470***	1.093***
	(0.167)	(0.306)	(0.269)	(0.207)	(0.347)	(0.335)
Interaction			-4.947***			-5.098***
			(0.903)			(1.138)
GDP pc (log)		0.0528	0.0566		0.0526	0.0536
		(0.107)	(0.109)		(0.101)	(0.101)
Pop. dens. (log)		-0.474**	-0.463**		-0.244	-0.240
		(0.195)	(0.203)		(0.203)	(0.211)
GVC part. (log)		0.417***	0.448***		0.219*	0.233*
		(0.153)	(0.159)		(0.123)	(0.126)
Patents (log)		-0.00901	-0.00634		-0.00692	-0.00454
		(0.0165)	(0.0167)		(0.0149)	(0.0151)
Constant	0.164***	0.172***	0.168***	0.158***	0.118***	0.117***
	(0.00411)	(0.00514)	(0.00497)	(0.00533)	(0.0418)	(0.0435)

Observations	24,552	24,552	24,552	13,743	13,742	13,742
R^2	0.026	0.070	0.071	0.027	0.090	0.092
Region FEs	NO	YES	YES	NO	YES	YES
Function FEs	NO	YES	YES	NO	YES	YES
Period FEs	NO	YES	YES	NO	YES	YES

Notes. All independent variables are mean centred and lagged by one period. Heteroskedasticity-robust standard errors (clustered at the regional level) are shown in parentheses. Coefficients are statistically significant at the * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ level.

The interaction between local and complementary relatedness densities turns out to be negative and significant for both diversification and upgrading. This points towards a substitution effect: regions with stronger local capabilities depend less on non-local sources of knowledge for diversifying and upgrading into more complex functions in GVCs. The complementary relatedness density obtained from trade partners plays a more important role for functional upgrading and diversification in regions lacking local capabilities. This is shown in Figure 2, where the marginal effects of the CRD on the entry (left) and upgrading (right) are plotted at different levels of LRD. In addition, it is interesting to highlight that while previous research found a positive and significant correlation between GVC participation and upgrading in value chains (Hernández-Rodríguez et al., 2023), when introducing the CRD, this effect considerably decreases. This is consistent with literature: interregional linkages are not *per se* sufficient, but what really matters are complementary interregional linkages (Boschma and Iammarino, 2009; Balland and Boschma, 2021).

Figure 2.- Marginal effects of complementary relatedness density on entry (left) and upgrading (right) at different levels of local relatedness density.

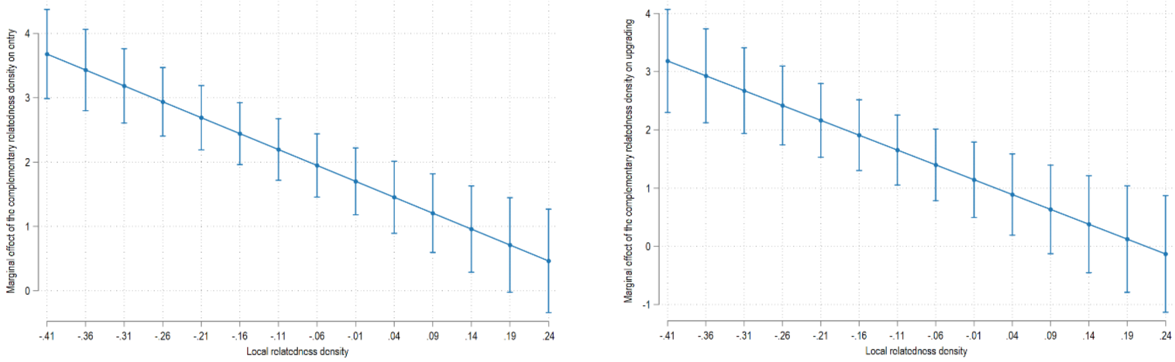


Table 3 presents the results for the role of interregional value chain linkages in functional exit and downgrading for EU regions. As expected, complementary interregional linkages reduce the chances of regions to exit (models 1-3) and downgrade (models 4-6) in functions along value chains. In the full models, a one standard deviation increase in CRD leads to a 6.9 and 10 percentage points lower likelihood of exiting and downgrading functions in GVCs, respectively, compared to their unconditional probabilities of 21.6% and 22.9%. This leads to validate hypotheses 2a and 2b. These results highlights that being engaged in value chains in which partner regions offer complementary capabilities reduce the chances of exiting and downgrading functions in value chains.

Again, as expected, the local relatedness density is found to be negatively and significantly associated with both functional exit and downgrading. A one standard deviation increase in LRD leads to about 12.5 percentage points decrease in the chances of both functional exit and downgrading. In line with the results for functional diversification and upgrading, local capabilities are found to be more relevant to prevent functional exit and downgrading than complementary capabilities. While both local and complementary capabilities matter when it comes to preserve the specialisation in complex functions in value chains, this effect is larger for local capabilities.

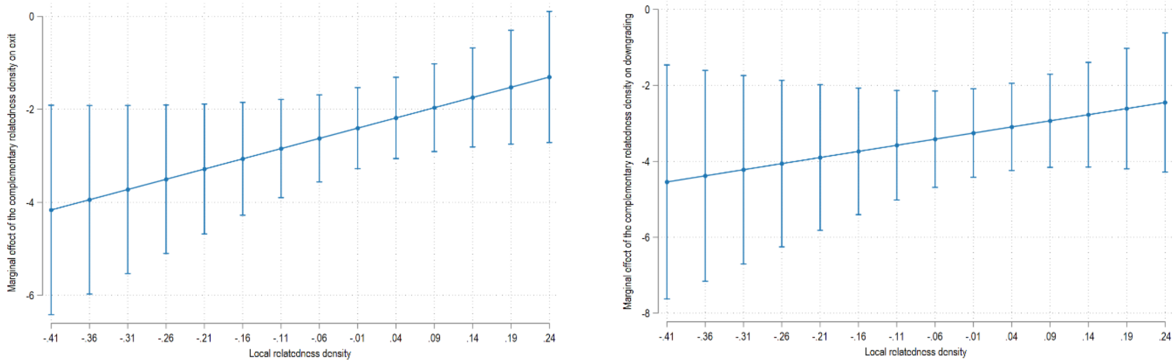
Table 3.- Complementary interregional value chain linkages and functional exit and downgrading.

	LPMs					
	Exit			Downgrading		
	(1) Baseline	(2) Full Model	(3) Interaction	(4) Baseline	(5) Full Model	(6) Interaction
Related. dens.	-0.948***	-1.743***	-1.730***	-0.944***	-1.811***	-1.805***
	(0.101)	(0.149)	(0.150)	(0.129)	(0.200)	(0.200)
Compl. rel. dens.	-0.271	-2.306***	-2.361***	-0.325	-3.217***	-3.223***
	(0.297)	(0.439)	(0.442)	(0.386)	(0.587)	(0.589)
Interaction			4.398*			3.221
			(2.507)			(3.371)
GDP pc (log)		-0.0627	-0.0510		-0.0857	-0.0764
		(0.117)	(0.118)		(0.154)	(0.154)
Pop. dens. (log)		-0.0130	-0.0359		-0.321	-0.337
		(0.346)	(0.346)		(0.424)	(0.424)
GVC part. (log)		-0.0210	-0.0392		-0.0453	-0.0568
		(0.215)	(0.216)		(0.298)	(0.297)
Patents (log)		-0.0241	-0.0281*		-0.0529***	-0.0559***
		(0.0152)	(0.0156)		(0.0193)	(0.0193)
Constant	0.245***	0.264***	0.268***	0.254***	0.285***	0.289***
	(0.00682)	(0.00638)	(0.00691)	(0.00877)	(0.0143)	(0.0150)
Observations	16,566	16,566	16,566	8,042	8,041	8,041
R^2	0.022	0.097	0.097	0.019	0.124	0.124
Region FEs	NO	YES	YES	NO	YES	YES
Function FEs	NO	YES	YES	NO	YES	YES
Period FEs	NO	YES	YES	NO	YES	YES

Notes. All independent variables are mean centred and lagged by one period. Heteroskedasticity-robust standard errors (clustered at the regional level) are shown in parentheses. Coefficients are statistically significant at the * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ level.

The interaction term between local and complementary relatedness density is not found to be significant for exit and downgrading. Although the sign of the coefficient points towards a substitution effect, the lack of statistical significance suggests that for retaining specialisations in complex functions in GVCs, local and complementary capabilities act through different channels. This substitution effect can be observed in Figure 3, where the marginal effects of CRD on exit (left) and downgrading (right) at different levels of LRD are displayed. The negative effect of CRD on both functional exit and downgrading decreases when regions have stronger local capabilities, although the difference is insignificant when comparing regions with different LRD.

Figure 3.- Marginal effects of complementary relatedness density on exit (left) and downgrading (right) at different levels of local relatedness density.



6.- CONCLUSIONS

The increasing relevance of global value chains and, particularly, the uneven spatial distribution of production functions impose several challenges to regions (Gereffi, 1999; Los et al., 2015; Timmer et al., 2015, 2019; Antràs, 2020). Since different production functions generate different levels of value added, regions seek to move up and climb the ladder of functions in GVCs (Humphrey & Schmitz, 2002; Gerefi et al., 2005; Giuliani et al., 2005; Ponte & Ewert, 2009; Capello & Dellisanti, 2024). Thus, it has become crucial for regions to upgrade into more complex functions in GVCs and to retain such functions over time, avoiding functional downgrading (Blažek , 2016; Gereffi, 2019; Buciuni et al., 2022).

This paper aimed to tackle the question on how interregional value chain linkages across 199 EU regions can act as a source of non-local capabilities to foster functional upgrading and to avoid functional downgrading. The empirical analysis used relatedness and economic complexity metrics by combining three sources of data: interregional input-output tables, regional labour structures, and regional income shares. Results show that regions exposed to complementary capabilities through GVCs are associated with a higher likelihood of functional upgrading. That is, they are more likely to upgrade into more complex functions in GVCs. Moreover, regions exposed to complementary capabilities through GVCs are associated with a lower likelihood of functional downgrading. In other words, they are less likely to downgrade and lose complex functions in GVCs.

Overall, these findings contribute to the further integration between EEG and GVC literatures (Yeung, 2021, 2024; Boschma, 2022, 2024). First, this paper points out how EEG concepts such as complementary capabilities, using relatedness and economic complexity metrics, are useful for studying upgrading and downgrading of GVCs (De Propris, 2024; Poon, 2024). Such metrics could also be used for other issues beyond upgrading and downgrading, such as strategic coupling (MacKinnon, 2012; Horner, 2014; Coe & Yeung, 2015; Yeung, 2015). Second, this paper introduces the role of interregional value chains linkages in evolutionary models of regional diversification, complementing the role of local capabilities (Boschma, 2017; Trippl et al., 2018; Whittle et al., 2020). It underlines the importance of complementary linkages over linkages in general, meaning that linkages *per se* are necessary but not sufficient (Boschma & Iammarino, 2009; Balland & Boschma, 2021). Third, this paper studies these issues at the subnational level, uncovering regional differences across the EU in functions in GVCs (Los et al., 2015; Crescenzi & Iammarino, 2017; Iammarino, 2018).

However, there are also limitations that need to be acknowledged. First, while this paper relies on the best possible sources of data available, it suffers from certain issues. For example, the time frame remains relatively short to capture large structural transformations such as functional upgrading and downgrading in GVCs. Also, the industrial classifications of sectors provided in EUREGIO and EULFS/EUSES are quite aggregated, limiting the level of granularity for the empirical analysis. Second, this paper focuses on economic upgrading and downgrading. There are also other dimensions that could be explored when looking at regional participation in GVCs, such as environmental and social downgrading (Ponte & Gibbon, 2005; Breau & Rigby, 2010; Bolwig et al., 2010; Lund-Thomsen & Nadvi, 2010; Barrientos et al., 2016; Krishnan et al., 2023). Third, the role of institutions in GVCs has been left unexplored in this paper. The literature has, however, underlined how regional institutions are crucial to help regions to benefit from GVCs, but also to avoid unintended negative consequences of GVCs (Rodríguez-Pose, 2021; Pardy, 2024).

Furthermore, this paper opens new windows for future research. First, while this paper focuses on complementary capabilities, it does not dig into other proximity dimensions such as cognitive, geographical, or social proximities (Boschma, 2005). EU regions may find it easier to connect in GVCs with neighbour regions, and particularly with regions within the same country (Bolea et al., 2022; Bachtrögler-Unger et al., 2023). Second, the EU is strongly calling for ensuring the resilience of the EU value chains and its strategic autonomy. The framework presented in this paper provides instruments to develop further analysis looking at the roles of EU regions in GVCs and their implications for resilience (Balland et al., 2015; Boschma, 2015; Xiao et al., 2018; Steijn et al., 2023). Third, although this paper looked at the negative side of GVCs in terms of functional downgrading, nothing has been said regarding other dimensions such as social rights, working conditions and the threat of rising intra- and interregional inequality. On this particular matter, more insights to understand how regional institutions shape these issues remain crucial (Morgan, 2007; Rodríguez-Pose, 2013, 2021; Barbero et al., 2021; Pardy, 2024). Also, the role of institutions is key to better understand how power is shared among actors and how this shapes the governance of GVCs (Humphrey & Schmitz, 2000; Gereffi et al., 2005, Gibbon & Ponte, 2008; Nadvi, 2008; Capello et al., 2023).

Finally, it is possible to draw some policy implications from the findings of this paper. While related regional capabilities are found to remain fundamental for triggering functional upgrading and diversification in GVCs, regions can also leverage on complementary non-local capabilities to do so. In this sense, regional policies such as Smart Specialisation should promote collaboration and trade partnership with other EU regions specialised in different but complementary stages of the value chains. Current Smart Specialisation Strategies focus little attention to interregional linkages, particularly to GVCs dynamics (Thissen et al., 2013; Radosevic & Stankova, 2015; Iacobucci & Guzzini, 2016; Sörvik et al., 2016; Uyarra et al., 2018; Barzotto et al., 2019; Santoalha, 2019; Varga et al., 2020; Giustolisi et al., 2023). The framework proposed here can be instrumental for finding strategic partner regions offering complementary capabilities to promote upgrading, and to prevent downgrading in GVCs.

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NOTES

1.- Kishimoto (2004) hinted already on the importance of local capabilities when studying the Taiwanese computer industry: previous knowledge in related production stages in the industry was required to get new orders.

2.- First, the region in which workers live was used when the region of the workplace was missing. Second, for some regions the data on wages was missing in the EUSES. Then, it was assumed that in Belgian regions, occupation (ISCO-88) 11 earns as 12, 61 as 71, and 92 as 93. In German regions, occupation 92 earns as 93, and 13 as 24. In Luxemburg occupation 61 earns as 71, and 92 as 93. Also, for Luxemburg and Portugal, wages for mining and energy were proxied by manufacturing. Third, when data for some countries was missing in the EUSES, similar criteria than Timmer at al. (2019) were followed and adjusted for the regional level: data for Slovakia was used for Slovenia, data from Finland was used for Austria, data from BE10 was used for DK01, and data from BE30 was used for the remaining of Danish regions.

Finally, as pointed out in detail in Hernández-Rodríguez et al. (2023), some restrictions were imposed to ensure a balance between the number of functions included in the analysis and their economic significance. Since some occupation-industry combinations were uncommon and contributed with very little value added, the following exclusions were applied. In the first place, both agricultural and education occupations were excluded. EUREGIO does not include information on the agricultural and public sector industries, thus, since these occupations are usually developed within them, they were excluded. Second, to avoid functions contributing with extremely low value added, we combined functions in which the sum of value added from an occupation across all sectors was lower than the 1% of the total domestic value added. This ensured that when applying the economic complexity methods, no small function will bias the results. Third, we required that the sum of value added from a sector for all its occupations should consist of at least 5% of the total domestic value added. This follows the same logic than we did before for occupations but applied to industries. This led to a merging between some sectors such as 'manufacturing' and 'mining', for example. Finally, a joint condition for both occupations and industries was applied: we excluded the smallest functions (cumulative 0.5% of total domestic value added). These correspond to very uncommon industry-occupation combinations like 'life scientist' in 'logistics'.

3.- The final number of NUTS-2 regions included in the empirical analysis is 199. Appendix I includes a detailed list of these 199 regions. Due to some data limitations and incompatibilities between the EUREGIO, EULFS, and the EUSES databases, some regions could not be included. For further details regarding the matching process see Hernández-Rodríguez et al. (2023).

4.- Since each dependent variable (upgrading, diversification, downgrading, and exit) has different number of observations, further individual descriptive statistics are provided in appendix II. Appendix III provides the correlation matrix. Notice that since upgrading/diversification and downgrading/exit are mutually exclusive, it is not possible to show the correlation between them.

5.- Traditionally, the literature on entry/exit models preferred linear probability models over logit and probit specifications. This is due to a potential bias or inconsistency when estimating these models with a large number of dummy variables and different fixed effects (Greene, 2012). In any case, similar results were obtained using logit and probits models, as shown in appendices IV and V, respectively. Furthermore, results hold after controlling for human capital, proxied by the percentage of population with tertiary education, and for regional industrial structures, proxied by the share of gross value added generated by the manufacturing sector, as shown in appendix VI. Data for both control variables was retrieved from Eurostat.

6.- These results are obtained by multiplying the coefficients from models 2 and 5 in Table 2 with the standard deviation (SD) of the complementary relatedness density in the respective subsamples of diversification and upgrading (see appendix II). Namely, 2.028*0.033 and 1.470*0.034. The same is then repeated for exit and downgrading using the coefficients from models 2 and 5 in Table 3.

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Appendix I.- List of the EU regions (NUTS-2) included in the analysis

AT11	CZ07	DEA1	ES23	FR30	GR42	ITF3	PT15
AT12	CZ08	DEA2	ES24	FR41	GR43	ITF4	PT16
AT13	DE11	DEA3	ES30	FR42	HU10	ITF5	PT17
AT21	DE12	DEA4	ES41	FR43	HU21	ITF6	PT18
AT22	DE13	DEA5	ES42	FR51	HU22	ITG1	SE11
AT31	DE14	DEB1	ES43	FR52	HU23	ITG2	SE12
AT32	DE21	DEB2	ES51	FR53	HU31	LT00	SE21
AT33	DE22	DEB3	ES52	FR61	HU32	LU00	SE22
AT34	DE23	DEC0	ES53	FR62	HU33	LV00	SE23
BE10	DE24	DED1	ES61	FR63	IE01	PL11	SE31
BE21	DE25	DED2	ES62	FR71	IE02	PL12	SE32
BE22	DE26	DED3	ES63	FR72	ITC1	PL21	SE33
BE23	DE27	DEE1	ES64	FR81	ITC2	PL22	SI00
BE24	DE30	DEE2	ES70	FR82	ITC3	PL31	SK01
BE25	DE41	DEE3	FI13	FR83	ITC4	PL32	SK02
BE31	DE42	DEF0	FI18	GR11	ITD1	PL33	SK03
BE32	DE50	DEG0	FI19	GR12	ITD2	PL34	SK04
BE33	DE60	DK01	FI1A	GR13	ITD3	PL41	
BE34	DE71	DK02	FI20	GR14	ITD4	PL42	
BE35	DE72	DK03	FR10	GR21	ITD5	PL43	
CZ01	DE73	EE00	FR21	GR22	ITE1	PL51	
CZ02	DE80	ES11	FR22	GR23	ITE2	PL52	
CZ03	DE91	ES12	FR23	GR24	ITE3	PL61	
CZ04	DE92	ES13	FR24	GR25	ITE4	PL62	
CZ05	DE93	ES21	FR25	GR30	ITF1	PL63	
CZ06	DE94	ES22	FR26	GR41	ITF2	PT11	

Appendix II.- Individual descriptive statistics for each dependent variable

A) Descriptive statistics for diversification

Variables	N	Mean	SD	Min	Max
Relatedness dens.	26,960	0.395	0.076	0	0.686
Compl. rel. dens.	26,960	0.14	0.033	0.031	0.315
Diversification	26,960	0.148	0.355	0	1
GDP per capita	26,960	23,350.512	9,036.813	7,342.212	68,114.922
GVC participation	26,960	0.639	0.09	0.341	0.838
Population dens.	25,557	280.372	675.311	3.3	6,744.633
Patents	26,960	778.191	1,366.577	0	9,324.06

B) Descriptive statistics for upgrading

Variables	N	Mean	SD	Min	Max
Relatedness dens.	15,238	0.396	0.073	0	0.662
Compl. rel. dens.	15,238	0.141	0.034	0.031	0.315
Upgrading	15,238	0.141	0.348	0	1
GDP per capita	15,238	21,929.4	8,671.961	7,342.212	68,114.922
GVC participation	15,238	0.635	0.102	0.341	0.838
Population dens.	14,448	217.386	538.437	3.3	6,744.633
Patents	15,238	496.449	985.366	0	9,324.06

C) Descriptive statistics for exit

Variables	N	Mean	SD	Min	Max
Relatedness dens.	18,239	0.447	0.072	0.006	0.682
Compl. rel. dens.	18,239	0.134	0.03	0.032	0.311
Exit	18,239	0.216	0.411	0	1
GDP per capita	18,239	23,268.339	9,090.336	7,342.212	68,114.922
GVC participation	18,239	0.638	0.088	0.341	0.838
Population dens.	17,255	294.339	690.916	3.3	6,744.633
Patents	18,239	726.906	1,282.356	0	9,324.06

D) Descriptive statistics for downgrading

Variables	N	Mean	SD	Min	Max
Relatedness dens.	8,833	0.442	0.069	0.008	0.673
Compl. rel. dens.	8,833	0.136	0.031	0.032	0.311
Downgrading	8,833	0.229	0.421	0	1
GDP per capita	8,833	23,333.79	9,107.248	7,342.212	68,114.922
GVC participation	8,833	0.638	0.088	0.341	0.838
Population dens.	8,362	306.397	720.759	3.3	6,744.633
Patents	8,833	746.478	1,302.129	0	9,324.06

Appendix III.- Correlation matrix

Notice that upgrading/diversification and downgrading/exit are mutually exclusive, meaning that they cannot be observed at the same time. Therefore, the correlation between such variables cannot be computed. Furthermore, upgrading and downgrading are subsets of diversification and exit, respectively. Thus, they are perfectly correlated. However, they are used in different equations as dependent variables, which should not imply any empirical issue.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Diversification	1.000									
(2) Upgrading	1.000	1.000								
(3) Exit	.	.	1.000							
(4) Downgrading	.	.	1.000	1.000						
(5) Related. dens.	0.208	0.207	-0.228	-0.215	1.000					
(6) Com. rel. dens.	-0.027	-0.026	0.084	0.070	-0.486	1.000				
(7) GDP pc	-0.013	0.020	-0.021	-0.076	-0.125	-0.027	1.000			
(8) Pop. dens.	-0.019	0.014	-0.028	-0.059	-0.008	-0.027	0.435	1.000		
(9) GVC part.	0.017	0.018	0.047	0.046	-0.051	0.169	0.067	-0.040	1.000	
(10) Patents	-0.033	0.016	-0.008	-0.065	-0.202	0.004	0.447	0.109	-0.013	1.000

Appendix IV.- Logit models

	Logit: Average marginal effects			
	(1)	(2)	(3)	(4)
	Diversification	Upgrading	Exit	Downgrading
Related. Den.	1.610***	1.350***	-1.682***	-1.686***
	(0.0861)	(0.116)	(0.136)	(0.188)
Compl. Rel. Den.	1.837***	1.532***	-2.289***	-3.023***
	(0.255)	(0.327)	(0.417)	(0.561)
GDP pc (log)	0.0353	0.0610	-0.0995	-0.127
	(0.112)	(0.118)	(0.134)	(0.183)
Pop. Den. (log)	-0.508**	-0.239	-0.0685	-0.424
	(0.203)	(0.227)	(0.388)	(0.467)
GVC part. (log)	0.467***	0.289	-0.00300	-0.0365
	(0.168)	(0.176)	(0.228)	(0.295)
Patents (log)	-0.00859	-0.00612	-0.0258*	-0.0493***
	(0.0171)	(0.0165)	(0.0151)	(0.0174)
Observations	24,552	13,742	16,566	8,041
Period FEs	YES	YES	YES	YES
Region FEs	YES	YES	YES	YES
Function FEs	YES	YES	YES	YES

Notes. All independent variables are mean centred and lagged by one period. Heteroskedasticity-robust standard errors (clustered at the regional level) are shown in parentheses. Coefficients are statistically significant at the * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ level.

Appendix V.- Probit models

	Probit: Average marginal effects			
	(1)	(2)	(3)	(4)
	Diversification	Upgrading	Exit	Downgrading
Related. Den.	1.599***	1.336***	-1.660***	-1.694***
	(0.0849)	(0.114)	(0.136)	(0.185)
Compl. Rel. Den.	1.817***	1.477***	-2.190***	-3.013***
	(0.253)	(0.326)	(0.418)	(0.557)
GDP pc (log)	0.0566	0.0661	-0.0816	-0.128
	(0.111)	(0.115)	(0.127)	(0.178)
Pop. Den. (log)	-0.468**	-0.201	-0.0468	-0.411
	(0.199)	(0.228)	(0.369)	(0.453)
GVC part. (log)	0.443***	0.249	0.00211	-0.0573
	(0.157)	(0.160)	(0.227)	(0.296)
Patents (log)	-0.00919	-0.00559	-0.0246	-0.0502***
	(0.0168)	(0.0158)	(0.0153)	(0.0178)
Observations	24,552	13,742	16,566	8,041
Period FEs	YES	YES	YES	YES
Region FEs	YES	YES	YES	YES
Function FEs	YES	YES	YES	YES

Notes. All independent variables are mean centred and lagged by one period. Heteroskedasticity-robust standard errors (clustered at the regional level) are shown in parentheses. Coefficients are statistically significant at the * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ level.

Appendix VI.- LPMs with additional control variables: human capital and industrial structures

	LPMs with additional controls							
	(1) Diversification	(2) Diversification	(3) Upgrading	(4) Upgrading	(5) Exit	(6) Exit	(7) Downgrading	(8) Downgrading
Relatedness dens.	1.616***	1.642***	1.310***	1.341***	-1.844***	-1.828***	-1.936***	-1.930***
	(0.0970)	(0.0952)	(0.126)	(0.127)	(0.153)	(0.154)	(0.206)	(0.207)
Complem. relat. dens.	2.045***	1.681***	1.457***	1.096***	-2.573***	-2.640***	-3.520***	-3.534***
	(0.301)	(0.275)	(0.344)	(0.336)	(0.455)	(0.459)	(0.609)	(0.612)
Interaction		-4.849***		-4.990***		5.078**		3.931
		(0.894)		(1.186)		(2.348)		(3.289)
GDP pc (log)	0.0397	0.0458	0.0839	0.0903	-0.128	-0.113	-0.139	-0.126
	(0.126)	(0.129)	(0.121)	(0.123)	(0.139)	(0.141)	(0.197)	(0.196)
Population dens. (log)	-0.439**	-0.443**	-0.307	-0.314	0.118	0.0927	-0.187	-0.205
	(0.194)	(0.205)	(0.194)	(0.203)	(0.308)	(0.310)	(0.406)	(0.409)
GVC participation (log)	0.419***	0.453***	0.274**	0.286**	-0.135	-0.157	-0.214	-0.228
	(0.156)	(0.163)	(0.134)	(0.138)	(0.218)	(0.219)	(0.307)	(0.306)
Patents (log)	-0.00159	0.000579	-0.00208	-0.000180	-0.0177	-0.0223	-0.0476**	-0.0511**
	(0.0168)	(0.0171)	(0.0149)	(0.0151)	(0.0162)	(0.0166)	(0.0208)	(0.0210)
Education (log)	-0.0647	-0.0522	-0.0815	-0.0670	-0.159**	-0.165**	-0.131*	-0.136*
	(0.0452)	(0.0436)	(0.0525)	(0.0515)	(0.0687)	(0.0684)	(0.0753)	(0.0755)
Industrial share (log)	0.0255	0.0160	-0.105	-0.117	0.0229	0.0206	0.0698	0.0664
	(0.0856)	(0.0871)	(0.0920)	(0.0938)	(0.131)	(0.131)	(0.174)	(0.175)
Constant	0.172***	0.169***	0.103**	0.102**	0.255***	0.260***	0.276***	0.280***
	(0.00679)	(0.00645)	(0.0418)	(0.0432)	(0.00857)	(0.00894)	(0.0162)	(0.0169)
Observations	23,859	23,859	13,345	13,345	16,027	16,027	7,781	7,781
R^2	0.071	0.072	0.091	0.092	0.101	0.102	0.126	0.126
Region FEs	YES	YES	YES	YES	YES	YES	YES	YES
Function FEs	YES	YES	YES	YES	YES	YES	YES	YES
Period FEs	YES	YES	YES	YES	YES	YES	YES	YES

Notes. All independent variables are mean centred and lagged by one period. Heteroskedasticity-robust standard errors (clustered at the regional level) are shown in parentheses. Coefficients are statistically significant at the * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ level.