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Abstract

Economic complexity indicators provide a better understanding of the long-term determinants of countries' economic growth. However, they do not account for intra-national spatial heterogeneity, even when regions, and not only countries, differ tremendously in their productivity. This paper tries to fill this gap by developing a methodology to estimate economic complexity at the subnational level using a unique trade database on intra-national trade flows for Spain. Specifically, we calculate international and intra-national economic complexity indicators for the provinces of Spain (NUTS-3) for the period running from 1995 to 2016. We find that regions tend to differ in complexity not only in time but also in their international and intra-national trade exposures. We also show that indicators that incorporate both types of trade flows are better predictors of future GDP growth. These findings shed light on the determinants of regional convergence patterns.

Measuring subnational economic complexity: An application with Spanish data

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1. Introduction

The accumulation and diffusion of knowledge are key drivers of long-term economic growth (Lucas, 1988). Even when the theoretical underpinnings are clear, the question of how to measure empirically knowledge creation remains open. Several approaches and data sources have been used for the measurement of knowledge creation including number of patents (Boschma, et al., 2014; Balland and Rigby, 2016), migration flows (Andersen et al., 2011), investment flows (OECD, 2013), and international trade flows (Hausmann and Hidalgo, 2011).¹ Concretely, Hausmann and Hidalgo (2009, 2011, 2014) improved upon the concept of economic complexity (EC from now onwards) and defined a national indicator that could measure the non-observable capabilities (know-how) embedded in the production of goods and services. This indicator is calculated through an iterative process between a country's diversification (the number of products that a country exports with revealed comparative advantage) and a product's ubiquity (the number of countries with revealed comparative advantage in that product). That is, countries with more capabilities can make more products (higher diversification), whereas products that also require more capabilities to be produced are accessible to fewer countries (lower ubiquity).

This points out to a positive relation between a country's capabilities and its future economic growth. Yet these capabilities may not be evenly distributed throughout a country's space or may even be concentrated over short distances: for example, cities (Díaz-Lanchas, et al., 2017). This is the starting point of our analysis. We resort to intra-national trade data and compute a complexity indicator for each Spanish subnational entity, attending to both its international and its intra-national trade dimensions. Specifically, we cover the 50 Spanish provinces (NUTS-3, in Eurostat terminology) with a 29-product disaggregation for the period 1995–2016. In line with previous research (Reynolds et al., 2017; Gao and Zhou, 2018), our contribution relies on the combination of inter and intra-national trade flows for each province and product, bridging the gap between the (desired and usually unobservable) intra-national complexity and the international one.²

Our goal is to contribute to the literature of economic complexity and regional science by taking a closer look at the spatial dimension. Provinces (NUTS-3) are good proxies for actual production locations and, therefore, amenable to the

¹ See Corrado and Hulten (2010) for an in-depth review.

² As stated in previous research (Hausmann et al., 2014), the empirical measurement of knowledge creation should be based on production data but is instead mainly based on international trade data, because of the latter's highly standardized and disaggregated features for most countries.

economic complexity framework. Besides, they are more comparable spatial units than regions (NUTS-2) in both size and geographic characteristics. Indeed, they are the most comparable spatial units to cities, for which trade data are not officially available neither estimated. This fine spatial scale and great trade granularity allow us to explore the heterogeneity across regions and sectors within countries, and to show thereby that only international trade-based complexity indicators lead to biased estimations of the computed indicators when spatial heterogeneous patterns are not accounted for.

Our estimation of subnational indicators begins with the complexity indicators provided by the Atlas of Economic Complexity (2011). Our data on international trade flows come from the official Border Custom database and have a high level of product disaggregation. For the interregional dimension, we draw from a unique database of intra-national flows for Spain (Llano et al., 2010) that enables us to categorise intra-national trade flows into interprovincial and intra-provincial bilateral flows, with disaggregation into 29 sectors for Spain. Both databases are compiled for the same time series (1995–2016) and represent a first attempt to merge two trade databases of different natures at a fine spatial level with the complexity indicators. Therefore, we believe that our analysis is a promising effort to estimate economic complexity indicators at the subnational level in Spain while taking into account both international and interregional dimensions.

An important limitation that arises when extending the approach in Hausmann and Hidalgo (2009) to subnational entities is the conceptual leap from production data to international trade data. First, trade intensity is higher within national boundaries due to the trade impediments posed by international borders (Álvarez et al., 2013; Gallego and Llano 2017). For instance, around 82% of the Spanish economy's total trade remains within national boundaries.³ Moreover, there is great spatial and sectorial variability in the share of international exports within countries, which may bias any complexity index not accounting for such spatial and sectorial heterogeneity.

To overcome these limitations, we use two different methodologies to estimate the economic complexity indices at the province level, and then compare and test the results. We expect these methodologies to shed light on at least three dimensions. First, they should allow us to see how the complexity framework is enriched when we incorporate intra-national trade into international flows. Second, they should help us understand the relationship between economic complexity indicators computed from international and intra-national flows for subnational entities and the consistent bias towards high-complex products. Our hypothesis is that the economic complexity computed for international flows should be higher than that for intra-national flows. This intuition is based on the trade literature on heterogeneous firms (Melitz, 2003; Melitz and Treffler, 2012; Melitz and Redding, 2014), according to which only the most productive firms can overcome the fixed costs of exporting, and on quality patterns (Hummels and Skiba, 2004; Hummels and Klenow, 2005) that emphasize the role of exporters in trading high-quality products overseas. Third, our methodology helps us to assess the appropriateness of our intra-national complexity indicator vis-à-vis the international one. That is, we try to determine whether international complexity or subnational interregional complexity is the more prominent indicator of future provincial GDP per capita. According to the results, our indicator containing all types of trade flows provides a better fit and has better predictive properties than an indicator that takes only international trade flows into account.

The remainder of the paper is organised as follows. Section 2 reviews previous works on regional complexity indicators to better frame the main contribution of our paper. Section 3 describes our methodology, and Section 4 does the same for data.

³ Own calculation from the C-intereg project, as explained below.

Section 5 contains the descriptive analysis and an econometric analysis of our indicators' validity. Section 6 concludes with a set of policy implications.

2. Theoretical framework

It is difficult to compute subnational trade-based EC indices because there are no official intra-national trade databases. Previous works have recently tried to get around this problem resorting to different and complementary databases. Reynolds et al. (2017) generated a rich dataset of EC indices for Australian subnational entities by drawing from a novel trade database of multi-regional Input-Output (IO) tables, with nine regions and 506 sectors. The authors isolated trade flows among Australian regions and between those regions and the rest of the world. Such work built upon previous research by Wood and Lenzen (2009) who provided a first estimate of EC indices using IO data from 1975 to 1999 for 344 intermediate industry sectors. However, they dealt only with national economic structures, whereas Reynolds et al. (2017) applied Hausmann and Hidalgo's EC concept (Hausmann et al., 2014; Hidalgo & Hausmann, 2009) to Australia's interstate and international exports, finding that small differences in industrial capabilities were crucial for relative measures of complexity. Concretely, they found that most Australian states (especially in Western Australia) were exporting primarily resource-intensive goods, whereas interstate trade mainly specialized in complex products that are not internationally exported.

Gao and Zhou (2018) estimated the EC of Chinese provinces for 1990–2015. Their work is novel in its use of firm-level data and allows them to consider both international and intra-national trade flows for goods and services. Their analysis points out potential problems in the calculation of EC indices with world trade data exclusive of industries that do not export abroad. They find that the EC ranking of Chinese provinces was stable over time, with coastal provinces having higher EC, but also that diversified Chinese provinces tended to have less ubiquitous industries.

Finally, Balland and Rigby (2016) offered an interesting analysis of subnational EC measures for the US. In contrast to the above articles, they addressed the spatial distribution and the change in complexity of US cities using an extensive patent database from the US Patent and Trademark Office. Identifying the technological structure of US metropolitan areas from 1975 to 2010, they found that knowledge complexity had an uneven spatial distribution among US cities. They also tested the spatial diffusion of knowledge to assess whether it was linked to complexity levels, finding that complex technologies were less likely to be located in remote cities. On the contrary, they found a high concentration of highly complex activities in a few productive locations.

This is not an exhaustive account, but these works have laid out the theoretical and empirical groundwork for our paper. We go beyond an analysis with IO tables to use Spain's international and intra-national bilateral trade flows at the smallest possible spatial units up to the present. We believe that controlling for these two types of (tradable) flows for 50 subnational entities and 29 sectors allows us to compute complexity indicators considering products' destination markets (international or intra-national) and accounting for biases in the computation of EC indicators. Moreover, we believe we can approximate complexity patterns over short distances (almost at the city level) and assess economic performance for these precise spatial locations.

3. Methodology for the estimation of subnational economic complexity

We take two approaches to build a subnational economic complexity indicator. In the main text we focus on our baseline indicator, leaving our second approach to Annex A.1.

3.1. Baseline approach

Our baseline approach relies on the estimation of EC indicators (ECIs) at the subnational NUTS-3 level (provinces) in Spain by matching product complexity indicator (PCIs) for international flows at the country level with our two trade databases at the province level.⁴ In this way we assume that a given product has the same level of complexity—i.e. skills embedded in its production—regardless of the location (or market) where the product is actually produced.

Prior to this, we calculate the region's comparative advantages (RCAs) in every product (or sector)⁵, for international, intra-national and total trade flows. These RCAs are compiled into a matrix (M) in the following form:

$$M_{srt}^F = \frac{X_{srt}^F}{\sum_{st} X_{srt}^F} / \frac{\sum_{rt} X_{srt}^F}{\sum_{srt} X_{srt}^F} \quad (1)$$

where X_{srt} refers to the exports of a certain product or sector (s) in a given region (r) at time (t) for each type of trade flow (F). Matrix M is similar in structure to the matrix in Hausmann and Hidalgo (2009), taking the value 1 when $RCA > 1$ and 0 otherwise.

The nature of our trade dataset leads us to calculate different ECIs for each province using different trade flows. In the case of international trade, there is a direct and equivalent product classification between the PCIs obtained by Hausmann and Hidalgo (2011) (at HS4 product classification) and our subnational international exports (from Border Customs).

A problem arises when merging international PCIs with intra-national trade flows. The latter flows use a different product classification, because of the different data sources used for their compilation. As a result, we need to match the international PCIs to a product classification that is similar in both the intra-national trade flows and the international PCIs. Then, we can aggregate the latter into an intra-national PCI consistent with our sectorial classification.⁶ More specifically, we calculate an equivalent PCI for each sector and region using international trade flows according to the following:

$$PCI_{srt}^{Inter} = \frac{\sum_{srt} PCI^{HH} X_{srt}^{Inter}}{\sum_{srt} X_{srt}^{Inter}} \quad (2)$$

⁴ Available at <http://atlas.cid.harvard.edu/>.

⁵ Throughout the analysis the two terms are used interchangeably

⁶ This sectorial classification is shown in Annex 2. We pursue three methods of aggregation: simple averages, weights using quantity flows (tons) and monetary flows (euros). We then test the performance of the three PCIs and ECIs obtained, and consider the weights in euros as the most appropriate.

where PCI^{HH} stands for the HS4 PCIs obtained by Hausmann and Hidalgo (2011) and X_{srt}^{Inter} stands for the HS4 international exports. Note also that PCI_{srt}^{Inter} is determined by the international product-mix in a given region's trade basket.

With PCI_{srt}^{Inter} , we can now recalculate our final PCI with the following expression:

$$PCI_{st}^F = \frac{\sum_{srt} PCI_{srt}^{Inter} X_{srt}^F M_{srt}^F}{\sum_{srt} X_{srt}^F M_{srt}^F} \quad (3)$$

where, again, F refers to each type of trade flow. Thanks to PCI_{st}^F , we can estimate the EC indicator for each region:

$$ECI_{rt}^F = \frac{\sum_{srt} PCI_{st}^F X_{srt}^F M_{srt}^F}{\sum_{srt} X_{srt}^F M_{srt}^F} \quad (4)$$

With expression (4), we estimate an ECI for international and intra-national flows. Additionally, as explained in the next section, our intra-national trade flows can be split into *interregional* trade flows (province to province) and *intraregional* flows (within the same province). Taking this advantage in granularity, we exploit the spatial heterogeneity of our subnational ECI and create two additional indicators: $ECI_{st}^{Interregional}$ and $ECI_{st}^{Intranational}$. This way, we come up with smaller (intraregional) indicators.

Finally, we develop an ECI for *total* trade flows regardless of destination market. To this end, we first aggregate international trade flows for Spanish provinces to the equivalent intra-national sectorial classification. Then we recalculate the RCAs (M_{srt}^F) in Equation (1) to get the PCIs using expression (3) and finally an ECI_{st}^{Total} indicator according to (4).

4. Data

Our dataset includes both international and interregional trade flows at the NUTS-3 level. The international trade flows correspond to the official records published annually by the Spanish Tax Agency (AEAT)⁷ for each Spanish province. The value of this type of data lies in its great product disaggregation (CN8-digits product classification). We collected data from 1995 to 2016 and compiled a database of around 38 million observations. We then matched the CN8-digits product classification with the HS4 product classification used by the PCI database (around 1,240 products per year) and aggregated the CN8-digits products to HS4 products with their corresponding complexity levels, weighted by monetary values.

The intra-national trade flows database is based on the C-intereg database,⁸ first compiled by Llano et al. (2010) and updated annually until 2016. This database includes bilateral trade flows between the 50 Spanish provinces at the NUTS-3 level, covering a long period of time (1995–2016). The compilers of the C-intereg database took the official data on bilateral flows by transport mode (road, railway, ship and aircraft) and then matched these flows with the official data on production and international exports, filtering by re-exporting flows at the province and sectorial levels for each year in the period 1995–2016. The result was a panel database with around 25 million observations encompassing all 50 provinces and 29

⁷ Data available at the Border Customs and Spanish Tax Agency (www.aeat.es).

⁸ Available at <http://www.c-intereg.es/>.

sectors. As reported in previous papers mixing this database with the official international trade flows for Spain, the range of products and destinations is wider here than it is for international flows (Díaz-Lanchas et al., 2019). Table 1 summarizes the spatial and sectorial disaggregation of both databases.

Table 1: Summary of trade data used

Trade flow	Territorial Disaggregation	Initial product disaggregation	Time period	Source
International	NUTS-3	More than 10000	1995-2016	AEAT
Intra-national	NUTS-3	29	1995-2016	C-intereg

Finally, for the econometric analysis, we complemented our panel database with NUTS-3 variables corresponding to factor endowments. Specifically, we included the (net) physical capital (PC) and the (economic value of) human capital (HC) for each region (province) in the period 1995–2013. Both variables are taken from Instituto de Investigaciones Valencianas (IVIE)⁹ and are used in Section 5.

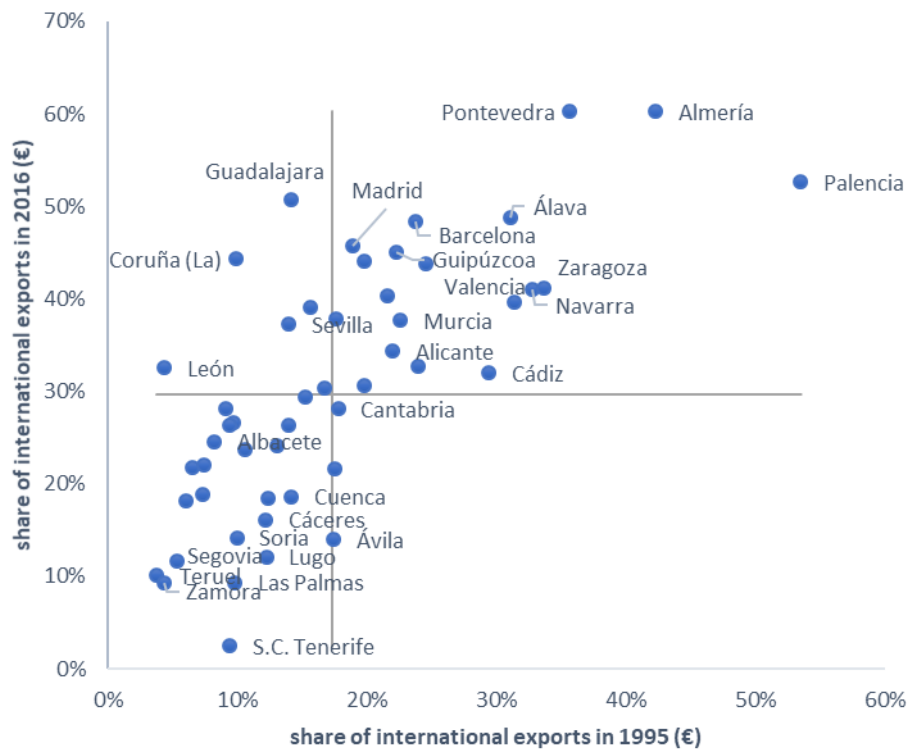
5. Results

5.1. Descriptive Analysis

First, we check the stability over time of the international trade structure. Figure 1 represents the share of international exports over total exports in 1995 and 2016 for each Spanish province. In line with Gao and Zhou (2018), the results clearly point to a stable trade structure but also, and differently from them, to a dichotomic internationalization of Spanish provinces. The shares of international exports of some provinces increase from 18% in 1995 to more than 27% in 2016, whereas half the provinces have below average values throughout the whole sample period. Recent evidence (Requena and Llano, 2010; Llano et al., 2017; Díaz-Lanchas et al., 2019) suggests that these differences in spatial internationalization result not only from differences in knowledge creation, but also from location determinants. This means that there's a tendency of firms within a country to select their location considering both the conditions of the local labour markets (factor endowments) and transport costs. Location determinants dictate the transport mode used as well as the average distance of each flow. Coastal locations have a comparative advantage in trading heavy products, such as minerals, iron-steel and windmill components, whereas internal regions specialize in other tradable products (Gallego et al., 2015).

⁹ Available at <https://www.ivie.es/>.

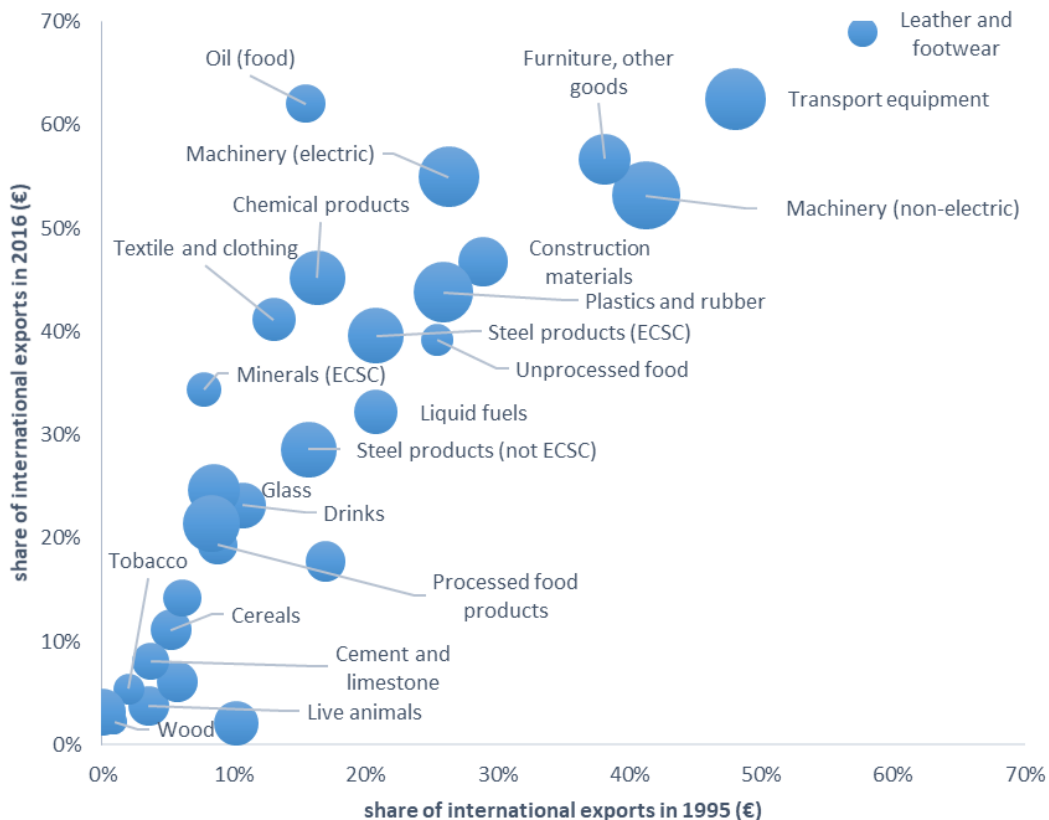
Figure 1: Change in share of international exports by province: 1995 vs 2016



Source: Own elaboration with C-intereg and AEAT data.

This stability in trade structures also holds when looking at the products' data. Figure 2 shows the share of international exports over total exports for each of the 29 sectors in 1995 and 2016. Again, the results suggest that more than half of the sectors are oriented towards the internal rather than the international market. Only six out of 29 sectors have more than 50% of their production geared towards international markets. Four of these are high-complex sectors (electric and non-electric machinery, transport equipment and furniture and other goods), whereas the other two are low-complex sectors (leather and footwear and food oil). Because of the spatial and sectorial trade structures in such cases, and their orientation chiefly towards internal national markets, the computation of ECI can result in biased indicators. We can therefore enrich our estimation of know-how in the regional production of these products by considering intra-national trade flows jointly with international flows, where only some (special) products are exported.

Figure 2: Change in share of international exports by product (R30). 1995 vs 2016.



Note: The size of the bubbles represents the sector's complexity in 1995.

Source: Own elaboration with C-intereg and AEAT data.

To further illustrate intra-national trade characteristics, Figure 3 plots the relationship between product complexity and the average distance travelled by product for all types of trade flows. The size of each bubble represents a product's total exports. It is easy to distinguish two groups of products. Those in grey, such as oil (food), correspond to low-complex products travelling long distances (more than the maximum average distance for intra-national trade flows). But there are also low-complexity products travelling mostly short distances, which points to an overconcentration of such trade flows within the country (the minimum and median average distance for inter-regional trade are 210 km and 400 km respectively). The second group, in blue, shows a positive relationship between trade intensity and distance. First, a number of low-complex products (cement; rocks, sand and salt; cereals; fertilizers; tobacco; wood; live animals) are associated with trade intensities over short distances. These are products traded mainly among Spanish provinces (and regions). We also observe trade flows in middle distances for products of average complexity (processed food), corresponding to large interregional flows (e.g. Cataluña-Andalucía-C. Valenciana-Madrid) and short international ones (Spain-EU countries). Finally, other sectors such as chemical products, machinery (electric and non-electric) and transport equipment, are characterised by high complexity and long-travel distances. Their share of international exports is the greatest. The pattern plotted in Figure 3 points to an overrepresentation of high-complex products in international trade statistics.

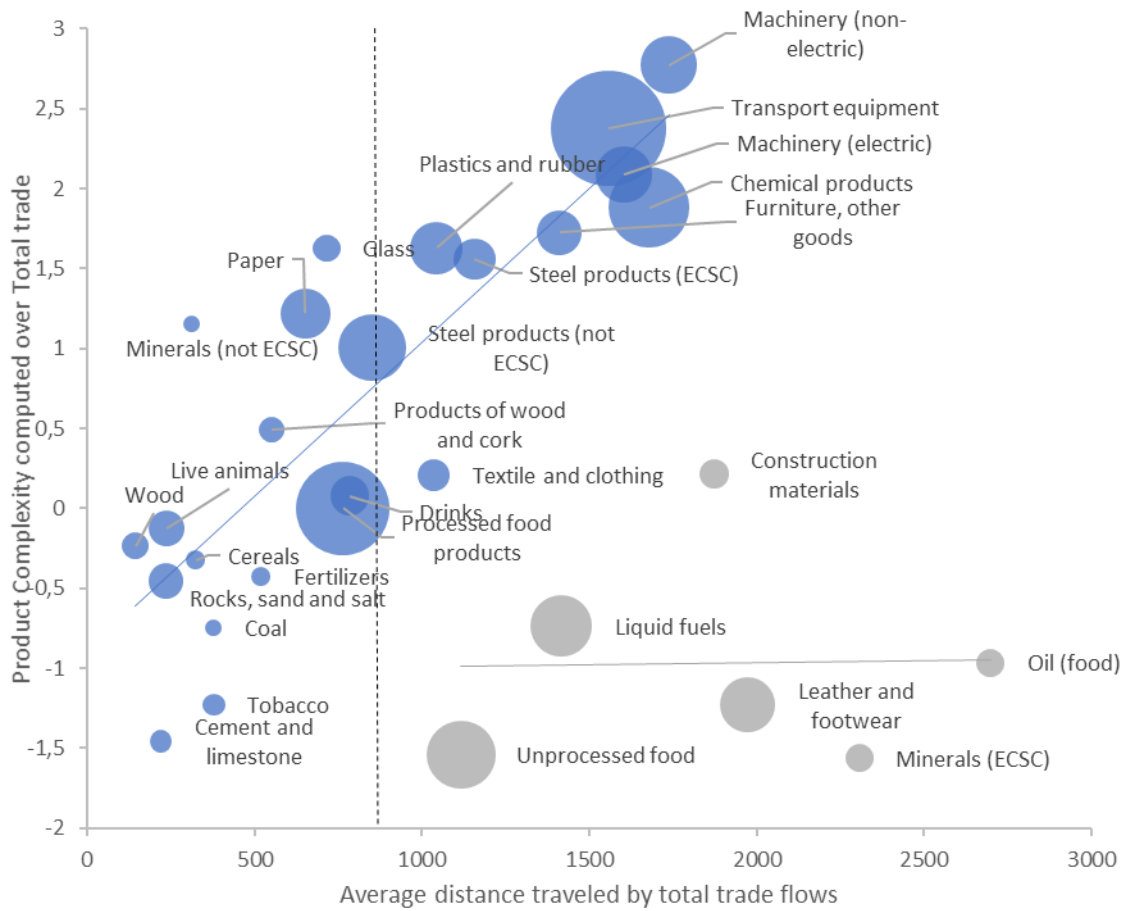
The previous patterns clearly point to heterogeneous spatial trade patterns; therefore, we should expect spatial differences in the ECI. In Figure 4, we split the

sample of 50 Spanish provinces into three groups according to their EC and using the ECI_{st}^{Total} indicator in 2016. The results for the beginning of the period (1995) are shown in Figure A.3 in Annex 3. The first group contains provinces in the first quartile (the 12 provinces with the lowest complexity); the second group contains provinces in second and third quantiles (26 mid-complexity provinces); and the third group is made by provinces in the fourth quartile (the 12 with the highest complexity). Additionally, each group is subdivided by the three EC indicators (for intraregional, interregional and international economic complexity) explained in Section 3.1. Panels A to C represent the trade structures for each group of provinces, with the median, minimum and maximum level of complexity added in for each trade typology, whereas the map in Panel D shows the geographic distribution of the total EC indicator.

Several points are worth mentioning here. Panels A to C highlight the positive relation between a product's economic complexity and the destination market, being the complexity higher the further the market (e.g. international destinations). Also interesting is the geographic distribution of complexity (Panel D). The most complex regions are the ones with the largest Spanish cities (Madrid, Barcelona and Valencia) and the ones hosting either innovation hubs (País Vasco and Navarra) or even complex industries such as the automotive sector (Valladolid, Palencia, Zaragoza and Pontevedra).¹⁰

¹⁰ In Annex 3, Figure A.3 shows the results for 1995. It highlights the spatial stability of EC indicators in time. There are only a few changes, mainly in the low-complexity group. In comparison with Figure 4 for 2016, EC indicators for 1995 point to higher levels of complexity, consistent with the recent decay in Spain's ECI published by the Atlas of Economic Complexity. Also note the higher complexity of the provinces (Guadalajara) surrounding provinces with big cities inside such as Madrid as a result of the agglomeration economies' effects of the latter.

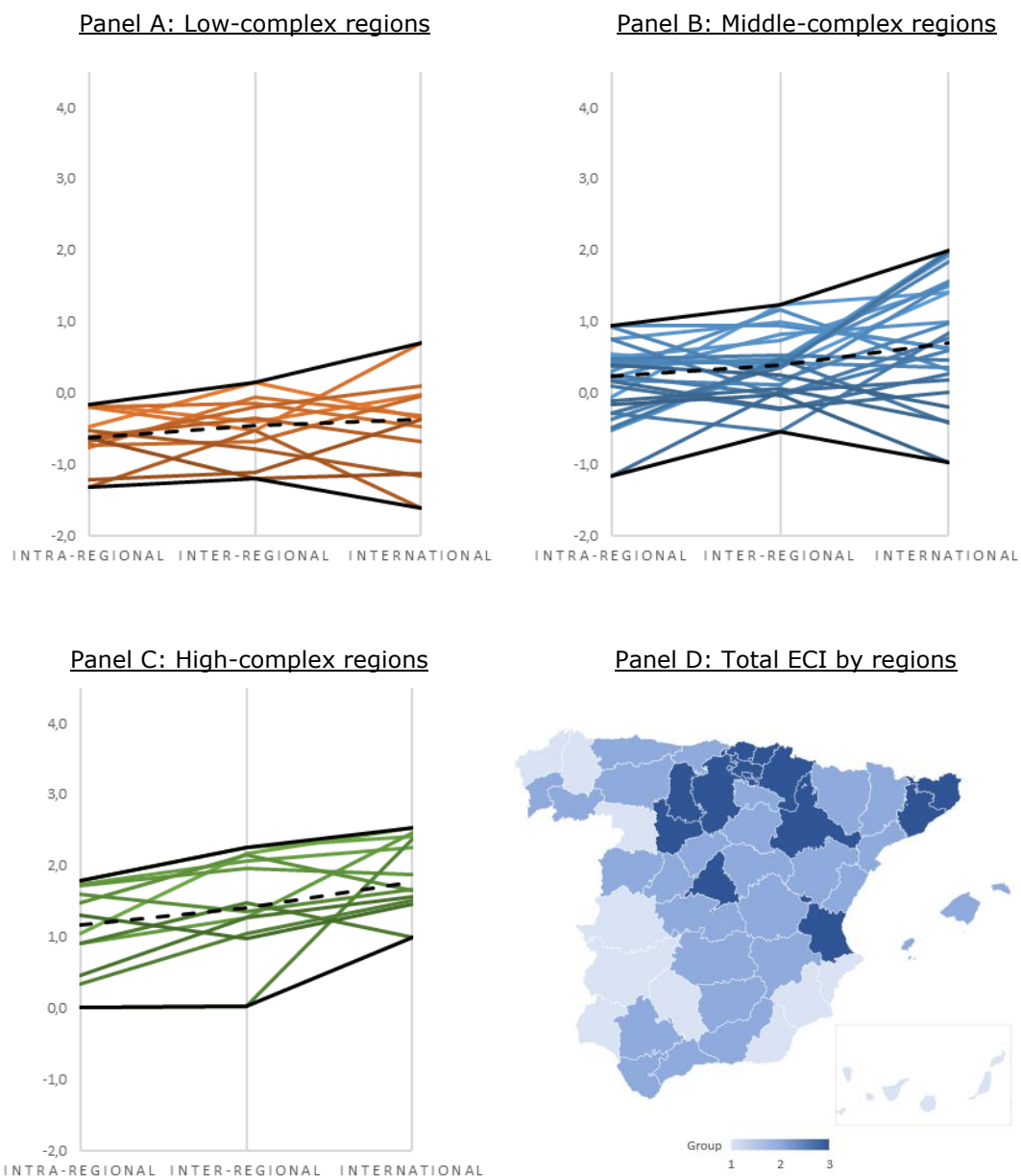
Figure 3: PCI (with total trade) and average distance travelled. 2016.



Note: The size of the bubbles represents the total trade of the sector (in €). The dotted line represents the maximum average distance travelled by intra-national trade flows (812 km).

Source: Own elaboration.

Figure 4: ECI by region and trade flow (2016)



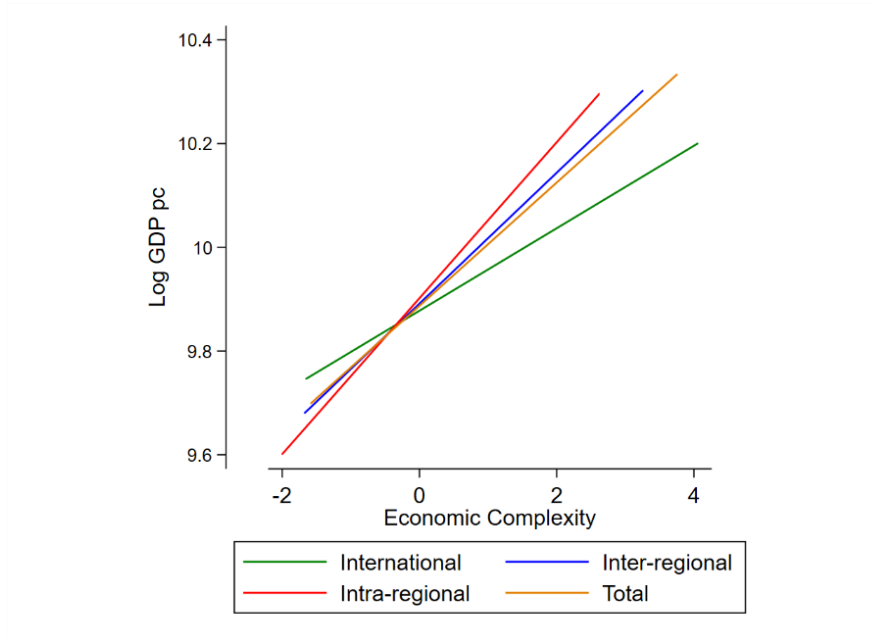
Panels A-C: Each colour bar belongs to a province (Nuts 3). Black lines refer to minimum and maximum complexity in each represented trade flow. The dotted line indicates the median of each group.

Panel D: Group 1 refers to low-complexity regions (first quartile), group 2 refers to mid-complexity regions (second and third quartiles) and group 3 to high-complexity regions (fourth quartile).

Source: Own elaboration.

The use of multiple ECI raises the question of their explanatory power. Figure 5 shows the relationship between GDP per capita (GDPpc) and the four ECI. While all indicators are strongly and positively related to GDPpc, the relationship is weaker for the ECI calculated only with international trade flows (this is particularly evident for high levels of EC). On the other hand, the total ECI with both international and intra-national trade flows provides a better explanation of GDPpc.

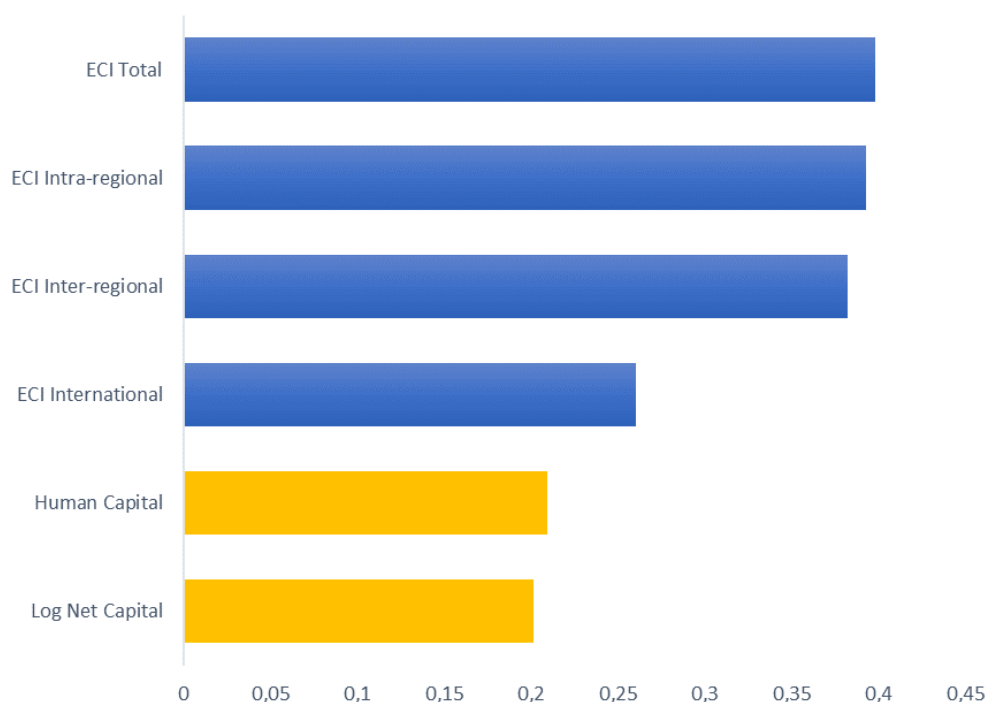
Figure 5: GDP per capita vs ECI at the province level (baseline approach)



Source: Own elaboration.

Figure 6 shows the R-squared obtained when regressing GDPpc ten years forward (including the whole sample) with each of the four EC indicators separately (detailed results not reported for the sake of brevity, but available upon request). We also estimate two additional versions of the model adding controls for factor endowments: namely, HC and PC, as drivers of GDP per capita. The results show that all variables have a positive and significant relation with future GDPpc. Figure 6 reinforces our hypothesis that intra-national trade flows are even more important than international trade flows in explaining future GDPpc. Indeed, the EC indicator for total trade flows provides outstanding results, explaining almost 40% of future GDPpc. For the provinces with zero or small share of international trade flows (as evidenced in Figure 1 for half of the provinces), intra-national EC indicators gain huge explanatory power. Finally, note that all the models including ECI report even larger R-squared than the models including standard variables in the literature (orange bars).

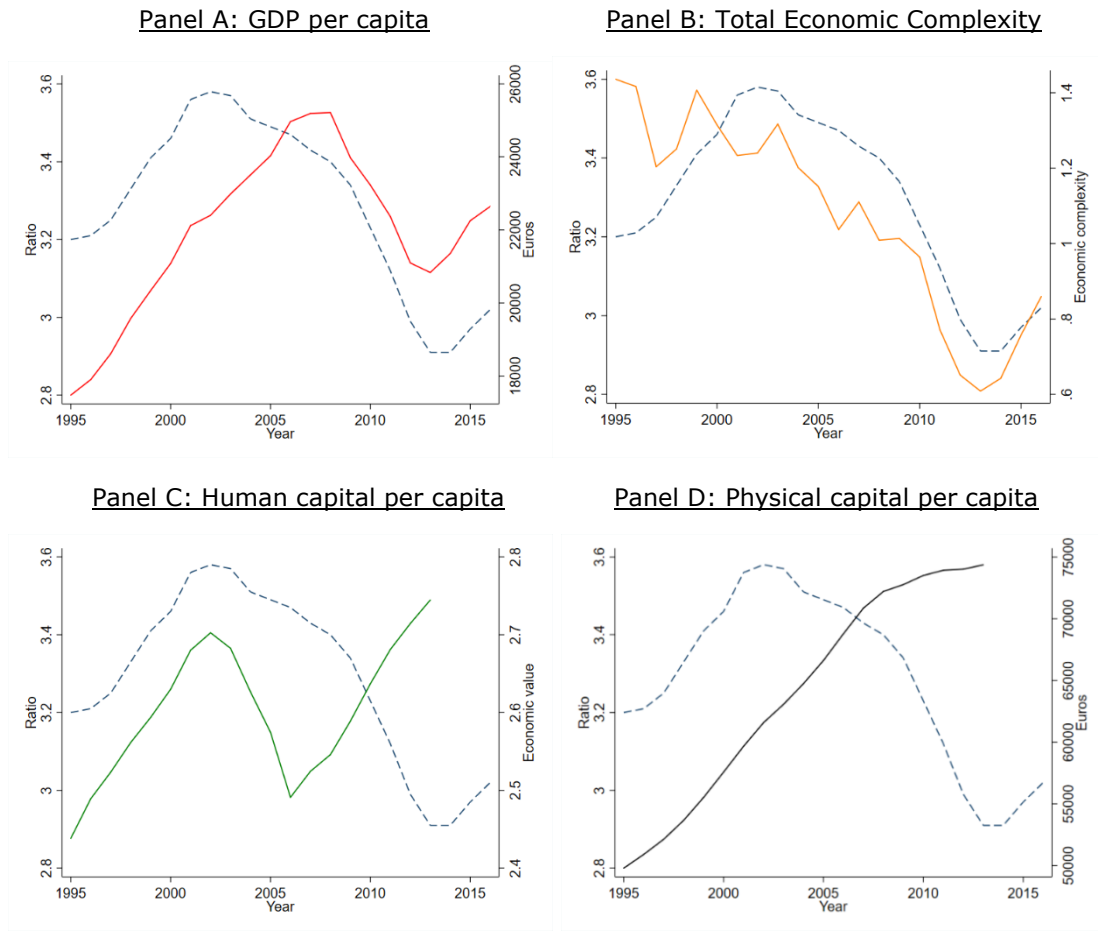
Figure 6: R-squared GDP per capita (t+10) and EC indicators (baseline approach)



Source: Own elaboration.

Even when the ECI obtained fit well with future (provincial) GDPpc, these regional indicators can also be affected by the country's specific dynamics. When a country such as Spain reduces its complexity with respect to the rest of the world, then it is reasonable to think that its regions (provinces) will undergo an equivalent process. To investigate this possibility, Figure 7 plots the Spanish GDPpc, the *total* ECI computed, and the classical regional economic growth factors (PC and HC) per capita. GDPpc is presented as a ratio of world GDPpc to assess whether relative changes in the Spanish economy have been accompanied with vis-à-vis changes in the world economy. Panel A shows the evolution of the Spanish GDPpc (red line) and its ratio in the world's GDPpc (dotted blue line). Both variables show a clear fall from 2008 to 2012, which becomes even more abrupt in the case of GDPpc relative to the world. Panels B-D compare this relative ratio with the ECI (Panel B), the physical capital (Panel C) and Human Capital (Panel D). As observed, the ECI is the variable that most clearly mirrors the dynamics of the Spanish GDPpc relative to the world's GDPpc. PC shows a monotonic growth path, whereas HC presents changes peaks and rebounds similar to GDPpc but some years in advance to the latter. These dynamics are coherent with the striking pattern of the Spanish economy by which it has drastically reduced its economic complexity in comparison to the rest of the world since the beginning of the crisis. Last, Figure 7 again emphasizes the explanatory features of the total EC index in detriment of its PC and HC counterparts.

Figure 7: Evolution of the Spanish GDPpc, the regional ECI and regional economic factors per capita (physical and human capitals). 1995-2016.



Note: Blue (dotted) lines represent Spanish GDP per capita over world GDP per capita. The red line represents Spanish GDP per capita. The orange line represents Spanish total economic complexity. The green line represents Spanish human capital per capita. The black line represents Spanish net capital per capita. All variables are in real terms.

Source: Own elaboration.

5.2. Econometric Analysis

The previous section was devoted to the illustration of the main features of the EC indices calculated with the Spanish data. This section deals with the econometric analysis aiming to explain future growth of income per capita. As previously stated, our specifications also include two variables widely discussed in the literature: PC and HC both in per capita terms. Thus, our two main specifications take the following form:

$$(GDPpc_i/WGDPpc)_{t+5} = \beta_1 ECI_{it}^F + \beta_2 PCpc_{it} + \beta_3 HCpc_{it} + \mu_t + \varepsilon_{it} \quad (5)$$

$$(GDPpc_i)_{t+5} = \beta_1 ECI_{it}^F + \beta_2 PCpc_{it} + \beta_3 HCpc_{it} + \mu_t + \varepsilon_{it} \quad (6)$$

Where $GDPpc$ refers to provincial GDP per capita, $WGDPpc$ does the same with world GDP per capita and μ_t controls with time-fixed effect. Note that equation (5) assesses the impacts of the ECI over the 5-years growth of a relative measure of

(world) GDP, whereas equation (6) does the same with the 5-years growth of the absolute value of provincial GDP.¹¹

Table 2 contains the results for equations (5) and (6) in a cross-section between the initial and the last year for each five-years period using OLS estimators with a year fixed effect for the last year. The main model (M1) refers to the complete specification with the ECI (considering total trade flows) and the PC and HC variables as regressors. In Models M2-M4 we combine different specifications dropping variables correspondingly. The last line of the table shows the change in R^2 over the main specification (M1) as a measure of the performance of our models.

Table 2: GDP per capita growth (t+5) by province. Baseline specifications. Cross-sections between the first and the last year every t+5 years. OLS estimators.

Years-Thresholds	1995-2000, 2000-2005, 2005-2010, 2010-2015							
	M1	M2	M3	M4	M1	M2	M3	M4
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
VARIABLES	GDPpc/World GDPpc (t+5)				GDPpc (t+5)			
Total ECI	0.393*** (0.0528)		0.395*** (0.0581)	0.437*** (0.0556)	0.316*** (0.0460)		0.318*** (0.0541)	0.398*** (0.0533)
Physical cap.	0.317*** (0.0784)	0.320*** (0.0861)		0.369*** (0.0571)	0.376*** (0.0728)	0.378*** (0.0774)		0.474*** (0.0557)
Human cap.	0.117 (0.0827)	0.317*** (0.0886)	0.277*** (0.0604)		0.219*** (0.0769)	0.379*** (0.0809)	0.408*** (0.0560)	
Observations	200	200	200	200	200	200	200	200
R-squared	0.551	0.425	0.483	0.543	0.603	0.518	0.503	0.573
Change in R-squared		22.90%	12.30%	1.50%		14.10%	16.58%	4.98%

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

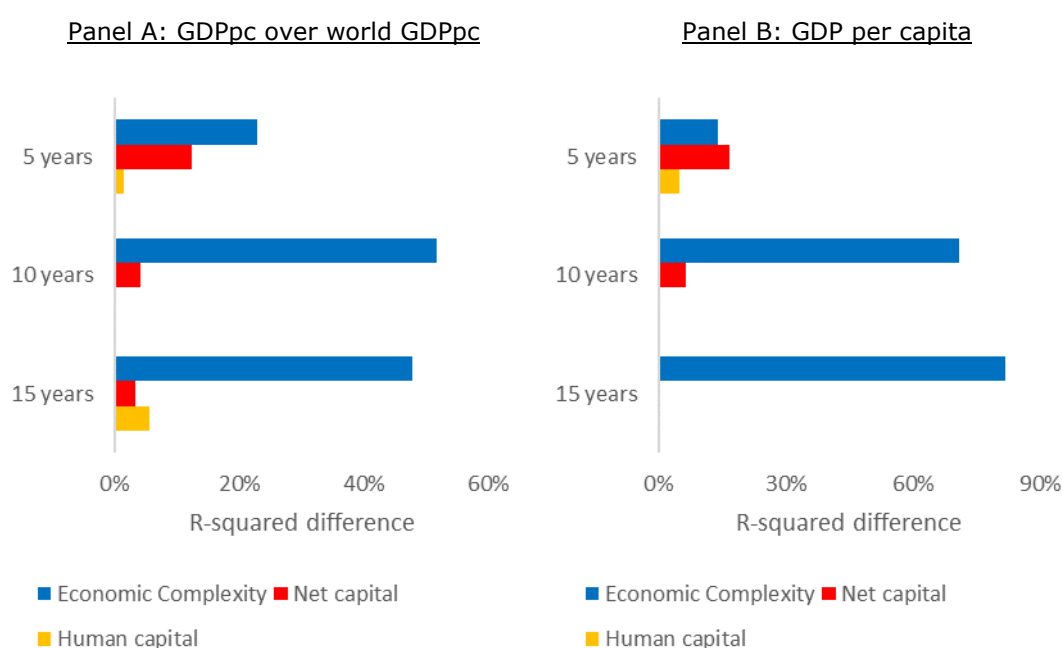
As seen in Table 2, the coefficient associated with total EC is positive and significant in all specifications, even when controlling for factor endowments. Physical capital is also associated with a positive and significant coefficient, whereas that of human capital becomes non-significant, although positive, when explaining relative GDP growth. The remarkable drop in R^2 by almost 23% takes place when the ECI variable is not included (M2 in Table 2), especially if compared to the 12% drop when physical capital is removed. Absolute GDP growth presents similar results, being all the variables' coefficients positive and significant in all cases. Additionally, we get consistent and robust results in Annex 4 when considering 10- and 15-years thresholds (Tables A.4.1 and A.4.2) and within-groups' estimators in a panel

¹¹ Growth is considered as the growth rate of GDP. In the main regressions we consider GDP per capita growth for a period of 5 years, but in the Annex 4, Tables A.4.1 and A.4.2 also consider growth in periods of 10 and 15 years. Additionally, Table A.4.5 splits EC indexes into their international, inter-regional and intra-regional EC counterparts. Finally, for the sake of comparability with the ECIs, physical and human capital variables are also standardized.

database (Tables A.4.3 and A.4.4). The EC indicators are always associated with positive and significant coefficients, and their impact appears to be even higher the longer the time period considered.

Figure 8 summarizes this information. Specifically, we show the change in the R^2 for different years-thresholds (5, 10, 15 years) when explaining (provincial) GDPpc. For shorter periods (5 years), PC appears to have a good explanatory power, particularly for the growth of absolute GDPpc. Nevertheless, EC becomes the only one variable capable of accounting for the largest proportion of provincial GDPpc (in relative or absolute values) in 10 and 15 years-periods. Thereby, we highlight the total EC index as clearly the most relevant variable explaining future long-run regional economic growth.

Figure 8: R^2 changes in explaining provincial (relative and absolute) GDP growth rates.



Source: Own elaboration.

Finally, Table A.4.5 (in the Annex 4) differentiates by the international, inter-regional and intra-regional EC indicators. The results are robust and consistent with those in Table 2, and confirm the higher impact of the international EC indicator over its intra-national counterparts, as argued in the descriptive analysis. This reinforces our hypotheses on the higher complexity levels of international trade flows, pointing out to an over-representation of complex products in international statistics. All these results allow us to conclude that ECI are key in explaining future GDPpc growth once we control for different factor endowments, in line with previous works (Hausmann and Hidalgo, 2009, 2011 and 2014). Nevertheless, our results give evidence on the biases introduced when using only international trade statistics. These problems are solved when adding intra-national trade flows in our analysis.

6. Conclusions

Knowledge is unevenly distributed in space. Up to now, several attempts measuring the concept of EC rely on country-level analysis using international trade statistics, even when the highest share of economic activity remains within national borders and present humongous heterogeneity across regions and places. This scarcity in intra-national analysis is due, at least partly, to the scarcity of publicly available subnational data.

In this paper we propose a novel approach to compute subnational ECIs for the case of Spain and its 50 provinces for the period 1995–2016. Our main methodological contribution entails the combination of international and intra-national trade flows statistics as well as economic complexity indicators. To the best of our knowledge, our analysis is the first attempt to estimate economic complexity indicators at the subnational level in Europe with bilateral trade data.

Thanks to this effort, we elaborate a new set of economic complexity indicators that allows us to account for cross-regional differences in income per capita. Our results reinforce the importance of economic complexity as a leading indicator of future GDP per capita. We also confirm that economic complexity is enriched by the inclusion of intra-national trade flows. Indeed, we show that economic complexity indicators based only in international trade statistics are usually biased towards most complex products. We also show a positive relation between complexity and the average distance of trade flows, and find that total EC indices outperform those that only consider international trade flows, especially in the very long run.

Our results entail interesting indications for future economic policies. One of the great problems in current economic policy is to determine at which level of territorial disaggregation we should apply political and economic measures for maximum efficacy. Most researchers consider cities and metropolitan areas to be the new nations. The methodology we propose reflects this notion and focuses on the lowest territorial disaggregation possible. This helps us to develop clever strategies to optimise the sectoral structures of lagging regions, making them more resilient and boosting their capacity to succeed in a more global economy. We expect to shed new and prominent light on this relation in future research, going deeper in the dynamics of those regions that seek both to penetrate the farthest markets (first within their country, then in the rest of the world) and to produce more innovative and competitive products.

7. References

- Alvarez, F.E., Buera, F.J., Lucas, R.E., Jr., 2013. Idea Flows, Economic Growth, and Trade. NBER Working Paper Series w19667.
- Andersen, T.B., Dalgaard, C., 2011. Flows of people, flows of ideas, and the inequality of nations. *Journal of economic growth* 16, 1-32.
- Balland, P.A., Rigby, D., 2017. The Geography of Complex Knowledge. *Economic Geography* 93, 1-23.
- Balland, P.A., Jara-Figueroa, C., Petralia, S., Steijn, M., Rigby, D., and Hidalgo, C., 2018. Complex Economic Activities Concentrate in Large Cities. *Papers in Evolutionary Economic Geography*, no 18,1-10.
- Boschma, R., Balland, P., Kogler, D., 2014. Relatedness and technological change in cities: the rise and fall of technological knowledge in US metropolitan areas from 1981 to 2010. *Industrial and Corporate Change* 24, 223-250.
- Díaz-Lanchas, J., Llano, C., Minondo, A., Requena, F., 2018. Cities export specialization. *Applied Economics Letters* 25, 38-42.
- Díaz-Lanchas J., Llano C., Zofío J. L., (2019). A trade hierarchy of cities based on transport cost thresholds, JRC Working Papers on Territorial Modelling and Analysis NO. 02/2019, European Commission, Seville, 2019, JRC115750.
- Duranton, G., Puga, D., (2001). 'Nursery cities: Urban diversity, process innovation, and the life cycle of products'. *American Economic Review*, 91(5), 1454-1477.
- Gallego, N., Llano, C., 2017. Thick and Thin Borders in the European Union: How Deep Internal Integration is Within Countries, and How Shallow Between Them. *The World Economy* 38, 1850-1879.
- Gallego, N., Llano, C., De La Mata, T., Díaz-Lanchas, J., 2015. Intranational Home Bias in the Presence of Wholesalers, Hub-spoke Structures and Multimodal Transport Deliveries. *Spatial Economic Analysis* 10, 369-399.
- Gao, J., Zhou, T., (2018). Quantifying China's regional economic complexity. *Physica A: Statistical Mechanics and its Applications* 492, 1591.
- Hausmann, R., Hidalgo, C.A., (2011). The network structure of economic output. *Journal of economic growth* 16, 309-342.
- Hausmann, R., Hidalgo, C.A., (2014). *The Atlas of Economic Complexity*, MIT Press, Cambridge.
- Hidalgo, C.A., Hausmann, R., (2009). The Building Blocks of Economic Complexity. *Proceedings of the National Academy of Sciences of the United States of America* 106, 10570-10575.
- Hummels, D., Klenow, P.J., 2005. The Variety and Quality of a Nation's Exports. *The American Economic Review* 95, 704-723.
- Hummels, D., Skiba, A., 2004. Shipping the good apples out? An empirical confirmation of the Alchian-Allen conjecture. *Journal of political Economy* 112, 1384-1402.

- Llano, C., De la Mata, T., Díaz-Lanchas, J., Gallego, N., 2017. Transport-mode competition in intra-national trade: An empirical investigation for the Spanish case. *Transportation Research Part A* 95, 334-355.
- Llano, C., Esteban, A., Perez, J., Pulido, A., 2010. Opening the Interregional Trade "Black Box": The C-Intereg Database for the Spanish Economy (1995-2005). *International Regional Science Review* 33, 302-337.
- Lucas, R.E., 1988. On the mechanics of economic development. *Journal of Monetary Economics* 22, 3-42.
- Marc J. Melitz, 2003. The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. *Econometrica* 71, 1695-1725.
- Melitz, M.J., Redding, S.J., 2014. Heterogeneous Firms and Trade, in Anonymous *Handbook of International Economics*. Elsevier B.V, pp. 1-54.
- Melitz, M.J., Trefler, D., 2012. Gains from Trade When Firms Matter. *Journal of Economic Perspectives* 26, 91-118.
- OECD, 2013. *Supporting Investment in Knowledge Capital, Growth and Innovation*. OECD Publishing, Paris and Washington, D.C.
- Requena, F., Llano, C., 2010. The border effects in Spain: an industry-level analysis. *Empirica* 37, 455-476.
- Reynolds, C., Agrawal, M., Lee, I., Zhan, C., Li, J., Taylor, P., Mares, T., Morison, J., Angelakis, N., Roos, G., 2018. A sub-national economic complexity analysis of Australia's states and territories. *Regional Studies* 52, 715-726.
- Wood, R., Lenzen, M., Foran, B., 2009. A Material History of Australia. *Journal of Industrial Ecology* 13, 847-862..

Annex 1: Subnational economic complexity indicator (Methodology 2).

Our second approach controls for regional *diversity* and product *ubiquity* within subnational entities. In addition to these two dimensions, which are already embedded in the original PCIs, these correction factors add the ubiquity and diversity properties of each province to the economic complexity indicator. We thereby account for products that are ubiquitous worldwide but unusually produced in Spanish provinces. The opposite also holds: that is, we correct for certain products that are ubiquitous within the frontiers of a given country but scarce in the global market (e.g. the wine produced in every region in Spain but never exported internationally). This way, we argue that results are driven by the decisions of firms to locate within a country. In other words, production-location decisions within intra-national borders are influenced by production-cost strategies, e.g. firms locate production plants in cost-saving areas (Duranton and Puga, 2001). The calculation of EC indices is affected by these decisions, and international trade databases fail to account for these trade flows.

The starting point is the same as with the baseline methodology. Starting from equation (1), we estimate a diversity and ubiquity measure with the data matrices (M_{srt}^F) as follows:

$$Diversity = k_{rt}^F = \frac{1}{S} \sum_s M_{srt}^F \quad (A.1)$$

$$Ubiquity = k_{st}^F = 1 - \frac{1}{R} \sum_r M_{srt}^F \quad (A.2)$$

where S is the maximum number of sectors and R the maximum number of regions. The *diversity* measure described in Equation (A.1) increases for regions with a high number of products in their export basket. Similarly, the *ubiquity* measure in Equation (A.2) decreases when a product s is traded by a wide range of Spanish regions.¹²

These corrections are included in the PCI_{st}^F obtained in Equation (3):

$$PCI_{st}^{F*} = PCI_{st}^F + k_{st}^F \quad (A.3)$$

where F refers to each type of trade flow. Finally, the new ECI_{rt}^{F*} equals:

$$ECI_{rt}^{F*} = ECI_{rt}^F + k_{rt}^F \quad (A.4)$$

The performance of these ECIs is shown in Figures A.1.1 and A.1.2. This second approach also points to superior higher explanatory power (Figure A.1) of intra-national and total ECI than the international ECI alone, but the explanatory (Figure A.2) properties of this approach is lower than those of our baseline indicators. These conclusions are reinforced in Table A.1. It shows the econometric results for our main specifications using equations (5) and (6). As seen, the EC index in the approach has a lower impact in explaining future (5 and 15 years) GDP growths than the one obtained with our baseline ECI (see Table 2).

¹² For homogeneity, we have also standardized both measures by taking their average and standard deviations.

Figure A.1.1: GDP per capita vs ECI at the province level using Methodology 2

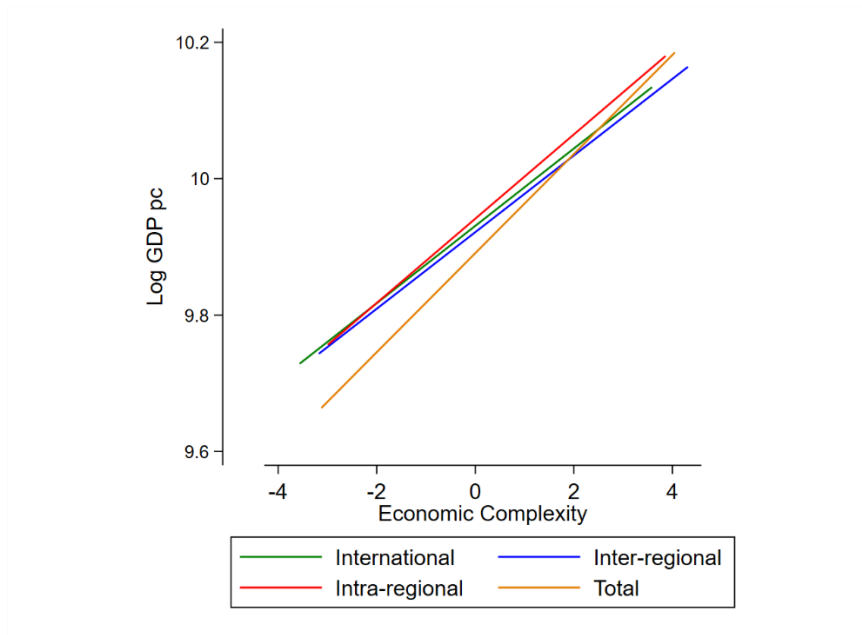


Figure A.1.2: R-squared GDP per capita (t+10) and EC indicators (Methodology 2)

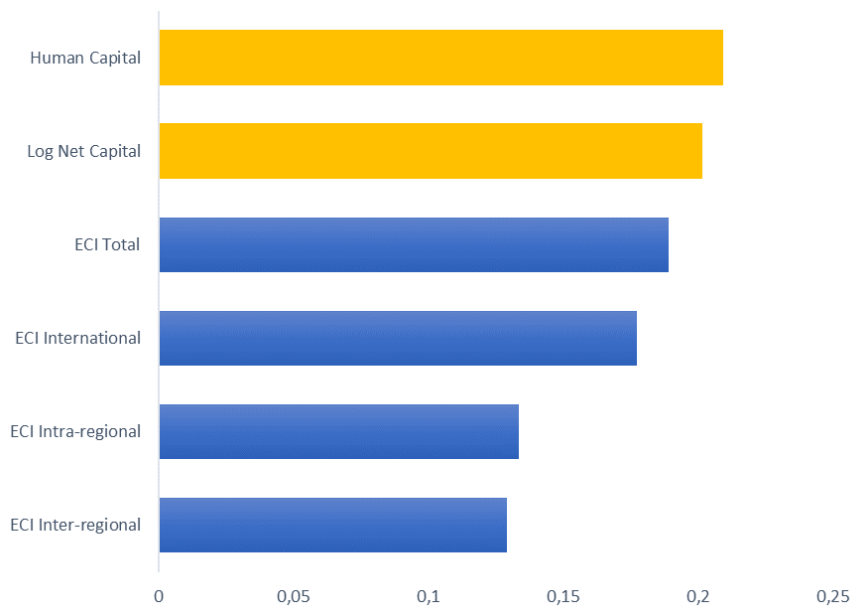


Table A.1: GDP per capita growth (t+5) and (t+15) by province. Growth relative GDPpc. Cross-sections every t+5 and t+15 years. OLS and within-groups' estimators.

Methodology 2. Robustness Analysis.

	M5	M6	M7	M8
	OLS	OLS	Within-Groups FE	Within-Groups FE
TIME FE	YES	YES	YES	YES
REGIONAL FE	NO	YES	YES	YES
Regional GDPpc/World GDPpc	t+5			t+15
ECI	0.136*** (0.0267)	0.161*** (0.0327)	0.0847** (0.0320)	0.0321 (0.0195)
Physical capital	0.423*** (0.0365)	-0.0140 (0.0852)	-0.638*** (0.0447)	-0.238*** (0.0882)
Human capital	0.371*** (0.0414)	0.303*** (0.0658)	0.297*** (0.0254)	-0.182*** (0.0417)
Observations	850	850	850	350
R-squared	0.599	0.874	0.588	0.393
Number of groups	50			50

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Annex 2: Product and NUTS-3 (provinces) codes

Table A.2.1 Products covered by the C–interreg database

Code	Product
R1	Live animals
R2	Cereals
R3	Unprocessed food
R4	Wood
R5	Processed food products
R6	Oil (food)
R7	Tobacco
R8	Drinks
R9	Coal
R10	Minerals (not ECSC)
R11	Liquid fuels
R12	Minerals (ECSC)
R13	Steel products (ECSC)
R14	Steel products (not ECSC)
R15	Rocks, sand and salt
R16	Cement and limestone
R17	Glass
R18	Construction materials
R19	Fertilizers
R20	Chemical products
R21	Plastics and rubber
R22	Machinery (non-electric)
R23	Machinery (electric)
R24	Transport equipment
R25	Textile and clothing
R26	Leather and footwear
R27	Paper
R28	Products of wood and cork
R29	Furniture, other goods

Source: Own elaboration based on C-interreg (www.c-interreg.es).

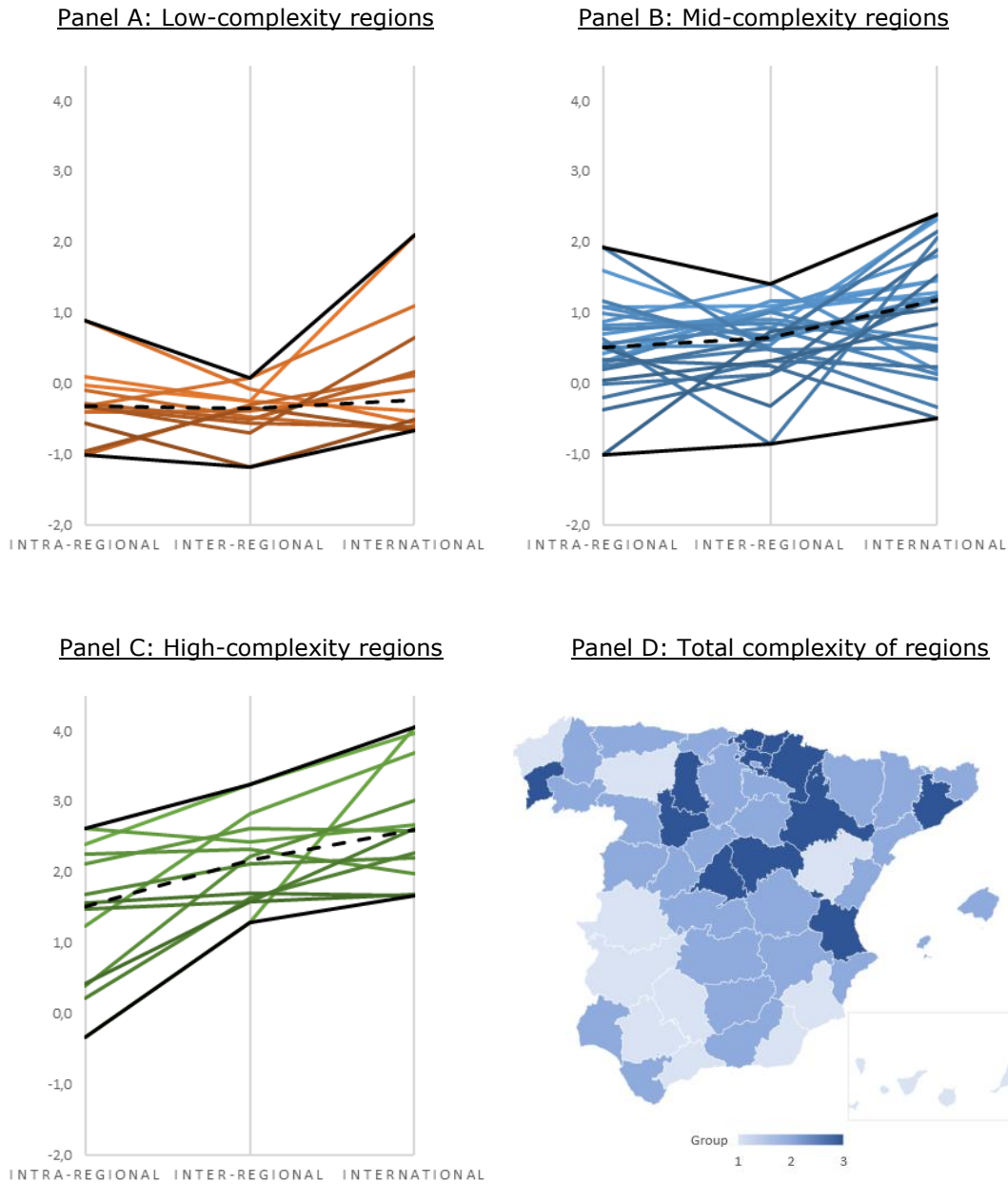
Table A.2.2 Classification of Spanish provinces by INE

Code	Province	Code	Province
01	Álava	35	Las Palmas
02	Albacete	24	León
03	Alicante	25	Lérida
04	Almería	26	La Rioja
33	Asturias	27	Lugo
05	Ávila	28	Madrid
06	Badajoz	29	Málaga
07	Baleares	52	Melilla
08	Barcelona	30	Murcia
09	Burgos	31	Navarra
10	Cáceres	32	Orense
11	Cádiz	34	Palencia
39	Cantabria	36	Pontevedra
12	Castellón	37	Salamanca
51	Ceuta	38	S.C. Tenerife
13	Ciudad Real	40	Segovia
14	Córdoba	41	Sevilla
15	Coruña (La)	42	Soria
16	Cuenca	43	Tarragona
17	Gerona	44	Teruel
18	Granada	45	Toledo
19	Guadalajara	46	Valencia
20	Guipúzcoa	47	Valladolid
21	Huelva	48	Vizcaya
22	Huesca	49	Zamora
23	Jaén	50	Zaragoza

Source: INE

Annex 3: Spatial ECI distribution by group of provinces

Figure A.3: ECI by region and trade flow (1995)



Panels A–C: Each colour bar represents a region. Black lines represent minimum and maximum complexity in each trade flow. The dotted line represents the group's median.

Panel D: Group 1 refers to low-complexity regions (first quartile), group 2 refers to mid-complexity regions (second and third quartiles) and group 3 to the high-complexity regions (fourth quartile).

Source: Own elaboration.

Annex 4. Econometric results.

Table A.4.1: GDP per capita growth (t+10) and (t+15) by province. Growth relative GDPpc. Cross-sections every t+10 and t+15 years. OLS estimator.

Year FE	1995-2005, 2005-2015				1995-2010			
	M1	M2	M3	M4	M1	M2	M3	M4
	YES	YES	YES	YES	YES	YES	YES	YES
VARIABLES	Regional GDPpc/World GDPpc (t+10)				Regional GDPpc/World GDPpc (t+15)			
Total ECI	0.537*** (0.0768)		0.530*** (0.0792)	0.524*** (0.0773)	0.414*** (0.0847)		0.396*** (0.0857)	0.456*** (0.0875)
Physical cap.	0.173 (0.114)	0.146 (0.139)		0.149** (0.0688)	0.138 (0.141)	0.0512 (0.174)		0.268*** (0.0760)
Human cap.	-0.0424 (0.109)	0.181 (0.132)	0.0596 (0.0679)		0.172 (0.121)	0.320** (0.150)	0.266*** (0.0522)	
Observations	100	100	100	100	50	50	50	50
R-squared	0.505	0.244	0.484	0.504	0.544	0.284	0.526	0.514
Change in R-squared		51.68%	4.16%	0.20%		47.79%	3.31%	5.51%

Robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

**Table A.4.2: GDP per capita growth (t+10) and (t+15) by province.
Absolute growth of GDPpc. Cross-sections every t+10 and t+15 years. OLS
estimator.**

	1995-2005, 2005-2015				1995-2010			
	M1	M2	M3	M4	M1	M2	M3	M4
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
VARIABLES	GDP per capita (t+10)				GDP per capita (t+15)			
Total ECI	0.562*** (0.0775)		0.555*** (0.0805)	0.548*** (0.0788)	0.535*** (0.103)		0.528*** (0.102)	0.547*** (0.100)
Physical cap.	0.190 (0.118)	0.162 (0.144)		0.165** (0.0711)	0.0479 (0.167)	-0.0648 (0.213)		0.0875 (0.0812)
Human cap.	-0.0445 (0.114)	0.189 (0.137)	0.0679 (0.0700)		0.0527 (0.146)	0.245 (0.186)	0.0851 (0.0618)	
Observations	100	100	100	100	50	50	50	50
R-squared	0.427	0.124	0.400	0.426	0.439	0.080	0.438	0.437
Change in R-squared		70.96%	6.32%	0.23%		81.78%	0.23%	0.46%

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A.4.3: GDP per capita growth (t+5) by province. Growth relative GDPpc. Panel-data fixed effects estimations. OLS and within-groups' estimator.

	M5	M6	M7	M8
	OLS	OLS	Within-Groups FE	Within-Groups FE
TIME FE	YES	YES	YES	YES
REGIONAL FE	NO	YES	YES	YES
Regional GDPpc/World GDPpc	t+5			t+15
Total ECI	0.305*** (0.0241)	0.623*** (0.0717)	0.144** (0.0625)	0.116*** (0.0425)
Physical cap.	0.400*** (0.0365)	0.0836 (0.0637)	-0.627*** (0.0434)	-0.235*** (0.0838)
Human cap.	0.233*** (0.0419)	0.177*** (0.0471)	0.298*** (0.0252)	-0.177*** (0.0409)
Observations	850	850	850	350
R-squared	0.645	0.913	0.586	0.406
Number of groups			50	50

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A.4.4: GDP per capita growth (t+5) by province. Growth absolute GDPpc. Panel-data fixed effects estimations. OLS and within-groups' estimator.

	M5	M6	M7	M8
	OLS	OLS	Within-Groups FE	Within-Groups FE
TIME FE	YES	YES	YES	YES
REGIONAL FE	NO	YES	YES	YES
GDP per capita	t+5			t+15
Total ECI	0.190*** (0.0257)	0.262*** (0.0441)	0.0701** (0.0295)	-0.0163 (0.0259)
Net cap.	0.420*** (0.0376)	0.109 (0.0762)	-0.601*** (0.0455)	-0.239*** (0.0887)
Human cap.	0.343*** (0.0401)	0.247*** (0.0535)	0.291*** (0.0257)	-0.185*** (0.0427)
Observations	850	850	850	350
R-squared	0.613	0.889	0.585	0.388
Number of groups			50	50

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A.4.5: GDP per capita growth (t+5) and (t+15) by province. International, inter-regional and intra-regional EC indices. Growth relative GDPpc. OLS and within-groups' estimator.

	M5	M5	M5	M6	M6	M6	M7	M7	M7	M8	M8	M8
							Within-Groups	Within-Groups	Within-Groups	Within-Groups	Within-Groups	Within-Groups
	OLS	OLS	OLS	OLS	OLS	OLS	FE	FE	FE	FE	FE	FE
ECI type	International	Inter-regional	Intra-regional	International	Inter-regional	Intra-regional	International	Inter-regional	Intra-regional	International	Inter-regional	Intra-regional
TIME FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
REGIONAL FE	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES	YES
VARIABLES	Regional GDPpc/World GDPpc (t+5)									Regional GDPpc/World GDPpc (t+15)		
ECI	0.138*** (0.0232)	0.305*** (0.0260)	0.320*** (0.0252)	0.546*** (0.0825)	0.449*** (0.0614)	0.290*** (0.0428)	0.0630 (0.0777)	0.0798* (0.0475)	0.0724* (0.0389)	0.172*** (0.0538)	0.0762** (0.0308)	-0.0120 (0.0263)
Physical cap.	0.414*** (0.0375)	0.406*** (0.0363)	0.378*** (0.0367)	0.126* (0.0743)	0.0607 (0.0654)	0.00965 (0.0728)	-0.634*** (0.0454)	-0.634*** (0.0450)	-0.630*** (0.0448)	-0.270*** (0.0872)	-0.217** (0.0859)	-0.238*** (0.0881)
Human cap.	0.354*** (0.0439)	0.230*** (0.0408)	0.284*** (0.0366)	0.223*** (0.0534)	0.200*** (0.0510)	0.224*** (0.0513)	0.295*** (0.0259)	0.299*** (0.0261)	0.297*** (0.0249)	-0.165*** (0.0408)	-0.186*** (0.0416)	-0.184*** (0.0423)
Observations	850	850	850	850	850	850	850	850	850	350	350	350
R-squared	0.599	0.645	0.664	0.894	0.902	0.892	0.580	0.583	0.585	0.417	0.401	0.388
Number of groups							50	50	50	50	50	50

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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