Spatial patterns in the textile sector in Ecuador: Exploring spatial clusters within the Systemic Competitiveness Framework

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Subject area: Location of economic activity, cluster and value chains

Abstract: This paper aims identifying clusters in the textile sector in Ecuador and exploring the relationship among identified spatial clusters with several determinants of the *meso-space* of the Systemic Competitiveness framework. The contribution of this paper is twofold. First, we use exploratory spatial analysis to identify clusters in the textile sector using data from the Economic Census or Enterprise Surveys of 2010. Second, we compare the spatial autocorrelation between the identified clusters and some activities at the meso-space defined in the SCF. Our results show a weak positive spatial autocorrelation (global) in the textile sector and suggest that employment generation by the textile sector occurs in better-provisioned and well-accessed meso-spaces in neighboring regions. Indeed, cantons with high levels of employment in the textile sector are surrounded by areas with better access to infrastructure and higher levels of provision and access to financial services.

Keywords: spatial analysis, spatial autocorrelation, LISA maps, textile sector, systemic competitiveness.

JEL codes: C21, C31, L67

1. INTRODUCTION

The concept of Systemic Competitiveness was developed by Esser, Hillebrand, Altenburg, Messner & Meyer-Stamer and emerged after the 1980s as an alternative to structural programs for promoting competitiveness in developing countries. This analytical framework in terms of Meyer-Stamer (2003) emphasizes that industrial competitiveness comes because of a “complex and dynamic interaction” between different agents such as “state, firms, intermediate institutions and organizational capacity of a society” to achieve advancing from comparative advantage to systemic competitiveness. Within the Systemic Competitiveness Framework (SCF), the analysis of industrial cluster formation and industrial agglomeration with development potential is essential for targeting policies and “strengthen development regions in which dynamic clusters are emerging” (Esser et al., 1995).

Despite the relevance of industrial cluster formation for the SCF (Meyer-Stamer, 2002), empirical analyzes to identify industrial clusters within this framework are almost non-existent. In fact, most of the literature focuses mainly on the different policies that governments in developing countries should enhance to implement the SCF[1] but none of those have explored the presence of industrial clusters. In this paper, we aim to examine spatial patterns and cluster formation in the textile sector in Ecuador and to explore the relationship between these clusters and several determinants of the SCF. The identification of industrial cluster would allow better targeting social, economic and environmental policies at national and regional levels to increase efficiency and competitiveness of firms though agglomeration advantages as proposed by the SCF (Esser, et. al. 1995).

Exploring spatial patterns in the textile sector within the SCF in Ecuador is important for several reasons. First, the systemic competitiveness concept appears in the Ecuadorian Constitution of (2008), in Article 284, and establishes that the system and economic policy must: "encourage national production, systemic productivity and systemic competitiveness”. From a policy perspective, the SCF has been included in the national development plans since 2009. The National Plan for Good Living (2009) initially established the implementation of systemic competitiveness and the identification of strategic sectors and industries in order to change the productive and

[1] See among others: (De la Puente, 2018; Schoen and Jenal, 2017; Sutz, 2002; Altenburg *et al.*, 1998)

energy matrix. Moreover, the following national plans of development[2] have focused on consolidating and creating new environmental conditions for promoting systemic competitiveness. More importantly, the sector is considered as a prioritized sector for the policy agenda to strengthen business networks and transform the primary-export structure (SENPLADES, 2013). In addition, the textile sector is the second employment generating industry after the food and processing industry (INEC, 2010b) and shows strong backward linkages in the economy reinforcing its relevance for economic development (Arghoty, 2013).

Analysis of spatial patterns and industrial cluster identification are more common in the literature of economy of agglomeration, especially among manufacturing firms. There is empirical evidence that explores spatial patterns at regional, country-specific and region-specific levels (Chávez-Martín del Campo, Juan Carlos and García Loredo, 2015; Liu, 2014; Murgante and Rotondo, 2013; Guillain and Le Gallo, 2010). There are also studies that focus on factors influencing industrial localization and agglomeration economies (Paci and Usai, 2008; Lafourcade and Mion, 2007; Chakravorty et al., 2005) while others explore if the proximity of the industry has positive spillover effects on knowledge and technology (Carboni, 2013; Cohen and Paul, 2005; Cohen and Paul, 2004; Ying, 2000). In contrast, literature about spatial analysis in the textile sector is scarce with the exception being the study of Rodrigues et al. (2012) that analyze the evolution of productive agglomeration in the Southern Brazil's clothing sector.

The contribution of this paper is twofold. First, we use exploratory spatial analysis to identify clusters in the textile sector using data from the Economic Census or Enterprise Surveys of 2010. Second, we compare the spatial autocorrelation between the identified clusters and some activities at the meso-space defined in the SCF. The second part of the analysis is relevant for exploring how traditional activities at the meso-space had influenced the localization of the textile sector in Ecuador. The remaining of this paper is organized as follows: we present in Section 2 a brief description of the Systemic Competitiveness Framework for promoting competitiveness in the industry. Section 3 describes the methodology we used and Section 4 explains the data we employed for the analysis. The results obtain are presented in Section 5, and finally, section 6 discusses the main conclusions and extensions for further research.

[2] The National Plan for Good Living for the periods of (2013) and (2017) propose the public investment and public policies as the main channels for promoting the systemic competitiveness.

2. THE SYSTEMIC COMPETITIVENESS FRAMEWORK

The Systemic Competitiveness framework (SCF) suggests that an economy's competitiveness can only be achieved by a "*deliberate interaction, coordination and building network creation among different actors in the economy*" (Esser et al., 1995). Within the SCF, the deliberate and dynamic interaction between government, firms, intermediary institutions and the organizational capacity of a society can promote competitiveness in a country, regions or sectors if a set of "purposive and intermeshed measures" are taken at four intertwined and interrelated systemic levels in the economy (Jenal and Wältring, 2017; Meyer-Stamer, 2003; Meyer-Stamer, 1998; Esser et al., 1994). The SCF includes four systemic levels that are shown in Figure 1. The meta level refers to the general and consensual long-term vision of the society as well as its social, political and cultural patterns towards enhancing and promoting competitiveness. The macro level includes a stable macroeconomic, political and juridical framework to stimulate the competition among firms and avoid monopolistic behavior in the industry. The meso level directs the attention to the specific environment in which firms operate, where both public and private actors at the national, regional and local levels intervene to promote the advantages of location and increase the relative competitiveness of firms. Finally, the micro level includes diverse firms and clusters of firms that attempt simultaneously achieving efficiency, quality, flexibility and responsiveness.

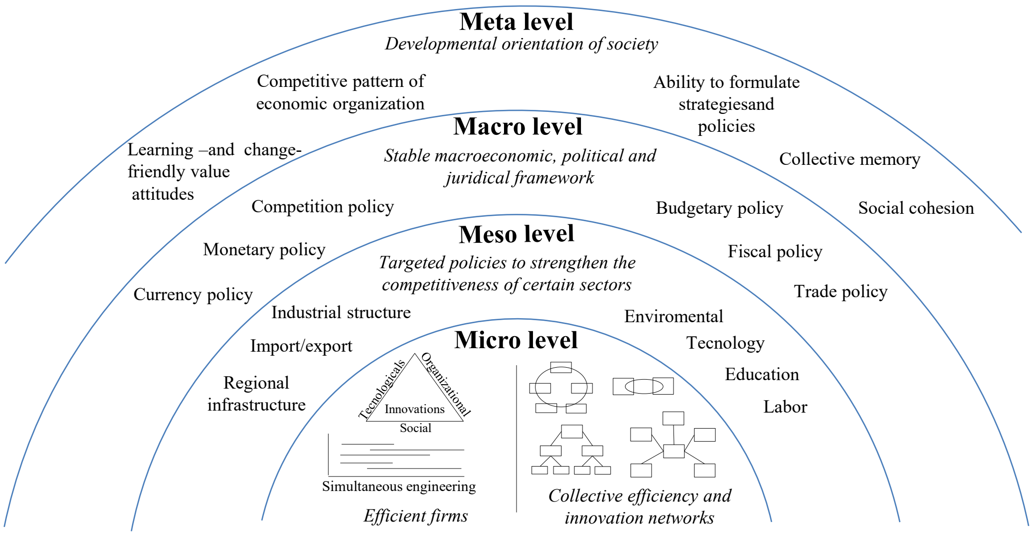

Figure 1. **Determinants of Systemic Competitiveness**. Reprinted from: "Understanding the determinants of vibrant business development: The systemic competitiveness perspective" by J. Meyer-Stamer, 2003, Duisburg: Mesopartner, p. 2.

Despite the relevance of dynamic interaction between the four levels for the SCF, the **meso** level is particularly important because it includes a set of direct impact instruments for increasing competitiveness of firms (Sutz, 2002). The meso level relates two central concepts: the *meso-policy* and the *meso-space* (Meyer-Stamer, 2003). The meso-policy is a set of selective policies designed to target limited groups of economic actors while the meso-space is the result of the selective meso-policies promoted by governments and individual or collective actors to strengthen the competitiveness of firms. The main characteristic of the meso-space is its provision of services and intangible products targeting specific actors at a micro level. The meso-policy includes infrastructure, education, finance, technology, foreign trade, and chamber and association policies[3]. Since the meso-space is the result of such policies, Meyer-Stamer (2003), proposes typical meso-space activities organized according to Porter's (1990) concept of evolution of factor conditions are presented in Table 1.

Table 1. Typical meso-space activities

	Basic functions	**Advanced functions**	**Specialized functions**
Infrastructure	- Roads - Water - Electricity - Telephony	- Reliable, efficient, high quality infrastructure	- Specialized, innovative infrastructure
Finance	- Credit - Investment capital	- Development Banks - Micro finance institutions - Collateral Banks	- Specialized, innovative finance institutions - Venture capital
Technology	- Measurement, standards, norms, quality assurance	- Technology transfer agencies	- Specialized R&D institutions
Education and training	- Secondary and higher education in basic disciplines	- Secondary and higher education in specialized disciplines	- Highly specialized, high quality training courses
Foreign trade	- Basic foreign trade transactions	- Export financing - Export credit insurance	- Advice and support for market research, design, packaging, etc.
Chamber and associations	- Elementary services - Ad-hoc-lobby	- Specialized services - Business networking	- Comprehensive services - Active role in locational policy

Note. Reprinted from: "Understanding the determinants of vibrant business development: The systemic competitiveness perspective" by J. Meyer-Stamer, 2003, Duisburg: Mesopartner, p. 15.

[3] Jenal and Wältring (2017) includes as another meso-policy the entrepreneurial capacity and promotion policies. However, since we based our research on the original systemic competitiveness framework we excluded this new category from the analysis.

The meso-space is not a territorial category in the sense of administrative regions (Meyer-Stamer, 2003). Instead, it refers to dynamic economic regions linking the systemic competitiveness framework with the territorial approach (Jenal and Wältring, 2017). In the meso-space social, economic, cultural and political characteristics as well as context specific aspects influence the territories. A restrictive environment in both meso-policy and meso-space constrains the long-term competitiveness in the territory and may cause firms to relocate and aggregate in regions with better services and intangible products at a meso level. The relocation of firms would allow taking advantage of the positive spillover effects of agglomeration and other spatial aspects (Esser et al., 1994)[4].

The meso level includes both economic and social policies being the most relevant business and employment promotion. According to Meyer-Stamer (2003), business promotion includes economic policies that aim to *"maximize competitiveness of firms"* as well as social policies implemented to ensure the "*survival of microenterprises"*. In addition, employment promotion consist of economic policies that aim strengthening the relationship between the formal labor market and competitiveness while social policies should focus to the segment of the population with little or no access to formal employment.

Empirical analyzes exploring competitiveness within the SCF are mainly qualitative in nature and aim to diagnose the weaknesses and strengths of industrial policies and institutions in countries, regions or specific sectors at the four levels defined in the framework. Altenburg et al. (1998) explored the meso-level in five case studies in Mexico, Brazil, Paraguay, Korea and Thailand. The common feature among the five case studies was the need to implement dialogue and coordinate efforts among social actors and the government to identify selective industry-related policies favorable for competitiveness. Hernández (2001) analyzed the small and medium-size enterprises (SMEs) in several countries in Central America and found that besides the increasing need for cluster formation among firms at the micro level, several selective policies at the meso level are required to improve competitiveness across SMEs. The author warns

[4] Meyer-Stamer (2003) argues that the Systemic Competitiveness Framework has a close relationship with several social and economic theories such as the economic geography that explores the relevance of agglomeration and industrial clusters and is widely explore in the literature of economy of agglomeration. See among others: Duranton et al. (2010) , Rosenfeld (1997), Glaeser et al. (1992), Krugman (1991), Porter (1990) or Marshall (1895).

about the risk of using meso-policy as an end rather than a means to achieve competitiveness. Rodriguez-Monroy and Fernández-Chalé (2006) described the textile sector using the SCF and recognized the importance of the meta level and stable macroeconomic conditions at the macro level but observed uncoordinated policies at a meso level particularly among micro and small enterprises promotion programs.

More recently, Schoen and Jenal (2017) studied the elements at meso and macro levels in Myanmar and concluded that despite the initial absence of the meso-space before the transition, recent efforts to improve the meso-space may become an important contribution to the growing competitiveness of Myanmar in various sectors. Finally, De la Puente (2018) explored the role of the government in the improvement of the medical tourism industry at a meso level and found that policies such as integral security, use of public spaces and training programs may enhance the quality and competitiveness of health services.

Considering the results at a meso level these studies highlights that weak, uncoordinated and fragile meso level (meso-policy and meso-space) is associated with low competitiveness in developing economies. However, these weaknesses can be understood at the same time as opportunities for diverse actors and governments in these countries to engage in the implementation of policies at a meso level to strengthen the meso-space for the analyzed regions. In this paper, we focus the analysis of the textile sector in Ecuador at two levels: micro and meso. The present article differs from previous literature in the quantitative nature of the analysis. We use Exploratory Spatial Data Analysis (ESDA) to identify clusters and economic regions based on their contribution to employment at a micro level and explore the relationship among those clusters with some meso-space activities defined at the meso level. In the following sector we explain the definition of spatial autocorrelation used in the analysis in both univariate (micro level) and bivariate (meso level) analyses.

3. METHODOLOGY

In this section we explain the Exploratory Spatial Data Analysis (ESDA) used to identify spatial patterns and industrial clusters in the textile sector and to explore the relationship among identified clusters and some meso-space activities of the SCF. ESDA is a subset of exploratory data analysis (EDA) that focuses on exploring and visualizing spatial autocorrelation and spatial heterogeneity (Anselin et al., 2007).

ESDA is relevant for this study because it allows identifying patterns of spatial association (spatial clusters) as well as atypical locations (spatial outliers) that are important for better targeting development and industrial meso-policies for promoting competitiveness in economic regions. The analysis includes the two traditional measures of spatial autocorrelation: Global Moran's I (Moran, 1948) and Local Indicators of Spatial Association (LISA) (Anselin, 1995). We include the univariate and bivariate versions of the indicators.

The global Moran's I test the null hypothesis of no spatial autocorrelation and is defined as (Anselin et al., 2007):

$$I = \sum_i \sum_j W_{ij}(x_i - \mu)(x_j - \mu) \Big/ \sum_i (x_i - \mu)^2, \tag{1}$$

where W_{ij} is the row-standardized contiguity matrix, x_i is the employment in the textile sector at a location i, and x_j is the employment in the textile sector at the location j. The statistic gives an indication of the degree of linear association (+/-) between the value of employment in the textile sector in the location i and the average employment in the textile sector at neighboring location (spatial lag). Positive statistically significant values of Moran's I indicates a positive spatial correlation, showing that the location have a high level of employment in the textile similar to their neighboring locations. Conversely, a negative and statistically significant value indicates negative spatial correlation, showing that locations have low level of employment in the textile similar to their neighboring locations. The Moran's I statistic can be visualized as the slop in the scatter plot of the spatially lagged variable (W_x) on the original variable (x) (Anselin, 1995).

The Moran's I statistic only indicates overall clustering but does not allow to identify spatial clusters and spatial outliers. Anselin (1995) decomposed the global Moran's I to identify local spatial patters (clusters and outliers) and developed the Local Moran Statistic defined by:

$$I = \frac{(x_i - \mu)}{\sum_i (x_i - \mu)^2} \sum_j W_{ij}(x_i - \mu), \tag{2}$$

where W_{ij} is the row-standardized contiguity matrix, x_i is the employment in the textile sector at a location i , and x_j is the employment in the textile sector at the location j. The local Moran shows the combination of four types of association: spatial clusters (high-high or low-low) and spatial outliers (high-low, low-high). The visualization of the four types of association refers as LISA Cluster maps. Significance of both the local and global versions of the Moran's I statistics is assessed by means of a permutation approach (Anselin et al., 2007; 2006).

The bivariate version[5] of the global and local Moran's is express in equations (3) and (4), respectively:

$$I = \sum_i \sum_j W_{ij}(x_i - \mu)(y_j - \mu)/\sum_i (x_i - \mu)^2, \quad (3)$$

and,

$$I = \frac{(x_i - \mu)}{\sum_i (x_i - \mu)^2} \sum_j W_{ij}(y_i - \mu), \quad (4)$$

where W_{ij} is the row-standardized contiguity matrix, x_i is the employment in the textile sector at a location i, and y_j is the activity at the meso-space at the location j. The activities at the meso-space included a set of indicators measuring infrastructure, finance, technology and education and training.

4. DATA AND SETTINGS

We used data from a National Economic Census conducted during 2010 and identify all economic establishments, legal entities and self-employed units that were part of the textile sector in Ecuador. We identified 47,043 enterprises of the textile sector in the manufacturing, commerce and service sectors using the International Standard Industrial Classification (ISIC) at four-digits classes[6] (Naciones Unidas [ONU], 2009). After listwise deletion[7] the final sample included information about 46,004 enterprises of the textile sector. The data was collapse across cantons[8] and standardize using the Empirical Bayes standardization (EB) (Anselin, Lozano et al., 2006). The EB standardization was used as a means to correct the spatial autocorrelations test statistics for varying

[5] The analysis of bivariate spatial autocorrelation is used to explore space-time local autocorrelation (Abdi *et al.*, 2018; Frigerio *et al.*, 2018; Bardhan *et al.*, 2016) and spatial autocorrelation between two different variables at the same time (Zhang *et al.*, 2018; Guo *et al.*, 2017; Cheng, 2016; Sambidi and Harrison, 2006).

[6] The National Institute of Statistics and Census of Ecuador defines the textile sector using the ISIC codes for manufacturing (Section C: 1311, 1312, 1313, 1391, 1392, 1393, 1394, 1399, 1410, 1420, 1430, 1511, 1512, 1520, 2826); commerce (Section G: 4611, 4751, 4771, 4782) and service establishments (Section S: 9523, 9601).

[7] We excluded information of public institutions and observations with missing data referring to employment and income losing a total of 2.27% of the valid sample.

[8] Ecuador is administratively divided in: Regions, Provinces, Cantons and Parishes. Since data of the variables included in the bivariate analysis is absent we use information at a canton level as the observational units.

population densities across cantons. The original rate is not smooth but transformed into a standardized random variable (with zero mean and unit variance) and uses information of the rest of the sample to control for variable instability (Anselin 2006). All spatial analysis was estimated using the GeoDa software package version 1.12.1.59 (Anselin, Syabri et al., 2006) using the queen spatial matrix (W_{ij}).

We use employment rates as the main variable for the analysis since the textile sector is the second employment generating industry in the country. We excluded the Galapagos Islands to avoid observations without neighbours. Figure 2 shows the distribution of standardize employment rates across cantons. As seen in the figure, most of the employment created by the textile industry locates in many cantons in the Highlands region (central region in the map). We also observe that in the Coast region (eastern edge) the only cantons with high employment rates are Guayaquil, Santa Rosa and Piñas while in the Amazon region (western edge) Pastaza, Morona y Yantzaza reflect high values of employment.We also observe that in the Coast region (eastern edge) the only cantons with high employment rates are Guayaquil, Santa Rosa and Piñas while in the Amazon region (western edge) Pastaza, Morona and Yantzaza reflect high values of employment.

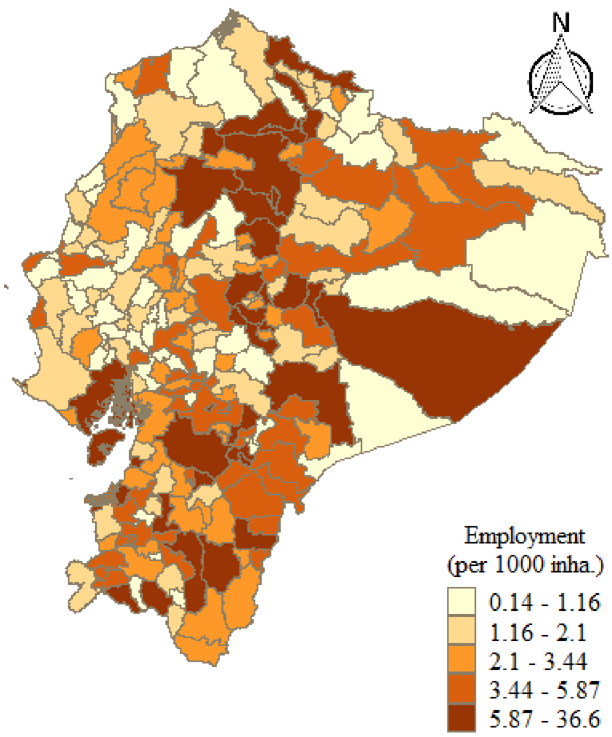

Figure 2. Spatial distribution of employment rates in the textile sector in Ecuador. The graph shows the spatial distribution of the EB employment rates using queen spatial weight matrix. Authors' calculation based on data from National Economic Census (INEC, 2010).

The summary of the variables[9] included in the bivariate spatial autocorrelation at a canton level is presented in Table 2. We identify some variables representing the activities at the meso-space in the SCF mainly at a basic level during 2010. We also included information about both provision and accessibility of infrastructure, finance and education and training activities. The table reflects major differences in variables relating to the number of enterprises: electricity, water and sanitation, transportation, ICT, financial institutions, professional and scientific and education establishments and credit. Therefore, we also standardized these variables to control for variable instability across cantons and results are discussed in the following section.

Table 2. Summary of the variables used in the bivariate spatial analysis

Meso-space activities	Type	Variable	mean	S.D.	obs.
Infrastructure	Provision	Industrial Specialization Index	0.721	0.486	221
		Electricity enterprises (No.)	0.986	2.356	221
		Water & sanitation enterprises (No.)	1.493	6.129	221
		Transportation enterprises (No.)	4.434	23.675	221
		Information & Communication Technology (ICT) enterprises (No.)	82.154	348.768	221
	Accessibility	Unsatisfied Basic Needs Index	0.759	0.137	221
		Households with sanitation services (%)	0.232	0.167	221
		Households with drinking water supply (%)	0.363	0.169	221
		Households with electricity service (%)	0.891	0.093	221
Finance	Provision	Financial Institutions (No.)	14.339	60.848	221
	Accessibility	Credit for the textile sector (MM $US)	2.054	13.230	221
Technology	Provision	Professional scientific & technology enterprises (No.)	5.339	30.707	221
Education and training	Provision	Educational establishments (No.)	55.624	223.144	221
	Accessibility	People with bachelor degree (%)	0.290	0.109	221
		People with University degree (%)	0.116	0.066	221
		People (15-17 years old) attending to High-School (%)	0.475	0.088	221
		People (18-24 years old) attending to University (%)	1.414	0.074	221

Note. Authors' elaboration based on data from Population Census (INEC, 2010a), National Economic Census (INEC, 2010b) and Superintendence of Banks of Ecuador (SBS, 2010).

5. RESULTS

5.1 Univariate Spatial Autocorrelation

Spatial patterns and cluster identification using employment of the textile sector are shown in Figure 3. The graph includes the Moran scatterplot (a) showing a positive

[9] A detail definition of the variables in included in Table A1 in the appendix.

statistically significant Moran's I statistic of 0.1911 (pseudo p <.1%)[10]. Therefore, we cannot reject the null hypothesis of no spatial autocorrelation (or spatial heterogeneity) and the results show positive but weak spatial dependence in the textile sector[11]. We also show the univariate LISA Cluster map (b) and identify statistically significant clusters and outliers (pseudo p<0.005) in the textile sector. As seen in the figure, we observed two differentiated spatial patters in the country: low values of employment surrounded by low values in neighboring cantons in the Coast region and the presence of three clusters of high values of employment surrounded by high values in neighboring cantons (HH) concentrated mainly in the Highlands. The graph shows the bigger group of HH clusters in the Northern Highlands around the capital (Quito) and two small HH groups of clusters in the central and Southern Highlands.

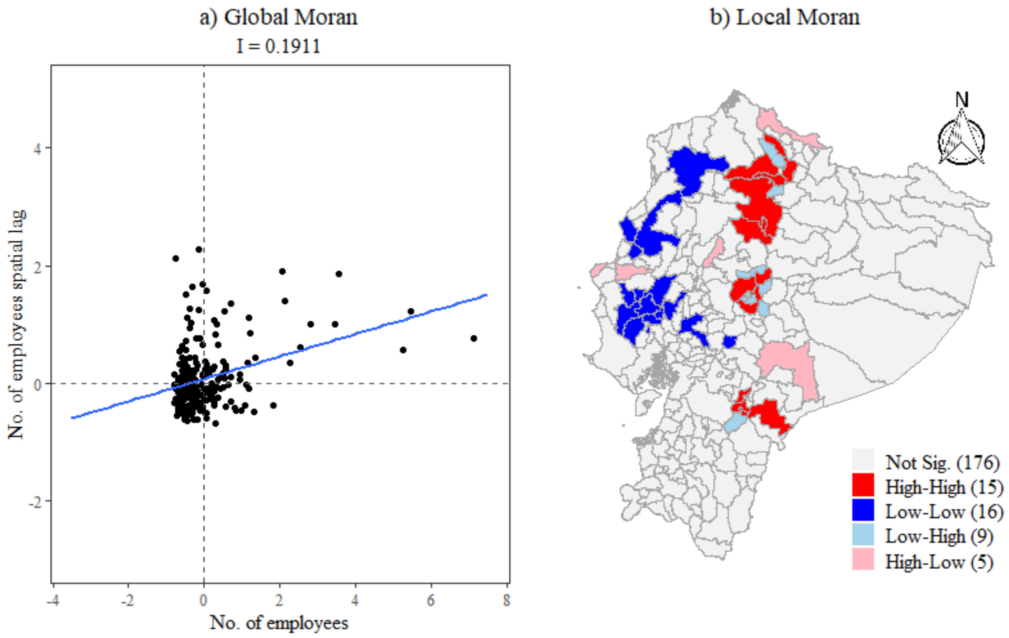

Figure 3. Spatial autocorrelation of employment rates in the textile sector in Ecuador. The graph includes the Moran scatterplot (a) and LISA Cluster map (b) of the EB employment rates using queen spatial weight matrix. The highlighted locations are statistically significant (p<0.05). Clusters: HH=High-High; LL=Low-Low. Outliers: LH=Low-High; HL=High-Low. Authors' calculation based on data from National Economic Census (INEC, 2010).

[10] The significance of the Moran's I statistics was assess using 9999 permutations.
[11] We also used from four to seven nearest neighbors to assess the sensitivity of the results to the selection of spatial weights and found similar results. The results are available upon request.

5.2 Bivariate Spatial Autocorrelation

The results of the bivariate global Moran's I statistics are shown in Table 3[12]. We can observe a weak spatial dependence in most of the variables included in the analysis. As seen in the table, employment in the textile sector is positive associated with variables that refer a good provision and accessibility of infrastructure in neighboring locations. More interestingly, variables of accessibility to several services are even more relevant than those of provision of infrastructure. The interpretation of the negative effect of the Unsatisfied Basic Needs Index is different from other variables since it refers to the multidimensional concept of poverty. Thus, the negative value indicates that employment in the textile sector is negatively associated with neighboring locations showing high degree of poverty. We also observe that the provision of financial services as well as the amount of credit for the textile sector show positive spatial dependence with employment. In fact, the two variables present the highest bivariate global Moran's I statistic of all the variables included in the analysis. In addition, employment in the textile sector also shows spatial dependence with professional, scientific and technology enterprises in neighboring locations. Finally, we included general indices of overall access to education and training but only those variables referring to the number of people that were currently attending to high-school and university in 2010 show a positive association with high levels of employment.

[12] Sensitivity analysis results are available upon request.

Table 3. Bivariate global Moran's I

Meso-space activities	Type	Variable	I	z-value	p-value	Sig ([a])
Infraestructure	Provision	Industrial Specialization Index	0,1311	3,9637	0,0011	**
		Electricity enterprises (No.)	0,0213	0,6675	0,2457	
		Water & sanitation enterprises (No.)	-0,0093	-0,2823	0,3996	
		Transportation enterprises (No.)	0,0555	1,7360	0,0498	*
		Information & Communication Technology (ICT) enterprises (No.)	0,1362	3,9578	0,0004	***
	Accessibility	Unsatisfied Basic Needs Index	-0,1623	-4,6262	0,0000	***
		Households with sanitation services (%)	0,1537	4,4009	0,0001	***
		Households with drinking water supply (%)	0,1508	4,3694	0,0001	***
		Households with electricity service (%)	0,1326	4,0646	0,0000	***
Finance	Provision	Financial Institutions (No.)	0,1799	5,3293	0,0000	***
	Accessibility	Credit for the textile sector (MM $US)	0,1771	4,9239	0,0004	***
Technology	Provision	Professional scientific & technology enterprises (No.)	0,1267	3,7251	0,0013	**
Education and training	Provision	Educational establishments (No.)	0,0114	0,3815	0,3474	
	Accessibility	People with bachelor degree (%)	-0,0102	-0,2547	0,4110	
		People with University degree (%)	0,0267	0,8410	0,1925	
		People (15-17 years old) attending to High-School (%)	0,0993	3,0370	0,0019	**
		People (18-24 years old) attending to University (%)	0,1143	3,3748	0,0015	**

Note. The results were estimating using queen spatial weight matrix. The significance of the Moran's I statistics was assess using 99999 permutations. Authors' elaboration based on data from Population Census (INEC, 2010a), National Economic Census (INEC, 2010b) and Superintendence of Banks of Ecuador (SBS, 2010).
([a]) Sig.: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

In the following of this section, we only present bivariate LISA (biLISA) cluster maps for those variables showing statistically significant results for the global Moran's I statistic. The biLISA allows identifying cluster/outliers locations that are associated with a favorable/restrictive meso-space in nearest regions. The clusters and outlier cantons in the biLISA using the Industrial Specialization Index variable as example can be interpreted as follows: high-high clusters (HH) represents locations with high value of employment surrounded by locations with high values of industrial specialization while low-low clusters (LL) corresponds to locations showing low values of employment surrounded by locations with low values of industrial specialization.

Conversely, low-high outliers (LH) include locations with low values of employment surrounded by locations with high values of industrial specialization locations while high-low outliers (HL) show locations with high values of employment surrounded by locations with low values of industrial specialization.

The biLISA cluster maps for the provision of infrastructure are shown in Figure 4. As seen in the figure, there are many cantons in the Coast region with low values of employment surrounded by locations with low provision of infrastructure, especially in variables such as transportation and ICT infrastructure (LL). Besides, the Industrial Specialization Index shows few and isolated cantons of (LL) clusters in the Coast and Amazon regions and HH clusters mainly in the Highlands. We can also observe cantons with high employment in the textile sector neighboring cantons with high number of ICT enterprises in the Northern and Central Highland regions.

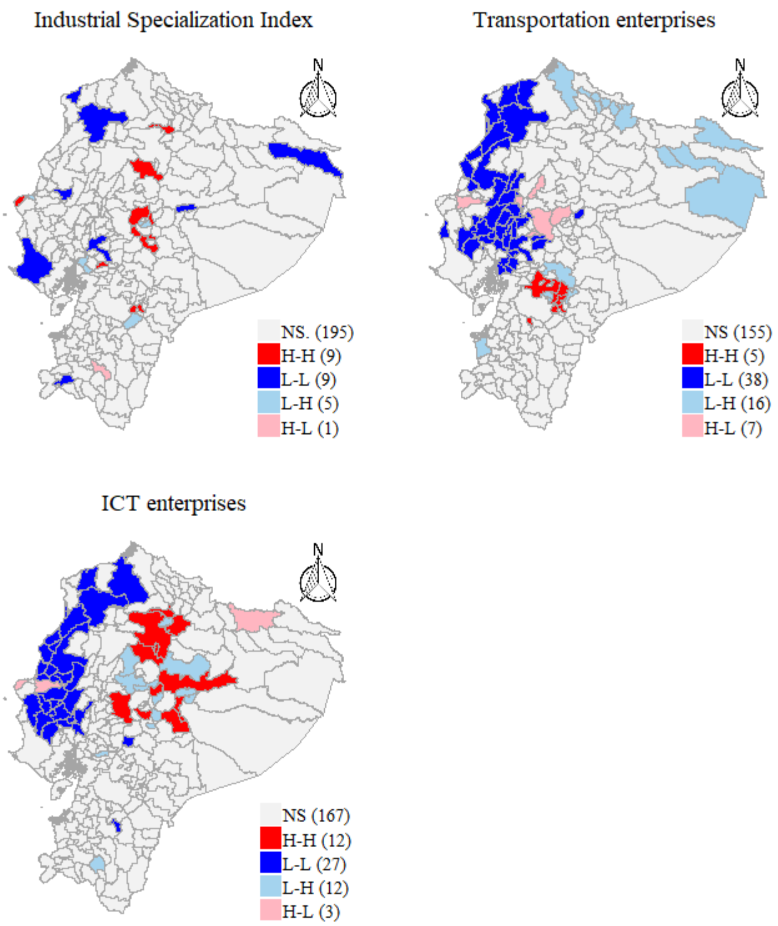

Figure 4. BiLISA cluster maps of employment rates in the textile sector and the provision of infrastructure in Ecuador. BiLISA Cluster map of the EB employment rates using queen spatial weight matrix. The highlighted locations are statistically significant (p<0.05). Clusters: HH=High-High; LL=Low-Low. Outliers: LH=Low-High; HL=High-Low. Authors' calculation based on data from National Economic Census (INEC, 2010).

The maps showing the biLISA cluster maps for variables of access of infrastructure are presented in Figure 5. We can observe several common spatial patterns across all the variables analyzed. First, clusters with high level of employment are surrounded by areas where households have high access to different services are concentrated in the Northern Highlands region. Second, cantons with low values of employment are surrounded with locations with low access to infrastructure mainly in the Coast region and in some cantons of the Amazon region. These results are consistent with the ones found in bivariate analysis including information of the provision of infrastructure for the Coast region. Finally, there are different cantons that are clusters (LL) and outliers (HL) in the Amazon region. Once again, the result of biLISA cluster maps of the Unsatisfied Basic Needs Index requires a separate analysis. As seen in the figure, there are many cantons in the Northern and Southern Highlands and just a few cantons in the Central Highlands with high employment surrounded by cantons with low levels of poverty (and thus better meso-space). On the contrary, we observe that many cantons in the Coast region with low levels of employment are surrounded with cantons with high levels of poverty.

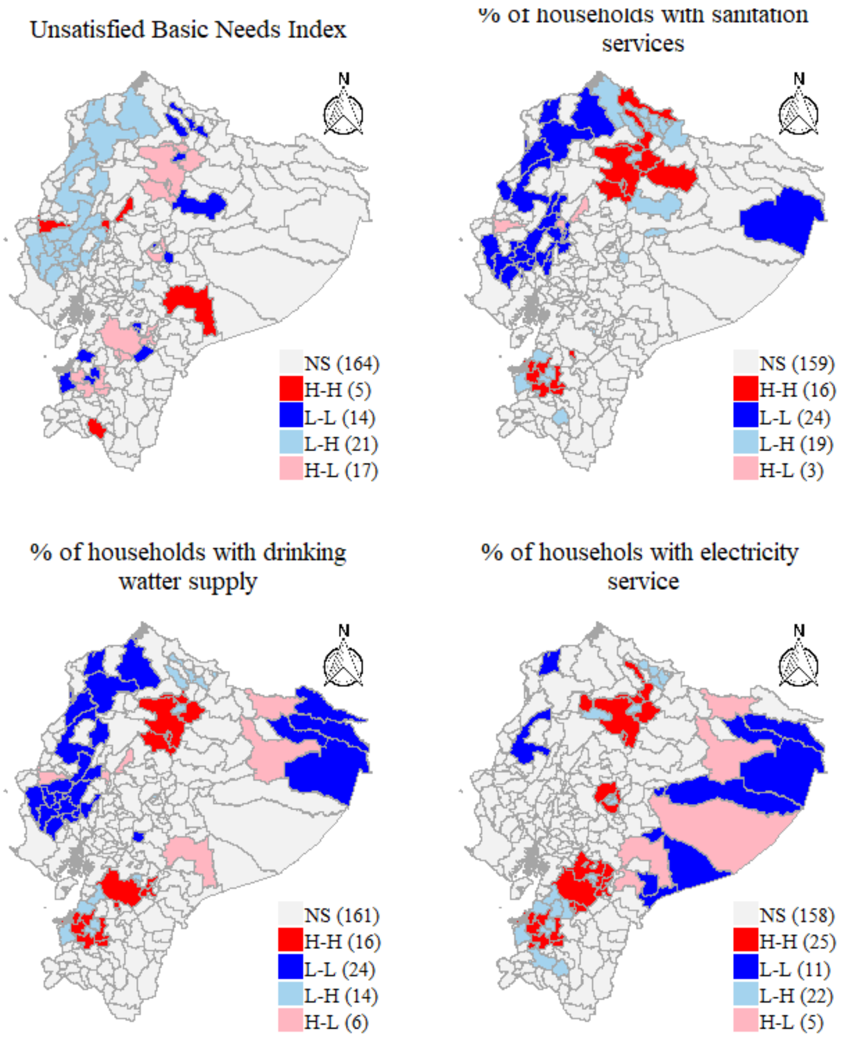

Figure 5. BiLISA cluster maps of employment rates in the textile sector and the access of infrastructure in Ecuador. BiLISA Cluster map of the EB employment rates using queen spatial weight matrix. The highlighted locations are statistically significant ($p<0.05$). Clusters: HH=High-High; LL=Low-Low. Outliers: LH=Low-High; HL=High-Low. Authors' calculation based on data from National Economic Census (INEC, 2010).

Figure 6 shows the biLISA cluster maps for the variables identified as financial activities of the meso-space. As seen in the figure, cantons in the Coast region shows low level of employment surrounded with locations with low levels of provision of financial services through Financial Institutions (FI). Clusters with high level of employment neighboring cantons with high presence of FI are concentrated in the Central and Southern Highlands regions. Conversely, access to credit for the textile sector shows HH clusters in several cantons of the Northern and Central Highland regions. Thus, cantons with high levels of employment are surrounded by locations with high access to credit for the textile sector in these regions.

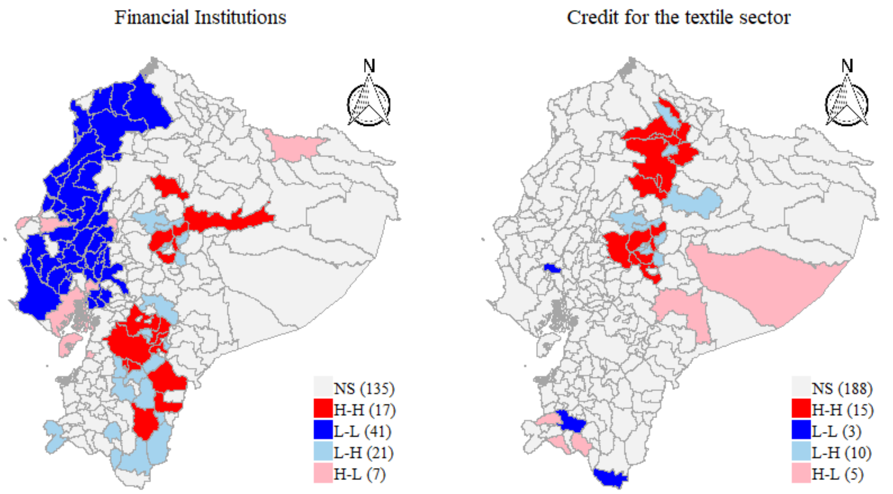

Figure 6. BiLISA cluster maps of employment rates in the textile sector and the provision and access to financial services in Ecuador. BiLISA Cluster map of the EB employment rates using queen spatial weight matrix. The highlighted locations are statistically significant (p<0.05). Clusters: HH=High-High; LL=Low-Low. Outliers: LH=Low-High; HL=High-Low. Authors' calculation based on data from National Economic Census (INEC, 2010).

We include the biLISA cluster maps for the number of professional, scientific and technology enterprises as a proxy of technology activities of the meso-space. The figure 7 shows cantons with high levels of employment neighboring cantons with high presence of professional, scientific and technology enterprises in cantons in the Northern Highlands. Not surprisingly, cantons in the Coast region show low levels of employment surrounded by cantons with low numbers of such enterprises.

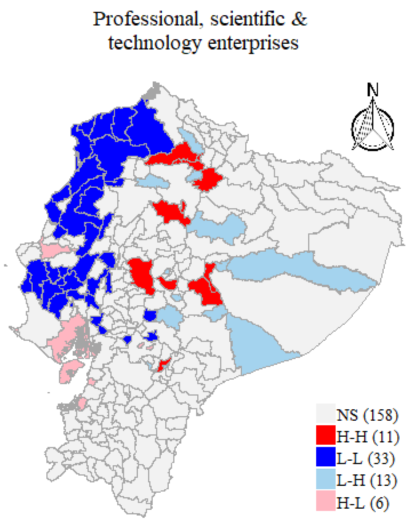

Figure 7. BiLISA cluster maps of employment rates in the textile sector and the provision of technology in Ecuador. BiLISA Cluster map of the EB employment rates using queen spatial weight matrix. The highlighted locations are statistically significant (p<0.05). Clusters: HH=High-High; LL=Low-Low. Outliers: LH=Low-High; HL=High-Low. Authors' calculation based on data from National Economic Census (INEC, 2010).

Finally, Figure 8 shows the bivariate maps for the variables of access to education. Consistent with results of previous variables, there are low values of employment in the Coast Region surrounded by areas with low levels of people attending to high-school and university. We can also observed clusters with high levels of employment in the textile sector surrounded by cantons with high levels of people attending to high-school in the Northern and the Central Highlands regions but only in the latter when the analysis considers the variable of people attending to university.

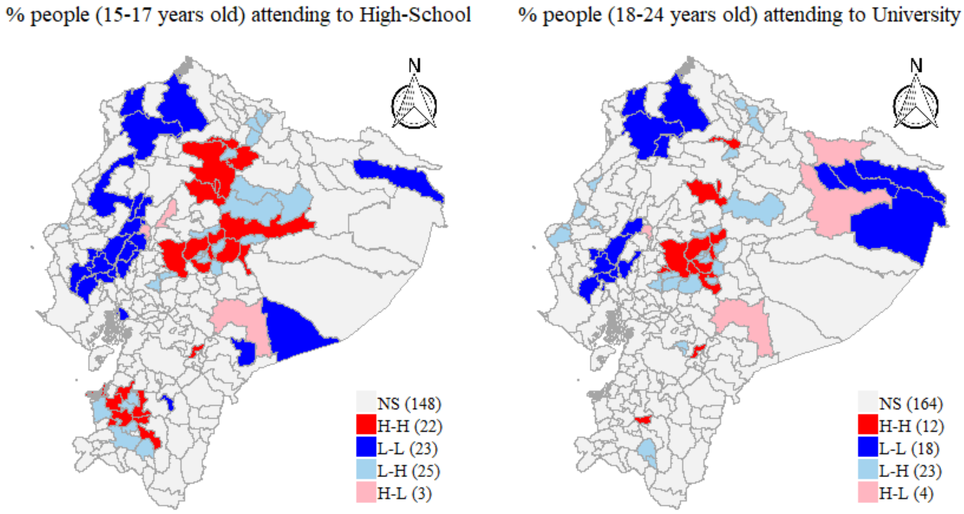

Figure 8. BiLISA cluster maps of employment rates in the textile sector and access to High-School and University. BiLISA Cluster map of the EB employment rates using queen spatial weight matrix. The highlighted locations are statistically significant ($p<0.05$). Clusters: HH=High-High; LL=Low-Low. Outliers: LH=Low-High; HL=High-Low. Authors' calculation based on data from National Economic Census (INEC, 2010).

6. Concluding Remarks

This paper contributes to the literature of the Systemic Competitiveness Framework through the quantitative analysis to identify the economic regions in the textile sector of Ecuador. The application of Exploratory Spatial Data Analysis to examine spatial patterns represents the first empirical analysis that shows if spatially aggregated regions at a micro level are associated with favorable or adverse meso-space in nearest regions. Our results show a weak positive spatial autocorrelation (global) in the textile sector and suggest that employment generation by the textile sector occurs in better provisioned and well-accessed meso-spaces in neighboring regions. Indeed, cantons with high levels of employment in the textile sector are surrounded by areas with better access to infrastructure and higher levels of provision and access to financial services.

Policies that aim promoting competitiveness in the textile sector should incorporate spatial information as the one presented in this paper. We identify that the higher contribution of employment generation of the textile sector is mainly concentrated in cantons located in the Highlands in Ecuador. Specifically, the bigger group of clusters showing high values of employment is located in the Northern Highlands around the capital. More interestingly, we also found that this cluster is highly correlated with favorable conditions of the meso-space in neighboring regions. The concentration of clusters with high level of employment in the textile sector near the capital is consistent with results for industrial clusters found in Torres (2017) and Ortega (Ortega-Vivanco, 2017). However, these results may mistakenly reinforce the idea that the industry may concentrate only nearby developed regions. Our results shows that Quito and Guayaquil shows a high level of employment in the textile sector but only regions near Quito shows similar high values while Guayaquil is surrounded by regions with low levels of employment.

Our results are consistent with certain policies of the Ecuadorian Government that identified the relevance of Highland region for enhancing the competitiveness of the textile sector also known as the "*Fondo de cuenca interandina norte-sur"*. Thus, social agents as well as governments should explore the possibility of fostering textile clusters in this region. Further analysis should explore if cultural and social patterns at a meta level enhance or constrain the cluster formation in this region. According to the SCF, if there is no predisposition to aggregation and cluster formation among the actors, policies that aim fostering clusters are doomed to failure.

The spatial patterns presented in this paper are descriptive in nature and only suggest possible associations between industrial clusters in the textile sector and activities in the meso-space. Since spatially disaggregated data were only available for 2010, our analysis limits updated conclusions for the textile sector. Moreover, we could only include few variables as proxy of meso-spaces activities. Further analysis should include spatial analysis with current data when this is available as well as confirmatory spatial data analysis such as spatial regression analysis to extent the validity of the results discussed in this paper.

REFERENCES

Abdi, O., Shirvani, Z. and Buchroithner, M. F. (2018): Spatiotemporal drought evaluation of Hyrcanian deciduous forests and semi-steppe rangelands using MODIS time-series in Northeast Iran, *Land Degradation & Development*.

Altenburg, T., Hillebrand, W. and Meyer-Stamer, J. (1998): *Building systemic competitiveness: concept and case studies from Mexico, Brazil, Paraguay, Korea and Thailand*, GDI.

Anselin, L. (1995): Local indicators of spatial association—LISA, *Geographical Analysis*, 27, 93-115.

Anselin, L., Lozano, N. and Koschinsky, J. (2006): Rate transformations and smoothing, *Urbana*, 51, 61801.

Anselin, L., Sridharan, S. and Gholston, S. (2007): Using exploratory spatial data analysis to leverage social indicator databases: the discovery of interesting patterns, *Social Indicators Research*, 82, 287-309.

Anselin, L., Syabri, I. and Kho, Y. (2006): GeoDa: an introduction to spatial data analysis, *Geographical Analysis*, 38, 5-22.

Arghoty, A. (2013): Encadenamiento productivo del sector textil en el Ecuador, in *Estudios industriales de la micro, pequeña y mediana empresa* (Eds) H. Jácome and K. King, Quito, Facultad Latinoamericana de Ciencias Sociales Sede Ecuador & Ministerio de Industrias y Productividad del Ecuador, pp. 175-244.

Asamblea Constituyente del Ecuador (2008): Constitución de la República del Ecuador. R. O. No. 449.

Bardhan, R., Debnath, R. and Bandopadhyay, S. (2016): A conceptual model for identifying the risk susceptibility of urban green spaces using geo-spatial techniques, *Modeling Earth Systems and Environment*, 2, 144.

Carboni, O. A. (2013): Spatial and industry proximity in collaborative research: evidence from Italian manufacturing firms, *The Journal of Technology Transfer*, 38, 896-910.

Chakravorty, S., Koo, J. and Lall, S. V. (2005): Do localization economies matter in cluster formation? Questioning the conventional wisdom with data from Indian metropolises, *Environment and Planning* A, 37, 331-353.

Chávez-Martín del Campo, Juan Carlos and García Loredo, K. (2015): *Identificación de Clusters Regionales en la Industria Manufacturera Mexicana*, N° 2015-19. Working Papers, Banco de México.

Cheng, Z. (2016): The spatial correlation and interaction between manufacturing agglomeration and environmental pollution, *Ecological Indicators*, 61, 1024-32.

Cohen, J. P. and Paul, C. J. M. (2005): Agglomeration economies and industry location decisions: the impacts of spatial and industrial spillovers, *Regional Science and Urban Economics*, 35, 215-37.

Cohen, J. P. and Paul, C. J. M. (2004): Public infrastructure investment, interstate spatial spillovers, and manufacturing costs, *Review of Economics and Statistics*, 86, 551-60.

De la Puente, M. (2018): Systematic Competitiveness in Colombian Medical Tourism: An Examination, in *Mobilities, Tourism and Travel Behavior-Contexts and Boundaries*, InTech, pp. 1125-1142.

Duranton, G., Martin, P., Mayer, T. and Mayneris, F. (2010): *The economics of clusters. Lessons from the French experience*, Oxford University Press.

Esser, K., Hillebrand, W., Messner, D. and Meyer-Stamer, J. (1994): *Competitividad Sistémica: Competitividad Internacional de las empresas y políticas requeridas*, Estudios e Informes 11/1994 edn, Instituto Alemán de Desarrollo, Berlín.

Esser, K., Hillebrand, W., Messner, D. and Meyer-Stamer, J. (1995): *Systemic Competitiveness. New Gobernance Patterns for Industrial development*, German Development Institute, Berlín.

Frigerio, I., Carnelli, F., Cabinio, M. and De Amicis, M. (2018): Spatiotemporal Pattern of Social Vulnerability in Italy, *International Journal of Disaster Risk Science*, 1-14.

Glaeser, E. L., Kallal, H. D., Scheinkman, J. A. and Shleifer, A. (1992): Growth in cities, *Journal of political economy*, 100, 1126-52.

Guillain, R. and Le Gallo, J. (2010): Agglomeration and dispersion of economic activities in and around Paris: an exploratory spatial data analysis, *Environment and Planning B: Planning and Design*, 37, 961-81.

Hernández, R. (2001): *Elementos de competitividad sistémica de las pequeñas y medianas empresas (PYME) del Istmo Centroamericano*, CEPAL.

Guo, Y., Chan, C. H. and Yip, P. S. (2017): Spatial variation in accessibility of libraries in Hong Kong, *Library & Information Science Research*, 39, 319-29.

INEC (2010a): Censo de Población y Vivienda, Instituto Nacional de Estadísticas y Censos del Ecuador.

INEC (2010b): Censo Nacional Económico. Instituto Nacional de Estadísticas y Censos del Ecuador.

Jenal, M. and Wältring, F. (2017): El nivel meso, el espacio meso y la relación con los territorios, in *Reflexión Anual 2017* (Ed) Mesopartner , pp. 8-13.

Krugman, P. (1991): Increasing returns and economic geography, *Journal of political economy*, 99, 483-99.

Lafourcade, M. and Mion, G. (2007): Concentration, agglomeration and the size of plants, *Regional Science and Urban Economics*, 37, 46-68.

Liu, Z. (2014): Global and local: Measuring geographical concentration of China's manufacturing industries, *The Professional Geographer*, 66, 284-97.

Marshall, A. (1895): *Principles of economics*, The English Language Book Society; London.

Meyer-Stamer, J. (2003): *Understanding the determinants of vibrant business development: the systemic competitiveness perspective*, Mesopartner, Duisburg.

Meyer-Stamer, J. (2002): Clustering and the creation of an innovation-oriented environment for industrial competitiveness: beware of overly optimistic expectations, *International Small Business Journal*, 20, 1-23.

Meyer-Stamer, J. (1998): Clustering, Systemic competitiveness and Commodity Chains: how firms, business associations and government in Santa Catarina/Brazil respond to globalization, in International Workshop "*Global Production and Local Jobs: New Perspectives on Enterprise Networks, Employment, and Local Development Policy*", ILO, Geneva, Citeseer.

Moran, P. A. (1948): The interpretation of statistical maps, *Journal of the Royal Statistical Society*. Series B (Methodological), 10, 243-251.

Murgante, B. and Rotondo, F. (2013): A geostatistical approach to measure shrinking cities: the case of Taranto, in *Statistical Methods for Spatial Planning and Monitoring* (Eds) S. Murgante and P. Perchinunno, , Springer, pp. 119-142.

Ortega-Vivanco, M. (2017): *Integración económica y localización de la actividad industrial en el Ecuador*. Doctoral dissertation, Universitat de Barcelona.

Paci, R. and Usai, S. (2008): Agglomeration economies, spatial dependence and local industry growth, *Revue d'économie industrielle* [Online], 7, 87-109.

Porter, M. E. (1990): ¿Dónde radica la ventaja competitiva de las naciones? *Harvard Deusto Business Review*, 3-26.

Rodrigues, M. A., Monteiro, W. d. F., Campos, A. C. d. and Parré, J. L. (2012): Identificação e análise espacial das aglomerações produtivas do setor de confecções na região Sul, *Economia Aplicada*, 16, 311-38.

Rosenfeld, S. A. (1997): Bringing business clusters into the mainstream of economic development, *European planning studies*, 5, 3-23.

Sambidi, P. R. and Harrison, R. W. (2006): Spatial clustering of the US biotech industry, in *American Agricultural Economics Association Annual Meeting*, Long Beach, CA.

SBS (2010): Base de datos de crédito otorgado, Superintendencia de Bancos y Seguros del Ecuador.

Schoen, C. and Jenal, M. (2017): La emergencia de un espacio meso - El caso país de Myanmar, in *Reflexión Anual 2017*, Mesopartner, pp. 46-51.

SENPLADES (2013): Plan Nacional del Buen Vivir 2013-2017: Todo el Mundo Mejor, Secretaría Nacional de Planificación y Desarrollo.

SENPLADES (2017): Plan Nacional del Buen Vivir 2017-2021: Toda una Vida, Secretaría Nacional de Planificación y Desarrollo.

SENPLADES (2009): Plan Nacional para el Buen Vivir 2009-2013: Construyendo un Estado Plurinacional e Intercultural, Secretaría Nacional de Planificación y Desarrollo.

Sutz, J. (2002): Los sistemas de innovación en Latinoamérica, in *América Latina competitiva: desafíos para la economía, la sociedad y el Estado* (Eds) T. Altenburg and D. Messner, Caracas, Instituto Alemán de Desarrollo, pp. 77-101.

Torres Gutiérrez, T. (2017): Ensayos sobre Economías de Aglomeración. Doctoral dissertation, Universitat de Barcelona.

United Nations (2008): International Standard Industrial Classification of All Economic Activities (ISIC), Rev. 4. United Nations Statistical Papers, 4.

Ying, L. G. (2000): Measuring the spillover effects: Some Chinese evidence, *Papers in regional science*, 79, 75-89.

Zhang, Y., Liu, Y., Zhang, Y., Liu, Y., Zhang, G. and Chen, Y. (2018): On the spatial relationship between ecosystem services and urbanization: A case study in Wuhan, China, *Science of The Total Environment*, 637, 780-90.

Table A1. Definitions

Meso-space activities	Type	Definitions
Infrastructure	Industrial Specialization Index	The specialization index measures the concentration that the industry has in a given region in relation to the concentration of that activity in the country.
	Electricity enterprises	Number of establishments with ISIC codes: section D – 3510, 3520
	Water & sanitation enterprises	Number of establishments with ISIC codes: section E – 3600, 3700, 3811, E3812, 3821, 3822, 3830, and 3900
	Transportation enterprises	Number of establishments with ISIC codes: section H – 4923, 5012, 5022, 5120, 5210.
	Information & Communication Technology (ICT) enterprises	Number of establishments with ISIC codes: section J – 6110, 6120, 6130, 6190.
	Unsatisfied Basic Needs Index	Number of people living in poverty conditions over the total population
	Households with sanitation services (%)	Number of households with sanitation services over the total households
	Households with drinking water supply (%)	Number of households with drinking water supply over the total households
	Households with electricity service (%)	Number of households that have electricity service over total households
Finance	Financial Institutions	Number of establishments with ISIC codes: section K – 6419, 6420, 6430, 6491, 6492, 6499, 6511, 6512, 6520, 6530, 6611, 6612, 6619, and 6630
	Credit for the textile sector	Amount of credits for the textile sector granted by Banks and Cooperatives controlled by the Superintendence of Banks of Ecuador in 2010.
Technology	Professional scientific & technology enterprises	Number of establishments with ISIC codes: section M – 7210, 7220, 7310, 7320.
Education and training	Educational institutions	Number of establishments with ISIC codes: section P – 8510, 8522, 8530, 8549, 8550
	People with bachelor degree (%)	People (+18-years-old) who has completed undergraduate studies.
	People with University degree (%)	People (+24-years-old) who have completed graduate studies.
	People (15-17 years old) attending to High-School (%)	People from 15 to 17 years old who attend high school by their corresponding age group population
	People (18-24 years old) attending to University (%)	People from 18 to 24 years of age who attend higher education by their corresponding age group population

Note. Authors' elaboration based on data from Population Census (INEC, 2010a), National Economic Census (INEC, 2010b) and Superintendence of Banks of Ecuador (SBS, 2010).