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Abstract

This paper adopts a relatedness-complexity framework to assess the likelihood of functional upgrading and downgrading in global value chains in EU regions in the period 2000-2010. We use relatedness and economic complexity measures based on value added content of gross exports and labour structures at the regional level. We show how economic complexity metrics can be used as an alternative for value added data, to measure both functional upgrading and downgrading in GVCs. We find that relatedness between functions (industry-occupations) is a factor impacting both functional upgrading and downgrading. Regions tend to functionally upgrade their global value chains towards more complex functions that are related to functions in which they are specialised. And regions are more likely to functionally exit and downgrade in global value chains when they are not specialised in related functions.

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

Keywords: Global value chains, upgrading, downgrading, economic complexity, relatedness, EU regions

1.- INTRODUCTION

Regions play different roles in global value chains (GVCs): some regions act as centers of corporate control and high-value activities like R&D, while other regions operate primarily as branch plant economies (Gereffi et al., 2005; Blažek, 2016). Recently, new World Input-Output data have shed new light on the fact that territories are specialised in functions, such as headquarters, R&D, management, and production (Los et al., 2015; Timmer et al., 2015, 2019). Because such functions in GVCs are characterized by different levels of value added, their geography is crucial to understand uneven spatial development (Pietrobelli & Rabellotti, 2007, 2011; Iammarino & McCann, 2013; Timmer & Pahl, 2021). This makes it a key challenge for regions to develop new functions and/or functionally upgrade existing ones along value chains (Humphrey & Schmitz, 2002; Giuliani et al., 2005; Morrison et al., 2008; Pietrobelli & Rabellotti, 2011).

We argue that the Evolutionary Economic Geography (EEG) framework on regional diversification can provide new insights to the process of functional upgrading. So far, EEG has focused primarily on the emergence of activities (industries, products, technologies, occupations, trademarks) rather than functions (Boschma, 2017). A key insight from this literature is that regions diversify in activities related to existing activities (Hidalgo et al., 2007; Neffke et al., 2011; Rigby, 2015). This applies especially to the development of complex activities (Balland et al., 2019) that combine a wide range of capabilities. This makes it hard for other regions to copy and develop complex activities (Fleming & Sorenson, 2001; Hidalgo & Hausmann, 2009). To the best of our knowledge, few attempts have been made to apply this evolutionary thinking to a value chain framework at the regional scale (Colozza et al., 2021; Boschma, 2022). Little has been said regarding the capacity of regions to diversify in new functions in GVCs, and whether these concern functions of high or low complexity, and thus contribute to upgrading or downgrading processes in GVCs in regions (Boschma, 2022).

This paper takes up these challenges. First, we apply the principle of relatedness (Hidalgo et al., 2018) to analyze opportunities of functional upgrading in GVCs in regions. We test whether the ability of a region to develop new or upgrade existing GVCs depends on the degree of relatedness with existing GVCs in the region. Second, we analyze functional downgrading in GVCs in regions (Blažek, 2016). We test whether a region is more likely to lose or downgrade existing GVCs when there is a lack of relatedness with other GVCs in the region. Third, we apply the notion of complexity (Hidalgo and Hausmann (2009), to measure upgrading and downgrading in GVCs in regions. We differentiate functions in GVCs in terms of their complexity, to capture the heterogeneity of capabilities that are needed to master a function. This enables to assess the propensity of regions to upgrade or downgrade their GVCs. Fourth, we investigates upgrading and downgrading in GVCs at the subnational level, using regional input-output data that have recently become available, whereas earlier work is primarily at the national scale (Los et al., 2015).

By addressing the above challenges this paper will first contribute to a further integration of the GVC and EEG literatures (Yeung, 2021; Boschma, 2022). It provides and applies a new framework to identify functional upgrading and downgrading in GVCs using relatedness and economic complexity metrics from the EEG literature. Second, it provides evidence on the role of relatedness in functional upgrading and downgrading in

GVCs across 199 EU regions between the years 2000-2010. Our findings show that regions functionally upgrade in GVCs towards functions that are related to the ones in which they are already specialised. And regions are less likely to functionally downgrade in GVCs when they are specialised in related functions.

The remainder of the paper is structured as follows. Next section gives a brief literature review. In Section 3, the data and variables used in the empirical analysis are explained. Subsequently, in Section 4, the empirical framework is defined. Section 5 presents the main empirical findings. The final section concludes.

2. Up- and downgrading in GVCs in regions: a relatedness/complexity framework

There is an extensive literature on the global dynamics of GVCs and how production stages have been split across territories, due to the decrease of transport costs, trade policies, and new ICTs (Antràs, 2020). This literature has addressed questions such as whether this spatial division of labour is subject to change, to what extent GVC participation enables territories to move up the economic ladder, and what is their ability to develop new value chains, and to upgrade existing ones (Humphrey & Schmitz, 2002; Giuliani et al., 2005; Morrison et al., 2008; Pietrobelli & Rabellotti, 2011; Iammarino & McCann, 2013; Gehl Sampath & Vallejo, 2018; Kergroach, 2019; Kano et al., 2020).

Traditionally, four kinds of upgrading are distinguished: process, product, functional upgrading and intersectoral upgrading (Humphrey & Schmitz, 2002; Giuliani et al., 2005; Ponte & Ewert, 2009). Early work on upgrading examined the influence of GVC governance on the scope of upgrading (Humphrey & Schmitz, 2002, 2004; Gereffi et al., 2005; Lane, 2008; Pavlínek & Ženka, 2011). Upgrading was often understood as moving up the value chain through the acquisition of capabilities, resulting from GVC participation (Ponte & Ewert, 2009). Scholars have highlighted the role of lead firms (Gereffi, 1999; Ernst & Kim, 2002; Hendersson et al., 2002 ; Coe et al., 2004, 2008; Ivarsson & Alvstam, 2011) and global buyers (Giuliani et al., 2005; Murphy, 2007).

There is a long history in fields like international economics, international business studies, and economic geography that have focused on geographies of functions rather than products or services (Hymer, 1972; Massey, 1994; Venables, 1999; Grossman & Rossi-Hansberg, 2008; Baldwin & Venables, 2013; Baldwin & Robert-Nicoud, 2014). This literature has shown that a spatial division of labor exists due to strategies of multi-national corporations to break down the value chain into functions and spread them geographically (Iammarino & McCann, 2013). This has implications for regional development because the type of capabilities required to develop each function or production stage differs (Pietrobelli & Rabellotti, 2007, 2011; Morrison et al., 2008; Crescenzi et al., 2014). Recently, international trade scholars (Los et al., 2015; Timmer et al., 2015, 2019) developed measures using new World Input-Output data to explain how much value added a territory generates through which functions.

However, few studies have applied evolutionary thinking to such a value chain framework at the regional scale. Evolutionary Economic Geography (EEG) has focused on the evolution of products (Hidalgo et al., 2007), industries (Neffke et al., 2011), technologies (Boschma et al., 2015; Rigby, 2015), occupations (Muneepeerakul et al., 2013; Farinha et al., 2019) and trademarks (Castaldi & Mendonça, 2022), rather than tasks and functions in GVCs in regions (Boschma, 2017). EEG highlights the key role of local capabilities that enable regions to diversify and upgrade their economies by developing activities of higher economic complexity. This body of literature proposed concepts (relatedness and complexity) and methods (network spaces) that have the potential to shed new light on the evolution of GVCs in regions in terms of upgrading, but also in terms of downgrading.

A key insight in EEG is that it is crucial for regions to diversify in new activities, in order to compensate for processes of decline and stagnation in other activities. There is overwhelming evidence that regions tend to diversify in activities that are related to existing activities (Neffke et al., 2011; Rigby, 2015; Boschma, 2017). Activities are considered related when they share similar capabilities. So, regions are more likely to develop new activities when they can build on local activities they are related to. However, few studies have yet explored whether regional capabilities also shape the evolution of GVCs using the principle of relatedness (Hidalgo et al., 2018). Little is known whether regions are more likely to develop new GVCs and new functions in existing VCs that are related to the ones in which they are already specialised. Taking up this question would be in line with Kano et al. (2020) and Yeung (2021) who expressed the need for studies to shed light on the interplay between local capabilities and GVCs.

EEG scholars have highlighted the key role of local capabilities that enable regions to functionally upgrade their local economies. Hidalgo and Hausmann (2009) developed an economic complexity measure to rank economic activities, depending on how difficult it is to master capabilities to produce an activity. Because complex activities bring higher economic benefits (Fleming & Sorenson, 2001; Hidalgo & Hausmann, 2009; Pintar & Scherngell, 2020; Mewes & Broekel, 2022; Rigby et al., 2022), regions have an incentive to develop them. What studies tend to show though is that few regions have the required capabilities (Balland & Rigby, 2017; Balland et al., 2019; Pinheiro et al., 2022). However, few studies exist that have examined the ability of regions to move into complex functions in GVCs. Applying a complexity measure makes it possible to make a hierarchy among functions in value chains that can act as an alternative for conventional rankings based on total value added, and to identify which stages of production in GVCs are more complex, and which opportunities regions have to upgrade their GVCs (Boschma, 2022). Some regional studies on GVCs (Koch, 2021; Colozza et al., 2021) have begun to apply such complexity metrics, but not at the level of functions.

Adopting such a complexity framework could also contribute to our understanding of downgrading processes in GVCs. The concept of downgrading has received much less attention than the notion of upgrading in the GVC literature (Gereffi, 2019). Downgrading has been associated with the dark side of GVC engagement, in terms of misuse of market power (Kaplinsky et al., 2010), environmental downgrading (Krishnan et al., 2022), or social downgrading (Barrientos et al., 2016). Studies have also looked at functional downgrading while investigating functional upgrading (Herrigel, 2004; Ponte & Ewert, 2009; Plank & Staritz, 2015). For example, Blažek (2016) developed a comprehensive categorisation of functional downgrading at the firm level.

What has not yet been done is the application of the relatedness/complexity framework to functional downgrading in GVCs. What one could expect is that functional downgrading is influenced by existing regional capabilities. A consistent finding in the regional diversification literature is that existing activities (technologies, industries, and jobs) are more likely to disappear from a region when unrelated to other existing activities in the region (Neffke et al., 2011; Kogler et al., 2013, 2017; Rigby, 2015). This means they are loosely embedded and weakly anchored in regional capabilities that do not provide any support in terms of knowledge and skills. When applying such a logic of exits to GVCs, one could expect that regions are more likely to lose their specializations in functions that are disconnected from (unrelated to) existing functions in their GVCs.

In sum, EEG offers a relatedness/complexity framework to study the evolution of GVCs in regions in terms of upgrading and downgrading. Traditionally, functional upgrading has been defined as "acquiring new, superior functions in the chain, such as design or marketing or abandoning existing low value added functions to focus on higher value added activities" (Giuliani et al., 2005, p.552). Using the complexity concept, one can define functional upgrading in regions as becoming specialised in more complex functions in GVCs. Based on the previous discussion, we formulate four hypotheses.

Hypothesis 1a: Regions are more likely to acquire or develop new functions in GVCs that are related to the functions in which they are already specialised.

Hypothesis 1b: Regions are more likely to acquire or develop complex functions in GVCs that are related to the functions in which they are already specialised.

Hypothesis 2a: Regions are more likely to lose functions in GVCs that are unrelated to the functions in which they are already specialised.

Hypothesis 2b: Regions are more likely to lose complex functions in GVCs that are unrelated to the functions in which they are already specialised.

3.- DATA AND VARIABLES

3.1. DATA

The paper investigates occupation-industry pairs in GVCs as a proxy for functions. We determine their level of complexity, which is known to be a measure positively correlated with economic growth (Hidalgo & Hausmann, 2009). This implies that developing more complex occupation-industry combinations results in functional upgrading of GVCs. The analyses are conducted at the sub-national scale. Most studies have been carried out at the national level (Pahl & Timmer, 2019; Timmer et al., 2019), as interregional input-output tables were lacking until recently (Los et al., 2015). However, the recent publication of the EUREGIO database allows to conduct analyses at the regional level, as it contains data on input-output flows for 249 regions from 24 European countries, 16 non-EU countries, the rest of the world, and 14 industries (NACE Rev. 1) between the years 2000-2010 (Thissen et al., 2018). We use the EUREGIO database to compute the domestic value added content of gross exports produced by each regional industry, mapping EU regions along and across GVCs.

In order to add the functional dimension into the GVCs, we use data on occupations and wages. Microdata from the EU Labour Force Survey (EULFS), provided by Eurostat, is employed to define the labour structures of the EU NUTS-2 regions. The EULFS is the largest European household sample survey including information on the number of workers by occupation (ISCO-88), industry (NACE Rev. 1) and EU regions (NUTS-2) between the years 1989 and 2020 (Eurostat, 2021).

Since just accounting for total number of workers can be misleading, we employ data on wages to complement EULFS data. Microdata from the EU Structure of Earnings Survey (EUSES) provided by Eurostat was used to compute the median wage of each occupation in each regional industry. EUSES is a large sample survey of enterprises that links wages, characteristics of employees, and those of the employer. EUSES includes information on the gross annual earnings of workers by occupation (ISCO-88 or ISCO-08, depending on the year), industry (NACE Rev. 1 or NACE Rev. 2, depending on the year) and EU regions (NUTS-1) for the years 2002, 2006, 2010, 2014 and 2018 (Eurostat, 2022).

Using three databases generate challenges. Firstly, a small number of regions in the EUREGIO tables do not match regions in EULFS. These regions were merged to be the same in all databases. Secondly, the occupations in EUSES for the year 2010 are at ISCO-08, while EULFS uses ISCO-88. To deal with this issue, only information from EUSES for the years 2002 and 2006 was used, assuming linear interpolation between these years and keeping fixed the values for the years before and after this time interval. Thirdly, sectors in EUREGIO were more aggregated than in EULFS and EUSES. We used the industrial classification of EUREGIO. Fourthly, regions in EULFS are defined at the NUTS-2 level, while EUSES use data at the NUTS-1 level. For this reason, we assumed wages were homogenous across NUTS-1. Finally, when data was missing in EUSES, the same criteria as Timmer et al. (2019) were followed and adjusted for regions and occupations.

In sum, we built a new database on value added content of gross exports, occupations and wages to explore the evolution of functional upgrading and downgrading in GVCs. The final panel includes information for 199 EU NUTS-2 regions[1] and 208 functions (occupation-industry pairs) between the years 2000-2010. Regional data for the control variables, namely GDP per capita, population density, and patent applications, was retrieved from Eurostat databases. The indicator of GVC participation was derived from the EUREGIO database.

3.2.- FUNCTIONAL SPECIALISATION OF REGIONS IN GVCs

Trade indicators on functions capture the origin of value added flows (Timmer et al., 2019). They quantify the domestic value added content of gross exports generated by each function in the production process. This enables to gain an understanding of the functional specialisation of regions in particular. There are different approaches to compute functional specialisation in trade of territories. Besides the seminal work by Leontief (1953) on the factor content of trade, more recent papers focus on the occupational content of exports, such as Wolff (2003) or Timmer et al. (2019). This paper uses the latter approach which follows a two-step process, in which first the domestic value added in exports is traced to the contribution of each industry, and, second, this industrial value added in exports is distributed across the different occupational functions.

Following Timmer et al. (2019), we consider e as a vector of exports of a region (with a dimension of G x 1), in which G stands for the total number of industries in the economy. The same computation applies to each region and each year. A^D is the G x G regional input-output coefficient matrix, containing a_{ij} as the traditional domestic input coefficients. The vector y (with dimension G x 1) can be derived, representing the total regional gross output required in each industry to generate their exports:

$$y = (I - A^D)^{-1} e \quad (1)$$

Notice that I is an identity matrix (with a dimension of G x G), and $(I - A^D)^{-1}$ is the Leontief inverse matrix. It is possible to define the vector d (G x 1) as the amount of domestic value added required for a region's exports, where V is the matrix (G x G) with diagonal element v_{gg} representing the value added to gross output ratio for industry g and zeroes otherwise:

$$d = V_y, \quad (2)$$

So, each element d_g represents the value added generated by domestic industry g in the region that contributes towards its gross export.

In the second step, we distribute industrial domestic value-added to occupations. Let B be defined as a matrix of dimensions K x G, where K is the number of occupations. The key element of this matrix (b_{kg}) represents the income of employees within a certain occupation k in industry g, expressed as the share of value added in g. Thus, we are able to compute the following measure f^{kg}, which is the value added produced by occupation k in industry g that contributes to the gross exports of the region:

$$f^{kg} = b_{kg}\, d_g, \quad (3)$$

To simplify notations, here forth we use s to indicate each economic activity that is jointly defined by occupation k in industry g, and the expression of $f^s_{r,t}$ stands for domestic value-added in the gross export of region r in year t, that is generated by the occupation-industry pair s. Based on this measure, it is then possible to compute the Functional Specialisation Index (FSI) as follows:

$$FSI_{r,s,t} = \frac{\dfrac{f^s_{r,t}}{\sum_s f^s_{r,t}}}{\dfrac{\sum_r f^s_{r,t}}{\sum_r \sum_s f^s_{r,t}}} \quad (4)$$

The FSI takes the form of the Revealed Comparative Advantage (RCA) index or location quotient following Balassa (1965). The numerator shows the share of domestic value added generated by occupation-industry pair s in region r at time t. The denominator measures the share of domestic value added generated by this occupation-industry pair s for all regions at time t.

It is important to underline that this FSI is computed using the income share of each occupation in each industry, and not the total number of employees. This is because some occupations require more quantity of workers than others. For example, R&D functions employ less people than assembly activities. In order to account for the real contribution of each function in the production process, wages give a better quantification of the contribution of each occupation.

It is also important to highlight that labour data is preferred over capital returns for several reasons. First, capital returns do not usually stay in the territories. For example, MNEs tend to concentrate capital returns coming from several locations in the region where their headquarters is located (Iammarino & McCann, 2013). Wages usually stay in the territories in which they are earned, since workers tend to live close to their workplaces. Second, capital returns are not easily matched with functions since several capital forms can be associated to various functions. For example, ICT equipment can be used to develop marketing campaigns (marketing functions), to develop research (R&D functions), and/or to provide a service (fabrication functions) (Timmer et al., 2019).

3.3.- ECONOMIC COMPLEXITY OF FUNCTIONS AND REGIONS IN GVCs

This paper is, to the best of our knowledge, the first attempt to propose economic complexity metrics as a way to define functional upgrading and downgrading in GVCs. These metrics are based on (1) which regions develop specific functions in GVCs and (2) how common these functions are across regions. Based on the value added content of gross exports generated by each function (occupation-industry pair) s in region r, complexity metrics are computed for both functions and regions. The methodology used for the computation of the complexity metrics is the eigenvector reformulation of the method of reflections (Hidalgo & Hausmann, 2009), following Balland et al. (2019).

A matrix of dimensions r x s is constructed for the period 2000-2010, where r is the number of regions at NUTS-2 level, and s is the total number of occupation-industry pairs. By making use of the *EconGeo* R package (Balland, 2017) and applying the eigenvector reformulation of the method of reflections, a r x s two-mode binary adjacency matrix $M = M_{r,s}$ of revealed comparative advantages (RCAs) is computed. The RCAs used in this case are a binary version of the FSIs, equal to 1 if $FSI_{r,s} \geq 1$, and 0 otherwise.

Following the method of reflections, the economic complexity of functions and regions is based on the diversity of regions and the ubiquity of functions:

$$Diversity = K_{r,0} = \sum_{s} M_{r,s} \qquad (5)$$

$$Ubiquity = K_{s,0} = \sum_{r} M_{r,s} \qquad (6)$$

Based on these two concepts, diversity and ubiquity, it is possible to define the economic complexity of functions and regions by subsequentially combining them in the following equations over a series of n iterations:

$$FCI_r = K_{r,n} = \frac{1}{K_{r,0}} \sum_{s} M_{r,s} \, K_{s,n-1} \qquad (7)$$

$$FCI_s = K_{s,n} = \frac{1}{K_{s,0}} \sum_s M_{r,s} K_{r,n-1} \quad (8)$$

Following Balland and Rigby (2017), the two-mode matrix *M* is row standardized along with its transpose (M^T), obtaining a square matrix (*P*) by multiplying both of them ($P=M*M^T$). Matrix *P* has dimensions equal to the total number of regions included in the analysis. The complexity of each region is provided by the second eigenvector of matrix *P*. By reversing the order of the matrix product (M^T*M), it is possible to obtain the square matrix *R* ($R=M^T*M$). Matrix *R* has dimensions equal to the total number of occupation-industry pairs, and its second eigenvector gives the complexity of each function.

We are interested in the complexity of FCI_s, which will be referred to as the Functional Complexity Index (*FCI*). This FCI_s allows to differentiate functions (i.e. occupation-industry pairs) based on their economic complexity. The differences in their complexity allows to empirically identify functional upgrading and downgrading in GVCs. Notice that for computing the complexity of functions, the matrix is constructed using the average value added across all time periods (2000-2010).

3.4.- RELATEDNESS BETWEEN FUNCTIONS IN GVCs

The key objective is to estimate the role of relatedness in shaping functional upgrading and downgrading in GVCs in regions. Following the relatedness literature (Hidalgo et al., 2007; Boschma et al., 2015; Balland et al., 2019), we compute a relatedness density indicator which is based on the degree of relatedness between functions (occupation-industry pairs) in GVCs. The degree of relatedness is derived from the contribution of each function to the value added content of gross exports generated in each region.

The degree of relatedness (ϕ) between the 208 pairs of occupations-industries (26 occupations and 8 industries) is obtained based on the value added content of gross exports generated by each pair. For that purpose, a co-occurrence analysis is carried out. The data is divided into sum-matrices for 4 non-overlapping time periods (*t*), 2000-2001, 2002-2004, 2005-2007, 2008-2010, with regions (*r*) in rows and occupation-industry pairs (*s*) in columns. The degree of relatedness (ϕ) is obtained applying a standardized method (Steijn, 2017) based on Van Eck and Waltman (2009). Results of the co-occurrence analysis are presented as a network or functional space in Appendix IX.

The relatedness density for each region *r* and occupation-industry pair *s* at time *t* is obtained by adding all the relatedness values of those occupation-industry pairs that are related to the occupation-industry pair s_i, and in which region *r* has a FSI higher than 1. Thus, parameter $x_{r,s,t}$ takes value 1 when the FSI of an occupation-industry pair *s* in the region *r* at time *t* is higher or equal to 1, and 0 otherwise.

$$Relatedness\ Density_{r,s,t} = \frac{\sum_s x_{r,s,t} \phi_{s_i,s_j,t}}{\sum_s \phi_{s_i,s_j,t}} \quad (9)$$

The relatedness density is computed for each region included in the sample with respect to the 208 occupation-industry pairs developed in GVCs for the above-mentioned four time windows using the *EconGeo* R package (Balland, 2017).

3.5.- FUNCTIONAL UPGRADING AND DOWNGRADING IN GVCs

The study uses as dependent variables measures of functional upgrading and downgrading. We make use of economic complexity metrics to differentiate functions (occupation-industry pairs) and construct a hierarchy of functions in terms of their FCI.

Functional upgrading is defined as becoming specialised in functions that are more complex than the average functional complexity of the region. The latter is further defined as the average of the *FCIs* in which the region was specialised in the previous period. This is captured by a dummy variable, taking value 1 when a region *r* becomes specialised in a new function (acquiring a FSI higher or equal to 1 in an occupation-industry pair *s*) in which it was not specialised in the previous period, and that is more complex (a higher FCI_s) than the previous average functional complexity of the region, and 0 otherwise. This can be formulated as follows:

$$Funct\ Upgrading_{r,s,t} = 1\ if\ FSI_{r,s,t} \geq 1\ and\ FSI_{r,s,t-1} < 1\ and\ FCI_s > \overline{FCI}_{r,t-1} \quad (10)$$

$$Funct\ Upgrading_{r,s,t} = 0\ if\ FSI_{r,s,t} < 1\ and\ FSI_{r,s,t-1} < 1\ and\ FCI_s > \overline{FCI}_{r,t-1} \quad (11)$$

Regions can also enter new functions, no matter whether it concerns functional upgrading. This is referred to as functional diversification in GVCs. It is captured by a dummy variable taking value 1 when a region *r* becomes specialised in a new function at time *t*, so acquiring a FSI higher or equal to 1 in an occupation-industry pair *s* in which it was not specialised in the previous period *t-1*, and 0 otherwise. This is formulated as follows:

$$Functional\ Diversification_{r,s,t} = 1\ if\ FSI_{r,s,t} \geq 1\ and\ FSI_{r,s,t-1} < 1 \quad (12)$$

$$Functional\ Diversification_{r,s,t} = 0\ if\ FSI_{r,s,t} < 1\ and\ FSI_{r,s,t-1} < 1 \quad (13)$$

Functional downgrading is defined as becoming unspecialised in functions that are more complex than the previous average functional complexity of the region. This is captured by a dummy variable taking value 1 when a region *r* becomes unspecialised in a function (acquiring a FSI smaller than 1 in an occupation-industry pair *s*) in which it was specialised at time *t-1*, and that is more complex (a higher FCI_s) than the previous average functional complexity of the region, and 0 otherwise. This can be formulated as follows:

$$Funct\ Downgrading_{r,s,t} = 1\ if\ FSI_{r,s,t} < 1\ and\ FSI_{r,s,t-1} \geq 1\ and\ FCI_s > \overline{FCI}_{r,t-1} \quad (14)$$

$$Funct\ Downgrading_{r,s,t} = 0\ if\ FSI_{r,s,t} \geq 1\ and\ FSI_{r,s,t-1} \geq 1\ and\ FCI_s > \overline{FCI}_{r,t-1} \quad (15)$$

Functional exit is defined as becoming unspecialised in a function regardless of its complexity. It may be captured by a dummy variable taking value 1 when a region *r* becomes unspecialised in a function (acquiring a FSI lower than 1 in an occupation-industry pair s) in which the region was already specialised in the previous time period $t-1$, regardless of its functional complexity, and 0 otherwise. This is formulated as follows:

$$Functional\ Exit_{r,s,t} = 1\ if\ FSI_{r,s,t} < 1\ and\ FSI_{r,s,t-1} \geq 1 \quad (16)$$

$$Functional\ Exit_{r,s,t} = 0\ if\ FSI_{r,s,t} \geq 1\ and\ FSI_{r,s,t-1} \geq 1 \quad (17)$$

3.6.- DESCRIPTIVE STATISTICS

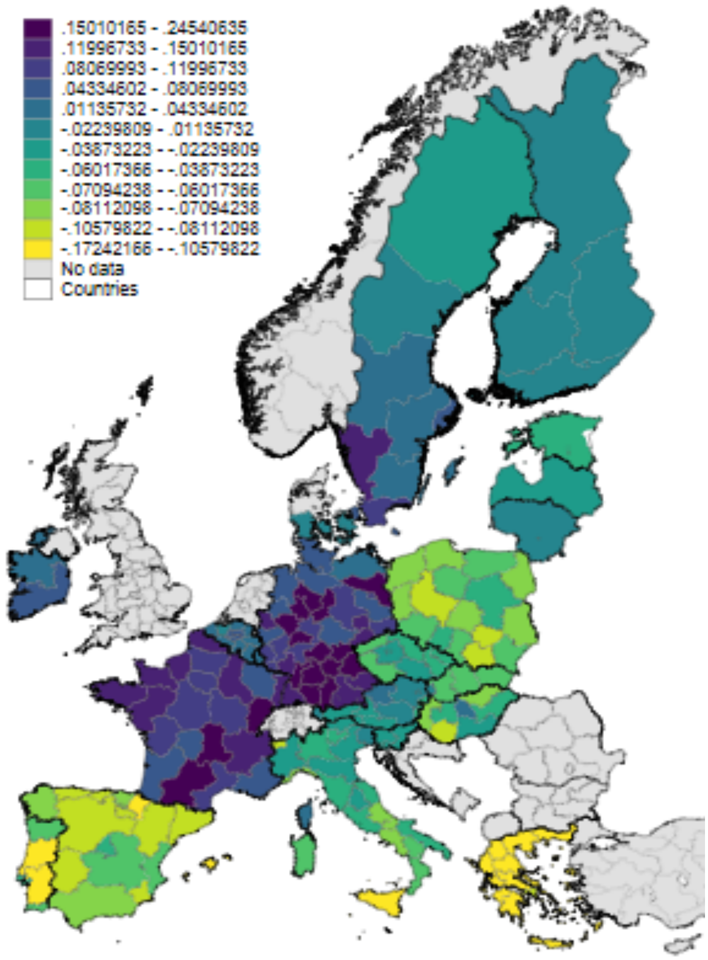
In Table 1, the descriptive statistics of the variables are summarised. Note that differences in the observations for the upgrading, downgrading, diversification, and exit dummies are due to the fact that if a region is already specialised (not specialised) in an occupation-industry, the next period it is not possible to become again specialised (not specialised).[2] The loss of observations in the relatedness density is due to missing information on four regions in the first period (i.e. DEB1, DEB2, DEB3 and DE41). These regions report no value added in this time window. The relatedness density of some functions could also not be computed due to missing values in the first period.

Table 1.- Descriptive statistics

Variables	N	Mean	SD	Min	Max
FSI	163,072	1.062	4.085	0	1,014
FCI_s	163,072	0.00481	0.0650	-0.127	0.191
Relatedness Den.	162,879	29.96	10.83	0	77.17
Upgrading	44,699	0.1359	0.3427	0	1
Diversification	85,379	0.14	0.347	0	1
Downgrading	17,976	0.322	0.467	0	1
Exit	77,693	0.521	0.500	0	1
GDP per capita	163,072	22,323	8,897	6,534	68,115
Population Den.	151,632	286.4	679.4	3.300	6,745
GVC participation	163,072	0.636	0.0876	0.341	0.838
Patents	163,072	684.2	1,242	0	9,324

Figure 1 shows a map of the functional complexity of regions, measured by the average of the FCI for regions (FCI_r) across periods. High-income countries such as France, Germany, Sweden and Finland, among others, have the most complex regions in the EU regarding functions in GVCs. Countries in the South of Europe, such as Spain, Italy and Greece, and some East-European countries like Poland, among others, have the least complex regions in terms of functions in GVCs.

Figure 1.- Average functional complexity of regions for the period 2000-2010



Source: Authors' own elaboration.

4.- ECONOMETRIC FRAMEWORK

This section presents the econometric framework. Since all the dependent variables take the form of dummy variables, two-way fixed effects linear probability models (LPM) are used.[4] The general form of these models takes the following form:

$$Func.Upg._{\ r,s,t} = \alpha + \beta_1\ Relatedness\ Density_{r,s,t-1} + \gamma\ X_{r,t-1} + \varphi_{r,s} + \theta_t + \\ + \varepsilon_{r,s,t} \quad (18)$$

As explained before, there are four dependent variables, that is, two variables capturing functional diversification and upgrading in GVCs to test hypotheses 1a and 1b, respectively, and two variables capturing functional exit and downgrading in GVCs to test hypotheses 2a and 2b, respectively. It is important to underline that all dependent variables are mean centred and lagged by one period.

The main variable of interest is the relatedness density of a region with regard to a function in the previous time period. X stands for a vector of control variables at the regional level. Following other studies on regional entries and exits (e.g. Neffke et al., 2011) we control for GDP per capita, population density, patents applications, and total GVC participation. GDP per capita is used to control for the level of economic development in a region, population density controls for urbanization economies, as proxied by the number of population per square kilometer, and the number of patent applications refers to the capacity of a regions to absorb new knowledge and technology. Total GVC participation measures the ability of a region to participate in global value chains (Colozza et al., 2021). Finally, $\varphi_{r,s}$, θ_t and $\varepsilon_{r,s,t}$, stand for region-function fixed effects, time fixed effects, and the regression residual, respectively.

In order to account for the presence of heteroskedasticity, standard errors are clustered at the regional level for all regressions. Notice that the time periods refer to the four time windows previously mentioned (2000-2001, 2002-2004, 2005-2007, 2008-2010).

5.- RESULTS

Table 2 presents the results on functional diversification in GVCs in regions. Our main variable of interest relatedness density turns out to show a positive and significant coefficient, indicating that a new functional specialisation in a region is positively correlated with relevant capabilities already present in the region. In this respect, a 10% increase in the relatedness density in a region is associated with a 22%-44% increase in the relative probability of experiencing functional diversification in that region.[5] In other words, regions tend to develop new functions in GVCs that are related to the ones in which they are already specialised, which confirms hypothesis 1a. Of all control variables, only GVC participation has a positive and significant coefficient in all specifications.

Table 2.- Functional diversification in EU regions

	Dependent variable: Diversification (=1)		
	Baseline (1)	Full model (2)	Full model (FE) (3)
Constant	0.1731*** (0.00294)	0.1736*** (0.002852)	0.0978*** (0.00724)
Relatedness density	0.00756*** (0.000268)	0.00755*** (0.000269)	0.00374*** (0.000335)
GDP per capita (log)		0.01682* (0.00953)	0.00901 (0.0364)
Population density (log)		-0.00475 (0.00292)	-0.0277 (0.119)
GVC participation (log)		0.0523*** (0.01595)	0.259*** (0.0833)
Patents (log)		-0.00078 (0.00158)	0.000513 (0.00634)
Reg.-Func. Fes	NO	NO	YES

Period Fes	NO	NO	YES
Observations	77,427	77,427	77,427
R^2	0.037	0.037	0.047

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 * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$ level.

Table 3 includes the results on functional upgrading in GVCs in regions. We find again a positive and significant coefficient of relatedness density which supports hypothesis 1b. Thus, regions tend to develop new specialisations in more complex functions in GVCs that are related to functions in which they are already specialised. Indeed, a 10% increase in the relatedness density in a region is associated with a 18%-43% relative increase in the probability of functional upgrading in a region.

Table 3.- Functional upgrading in EU regions

	Dependent variable: Upgrading (=1)		
	Baseline	Full model	Full model (FE)
	(1)	(2)	(3)
Constant	0.1693***	0.1706***	0.0666***
	(0.00373)	(0.0034)	(0.0165)
Relatedness density	0.00724***	0.00682***	0.00315***
	(0.000341)	(0.00033)	(0.000445)
GDP per capita (log)		0.00893	-0.0222
		(0.00962)	(0.0476)
Population density (log)		-0.00704**	-0.167
		(0.0033)	(0.143)
GVC participation (log)		0.0301	0.248**
		(0.01839)	(0.104)
Patents (log)		0.00665***	-0.00819
		(0.001934)	(0.00859)
Reg.-Func. FEs	NO	NO	YES
Period Fes	NO	NO	YES
Observations	40,308	40,308	40,308
R^2	0.032	0.034	0.047

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 * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$ level.

Table 4 includes the results for hypothesis 2a on the likelihood of exits of functions in GVCs in regions. The findings confirm that relatedness density shows a negative and significant coefficient. A region is more likely to exit functions in GVCs when the region is not specialised in related functions in the value chains. To be precise, a 10% decrease in the relatedness density in a region is associated with an 10%-26% increase in the relative probability of exiting a function, regardless of its complexity. With respect to the control variables, GVC participation shows a positive and significant coefficient. Combined with the finding in Table, 2, the latter means that GVC participation is positively associated with both entry and exits of functions in GVCs.

Table 4.- Functional exit in EU regions

	Dependent variable: Exit (=1)		
	Baseline (1)	Full model (2)	Full model (FE) (3)
Constant	0.396***	0.397***	0.136***
	(0.00726)	(0.00709)	(0.0144)
Relatedness density	-0.0101***	-0.0103***	-0.00384***
	(0.000562)	(0.000544)	(0.000577)
GDP per capita (log)		-0.0290	-0.299***
		(0.01766)	(0.0976)
Population density (log)		0.00155	-0.545***
		(0.00415)	(0.206)
GVC participation (log)		0.14324***	0.953***
		(0.03394)	(0.187)
Patents (log)		0.01054***	-0.0135
		(0.002837)	(0.0166)
Reg.-Func. Fes	NO	NO	YES
Period Fes	NO	NO	YES
Observations	33,479	33,479	33,479
R^2	0.044	0.047	0.125

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 * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$ level.

Table 5 presents the results for hypothesis 2b on functional downgrading in GVCs. Relatedness density has a negative significant association with functional downgrading in regions. That is, regions are more likely to lose functions of high complexity when regions are not specialised in related functions in the value chain. These results support the hypothesis. A 10% decrease in the relatedness density in a region is associated with an 8%-24% increase in the relative probability of experiencing functional downgrading in a region. Interestingly, GVC participation shows a positive and significant coefficient again. Combined with findings in Table 3, our results show that GVC participation is positively associated with both functional upgrading and downgrading in regions.

Table 5.- Functional downgrading in EU regions

	Dependent variable: Downgrading (=1)		
	Baseline (1)	Full model (2)	Full model (FE) (3)
Constant	0.3937***	0.3925***	0.182***

	(0.00773)	(0.00761)	(0.0183)
Relatedness density	-0.009299***	-0.00903***	-0.00324***
	(0.0006802)	(0.000683)	(0.000820)
GDP per capita (log)		-0.000275	-0.345**
		(0.01974)	(0.137)
Population density (log)		0.00187	-0.744**
		(0.00482)	(0.286)
GVC participation (log)		0.1088**	1.251***
		(0.04422)	(0.347)
Patents (log)		-0.00746**	0.0198
		(0.00359)	(0.0229)
Reg.-Func. Fes	NO	NO	YES
Period Fes	NO	NO	YES
Observations	16,521	16,521	16,521
R^2	0.033	0.035	0.142

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 * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$ level.

6.- CONCLUSIONS

This paper has connected empirically the EEG and GVC literatures that showed little interaction so far (Yeung, 2021; Boschma, 2022). We adopted an evolutionary framework to identify functional upgrading and downgrading in GVCs in regions using relatedness and economic complexity metrics. By measuring the complexity of functions, we were able to identify functional upgrading in regions, but also functional downgrading which has received less attention in the GVC literature (Gereffi, 2019). Doing so, we were able to apply a functional approach in GVCs from an evolutionary angle and to assess the likelihood of functional upgrading and downgrading in GVCs in EU regions, using unique inter-regional input-output tables, and combining them with labour data.

We found evidence that the principle of relatedness holds for both functional upgrading and downgrading in GVCs at the regional level. Relatedness in GVCs is a factor impacting functional upgrading and downgrading. Our study showed that functional diversification and upgrading in GVCs are positively correlated with the existing set of capabilities in regions. That is, EU regions tend to functionally upgrade and diversify in GVCs towards functions that are related to the ones in which they are already specialised. Also functional exits and downgrading in GVCs are influenced by existing regional capabilities. Our study shows that EU regions are less likely to exit functions in GVCs and to experience functional downgrading when they are specialised in related functions.

This study is not without limitations. First, we made use of unique input-output data at the regional scale that has become available only very recently, but the level of detail with respect to industries is still very limited, especially for manufacturing. This is clearly a limitation of doing such analyses at the regional scale in the EU, which is less severe at the country level. Second, it remains unclear whether functional upgrading and downgrading in GVCs contribute to regional convergence in Europe (Comotti et al., 2020), and to what extent (less developed) regions are stuck in low-complex functions, following Pinheiro et al. (2022). The latter study identified low-complexity traps in European regions where diversification opportunities in high-complex activities were severely limited due to their low degree of relatedness. Doing such a study on GVC following our framework could shed additional light on the nature of low value-added traps (e.g. Phelps et al., 2003; MacKinnon, 2012; Yeung, 2015; Stöllinger, 2019), and what are the options of regions to overcome such traps. Third, our study found that GVC participation of regions was positively associated with functional upgrading and downgrading: the higher their participation, the higher their chances of upgrading but also of downgrading. Apparently, GVC participation has a bright side (functional upgrading) as well as a dark side (functional downgrading) (see also Werner & Bair, 2019). However, it remains unclear what are the mechanisms behind that, especially in the case of functional downgrading. Fourth, what is still missing is the explicit role of institutions for functional diversification, upgrading and downgrading in regions (McKinnon, 2012; He et al., 2017; McKinnon et al., 2019). Rodríguez-Pose (2021) stated that the local benefits of GVCs might be mitigated by the quality of regional institutions (see also Pietrobelli & Rabellotti, 2011; Yeung & Coe, 2015; Kergroach, 2019). EEG has explored how such institutions affect the degree and nature of diversification in regions (e.g. Boschma & Capone, 2015; Rodríguez-Pose & Di Cataldo, 2015; Cortinovis et al., 2017), but this has not yet been fully applied at the level of GVCs (Rodríguez-Pose, 2021).

A key challenge is to derive policy implications from our evolutionary study on GVCs (see also Lee, 2019 ; Brennan & Rakhmatullin, 2015; Dannenberg et al., 2018; Comotti et al., 2020). The main finding of the study is that relevant capabilities are crucial to enhance functional upgrading but they also prevent functional downgrading in GVCs in regions. This implies that regional policy should target those functions in GVCs that provide diversification opportunities for each specific region. This means no 'one-size-fits-al' policy is a prerequisite: regions should base their development strategies on the capabilities they already master and build upon them to develop new functions along and across value chains. This comes close to the key principle of Smart Specialization policy (Foray, 2015; McCann & Ortega-Argilés, 2015; Uyarra et al., 2018; Balland et al., 2019). However, current Smart Specialisation Strategies in the EU do not yet account fully for the role of functions in GVCs when selecting opportunities and setting priorities to foster regional development (Radosevic & Ciampi Stankova, 2015). This needs to be taken up in Smart Specialization policies, and our framework could be instrumental for that.

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NOTES

1.- Due to data unavailability and mismatches between the databases, the final number of NUTS-2 EU regions is 199 (see Appendix 1). Data for Romania and Bulgaria is not regionalised in EUREGIO, and data for the UK and the Netherlands suffered from similar issues in the EULFS and the EUSES. These data limitations explain why some European regions were not included in the analysis. For a detailed explanation of the criteria followed in the data matching between the EULFS and the EUSES, see Appendix II.

2.- Notice that upgrading is a subset of diversification, as downgrading is a subset of exit. Since each dependent variable (diversification, upgrading, exit and downgrading) has different number of observations, further descriptive statistics tables are provided in Appendix III. This is also reflected in the correlation matrices in Appendix IV.

3.- LPMs are used over logit and probit since these models may lead to bias or inconsistency when estimated with a large number of dummy variables (Greene, 2012). In any case, similar results were obtained using logit and probit models. For further details see Appendices V and VI. Also, similar results were found using different combinations of region, function, and time fixed effects, as shown in Appendix VII. In Appendix VIII similar results are obtained 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.

4.- In the baseline model (1), the unconditional probability of diversification is 17.3%. An increase by 10% in relatedness density increases the relative probability of diversification by (0.00756*10)/0.173 = 43.7%. In the most conservative model, the two-way fixed effects model (3), there is an increase in the relative probability of diversification of about (0.00374*10)/ 0.1736 = 21.5%. The intercept in a fixed effect model cannot be interpreted as the unconditional probability of diversification by definition. The unconditional probability of diversification for this model can be found as the intercept of model 2.

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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.- Matching criteria EULFS and EUSES.

In the first place, when the region of the workplace was missing in any individual observation, the region of residence was used. It was assumed that workers tend to live close to their workplaces. In the second place, in the EUSES, data on wages was missing for some regions. In this sense, 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.

Finally, since data for some countries was missing in the EUSES and, in order to minimise the loss of regions, similar criteria than Timmer at al. (2019) were followed and adjusted for the regional level. In this sense, 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.

Appendix III.- Individual descriptive statistics for each dependent variable.

Variables	N	Mean	SD	Min	Max
Relatedness Den.	85,379	27.23	9.716	0	72
Diversification	85,379	0.140	0.347	0	1
GDP per capita	85,379	23,287	9,007	7,342	68,115
GVC participation	85,379	0.637	0.0907	0.341	0.838
Population Den.	80,826	278.5	660.7	3.300	6,745
Patents	85,379	766.7	1,345	0	9,324

Variables	N	Mean	SD	Min	Max
Relatedness Den.	44,699	27.05	9.313	0	70.30
Upgrading	44,699	0.136	0.343	0	1
GDP per capita	44,699	22,718	9,089	7,342	68,115
GVC participation	44,699	0.636	0.0969	0.341	0.838
Population Den.	42,248	263.8	637.7	3.300	6,745
Patents	44,699	625.6	1,193	0	9,324

Variables	N	Mean	SD	Min	Max
Relatedness Den.	77,500	32.97	11.19	0	77.17
Exit	77,693	0.521	0.500	0	1
GDP per capita	77,693	21,263	8,651	6,534	68,115
GVC participation	77,693	0.634	0.0840	0.341	0.838
Population Den.	70,806	295.4	700.1	3.300	6,745
Patents	77,693	593.5	1,112	0	9,324

Variables	N	Mean	SD	Min	Max
Relatedness Den.	17,976	36.55	9.758	0	70.93
Downgrading	17,976	0.322	0.467	0	1
GDP per capita	17,976	23,948	9,057	7,342	68,115
GVC participation	17,976	0.644	0.0775	0.341	0.838
Population Den.	17,069	315.0	740.0	3.300	6,745
Patents	17,976	869.9	1,419	0	9,324

Appendix IV.- Correlation matrix.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Diversification	1.000								
(2) Upgrading	1.000	1.000							
(3) Exit			1.000						
(4) Downgrading			1.000	1.000					
(5) Relatedn. Den.	0.376	0.369	-0.574	-0.450	1.000				
(6) GDP per cap.	0.010	0.042	-0.091	-0.043	0.047	1.000			
(7) Popul. Den.	0.010	0.022	-0.016	-0.017	0.080	0.435	1.000		
(8) GVC part.	0.047	0.058	-0.016	0.043	0.087	0.067	-0.040	1.000	
(9) Patents	-0.016	0.036	-0.045	-0.042	-0.042	0.447	0.109	-0.013	1.000

Appendix V.- Logit models.

	Logit models											
	Dep. variable: Diversification (=1)			Dep. variable: Upgrading (=1)			Dep. variable: Exit (=1)			Dep. variable: Downgrading (=1)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Baseline	Full	Full-FE	Baseline	Full	Full-FE	Baseline	Full	Full-FE	Baseline	Full	Full-FE
Constant	-1.651***	-1.650***		-1.666***	-1.664***		-0.419***	-0.417***		-0.432***	-0.440***	
	(0.0202)	(0.0189)		(0.0265)	(0.0235)		(0.0321)	(0.0315)		(0.0334)	(0.0331)	
Related. Den.	0.0607***	0.0602***	0.0337***	0.0597***	0.0562***	0.0322***	-0.0492***	-0.0504***	-0.0332***	-0.0442***	-0.0430***	-0.0358***
	(0.00211)	(0.00211)	(0.00328)	(0.00294)	(0.00275)	(0.00453)	(0.00283)	(0.00276)	(0.00499)	(0.00343)	(0.00345)	(0.00716)
GDP pc (log)		0.112	1.461***		0.0251	1.818**		-0.159*	-1.553*		-0.0150	-0.565
		(0.0743)	(0.531)		(0.0833)	(0.726)		(0.0888)	(0.806)		(0.0927)	(1.263)
Pop. Den. (log)		-0.0333	1.029		-0.0492**	-0.541		0.00849	-6.617***		0.0113	-10.57***
		(0.0210)	(1.208)		(0.0241)	(1.651)		(0.0207)	(1.885)		(0.0231)	(2.830)
GVC part. (log)		0.526***	1.509*		0.535***	1.832		0.681***	9.946***		0.522**	14.49***
		(0.132)	(0.917)		(0.168)	(1.273)		(0.170)	(1.650)		(0.203)	(2.406)
Patents (log)		-0.00245	-0.0164		0.0691***	-0.118		0.0527***	-0.209**		-0.0322*	-0.0510
		(0.0130)	(0.0669)		(0.0167)	(0.0922)		(0.0142)	(0.106)		(0.0165)	(0.166)
Observations	77,427	77,427	14,634	40,308	40,308	7,426	33,479	33,479	8,614	16,521	16,521	4,432
Reg.-Func. FEs	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES
Period FEs	NO	NO	YES	NO	NO	YES	NO	NO	YES	NO	NO	YES
R^2	0.0437	0.0446	0.174	0.0387	0.0423	0.178	0.0363	0.0394	0.357	0.0270	0.0283	0.407

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 for all models but the two-way FEs (3, 6, 9 and 12). Coefficients are statistically significant at the * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$ level.

Appendix VI.- Probit models.

	Probit models							
	Dep. Var: Diversification (=1)		Dep. Var: Upgrading (=1)		Dep. Var: Exit (=1)		Dep. Var: Downgrading (=1)	
	(1) Baseline	(2) Full model	(3) Baseline	(4) Full model	(5) Baseline	(6) Full model	(7) Baseline	(8) Full model
Constant	-0.980***	-0.979***	-0.989***	-0.987***	-0.262***	-0.261***	-0.271***	-0.275***
	(0.0113)	(0.0106)	(0.0146)	(0.0130)	(0.0196)	(0.0193)	(0.0206)	(0.0204)
Related. Den.	0.0337***	0.0334***	0.0329***	0.0309***	-0.0294***	-0.0302***	-0.0265***	-0.0258***
	(0.00117)	(0.00117)	(0.00161)	(0.00149)	(0.00169)	(0.00164)	(0.00205)	(0.00206)
GDP pc (log)		0.0695*		0.0288		-0.0861*		-0.000986
		(0.0413)		(0.0453)		(0.0522)		(0.0561)
Pop. Den. (log)		-0.0184		-0.0280**		0.00473		0.00622
		(0.0118)		(0.0136)		(0.0124)		(0.0140)
GVC part. (log)		0.293***		0.285***		0.424***		0.327***
		(0.0714)		(0.0904)		(0.101)		(0.123)
Patents (log)		-0.00222		0.0356***		0.0316***		-0.0203**
		(0.00710)		(0.00901)		(0.00837)		(0.0100)
Observations	77,427	77,427	40,308	40,308	33,479	33,479	16,521	16,521
Reg.-Func. FEs	NO	NO	NO	NO	NO	NO	NO	NO
Period FEs	NO	NO	NO	NO	NO	NO	NO	NO
R^2	0.0441	0.0451	0.0390	0.0427	0.0361	0.0393	0.0268	0.0281

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 * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$ level.

Appendix VII.- LPMs with individual region and function FEs.

	LPMs with individual region and function FEs							
	Divers. (1)	Upgrading (2)	Exit (3)	Downgrading (4)	Divers. (5)	Upgrading (6)	Exit (7)	Downgrading (8)
Constant	0.0560	0.0782	0.329**	0.101	0.135***	0.134***	0.517***	0.511***
	(0.0729)	(0.0794)	(0.130)	(0.177)	(0.0138)	(0.0141)	(0.0539)	(0.0537)
Related. Den.	0.00879***	0.00800***	-0.0142***	-0.0127***	0.00766***	0.00676***	-0.0108***	-0.0103***
	(0.000322)	(0.000431)	(0.000556)	(0.000787)	(0.000278)	(0.000322)	(0.000452)	(0.000512)
GDP pc (log)	0.164***	0.187***	-0.183	-0.202	0.0192**	0.0111	-0.0336*	-0.0289
	(0.0534)	(0.0554)	(0.111)	(0.132)	(0.00958)	(0.00945)	(0.0189)	(0.0210)
Pop. Den. (log)	-0.364***	-0.310**	0.214	-0.116	-0.00576**	-0.00898***	-0.00154	0.00178
	(0.125)	(0.131)	(0.218)	(0.307)	(0.00282)	(0.00331)	(0.00379)	(0.00463)
GVC part. (log)	0.233*	0.160	0.358*	0.463	0.0630***	0.0372**	0.148***	0.0934**
	(0.133)	(0.122)	(0.214)	(0.305)	(0.0157)	(0.0188)	(0.0316)	(0.0413)
Patents (log)	-0.00304	-0.00221	-0.0454***	-0.0546***	-0.000916	0.00763***	0.00605**	-0.00949***
	(0.00708)	(0.00759)	(0.0151)	(0.0210)	(0.00155)	(0.00191)	(0.00297)	(0.00358)
Observations	77,427	40,308	33,479	16,521	77,427	40,308	33,479	16,521
R-squared	0.048	0.049	0.080	0.077	0.065	0.063	0.158	0.159
Region FEs	YES	YES	YES	YES	NO	NO	NO	NO
Function FEs	NO	NO	NO	NO	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 * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$ level.

	LPMs with individual region and function FEs			
	Divers.	Upgrading	Exit	Downgrading
	(9)	(10)	(11)	(12)
Constant	0.181***	0.162***	0.411***	0.437***
	(0.00305)	(0.0106)	(0.00510)	(0.0184)
Related. Den.	0.00877***	0.00752***	-0.0129***	-0.0116***
	(0.000314)	(0.000420)	(0.000453)	(0.000585)
GDP pc (log)	0.164***	0.173***	-0.0889	-0.104
	(0.0519)	(0.0519)	(0.0945)	(0.118)
Pop. Den. (log)	-0.348***	-0.284**	0.101	-0.303
	(0.121)	(0.124)	(0.192)	(0.285)
GVC part. (log)	0.224*	0.143	0.397**	0.579**
	(0.131)	(0.113)	(0.193)	(0.272)
Patents (log)	-0.00378	-0.00269	-0.0418***	-0.0504**
	(0.00701)	(0.00742)	(0.0133)	(0.0198)
Observations	77,427	40,308	33,479	16,521
R-squared	0.075	0.077	0.178	0.182
Region Fes	YES	YES	YES	YES
Function FEs	YES	YES	YES	YES
Period 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 * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$ level.

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

	LPMs with additional controls			
	(1) Diversification	(2) Upgrading	(3) Exit	(4) Downgrading
Constant	0.103***	0.0679***	0.118***	0.177***
	(0.00772)	(0.0176)	(0.0177)	(0.0240)
Related. Den.	0.00362***	0.00313***	-0.00366***	-0.00299***
	(0.000347)	(0.000474)	(0.000598)	(0.000855)
GDP pc (log)	0.0135	-0.0256	-0.333***	-0.326**
	(0.0381)	(0.0531)	(0.109)	(0.151)
Pop. Den. (log)	-0.0367	-0.170	-0.486**	-0.692**
	(0.129)	(0.146)	(0.211)	(0.278)
GVC part. (log)	0.246***	0.240**	0.955***	1.222***
	(0.0778)	(0.107)	(0.201)	(0.376)
Patents (log)	-0.00253	-0.00777	-0.00674	0.0133
	(0.00675)	(0.00881)	(0.0178)	(0.0238)
Education (log)	0.0708***	0.0124	-0.0749*	0.109*
	(0.0227)	(0.0252)	(0.0401)	(0.0623)
Ind. Share (log)	0.0355	-0.0123	0.0523	0.207**
	(0.0360)	(0.0513)	(0.0678)	(0.102)
Observations	75,227	39,092	32,358	15,971
R-squared	0.047	0.047	0.124	0.142
Reg.-Func. FEs	YES	YES	YES	YES
Period 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 * $p < 0.10$, ** $p < 0.05$ and *** $p < 0.01$ level.

Appendix IX.- The functional space of GVCs in EU regions.

This Appendix presents the results of the co-occurrence analysis. Each node is a occupation-industry pair. All pairs (208) are included. We only show the significant linkages (with a relatedness score higher than 1.5). Nodes are coloured by industry. The closer two nodes are in the network, the higher the relatedness between them.