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FULL ARTICLE

The role of regions in global value chains: an analysis for the European Union

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Abstract

While considerable attention has been directed to the national-level impacts of global value chains, far less attention has been focused on the way in which global production fragmentation has affected regional economies. Using some measures derived from a multiregional, multisectoral input–output model, this paper analyzes the *position* and *share* of EU regions in Global Value Chains (GVC). The spatial determinants of these two dimensions are explored using spatial econometric methods to capture the influence of neighboring regions on these outcomes. Empirically, the focus is on a set of NUTS2 European regions for the most recent year (2010) of the EUREGIO database. Our results confirm the hypothesis of spatial dependence between regions conditioning the engagement and position GVCs, suggesting that global production processes are influenced by regional and local factors. In particular, spatial spillover effects play a significant role conditioned by both geographical proximity and similarity of production structures. The results show that sharing certain characteristics, some of them associated to their degree of proximity and the neighbouring situation of regions condition their specialization, participation and positioning in GVC, generating some important insights informative for the formulation of regional development policies.

KEYWORDS
European regions, global value chains, input–output, multiregional, spatial dependence

JEL CLASSIFICATION
F43, O52, R15, R12

1 | INTRODUCTION

Economic growth, international trade and production processes are increasingly structured around the so called "Global Value Chains" (GVC). Timmer et al. (2013) define GVCs as "all activities directly and indirectly required to produce a final manufactured product." The spatial fragmentation of the production processes across countries has led production chains and income generation to be seen as increasingly characterized as "global." Indeed, "linking into GVCs" has become one of the important new development challenges for many developed and developing economies (see Banga, 2015; Ojala et al., 2008). The recent (2020) experience with the COVID-19 pandemic has also highlighted the complex degree of dependence that most economies, both national and regional, exhibit and the disruptive effects of bottlenecks/supply shortages in generating negative impacts on growth.

The economic performance of economies regarding their engagement in GVCs has been assessed through the concepts of participation and position (Gereffi, 1999). The participation of countries in GVCs, that is, the country's share of value added embodied in exports over the world total, yields insights on their gains from the globalization process. The engagement in GVCs allows countries and regions to participate in the global economy exploiting their comparative/competitive advantages to concentrate in specific production processes, create more employment opportunities and boost technology transfer (Meng et al., 2020).

However, the benefits and risks of joining GVCs may be different depending on the position in the value chain in which the country or region operates. In general, the specialization in relatively downstream versus upstream stages of global value chains is believed to ensure higher value-added shares and increased technological complexity (see Hagemejer & Ghodsi, 2017; Hummels et al., 2001). As a consequence, upgrading the country's position in GVC has become a priority for some countries (see for instance Kummritz et al., 2017). However, and according to the GVCs' literature on the concept of "*smile curve*" (see Mudambi, 2008; Shin et al., 2012, among others) regarding the risks, Meng et al. (2020), draw attention to the differences in comparative advantages. Less developed countries may tend to engage in low-end production activities such as manufacturing and assembly, often undertaken by low-skilled and low-paid workers, with the risk for their economies of becoming trapped at the bottom of the "smile curve." On the contrary, rich countries/regions may tend to engage in high-end, often intangible production activities, also with risks, in this case associated with the offshoring of certain non-technological activities to low-wage countries. As a consequence, a better understanding of the elements contributing not only to the increase in GVC participation but also to the complexity of production networks will help to better understand how regions and countries specialize and relate, the associated implications for their economic growth and the nature and strength of dependence and vulnerability. However, most of the work on global value chains has operated at the country level; the degree of heterogeneity across regions within countries is well-known but has not been fully integrated into the GVC literature. This is the primary focus of this paper, drawing on the concepts of *participation* and *position* in GVCs and exploring the nature of what might be referred to as spatial conditioning (the influence of neighboring regions) on these two dimensions.

More specifically, this paper aims to bridge national and regional literatures to evaluate the involvement of regions in GVCs and the associated role of spatial dependency. In particular, this paper addresses questions such as:

Do local factors influence the involvement of regions and sectors in global value chains in terms of their *share* in these chains and their *position*?

Does the behavior of neighboring regions influence these regional outcomes? In other words, is there any evidence of spatial dependence in the European global value chains?

Does the proximity of territories lead them to share patterns of behavior and/or specialization that bring them closer in their engagement in global value chains? What type of "proximity" is most relevant for this issue?

The remainder of this paper is structured as follows. Section 2 provides a review of the relevant literature and highlights some important needs that have yet to be explored. Drawing on this review, section 3 offers a presentation of the methodology and methods, along with a description of the explanatory variables that will be explored in this paper. In addition, we introduce our variables of interest related to GVC (*Participation* and *Position*) as well as the corresponding methods to define them within the multiregional input–output framework. In section 4, we show the main results, focusing on the spatial role of neighbors in regional economic growth. Section 5 concludes the paper and offers some future direction for research.

2 | LITERATURE REVIEW

2.1 | National Perspective

Global value chains have been considered a defining feature of the current wave of globalization. Methodologically, multiregional input–output models (MRIO) are valuable instruments to assess the involvement of countries in global and regional value chains (Escaith & Inomata, 2013), given their capacity to capture intersectoral and interregional links and to approximate the involvement, participation and position of economies and sectors in GVCs (Antràs et al., 2012; Dietzenbacher & Romero, 2007; Johnson & Noguera, 2012a; Koopman et al., 2014, among others).

A broad set of GVCs indexes have been proposed in the input–output literature, particularly for the measurement of international production fragmentation and the countries and sectors participation in GVCs. Johnson (2018) provides a review of these measures and their formulation in an input–output framework, while Los and Timmer (2018) offer a general methodology based on the use of the hypothetical extraction method that allows obtaining the main measures, pointing out their relationships and differences.

Johnson (2018) suggests that exports are a sign of participation in global value chains and explains that the literature has been grouped into two broad, but not exclusive, strands. A first group has focused on the value-added decomposition of gross exports, identifying the domestic value-added content of gross exports and, as a complement, the imported content of these exports. This is the approach, for example, of Hummels et al. (2001) and Koopman et al. (2014) who decompose gross exports into different terms representing the domestic value-added content of exports, complementarily, the import context of exports (which they identify as "vertical specialization trade") and other double-counted items. Other indices along these lines can be found in Johnson and Noguera (2012a), Los et al. (2016) and Wang et al. (2013). However, this decomposition of gross exports in a multilateral framework as an indicator of GVC participation, in addition to including double-counted terms, casts some doubts on the underlying theoretical motivation regarding the foreign value-added (Johnson, 2018), given the dependence of the foreign value to output ratio on domestic exports.

In this context, another important line of work has focused on the study of the so-called trade in value added, referring to the value-added content in final goods. Within this approach, two complementary perspectives can be highlighted, which differ fundamentally in the decomposition assumed for final goods. For example, Johnson and Noguera (2012a, 2012b), in their identification of the value-added in exports, aim to trace value added from the country where it is generated to the country in which the product is finally consumed (consumption perspective). Timmer et al. (2013), Timmer et al. (2014) and Los, Timmer, and de Vries (2015), among others, use the decomposition of final demand by allocating parts of the value added embodied in these final goods to the countries where they are produced (production perspective). According to Johnson (2018), this approach to final demand decomposition, which will be followed in this paper, is close to the previous literature on offshoring and task trade and improves on traditional measures of offshoring by incorporating the multilateral nature of global value chains.

Moreover, while the main focus of this literature has been on the country features driving its higher or lower trade orientation (and the associated value added embodied), we are more interested here in developing a complementary approach, looking at the factors that lead different European regions to have a higher or lower shares than others in the European GVCs. In other words, we are interested in analyzing not only the factors driving the individual propensity to incorporate higher parts of their value added in trade, but also the local, regional and spatial factors that condition the regional competitiveness in GVCs, that is, their share in GVCs.

Regarding the measures of position in an input–output framework, as a way to better understanding the increasing complexity of GVCs, Dietzenbacher and Romero (2007) proposed the *Average Propagation Length* to measure participation under a MRIO framework and study the relations among industries in six European countries using the 1985 intercountry input–output table. Escaith and Inomata (2013) extend this approach to the Asian international context.

Nested within this approach, the influential papers by Antràs et al. (2012) and Antràs and Chor (2013) present two different approaches to building a measure of position indicator (first, the average distance from final use and secondly, the average distance from primary factors). Initially, it is in the work of Fally (2012) where these position measures (upstreamness and downstreamness) are proposed. These two indicators were further explored in Antràs, Chor, Fally, and Hillberry (2012) and Antràs and Chor (2013), respectively. However, there is a matter of inconsistency between them, noted later in Antràs and Chor (2017). Interestingly, the paper by Antràs and Chor (2017), using data from the WIOD database for the period 1995–2011 to compute the upstream and downstream measures proposed in their previous works (Antràs & Chor, 2013; Antràs et al. 2012) found two systematic and surprising facts that they called "puzzling findings:" those countries that appear to be upstream according to their production-staging distance from final demand (upstreamness) were at the same time recorded to be downstream according to their production-staging distance from primary factors (downstreamness). In other words, the two measures presented (upstream and downstream) show a clear, positive correlation. Antràs and Chor (2017) state that this "puzzling finding" is due to the reduction of commercial costs in all areas, and to the increase in the participation of services in economies. For this reason, and due to the increasing interregional linkages established between economies, it is important to explore what happens at the regional level. In this way, it could be ascertained whether behaviors observed at the national level are, in essence, good predictors of what might happen at the regional level.

2.2 | Regional focus and spillover effects

Notwithstanding the extensive literature on the nature and evolution of GVCs, relatively little attention has been directed so far to the fact that the international fragmentation of production also has an important regional (subnational) dimension, taking place among groups of neighboring regions. In this regard, the literature suggests that while regions are competing with each other, the processes of fragmentation that have given rise to global value chains that may also be generating increased interregional dependencies. Drawing on these ideas, Thissen et al. (2018) establish that differences in the regional compositions of economic activities are of course not the only determinant of within-country differences in economic performance. The variations in supplier-user linkages to industries in other regions also play an important role. Thus, as stated in Thissen et al. (2016), a region might be seriously affected by an economic downturn in another region if it sells much of its output to that region, while regions less dependent on that region might be hurt to a much lesser extent.

This phenomenon has been advanced as a source of explanation for differences in regional business cycle behavior even between regions that are each other's major trading partners (see Park & Hewings, 2012) as well as the possibility of asymmetry in the signs of spillover effects between any two regions (Chung & Hewings, 2015). In this same framework, some other papers have explained the configuration of clusters among industries (Engelberg et al. 2018; Escaith & Inomata, 2013; Gereffi & Lee, 2016; Humphrey & Schmitz, 2000; Oosterhaven et al. 2001), showing how differences in transportation and coordination costs, as well as regional policies play an important role in the configuration of these clusters. However, little attention has been focused on the potential spillovers among these actors or the role of heterogeneity and spatial dependence.

The role of spatial heterogeneity and spatial dependence in regional economic growth, has been extensively studied in the regional economics literature, with a broad consensus that the economic growth of a specific region not only depends on its structural and economic characteristics but also on the economic conditions of its neighbors through spatial spillovers (see López-Bazo et al., 2004; Ertur & Koch, 2006 among many others).

For instance, López-Bazo et al. (2004) analyze how the spatial technological conditions between economies can influence the process of economic growth and convergence of a specific region, finding that the spillover or spatial effects of neighbors are really significant. Ertur and Koch (2006), propose an economic growth model with technological externalities and spatial spillovers, finding that there is a different convergence speed for each economy in the sample and that the speed is influenced by the closest neighbor's speed. Similarly, Márquez et al. (2014) study the existence of growth spillover effects for the Spanish regions finding spatiotemporal regional spillovers of growth output among regions. In our paper, and following this previous literature, it is expected that the spillover effects would generate a significant and positive effect in the regions in global value chains, to some extent given the still distance-dependent nature of trade, despite the significant reduction of transportation costs in the last decades (Carrère et al., 2020). In this context, the literature highlights positive and significant spillovers among the closer neighbors, even behaving as clusters or taking advantage of agglomeration economies (Hu et al., 2020; Keilbach, 2000; Tappeiner et al., 2008).

Regarding the consideration of regional and geographical aspects in the assessment of the economies' involvement in GVCs using a MRIO perspective, some authors suggest a need to focus on important cross-regional heterogeneity when looking at the GVCs inside countries, the existence of positive spillovers among regions from their participation in GVCs, and a still significant role of geographical distance explaining the value added content of bilateral trade flows (Dietzenbacher et al., 2012; Krishnan, 2018; Sturgeon et al., 2008). In this regard, Johnson and Noguera (2012b), in their study focusing on the value added content of bilateral trade flows at the international level, find that the geographical distance between countries is important in bilateral trade even in the context of increasingly globalized supply chains. Our paper also provides evidence on the role of geographical proximity on the engagement of European regions in GVCs. On the one hand, we ask whether the "proximity" of territories, regions, leads them to share patterns of behavior or specialization that lead to close positions in the global value chain and/or close participations in these chains. On the other hand, and going deeper into this idea, in this paper we have considered different approaches to "proximity" through the selection between different weight matrixes for the spatial econometric model.

2.3 | Focus of the paper and empirical database

To the best of our knowledge, this is the first paper that analyzes the *share* and *position* of European regions in GVCs and their spatial determinants by providing systematic evidence of the spatial influence of neighborhood closeness.

To illustrate the mechanisms at work in generating the results, we control for the economic, educational, and technological characteristics of regions explaining their performance in GVCs. Moreover, the use of spatial econometric techniques allows us to address the spatial heterogeneity and spatial dependence in the analysis of the production processes, showing the key role of spatial factors in the formation of global production chains.

Empirically, the calculation of the value added embodied in the supply chain at the regional level, requires access to multiregional input–output tables that cover the full supply chain in the world economy. We use the new regional input–output database EUREGIO for the year 2010 (see Thissen et al., 2018). The data provide information at the NUTS2 level and cover 249 European regions and 17 non-European countries at the country level with a disaggregation of 14 economic sectors.[1] This database contains regional detail for the European Union along with information on its entire large trading bloc, being fully consistent with the trade-linked WIOD database and is already balanced. Moreover, all the data used in the construction of the database are survey data and only non-behavioral assumptions have been made to estimate the EUREGIO dataset. As noted in Thissen et al. (2018), the advantage is that these characteristics allow empirical analyses *"to focus on impacts of changes in behavior without endogenously having this behavior embedded."*[2] On the other hand, a serious drawback can be the high level of industry aggregation. The bias introduced by the aggregation level in an input–output framework has attracted attention in the literature since the 1950's, with the general consensus that greater sectoral disaggregation is preferable (Lenzen, 2011). However, as noted in Miller and Blair (2009), at the regional level, good data are often unavailable or very difficult to obtain. In this context, while recognizing this bias, (Miller & Blair, 2009) find that aggregation in multiregional input–output models produces 'acceptable, not large' errors in gross output.[3] Hence, given that our unit of analysis is the region, it could be expected that our results would not to be significantly affected by this issue. In any case, a necessary caution should be included in this regard.

3 | METHODOLOGY

3.1 | GVCs in a MRIO framework

In this section, we present the methodology used to calculate both our *participation* and *position* measures in GVCs, and the specification of the regressions to explain these two outcomes at the regional level; recall that our measures are calculated using a MRIO framework (see in Appendix A a 2 $\times$ 2 MRIO table as an example). Our starting point is the representation of a closed global economy with n industries and m regions, where $\mathbf{x}$ denotes the total output, and x^r the total output generated by region r, and $Z = z_{ij}^{rs}$ is mn x mn matrix of multiregional intermediate flows. In this context, $\mathbf{y}$ is the vector mnx1 of total final demand of regions, where each element y^r represents the worldwide final demand for products of the industry in region r, and $\mathbf{i}$ a unitary vector mnx1.

$$x = Zi + y. \tag{1}$$

We denote by A the matrix mn x mn of regional purchase coefficients in the multiregional framework, where each element a_{ij}^{rs} represents the volume of intermediate input i sourced from region r that is needed to produce a unit of output j in region s. Substituting $\mathbf{Ax}$ for $\mathbf{Zi}$, the Leontief inverse matrix $\mathbf{L}$ for the whole economy will be as follows:

[1] The classification of economic sectors is: S1 (Agriculture); S2 (Mining, quarrying and energy supply); S3 (Food, beverages and tobacco); S4 (Textiles and leather); S5 (Coke, refined petroleum, nuclear fuel and chemicals etc.); S6&S7 (Electrical, optical and transport equipment); S8 (Other manufacturing); S9 (Construction); S10 (Distribution); S11 (Hotels and restaurants); S12 (Transport, storage and communications); S13 (Financial intermediation); S14 (Real estate, renting and business activities); and S15 (Non-market services).

[2] This construction characteristic allows us to develop the spatial dependency analysis and not invalidate the analysis.

[3] Similarly, Bullard and Sebald (1988) in a Monte Carlo sensitivity analysis of the input–output model concluded that the prediction bias seems to be quite insensitive to the level of aggregation.

$$x = Ax + y \Rightarrow x = (I - A)^{-1} y$$
$$x = y + Ay + A^2 y + A^3 y + A^4 y + \ldots + A^m y + \ldots \Rightarrow x = Ly. \tag{2}$$

Here, each element of $L = l_{ij}^{rs}$ represents all the production generated in sector i in region r to fulfil the demands of inputs incorporated in all the steps of the production chain and ending in the final demand of sector j in region s. Therefore, the elements in **L** capture the production embodied in all the economic flows linking sectors i and j, and regions r and s through the international supply chains.

Given this structure, let us define the following *mnxmn* matrix Ω that contains the value-added generated in the whole world and incorporated in all goods (domestically consumed and traded with other countries), that is to say, it contains the value added generated in each region-industry involved in a supply value chain:

$$\mathbf{\Omega} = \left(\omega_{ij}^{rs}\right) = \widehat{v} L \widehat{y}. \tag{3}$$

In this equation, $\widehat{\mathbf{v}}$ is a diagonalized vector with value added per unit of gross output; **L** the Leontief inverse matrix; and $\widehat{\mathbf{y}}$ is the diagonalized vector of final demand that determines which value chain is considered. More specifically, the generic element in matrix $\mathbf{\Omega}$ $\omega_{ij}^{rs} = v_i^r l_{ij}^{rs} y_j^s$ represents the value added from sector i and region r embodied in final goods j produced by country s.

Hence, the reading by columns and rows of the matrix provides information on the origins and destinations of value added through the global production chains. Since our interest is the study of regions as a unit of analysis and their relationships, we aggregate the sectoral information for each one of them, and we obtain $\mathbf{\Phi} = (\Phi^{rs}) = \mathbf{E\Omega E}'$, where **E** is a sectorial aggregation matrix *m* x *mn*..[4]

Note that for each region, we can distinguish between the value added directly and indirectly incorporated in the production of the final demand of the region (domestic component $[\overline{w}^r = \Phi^{rr}]$), and the regional value added incorporated in the intermediate inputs sold to other regions and countries to fulfill their final demands, that is, incorporated in the global production chains ($\widetilde{w}^r = \sum_{s \neq r} \Phi^{rs}$).

In order to calculate the our measure of *participation (PA)* of a region *r* in GVCs, we compute the share of the value added embodied in exports of region *r* to other regions[5] and countries in the total value added embodied in exports across the regions:

$$PA^r = \frac{\widetilde{w}^r}{\sum_h \widetilde{w}^h}. \tag{4}$$

We will use this share to measure the *participation (PA)* of each region in global value chains in section 4. The higher the value of this measure, the greater is the share of the region in the European GVCs.

As noted in the previous section, this measure complements the traditional view that explores how each country/region benefits from participating in GVCs, thus offering an approximation to the competitiveness of the European regions in global value chains.

Regarding the *position (POS)*, we follow the proposal of Antràs et al. (2012) to build a measure of industry "upstreamness" (or average distance from final use):

$$POS^r = \frac{y^r}{x^r} + 2 * \frac{\sum_s a^{rs} y^s}{x^r} + 3 * \frac{\sum_s \sum_k a^{rk} a^{ks} y^s}{x^r} + 4 * \frac{\sum_s \sum_k \sum_t a^{rk} a^{kt} a^{ts} y^s}{x^r}$$
$$+ 5 * \frac{\sum_s \sum_k \sum_t \sum_d a^{rk} a^{kt} a^{td} a^{ds} y^s}{x^r}. \tag{5}$$

[4]**E** contains ones and zeros in a way that all the sectors in each region are aggregated. See an example for 2 × 2 economy in Appendix A.
[5]The shares include both exports of intermediate inputs and of final products.

The interpretation of this measure is that larger values of *position* are associated with higher levels of upstreamness of a region. That is to say, the higher the value of the *position*, the higher the level of upstreamness; in this case, the region is situated in the early stages of the global value chain, with its production process more focused on intermediate inputs and less on final goods. In essence, the distance to the final consumer will be higher. In contrast, the lower the value of the *position* measure, the higher the level of downstreamness of the region, with its production process more focused on final goods and less on intermediate inputs. More recently, Antràs and Chor (2017), show that *position* can be measured not only as its distance from final demand but also as its distance from primary factors.

According to Antràs and Chor (2017), the downstreamness *position* indicator (*POS_D* from here on) is based on a country-industry pair's use of intermediate inputs and primary factors of production. Given this second *position* measure, it is expected that the regions that incorporate a significant amount of intermediate inputs in their production processes in relation to their use of primary factors of production will be downstream in global value chains. That is, they find that countries that are upstream with respect to final demand are downstream with respect to primary factors at the same time. In other words, both measures are complementary, as they show different facets of the same phenomenon. As we will see later, making use of the regional data, the same conclusion can be obtained for the European regions.[6]

3.2 | Empirical approach

Once the variables of interest have been defined in this MRIO framework, attention can be directed to explore their potential determinants and the empirical strategy to capture the main relationships. Thus, drawing on the literature on GVC, we will look at the role of certain aspects such as population, human capital and the productive structure now with the focus at the regional level. Moreover, in this regional framework, it would be important to test for the existence of neighborhood effects, something that has not been undertaken in previous work. In this case, the neighborhood comprises regions that are contiguous with the region of interest.

First, the total population of each region has been introduced to control for the market size effect, and indirectly the heterogeneity of different regions in our sample. As expected, our results show that the size of the region (here controlled with the regional population) is directly related with its participation in GVCs. Further, it is also expected that the involvement of a region in GVCs will be affected by the business environment within the region. To capture this feature, we use the SBS data (Structural Business Statistics) that describe the economy through the observation of the activity of units engaged in an economic activity. In particular, we focus on the degree of performance of active local units (it includes monetary, business demography and employment aspects) expressed as an index, ranging from 0 (the lowest performance) to 100 (the highest performance) (see Sturgeon et al., 2008). Thus, this index, built from a questionnaire, incorporates the structure, activity, competitiveness and performance of economic activities within the business economy. The higher the SBS index, the stronger the business structure of each region, generating a higher capability of the region to be involved in GVCs and in an upgraded position. In addition, human capital is another variable introduced in the previous literature (see Basile et al., 2012) as a key factor to explain the fragmentation of global value chains. It is assumed that the greater the human capital the more income generated and therefore, a higher fragmentation of global value chains from the production side, and a downstream *position* of the region (closer to the final product). Two independent variables are used; the first is "Tertiary education" measured as a percentage of the region's population with tertiary education. The second is "People in science and technology" that represents the number of people who work in the high technology sectors; in the analysis this is transformed into a ratio by dividing it by the total active population of each region.[7]

[6]Results can be found in Appendix C.

[7]The explanatory variables considered are derived primarily from EUROSTAT.

In addition, the specialization degree of countries can be a driver of regional participation and position evolution in the GVCs,[8] especially for some specific sectors such as agricultural, textile and automotive sectors (see for instance Kaplinsky, 2000, Silveira et al., 2020). These sectors are representative of the different technological levels and we decided to control for the specialization of the region in these economic sectors in order to have a picture of the two sides of the coin. Thus, the agricultural sector is not a typical globalized sector, with important technological and supply roots in local environments. On the contrary, the textile and automobile sectors are highly globalized allowing us to explore the degree of globalization in the production processes of the regions (see for instance Lampón, Lago-Peñas, & Cabanelas, 2014). Therefore, it is expected that a higher specialization in primary sectors would act in the opposite direction to upgrading and participation in GVCs given the lower value added and the lower weight of international relations of these sectors. Analytically, we have estimated regional specialization indexes for these sectors.[9]

We also include in the model a "Mobility" variable (Agiomirgianakis & Zervoyianni, 2001), that measures the percentage of the population in each region that has moved their residence from another region in the same country or another country. It represents the percentage of new residents, between 18 and 59 ages, over total newcomers from another region capturing, in essence, the in-migration into the region.[10] Mobility of people nowadays is a significant variable in European countries, as migration of high-skilled young people from Mediterranean countries to countries such as Germany, Netherlands, or UK, has been strong. In that sense, migration can be considered as the transfer of "regional capabilities" from one region to other. As a result, higher mobility, that is, a greater attraction of people, is expected to be related to a better performance of the region in the GVCs (greater *participation*, greater international and interregional trade). However, an effect on upgrading could not be deduced a priori. On the one hand, it could be expected that more targeted sectors, such as services, would attract people with more human capital, but also more labor-intensive basic sectors (primary sector or manufacturing) would also be a factor of attraction.

One of the factors that can also influence the trade among regions and countries is their rural or urban character (see Nadvi, 2008). We include 4 dummy variables (the omitted category is typology 5, that is, the most rural category) to measure whether the degree of urbanization or ruralization of a region influences the engagement of the regions in the global value chain.

Finally, to test for the existence of a border effect on the globalization level of the regions (Antràs & Chor, 2013), we include a "Border" variable. Thus, the "Border" variable is a dummy, taking on the value 1 when the region has a border with another country and 0 otherwise. In this way, with this independent variable, we try to measure whether having an international border is key to measure the degree of globalization of the regions. It would be expected that this variable would have a positive and significant influence on the degree of share of the regions in the GVC.[11]

In addition, as previously noted, we test for the existence of spatial dependence between the regions that modifies their behavior depending on the nature and magnitude of the spillover effects of the neighbors. It is expected that the spatial dependence will be positive, and that the spillover effects would generate an increase in the *participation* and *position* of the neighboring regions in global value chains. This positive effect on economic growth and region capabilities and knowledge is also expected to boost *participation* of regions in GVCs and to facilitate regional upgrading to more knowledge intensive sectors.

In Table 1, we show the description of the measures and expected signs of the independent variables, both for direct and indirect effects. An indirect effect can be defined as the effect of the performance of my neighbor over

[8]See Haddad and Araújo (2020) where they establish that the similarity in productive structures leads to similar levels of participation of regions in the GVCs.

[9]The specialization indexes are calculated as the rate between the share of the specific sector in the region and the share of the sector for the full regional sample in Europe.

[10]For more detail of the variable, see https://ec.europa.eu/eurostat/web/regions/data/database

[11]Additionally, we have also initially considered other border variable "Outside-EU Border" to specifically check whether having a border with a region of a country that does not belong to the European Union is significant explaining the selected variables. This variable is not significant with either of the two endogenous variables, therefore it has been removed from the models and we only work with the more general variable "Border".

TABLE 1 Description, measurements and expected direct and indirect signs of variables in the intensity model on participation (PA) and position (POS)

Variables	Description	Measurement	Expected direct sign (PA/POS)	Expected indirect sign (PA/POS)
POP	Population	Thousands of people	+/+	+/+
SBS	Structural business statistics	Index	+/−	−/+
T_edu	Tertiary education	Percentage of people with advanced education	+/−	+/+
People_ST	People in Science and Technology	Percentage of people who works in science and technology	+/+	+/−
Mobility	Mobility	Amount of population that changes their residence to another region (in-migration)	+/−	+/+
Border	Border	Dummy: 1 = if there is a frontier with another country; 0 = if there is no	+/+	+/+
SI_AGRI	Specialization index in agriculture sector	Ratio	−/−	−/−
SI_TEX	Specialization index in textile sector	Ratio	−/−	−/−
SI_AUTO	Specialization index in automobile sector	Ratio	+/+	+/+
Rtypology_1	Regional typology 1	Dummy: 1 = if the level of urbanization is maximum	+/+	+/+
Rtypology_2	Regional typology 2	Dummy: 1 = if the level of urbanization is in the second level	+/+	+/+
Rtypology_3	Regional typology 3	Dummy: 1 = if the level of ruralization is in the second level	+/+	+/+
Rtypology_4	Regional typology 4	Dummy: 1 = if the level of ruralization is maximum	+/+	+/+

Source: Own elaboration.

my own performance. In the case of indirect effects, it is more difficult to know what to expect, as there are many variables involved such as competence, scale economies, etc.

In summary, we can observe that the expected direct sign for the majority of the independent variables is positive with some exceptions. The expected direct signs of the specialization indexes of the agricultural and textile sectors are negative since, as explained below, the first is as globalized a sector as others (while large volumes of agricultural products are exported and enter important food value chains, they may be simple chains with small average propagation lengths), and the second is not globalized in the European Union either. In addition, as explained above, the dummy of typology 5 has been omitted (the most rural case), which causes the expected signs of all of them to be positive if we compare them with the typology 5 dummy. The expected direct signs are positive for *participation* and *position*, since it is expected that the less urban a region is, the lower its degree of *participation* in the global value chain, and the lower will be the degree of upstreaming. The expected signs of the indirect (spillover effects) are similar signs to direct ones. It is expected that, as with the direct effects, if the closest neighbors of a region have a high level of specialization in agriculture or textiles (being two non-globalized sectors in the European Union), the region under study presents a low level of *participation* and *position*.

After the discussion of the main variables of the analysis, we discuss the empirical strategy. For each region, the following specifications are proposed.

Let PA^r denote the *participation* in a GVC for region *r*. For each region, the proposed specification is:

$$\begin{aligned} PA^r = {} & \alpha + \beta_1 TotatPOP^r + \beta_2 SBS^r + \beta_3 Tedu^r + \beta_4 PeopleST^r + \beta_5 Mobility^r + \\ & \beta_6 Border^r + \beta_7 SI_{AGRI}{}^r + \beta_8 SI_{TEX}{}^r + \beta_9 SI_{AUTO}{}^r + \beta_{10} Rtypology1^r + \beta_{11} Rtypology2^r + \\ & \beta_{13} Rtypology3^r + \beta_{14} Rtypology4^r + \varepsilon, \end{aligned} \tag{6}$$

where PA^r is the *participation* of region r in GVC and ε is the error term of the equation.

The linear expression of the other endogenous variable (*position*) can be expressed as follow:

$$\begin{aligned} \ln(POS^r) = {} & \alpha + \beta_1 \ln(TotatPOP^r) + \beta_2 SBS^r + \beta_3 Tedu^r + \beta_4 PeopleST^r + \beta_5 Mobility^r + \\ & \beta_6 Border^r + \beta_7 SI_{AGRI}{}^r + \beta_8 SI_{TEX}{}^r + \beta_9 SI_{AUTO}{}^r + \beta_{10} Rtypology1^r + \beta_{11} Rtypology2^r + \\ & \beta_{13} Rtypology3^r + \beta_{14} Rtypology4^r + \varepsilon, \end{aligned} \tag{7}$$

where POS^r is the value of *position* in a GVC for each region *r* and ε is the error term of the equation. In this case, a log–log linear equation is used to smooth the position values.

4 | SPATIAL ECONOMETRIC MODEL AND RESULTS

The behavior of European regions in global value chains depends, as previously stated, on a series of variables that modify or alter the spatial distribution of *participation* and *position* in the GVCs. Following guidelines from the literature, we first run the OLS model to measure the significance of the explanatory variables and study their behavior. However, as is well-known, the OLS model assumes that each region operates independently of other regions. The objective is to explore the nature and strength of any potential spatial dependence that may exist. Therefore, to capture this dependence, a queen weight matrix has been used where all the neighbors surrounding each region are considered.[12] Table 2 presents the results for the spatial dependence tests (Anselin et al., 1996).

From Table 2, using the queen contiguity weight matrix, Moran's *I* is significant, indicating the presence of global spatial autocorrelation. For the case of *participation*, results suggest strong spatial dependence, and clearly point to the spatial error model (SER) as the preferred specification[13] (or the SAC model[14]). The results change when we focus on the *position*. In this case, the test for the spatial lag and its robust version do not reject the null hypothesis, so it is clearer than in the previous case that the spatial error model could be the most correct specification. Therefore, these results show us that there is a clear spatial dependence between European regions and are consistent with the results obtained with the Moran's *I* test.

In a second step, we select the most appropriate spatial econometric model and we present the results obtained. For the sake of brevity, Table 3 summarizes the results obtained for *participation* and *position* of the European regions after running the Spatial Durbin Model (SDM),[15] the preferred model.[16]

In both cases, *participation* and *position*, the coefficient associated with spillover effects across regions, ρ, is statistically significant, positive and large in magnitude, indicating the existence of spatial dependence in the data. Thus, results for the sample of EU regions support our thesis regarding the importance of spillovers. Additionally, the LM

[12]As will be seen later, the results have been checked with other weight matrices.

[13]The robust version of the Lagrange Multiplier error test rejects its null hypothesis of no spatial dependence, while the test for the spatial lag does not.

[14]A combination of spatial lag model (SAL) and SER.

[15]The Spatial Durbin Model (SDM) is a combination of SAL and SLX model (SDM = SAL+SLX). It is used when at least one of the regressors is correlated with the omitted variables. The advantage of the SDM is that its spillover effects are flexible.

[16]The rest of the spatial models (Spatial Autoregressive Lag Model (SAL) and Spatial Autoregressive Combined Model (SAC)) and the corresponding robustness checks are available upon request.

TABLE 2 Testing the spatial dependence

Control variables	Model: PA	Model: ln (POS)
Moran's I test	MI = 2.419*** p-value = 0.007	MI = 3.174*** p-value = 0.001
LM spatial lag	LM = 7.563*** p-value = 0.006	LM = 0.553 p-value = 0.457
LM spatial error	LM = 5.058** p-value = 0.024	LM = 9.588*** p-value = 0.002
Robust LM spatial lag	LM = 2.885 p-value = 0.089	LM = 0.032 p-value = 0.856
Robust LM spatial error	LM = 5.380*** p-value = 0.005	LM = 9.067*** p-value = 0.003

Notes:
*imply 10% level of significance.
**imply 5%.
***imply 1%.
Source: Own elaboration.

test for autocorrelation error indicates there is no significant evidence of remaining spatial dependence once we include the spillover effects across European regions in both models. The spatial Hausman test is statistically significant, indicating that the preference for the SDM for both endogenous variables because the SAL or SER model coefficients are inefficient. Focusing on the results, it is noteworthy that, by introducing the spillover effects through the weight matrix, it can be seen how most of those variables are significant. That is to say, structural business, tertiary education, the "border" variable, some of the specialization indexes and typology dummies of the closest neighbors, have effects in the region of interest.

However, notwithstanding what the results reflect, it should be noted that the coefficients of the SDM model do not directly reflect the spillovers effects of the corresponding explanatory variables on the dependent variable (LeSage & Pace, 2010). Therefore, it is necessary to calculate the direct, indirect and total effects of the models and this is shown in Tables 4 and 5.[17]

The direct effect represents an impact, due to changes in the independent variable(s) on *participation* and *position* in GVC, at a particular region. The indirect effect represents an impact due to changes in independent variables, in other regions, on the local *participation* and *position*. The total effect is simply the sum of the direct and indirect effects. The coefficients of the direct effects are in line with the results provided in Table 2. We can observe that the direct effects of the explanatory variables are different from their coefficient estimates in the previous table. The reason is the spillover or indirect effects that arise as a result of impacts passing through neighboring regions and back to the region of focus itself. As we are working with the Spatial Durbin Model, the indirect effects show the result of the exogenous influence of the closest neighbors, as well as their corresponding spatially lagged endogenous effect.

Therefore, some interesting interpretations emerge from these results. If we focus on Table 4, for the SBS variable, the spillover effect is −0.014, indicating that the higher the business structure observed in the neighboring regions, the lower the value of the *participation* in GVC of the local region. As we established in Table 1, we could expect that the stronger the business structure of the local regions, the higher the *participation*. If the neighboring regions have a stronger business structure (high level of SBS), the local region will have less *participation* in a GVC, as expected. In this case, the negative spillover effect is greater than the positive direct effect, leading to a negative total effect of the SBS variable. In that sense, the business structure variable is indicating that it has a negative influence on the local region due to the weight of the indirect spillover effect generated by the closest neighboring regions. In other words, if the neighbors have a strong business structure, the local region is negatively affected in terms of its level of *participation* in the GVC. This reflects a competitive process; those regions with better business

[17]Following the previous literature (see, for example, You & Lv, 2018), one way to check the robustness of the results obtained with our weight matrix is to check what happens if other weight matrices are used. The results obtained with other weight matrices indicate robustness and appear in the Appendix E.

TABLE 3 Spatial econometric model for *Participation* and *Position* in European regions, 2010

	SDM model PA	SDM model Ln (POS)
λ	−1.203 (0.722)	**−1.563** ** **(0.043)**
ρ	**0.172** ** **(0.046)**	**0.188** ** **(0.023)**
Total_POP	**0.002** *** **(2.2e-16)**	**0.532** *** **(2.2e-16)**
SBS	**0.009** *** **(0.001)**	**0.001** *** **(0.0003)**
T_education	**−0.028** * **(0.037)**	**−0.011** ** **(0.012)**
People_ST/Active_POP	0.265 (0.731)	0.035 (0.744)
Mobility	−0.004 (0.873)	−0.002 (0.556)
Border	**0.823** ** **(0.015)**	**0.023** ** **(0.047)**
SI_AGRI	**−1.015** *** **(0.002)**	**−0.242** *** **(5.81e-08)**
SI_TEX	0.212 (0.376)	0.004 (0.899)
SI_AUTO	**0.192** * **(0.054)**	**0.050** ** **(0.039)**
R_typology_1	**3.318** *** **(0.0003)**	**0.587** *** **(5.95e-06)**
R_typology_2	0.397 (0.573)	**0.381** *** **(0.0001)**
R_typology_3	0.750 (0.334)	**0.315** *** **(0.004)**
R_typology_4	1.231 (0.083)	0.252 (0.105)
W*lnTotal_POP	0.0003 (0.442)	**−0.120** ** **(0.017)**
W*SBS	**−0.014** *** **(0.001)**	−0.0001 (0.709)
W*T_education	**0.099** *** **(0.009)**	**0.012** ** **(0.018)**
W*People_ST	0.802 (0.681)	−0.051 (0.851)
W*Mobility	0.006 (0.882)	0.001 (0.897)
W*Border	**1.040** ** **(0.022)**	**0.108** ** **(0.035)**
W*SI_AGRI	**−0.984** * **0.052)**	**0.067** ** **(0.033)**
W*SI_TEX	−0.301 (0.443)	−0.057 (0.291)
W*SI_AUTO	**0.011** *** **(0.005)**	**0.101** ** **(0.022)**
W* R_typology_1	**2.322** ** **(0.014)**	**0.044** * **(0.054)**
W* R_typology_2	−1.035 (0.387)	0.136 (0.439)
W* R_typology_3	−0.344 (0.797)	0.204 (0.283)
W* R_typology_4	0.722 (0.567)	−0.147 (0.411)
R^2	0. 4664	0.4365
Loglikelihood	−638.90	−147.96
AIC	1337.8 (for lm: 1339.8)	355.92 (for lm: 359.03)
Spatial Hausman test	2.58 p-value = 0.027	20.18 p-value = 0.012
LM test for autocorr error	LM = 0.58 p-value = 0.44	LM = 0.855 p-value = 0.075
Observations	249	249

Notes:
*imply 10% level of significance;
**imply 5%.
***imply 1%.
Source: Own elaboration.

TABLE 4 Direct, indirect and total effects (SDM) for *Participation*

	Direct effects		Indirect effects		Total effects	
	Coefficients	p-values	Coefficients	p-values	Coefficients	p-values
	Queen contiguity weight matrix					
TotalPOP	**0.002*****	**2.22e-16**	0.001	0.096	**0.003*****	**1.98e-07**
SBS	**0.008*****	**0.002**	−**0.014*****	**0.004**	−**0.006****	**0.029**
T_education	−0.024	0.415	**0.109*****	**0.007**	**0.085*****	**0.006**
People_ST/Act_POP	0.301	0.668	0.972	0.634	1.273	0.579
Mobility	−0.004	0.868	0.006	0.884	0.002	0.965
Border	−0.786	0.161	**1.031****	**0.030**	0.244	0.793
SI_AGRI	−**1.063*****	**0.001**	−**1.328****	**0.014**	−**2.391*****	**7.57e-06**
SI_TEX	0.201	0.419	−0.304	0.485	−0.104	0.822
SI_AUTO	**0.193*****	**0.006**	**0.050****	**0.051**	0.243	0.644
R_typology_1	**3.439*****	**0.0002**	**3.317****	**0.051**	**6.756*****	**0.001**
R_typology_2	0.357	0.616	−1.109	0.425	−0.752	0.649
R_typology_3	0.741	0.322	−0.247	0.919	0.494	0.728
R_typology_4	1.271	0.060	1.071	0.419	2.342	0.158

Notes:
*imply 10% level of significance.
**imply 5%.
***imply 1%.
Source: Own elaboration.

performance will be more trusted and hence, as a result, they will have a negative effect on their neighbors. A similar result is found with the specialization index of agricultural sector (SI_AGRI) where the spillover effect amounts to −1.328, which means that if the neighboring regions are more specialized in the agricultural sector than the European average, the local region will have a lower *participation* in the GVC. In essence, being surrounded by regions that are focused on primary sectors, that are generally more oriented towards domestic markets, will lead to a lower local *participation* in the GVC. On the other hand, there are some explanatory variables that present a positive sign of their spillover effect. This is the case of the tertiary education, the specialization index of the automobile sector, and the dummies that reflect the existence of an international border and a high level of urbanization. In Table 1, we established that the greater the human capital together with the existence of an international border, the greater the *participation* of the regions in the GVC. So, as we expected, the variables that represent the human capital and international border have positive effects, not only in the local region, but also in the neighboring regions. Therefore, being surrounded by highly urbanized regions, with an international frontier, with a large percentage of population with tertiary education and very specialized in the automobile sector together have positive effects and cause an increase in the level of *participation* of local region. Hence, we observe positive externalities from the level of development of the regions, reflected by human capital, urbanization, industrial structure, etc. All these results are in line with the expected signs that we showed previously in Table 1.

If we focus on Table 5, we can observe several findings regarding the indirect effects. First, we can see how only the spillover effects of the variables "tertiary education," "border," the specialization index of the agricultural and automobile sector, and the dummy variable of more urban typology are significant. The results show that if the closest neighbors present a high percentage of the population with tertiary education, have a border with another region of another country, are specialized in the production of the automobile sector and are urbanized regions, the value of the *position* in the global value chain of the local region will be higher. That is, if these characteristics are in the closest neighbors, the local region will be more likely to be an exporter of intermediate inputs (more basic in the

TABLE 5 Direct, indirect and total effects (SDM) for *Position*

	Direct effects		Indirect effects		Total effects	
	Coefficients	p-values	Coefficients	p-values	Coefficients	p-values
	Queen contiguity matrix					
lnTotalPOP	**0.531*** **	**2.22e-16**	−0.023	0.842	**0.509*** **	**7.05e-07**
SBS	**0.001*** **	**0.004**	−0.0005	0.923	**0.001***	**0.052**
T_education	**−0.011** **	**0.014**	**0.013** **	**0.023**	**0.002** **	**0.027**
People_ST/Act_POP	0.033	0.778	−0.052	0.925	−0.018	0.999
Mobility	−0.002	0.558	0.0003	0.950	−0.002	0.763
Border	0.028	0.705	**0.132** **	**0.029**	0.160	0.174
SI_AGRI	**−0.241*** **	**8.86e-09**	**−0.025*** **	**0.001**	**−0.266*** **	**0.003**
SI_TEX	0.002	0.925	−0.065	0.295	−0.064	0.349
SI_AUTO	0.055	0.362	**0.128** **	**0.013**	**0.184** **	**0.011**
R_typology_1	**0.594*** **	**8.81e-06**	**0.182***	**0.051**	**0.766** **	**0.017**
R_typology_2	**0.391*** **	**5.02e-05**	0.243	0.241	**0.634*** **	**0.006**
R_typology_3	**0.327*** **	**0.003**	0.308	0.175	**0.634** **	**0.014**
R_typology_4	**0.248** **	**0.014**	−0.116	0.578	−0.132	0.642

Notes:
*imply 10% level of significance.
**imply 5%.
***imply 1%.
Source: Own elaboration.

production process). On the other hand, whether the closest neighbors are more specialized in the agricultural sector, the value of the *position* in the GVC will be lower, that is to say, the local region will be an exporter of final goods because it is surrounded by regions that are more basic in the production process, focused on the production of a less globalized sector. The results obtained are also in line with the expected signs shown in Table 1. However, we obtain a different sign in the case of direct effects and for level of urbanization. When we talk about urbanized regions, it could be expected that these are areas where there are a large number of services (production of final goods). However, the urbanized regions also concentrate a great weight of the industrial sector. Therefore, as we established previously, one would expect that those regions will be more downstream, but the results show the opposite, in contrast to the expected signs established above, and showing the great importance of the industrial sector in the most urbanized regions.

In summary, European regions seem to be influenced by their closest neighbors. Spillover effects have a significant role in explaining the evolution of regions in global production processes, showing similar behaviors according to geographical proximity and production structures. The results obtained in this work indicate that there are clusters between European regions, caused by the behavior of their closest neighbors and their characteristics.[18]

5 | CONCLUSIONS

Given the importance of globalization and the growth of international trade among countries, this paper has explored the role played by spatial dependence in explaining the *participation* and *position* in GVC of European regions. In order to capture the spatial character of GVCs, we use a multiregional and multisectoral input–output framework linked with further explanatory analysis using spatial econometrics. One of our main contributions is to explore the role of regional spillovers in the engagement and position of regions in global value chains, focusing our study on the European regions in 2010.

The results indicate that spatial dependence is an important component of the explanation of the determinants of the engagement of a specific region in a global value chains. In fact, the spatial spillover effects are significant, especially for variables that represent human capital; the degree of urbanization of the regions; the sectoral structure of the regions in production processes and those that represent the level of development of the region. In other words, the role of an individual region in the global value chain is affected by the behavior of their neighbors, i.e., the behavior of those neighbors influences the production structure of a specific region as well as the globalization level of its production processes. Furthermore, the globalization process at the regional level seems to be important and regions tend to behave depending on the behavior of their closest neighbors. Therefore, the globalization processes in which industries and countries are involved, has a clear regional and spatial dimension that conditions the performance or economic activity and, consequently, the internationalization and specialization of production chains.

Based on the empirical findings of this study, we can draw some relevant policy implications as follows. First, as we previously commented, we find that spatial spillover effects of explanatory variables have a significant effect on the local region and its neighbors. Therefore, policies aimed at stimulating the economic growth, boosting export promotion and industrial development should focus not only on the effects of the local region but also in its closest neighbors, taking advantage of the regional spillover effects. However, not all spillover effects will be positive; it is this mix of complementary and competitive forces that challenges regional development policy; as Chung and Hewings (2015) have noted, the signs of these effects may be asymmetric between two regions. In that sense, when making decisions of great relevance to a region of focus, the effects on neighboring regions should also be taken into account. It should be note that, in general, the level of development of the neighboring regions has positive externalities on the local region, showing the importance of the characteristics of the neighbors for the future development of the local region. In addition, our results suggest that a region surrounded by prosperous economies could achieve higher economic growth rates. Therefore, policies within the same country might be centered on groups of regions. In this way, spillover effects can be boosted. In other words, countries should take advantage of the regional clusters that have been generated during the globalization process. What is more, these policies should be complementary to the national and international ones, as in a globalized world, the different scales matter. In addition, the existence of intraregional spatial dependence could offer options for innovative geographical strategies among certain regions. The regionalization of global value chains could generate an advantage to regions surrounded by large economies. In other words, the phenomenon of regionalization and the existence of clusters within the same country could allow the lagging regions to benefit if they are surrounded by economies with high growth rates.

The results also suggest that while regions are competing with each other, the processes of fragmentation that have given rise to global value chains may also be generating increased interregional dependencies – as evidenced by the results presented in the previous section. The nature of these dependencies may vary according to *position* in GVCs. As many authors have indicated, trade is becoming increasingly dominated by intra-industry rather than inter-industry trade; this has important implications for the development of networks of regional economies.

Finally, this paper contributes to literature with an explicit consideration of spatial and regional factors in the composition of global value chains, offering an empirical application to the EU regions. In our view, this paper opens the door to a new line of research with strong implications in the GVC framework. The methodology proposed can be naturally extended both geographically and temporally to confirm the insights obtained in different world regions and to study the evolution of these trends over time. All in all, the behavior of GVCs has different dimensions and, as we showed here, interactions among regions which may differ in different world areas, could mediate the way in which industries, regions and countries engage in GVC.

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APPENDIX A: 2 × 2 MRIO TABLE AND E MATRIX

TABLE A.1.1. 2 × 2 MRIO table

		Region 1		Region 2		Final demand		Output
		Sector 1	Sector 2	Sector 1	Sector 2	Region 1	Region 2	
Region 1	Sector 1	z_{11}^{11}	z_{12}^{11}	z_{11}^{12}	z_{12}^{12}	y_1^{11}	y_1^{12}	x_1^1
	Sector 2	z_{21}^{11}	z_{22}^{11}	z_{21}^{12}	z_{22}^{12}	y_2^{11}	y_2^{12}	x_2^1
Region 2	Sector 1	z_{11}^{21}	z_{12}^{21}	z_{11}^{22}	z_{12}^{22}	y_1^{21}	y_1^{22}	x_1^2
	Sector 2	z_{21}^{21}	z_{22}^{21}	z_{21}^{22}	z_{22}^{22}	y_2^{21}	y_2^{22}	x_2^2
Value added		w_1^1	w_2^1	w_1^2	w_2^2			
Output		x_1^1	x_2^1	x_1^2	x_2^2			

Source: Own elaboration.

TABLE A.1.2. 2 × 2 E matrix

		Region 1	Region 2
Region 1	Sector 1	1	0
	Sector 2	1	0
Region 2	Sector 1	0	1
	Sector 2	0	1

Source: Own elaboration.

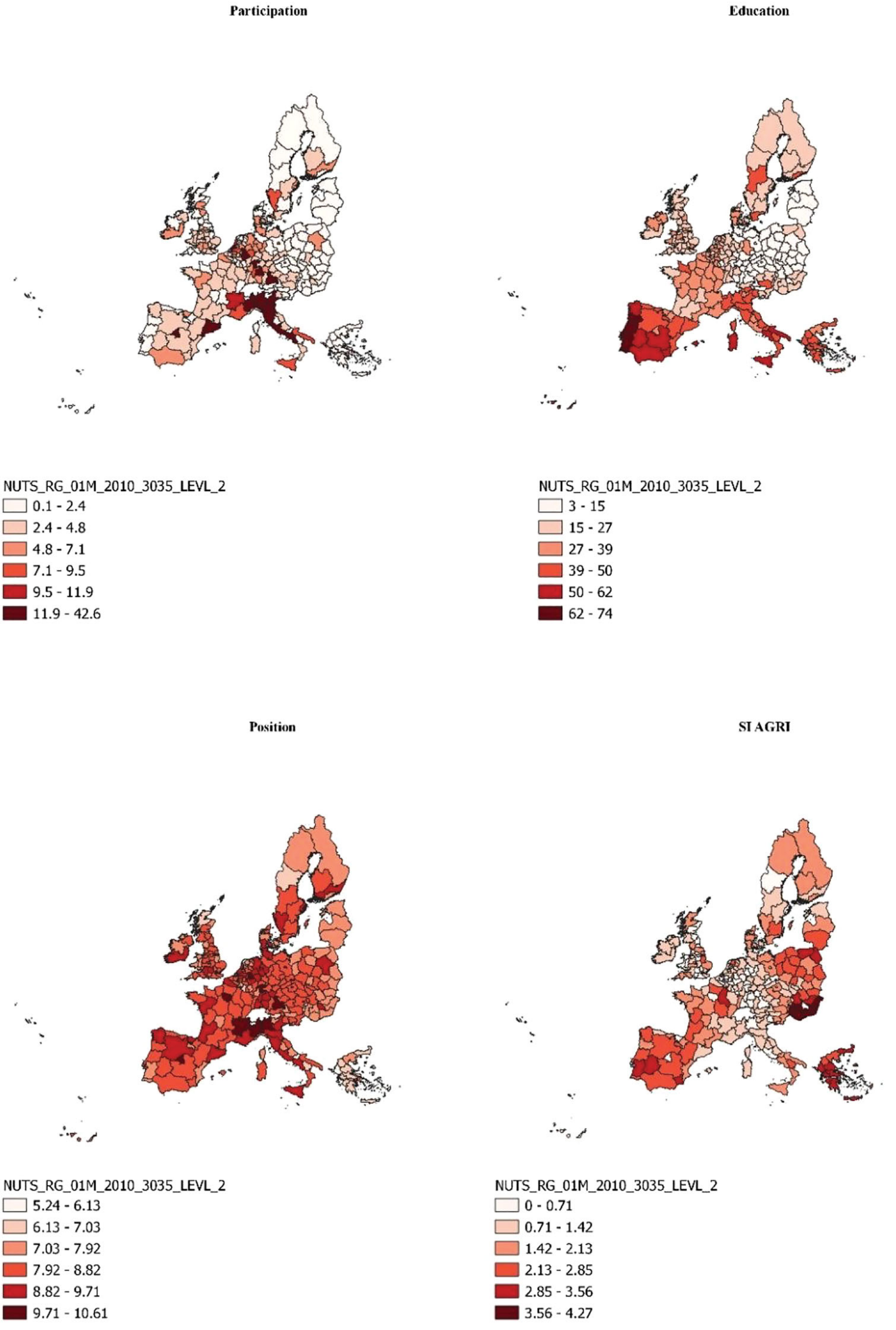

FIGURE A.2.1 Mapping of *participation*, *position* and other independent variables. Source: Elaborated with QGIS

APPENDIX B: INITIAL, SAMPLE FINDINGS

As a first way of evaluating the behavior of regions with respect to our variables of interest and the potential heterogeneity across Europe, Figure A.2.1 shows the performance EU regions according to different *participation* and *position* levels. We also draw the corresponding maps for other explicative variables used in the analysis such as Tertiary education and Agricultural specialization index. The maps for other explicative variables are available upon request.

Referring to Figure A.2.1, where we show the mapping of *participation*, *position*, tertiary education and the index of specialization in agriculture, we can observe that all the variables are quite clustered. In the case of *participation*, this is especially visible in Germany, Austria, Czech Republic, Netherlands and north and center Italy, areas with high levels of participation. Also note the case for *position* in north Italy and the border regions of France or some regions of Germany that share border with Netherlands, showing the significance of the border variable. Indeed, it is in these regions where we find the highest values of *position*, that is, they are upstream regions. By contrast, some regions of Denmark and Sweden are the most downstream, perhaps associated with high levels of human capital. In the case of tertiary education, the cluster pattern is also clear in all countries, mainly Spain, France, Italy and Poland, among others. Turning attention to specialization in agriculture, countries such as Poland or Hungary stand out. To sum up, a first look to the data seem to confirm our statement, regions closeness matters and it should be analyzed.

From Table A.3.1, we can observe that the "puzzling finding" is fulfilled. The vast majority of European regions that adopt an upstream position (*POS*) with respect to final demand are those that have a more downstream position (*POS_D*) with respect to the primary factors. In other words, if a region depends a lot on the size of intermediate inputs in relation to final goods, at the same time it depends to a greater proportion on intermediate inputs in relation to primary factors. The reasons for this positive correlation between both measures seem to coincide with those established

TABLE A.3.1 Upstreamness vs. downstreamness position values in GVCs in the top 20 European regions

By region		POS	By region		POS_D
FR10	Ile_de_France	6.228	UKI1	Inner_London	2.065
ITC4	Lombardia	5.969	SE33	Vastsverige	1.939
UKI1	Inner_London	5.612	ITC4	Lombardia	1.846
ES30	Comunidad_de_Madrid	4.486	DE71	Darmstadt	1.814
ITC1	Piemonte	4.275	DEA1	Dusseldorf	1.787
ITE4	Lazio	3.856	DE60	Hamburg	1.780
DE21	Oberbayern	3.379	DEA2	Koln	1.775
DE71	Darmstadt	3.301	NL11	Groningen	1.750
ITD3	Veneto	3.227	FR10	Ile_de_France	1.735
DEA1	Dusseldorf	3.051	ES30	Comunidad_de_Madrid	1.727
PL12	Mazowieckie	3.043	BE10	Region_de_BruxellesCapitale	1.717
DE11	Stuttgart	3.028	DE21	Oberbayern	1.714
GR30	Attiki	3.026	DE11	Stuttgart	1.710
ITD5	EmiliaRomagna	2.966	DE30	Berlin	1.709
FI18	EtelaSuomi	2.886	DE42	Brandenburg__Sudwest	1.693
NL11	Groningen	2.877	FR71	RhoneAlpes	1.691
DEA2	Koln	2.844	FI18	EtelaSuomi	1.685
FR71	RhoneAlpes	2.750	DE91	Braunschweig	1.678
ITF3	Campania	2.646	DEC0	Saarland	1.663
ITE1	Toscana	2.597	DE12	Karlsruhe	1.663

Source: Own elaboration.

in the work by Antràs and Chor (2017). The global economy has experimented a clear reduction in trade costs, which has led to an increase in global value chains. In this way, those European regions that have focused more on the production of goods are those with the highest upstream value (POS) and the highest downstream value (POS_D). On the other hand, the European regions that have focused on the production of services are those that have more final production processes (lower upstream value) and have higher spending on primary factors (lower downstream value).

APPENDIX C: UPSTREAM VS. DOWNSTREAM POSITION

Globalization, technological change and the expansion of international trade have altered the international organization of production. The rise of GVCs has changed the behavior of countries, regions and industries, and production specialization has become the focus of study. Thus, and as established before, some recent papers in international trade has contributed to understand how to measure the positioning of economies in GVCs. In this context, Antràs and Chor (2017) show a "puzzling finding" at country level. To capture it at regional level, Table A.3.1 presents the results for *POS* and *POS_D*.

APPENDIX D: OTHER SPATIAL CHECKS

Since the results show that there is a clear spatial dependence/autocorrelation between European regions, to make explore what kind of spatial autocorrelation is involved, we draw the Moran's *I* scatterplot for the two endogenous variables in Figure A.4.1.

It can be seen how, in both cases, there is positive spatial autocorrelation, not only for the value of the Moran's *I* test (MI $=$ 4.75; MI $=$ 5.18, respectively), but also for the quadrants where are the observations of the regions in both cases (first and third quadrant: high-high, low-low). Therefore, the *participation* and *position* of the regions in the GVC in Europe presents significant positive spatial autocorrelation. These results show that the regions are clustered, that is, the regions with the highest *participation* and *position* values are close to each other. Therefore, the results obtained with the Moran's *I* index and its corresponding positive spatial autocorrelation could have effects on the design of regional economic policies. In this sense, the application of measures to improve the *participation* and *position* of regions with great economic potential would have very positive effects on their closest neighbors.

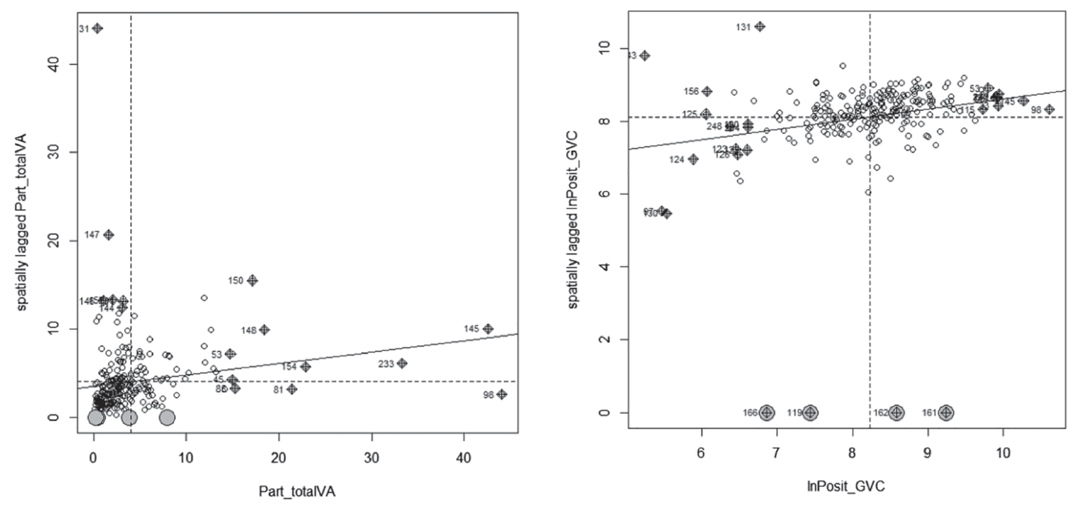

FIGURE A.4.1 Moran's I scatterplot: *Participation* and *Position*, respectively. Source: Elaborated with R-studio

APPENDIX E: CHECKING WITH OTHER SPATIAL WEIGHT MATRICES

It can be verified that when we use the weight matrix of the Great Circle Distance weight matrix, considering a radio of 200 km and the 4-neartest neighbor weight matrix, the results show that the different spatial weight matrices generally provide similar estimates for direct, indirect and total effects. It should be noted that, since in these weight matrices most of the elements are zero, the indirect effects or spillovers and the total effects are less significant.

TABLE A.5.1. Direct, indirect and total effects for *Participation*

Great circle distance weight matrix (200 km)						
TotalPOP	0.002***	2.22e-16	−0.0006	0.930	0.002***	0.003
SBS	**0.009*****	**0.002**	**−0.013****	**0.050**	**−0.004****	**0.049**
T_education	−0.004	0.967	**0.040****	**0.043**	0.044	0.116
People_ST/Act_POP	−0.337	0.721	1.847	0.398	1.510	0.507
Mobility	−0.017	0.473	0.046	0.547	0.029	0.699
Border	−0.805	0.124	**2.203****	**0.042**	1.397	0.269
SI_AGRI	**−0.767****	**0.034**	**−1.401****	**0.042**	**−2.168*****	**0.001**
SI_TEX	0.256	0.251	0.429	0.444	0.685	0.187
SI_AUTO	−0.060	0.887	**0.494*****	**0.005**	0.434	0.573
R_typology_1	**2.194****	**0.025**	**1.327*****	**0.001**	**3.521*****	**0.009**
R_typology_2	−0.382	0.621	−0.641	0.800	−1.022	0.702
R_typology_3	−0.048	0.951	3.008	0.261	2.960	0.295
R_typology_4	0.293	0.711	−2.109	0.403	−1.815	0.516
K nearest weight matrix (4 nearest neighbors)						
TotalPOP	**0.002*****	**2.22e-16**	0.0004	0.226	**0.002*****	**1.35e-07**
SBS	**0.009*****	**0.001**	**−0.013*****	**0.004**	**−0.004****	**0.045**
T_education	0.002	0.968	**0.040****	**0.028**	0.042	0.096
People_ST/Act_POP	−0.168	0.865	0.388	0.801	0.220	0.884
Mobility	0.004	0.869	0.046	0.309	0.050	0.250
Border	−0.775	0.138	**0.975****	**0.028**	**0.200****	**0.048**
SI_AGRI	**−0.969*****	**0.003**	−0.691	0.199	**−1.660*****	**0.001**
SI_TEX	0.258	0.273	0.537	0.192	0.795	0.056
SI_AUTO	−0.037	0.966	**0.247****	**0.016**	0.210	0.603
R_typology_1	**3.323*****	**0.001**	**2.298****	**0.020**	**5.621*****	**0.007**
R_typology_2	−0.057	0.941	−0.080	0.946	−0.137	0.924
R_typology_3	0.510	0.526	2.114	0.150	2.624	0.133
R_typology_4	0.501	0.471	−0.478	0.686	0.023	0.987

Notes:
* imply 10% level of significance.
** imply 5%.
*** imply 1%.
Source: Own elaboration.

TABLE A.5.2. Direct, indirect and total effects for *Position*

Great circle distance matrix (200 km)						
lnTotalPOP	0.561*	2.22e-16	−0.218	0. 288	0.343*	0.016
SBS	**0.001***	**0.004**	0.0003	0.773	**0.001***	**0.028**
T_education	**−0.012***	**0.007**	**0.016***	**0.029**	**0.004***	**0.047**
People_ST/Act_POP	−0.004	0.981	0.610	0.136	0.606	0.170
Mobility	−0.002	0.607	−0.004	0.748	−0.006	0.642
Border	0.004	0.964	**0.582***	**0.009**	**0.586***	**0.007**
SI_AGRI	**−0.118***	**0.009**	**−0.217***	**0.009**	**−0.335***	**0.005**
SI_TEX	0.020	0.492	**−0.180***	**0.046**	**−0.160***	**0.052**
SI_AUTO	0.055	0.238	**0.058***	**0.017**	**0.113**	**0.381**
R_typology_1	**0.508***	**0.0002**	**0.762***	**0.015**	**1.270***	**0.010**
R_typology_2	**0.343***	**0.0007**	0.389	0.408	0.732	0.142
R_typology_3	**0.262***	**0.022**	0.521	0.221	0.783	0.091
R_typology_4	0.164	0.116	−0.101	0.790	0.063	0.893
K-nearest neighbor weight matrix (4 nearest neighbors)						
lnTotalPOP	**0.538***	**2.22e-16**	0.086	0.347	**0.624***	**1.31e-09**
SBS	**0.001***	**0.001**	0.0001	0.777	**0.001***	**0.008**
T_education	−0.004	0.395	**0.007***	**0.019**	**0.003***	**0.041**
People_ST/Act_POP	−0.010	0.381	0.114	0.543	0.014	0.943
Mobility	−0.005	0.205	0.004	0.457	−0.001	0.944
Border	−0.008	0.926	**0.201***	**0.010**	**0.193***	**0.012**
SI_AGRI	**−0.210***	**3.32e-07**	**−0.037***	**0.042**	**−0.247***	**0.0003**
SI_TEX	0.033	0.304	**−0.156***	**0.003**	**−0.123***	**0.021**
SI_AUTO	0.036	0.485	**0.137***	**0.041**	**0.173**	**0.006**
R_typology_1	**0.660***	**1.81e-07**	−0.178	0.477	**0.482***	**0.045**
R_typology_2	**0.373***	**5.06e-05**	0.068	0.687	**0.441***	**0.032**
R_typology_3	**0.325***	**0.002**	0.221	0.239	**0.546***	**0.018**
R_typology_4	**0.257***	**0.007**	−0.136	0.431	0.121	0.545

Notes:
* imply 10% level of significance.
** imply 5%.
*** imply 1%.
Source: Own elaboration.