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Creation and Diffusion of Knowledge across Creative Industries in Metropolitan Areas: the cases of Mexico and Spain

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CREATION AND DIFFUSION OF KNOWLEDGE ACROSS CREATIVE INDUSTRIES IN METROPOLITAN AREAS: THE CASES OF MEXICO AND SPAIN

ABSTRACT

This study proposes a spatial interaction model to analyze the level of creativity across Metro Areas (MAs) in a country. The model postulates that increasing creativity depends on the proportions of common knowledge and differential knowledge that MAs face when they interact with each other. We rely on an agent-based approach that allows incorporating GIS and spatial interaction between MAs under local and global network conditions. We chose the cases of Mexico and Spain to get a first glance of how the model works with real data. We find that the MAs of Spain (2001) and Mexico (2003) share the same level of common and differential knowledge in the creative industries and, that knowledge spillovers spread better under inter metropolitan conditions of interaction instead of intra ones. The simulations suggest that Spain is better suited to produce higher knowledge externalities under conditions that are not restricted by physical distance, which make policy intervention in Spain more effective to diffuse creative ideas.

Keywords: Externalities, knowledge spillovers, creative industries, urban spatial models, computational modeling

JEL codes: D830, C630, O180

RESUMEN

Este trabajo propone un modelo de interacción espacial entre zonas metropolitanas (ZMs) para analizar el nivel de creatividad en un país. El modelo postula que la producción de creatividad depende del balance entre el conocimiento común y el diferenciado que ZMs enfrentan cuando están en disposición de interactuar. La investigación utiliza un enfoque de modelos basados en agentes que incorpora SIGs e interdependencia espacial de ZMs bajo condiciones de interacción global y local. Para tener una primera aproximación de cómo funciona el modelo con datos reales, se decidieron estudiar las zonas metropolitanas de España (2001) y México (2003). Los resultados arrojan que las ZMs de España y México comportan el mismo nivel de conocimiento común y diferenciado, y que las derramas de conocimiento son mayores a nivel de interacción inter-metropolitana que intra-metropolitana. Las simulaciones también indican que España está en mejores condiciones para producir más externalidades de conocimiento bajo condiciones de intervención pública que no está reesringida por la distancia física.

Palabras clave: externalidades, difusión del conocimiento, industrias creativas, modelos urbanos espaciales, modelación computacional

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1. INTRODUCTION

A model of knowledge creation in creative industries is analyzed in this paper under spatial interaction conditions across Metropolitan Areas (MAs). The purpose of this study is to show that this is an alternative way to measure creativity in a region as opposed to those traditional attempts that rely on indexes or aggregate measurements to proxy creativity (Correia & Costa, 2014). Our proposal has the advantage that it is a bottom-up approach to measure creativity from behavior of regional units (i.e., MAs) that are engaged to increase creativity either individually or collectively by means of spatial interaction.

Indicators of the level of creativity in a region can be important inputs for policy design. Typically these measurements (i.e, indexes) are generated by aggregate variables of a region such as human capital, R&D investment, creative class occupations, surveys about tolerance, and so forth (Florida et al, 2011). Nevertheless, these indicators lack of appropriate "microfoundations" because they do not provide a history (or explanation) of why creativity raises from behavior of economic agents. One way to overcome this bias is to consider creativity as product of knowledge transmission and joint knowledge creation between agents (or economic sectors) that are engaged in social interaction and learning. Two key factors that can be central in this process are common and differential knowledge. An appropriate balance between these two factors can be central for knowledge creation (i.e. rising creativity). Berliant and Fujita (2009) studied these elements theoretically in a standard microeconomic model that tries to explain knowledge creation and knowledge transfer between a pair of agents. In this paper, we adapt some of these insights to construct a model of interacting regional units (MAs) that are able to transfer and receive knowledge (in creative industries) with the goal to create additional knowledge. The central purpose is to get a reliable measurement of the aggregate level of creativity that these mechanisms of knowledge transmission produce in a region. We have chosen as cases of study the metropolitan areas of Mexico and Spain to show how the model can be implemented with actual data.

The paper is structured as follows. In section 1, we provide a brief review of the literature that supports our main argument about the advantages to measure creativity from the bottom up. In section 2, we present some stylized facts about the creative industries (measured by UNCTAD´s criterion) in the MAs of Mexico and Spain. In section 3, the model is advanced and some simulations aimed to measure common and differential knowledge are discussed. In section 4, we present key simulation results of the model for the cases of Mexico and Spain. We conclude with a section of final remarks that discusses the policy implications of the methodology presented in this paper.

2. BRIEF REVIEW OF THE LITERATURE

Creative class and creative industries have been two of the most studied subjects in the contemporary agenda of urban and regional economics. The vast number of papers and books that can be found in the specialized literature shows that this is an active line of research for many scholars and practitioners interested in analyzing the key modern-day factors that boost economic growth in urban areas. Research on economic creativity is in particular interested in analyzing some key factors of localization between firms and workers, and it develops two main perspectives. In one of the approaches –which is commonly associated with Richard Florida (2005) and Glaeser (2008) and other followers, it emphasizes supply side factors of the labor markets , i.e. firms just follow workers´ decisions of mobility (being amenities key factors for the latters). While the second approach –without neglecting the relevance of skilled and talented people– puts more roles on the demand side of the labor markets, i.e. workers follow firms´ decisions of localization. Under this last line of research, which runs along the criticism of Storper (2013) to the role of amenities in the subject, most of the European regional research is conducted by focusing more on industries and sectors rather than occupations. Nevertheless, it would be fair to say that many times empirical studies adopt an interrelated (and sometimes unclear) way about the causal links between localization´s decisions of firms and workers in creative industries.

Regardless of which of the two above mentioned approaches is more suitable to study creative industries, the literature still lacks of studies oriented to provide some "microfoundations" in the discussion of creativity. In particular, it is interesting to find that even when the subject of creativity carries out implicitly the concept of externalities (and much empirical research is conducted under this direction), few studies are aiming at exploring how creativity is "created" and transmitted from the bottom-up through agent interactions. This limitation has been discussed partially by Sacco et al (2014) who criticize the approach to model creative class effects from a top-down perspective, such that the depicted by Michael Porter´s theory of advantage competitiveness. Even when the top-down approach could be useful theoretically and for policy design purposes, its main problem is that makes abstraction of the cultural and contextual space in which is analyzed the creative process –the same critique applies to Richard´s Florida "plug and plays" perspective where the main focus is on attracting only external talented people that would reshape alone local contexts.

An interesting attempt to overcome the restrictiveness of top-down approaches in creative economic studies is provided by Spencer (2012), who from an agent based modeling perspective analyzes the emergence of creativity as product of agent interaction through intra and inter networks. An attractive feature in Spencer´s approach is the use of the concept of homophily that indicates that people tend to choose to interact with others that are similar to them. That is, agents are compared in terms of their cognitive distances which make them closer or farther to each other in terms of their knowledge profile: interaction between agents would be more likely, the smaller the cognitive distance between them and, vice versa. A similar idea is developed further by Fujita (2007) and Berliant-Fujita (2009), under standard microeconomic precepts, to analyze the creation of knowledge through non-pecuniary externalities. But Fujita and Berliant in addition to homophily (that they called "common knowledge") introduce also the role of differential knowledge as a key factor for agent interaction and knowledge creation. The model is conceived for a more abstract setting of knowledge creation, but it can be considered to analyze the rise of creativity as it is attempted in the present paper. In section 3, we propose a model of knowledge creation (i.e. creativity formation) that takes into account some of the key insights of Berliant-Fujita (2009) but they are adapted in a more complex setting of heterogeneous interacting agents such that advanced by Spencer (2012).

Policy discussion in the subject of creativity relies on the generation of reliable macro indicators of creativity. In fact, Florida has been one the main promoters of considering creativity indexes (commonly based on a set of aggregate variables associated with creativity) as good proxies for creativity in urban settings (in particular, as an approximation to the 3 t´s of Florida –tolerance, technology and talent). (Florida et al, 2011). In the same sense, when policy is concerned to promote creative industries, a measurement of creativity that indicates the weight (and relevance) of creative sectors (or occupations) in the whole economy becomes essential for policy purposes. A plethora of documents and methodologies attempting to measure creativity under this direction has been elaborated; for example, some of the most used measurements of the presence of creative sectors in the economy are –to quote only a few of them: the NESTA occupational mapping elaborated for the case of UK (Bakhshi et al, 2013), the UNCTAD measurement of creative industries (United Nations-UNDP-UNESCO, 2013) and the trident approach that combines occupational and sectorial components of creativity (Markusen et al 2008; Santos-Cruz and Texeira, 2012).

But as good as those indicators can be, they are not per se indicators derived from an explicit theoretical framework that shows how creativity rises or spillovers across sectors because of agent´s choices and interactions. With this respect, our goal in this paper is to propose a model of knowledge creation (or let us call it "creativity rising") along the lines of Fuijta-Berliant (2009) insights, which is implemented by using UCNTAD (2010) classification of industrial sectors for the case of the metropolitan areas of Mexico and Spain. From our perspective, the methodology is useful for policy purposes because illustrates how much creativity could rise under a specific spatial urban structure and real endowments of knowledge that are in principle embedded in the creative sectors of actual metropolitan areas.

3. Creative Industries Data across Metropolitan Areas in Mexico and Spain

In this section, we show stylized facts about the presence of creative industries across metropolitan areas in Mexico and Spain with the purpose to show the types of inputs that the model we present in next section requires for its implementation. First, it is important to mention that we rely on the UNCTAD (2010) classification of creative industries –somewhat following the adaptation done by Boix-Lazzeretti (2012) and others– . The UNCTAD classification is a standard measurement for creative industries that is best for comparative purposes across regions. Also, we match UNCTAD´s classification with the corresponding industry categories of the NAICS and NACE classification in which available data for Mexico and Spain are based on.

We were able to obtain information of employment in creative industries at Metro Area level in Spain only for 2001; therefore, we had to use data for Mexico from 2003 in order to make time period relatively compatible. The number of Metro Areas analyzed was 67 and 59 for Spain and Mexico respectively. The creative industries that are considered in the exercise (and their compatibility) are displayed in table 1:

Table 1

Creative industries used in the comparative excercise betweeen Spain and Mexico

Spain 2001, NACE Rev 1 codes		México 2003, NAICS codes	
221	Publishing	511	Publishing Industries (except Internet)
222	Printing and service activities related to printing	5414	Specialized Design Services
		54192	Photographic Services
223	Reproduction of recorded media	5122	Sound Recording Industries
722	Software consultancy and supply	5415	Computer Systems Design and Related Services
726	Othe computer related activities	51913	Internet Publishing and Broadcasting and Web Search Portals
		518	Data Processing, Hosting, and Related Services
731	Research and experimental development on natural sciences and engineering	54171	Research and Development in the Physical, Engineering, and Life Sciences
732	Research and experimental development on social sciences and humanities	54172	Research and Development in the Social Sciences and Humanities
742	Architectural and engineering activities and related technical consultancy	5413	Architectural, Engineering, and Related Services
744	Advertising	5418	Advertising, Public Relations, and Related Services
921	Motion Picture and Video activities	5121	Motion Picture and Video Industries
922	Radio and Televesion activities	515	Broadcasting (except Internet)
923	Other entertainment activities	7111	Performing Arts Companies
		7115	Independent Artists, Writers, and Performers

Source: INE (2001) and INEGI (2004).

Table 2 shows the summary of statistics of the data used in the exercise. Firstly, the employment in metro areas explained the 77% and 74% of total employment in Spain and Mexico respectively. The share of creative employment in all metro areas is 4.9% and 2.3% for Spain and

Mexico in that order. An estimation of the share distribution across MAs using kernel methods -including the associated normal distribution reported by data- is provided in figure 1 and figure 2. The estimation for the Mexican case shows a skewed distribution to the left in contrast to Spain´s distribution, which is sharpest. The skewness pattern sometimes is stressed by the empirical literature of creative industries but not with the necessary accent. For example, some studies aim at the fact that incomes in creative occupations (mainly artists of any kind) are highly skewed –see Potts, 2011- and, a known economic report of creative occupations in UK called NESTA (Bakhshi et al, 2013, p. 17) highlights that distribution employment in the non-DCMS creative industries (that is, the classifications that include software related occupations –like the one used by UNCTAD-) is skewed toward cero like in the Mexican case.

Table 2
Summary of descriptive statistics

	Spain, 2001	Mexico, 2003
Number of Metro Areas	67	59
Creative employment in Metro Areas	585,939	270,220
Total employment in Metro Areas	11,845,300	12,000,859
Share of creative employment in Metro Areas	4.9%	2.3%
Total employment country	15,267,762	16,239,536
Share of creative employment in the country	3.8%	1.7%
Maximun share	8.4%	3.47%
Minimum share	0.6%	0.55%

Specialized MAs (only MA employment)	4	6
	6%	10%
List of MAs Specialized	Barcelona, Bilbao, Donostia-San Sebastián, Madrid	Colima-Villa de Álvarez, Juárez, Mexico City, Toluca, Villahermosa, Jalapa,
Specialized MAs (All country employment)	6	1
	9%	2%
List of MAs Specialized	Barcelona, Bilbao, Donostia-San Sebastián, Madrid, Pamplona, Santiago Compostela	Mexico City

Source: INE (2001) and INEGI (2004).

Figure 1. **Spain 2001**
Creative Employment Share

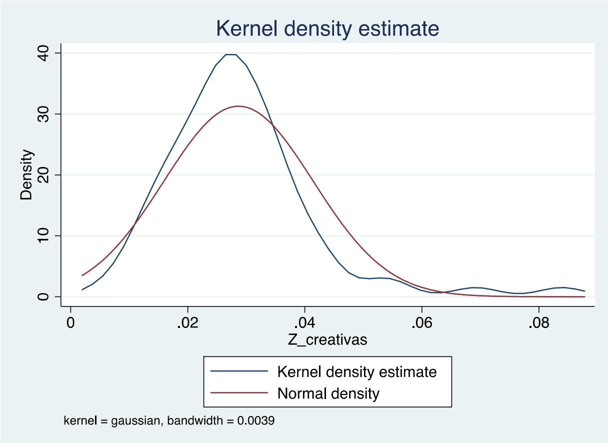


Figure 2. **Mexico 2003**
Creative Employment Share

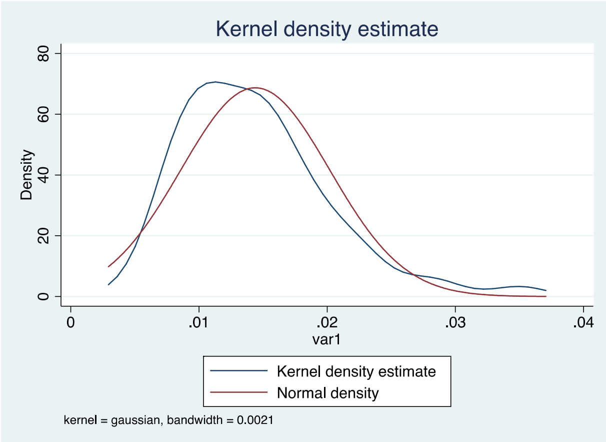


Table 2 also shows the number of metro areas specialized in creative industries according to a standard location quotient of the form LQ= ei/e / Ei/E to be applied in each of the metro areas (ei). If we consider only the total employment of metro areas, Spain reports four metro areas specialized in creative industries (Barcelona, Bilbao, Donostia-San Sebastián, Madrid) which represent 6% of all MAs, while Mexico has 6 metro areas (Colima, Juárez, Mexico City, Toluca, Villahermosa and Jalapa) which represents 9% of all MAs. Nevertheless, if we consider the total national employment as denominator for the location quotient, Spain increases to 6 the number of specialized metro areas (Barcelona, Bilbao, Donostia-San Sebastián, Madrid, Pamplona, Santiago de Compostela) while Mexico only obtains one metro area specialized (Mexico City). These changes are due to the fact that creative employment is more concentrated in Metro Areas of Spain (92%) than in Mexico (84%).

4. The Model

The discussion of creativity –specifically in the efforts to measure it through indexes– typically disregards any line of analyses that provides micro behavior. Even when we can find in the contemporary literature of Urban Economics standard models (such that of spatial equilibrium à la Glaeser or others like NGE models) that can provide guidelines to model creativity from agents´ choices, this line of thought is scarcely explored in the literature [Among the exceptions are Batabyal and Nijkamp (2013) who discuss unbalanced growth in an urban economy under preferences of the creative class]. Maybe one of main reasons to neglect "microfoundations" is because discussion of creativity in the literature tends to be dominated by a more heterodox and eclectic line of reasoning. Even though an eclectic approach can be suitable to analyze creativity –and it is relevant to differentiate it from standard concepts like human capital–, this must not automatically translate in rejecting microfoundations or any other "bottom up" approach. On the contrary, creativity seems to be more a product of complex interactions between individuals engaged in learning and adaptation who are bounded by particular labor market settings and sociocultural contexts. Moreover, creativity can be analyzed as an emergent property originated by complex interactions from the bottom up –Spencer (2012). Along this last line of thought, we present a model to measure creativity in the aggregate as product of agents´ decisions that engage in interaction to learn "ideas" from other agent and, importantly, to create knowledge when some conditions of common knowledge and differential knowledge prevail between a pair of individuals. In particular, we adapt some of the key insights advanced by Berliant and Fujita in a series of papers (2007, 2009) that provide a canonical model creation of knowledge and transfer for a dual agent case. In our model, we incorporate N agents under typical assumptions of agent based modeling (bounded rationality, heterogeneity, local interaction, agents behave out of equilibrium, etc.) for which our approach departs considerably from a more neoclassical approach as the one developed by Berliant-Fujita (2009).

Let us define ni,k(t) as the ideas known of agent i has of creative sector k at time t (n can be treated as binary variable indicating presence or absence of a given idea, but also can be continuous). Then the total knowledge of agent i in all creative sectors of the economy is:

$$\sum_{k=1}^{m} n_{i,k}(t) = Tk_i\,(t) \qquad (1)$$

where m is the total of industrial sectors classified as creative.

Then, total knowledge in the economy is given by:

$$\sum_{i=1}^{N} Tk_i(t) = TK\,(t) \qquad (2)$$

where N is the total of agents.

A key variable in the modeling is Common Knowledge indicating if agent i and j share the same idea or knowledge (it can be seen as if two agents are employed in a highly specialized creative sector that requires many "specialized ideas" for each worker, some workers can share some "ideas"). Therefore, common knowledge between i and j is depicted by:

$$CK_{i,j}(t) = \sum_{k=1}^{m} n_{i,k}(t) \cdot n_{j,k}(t) \qquad (3)$$

Now, it could be the case that agent i and j do not share ideas, therefore let us define DFKi,j as the differential knowledge that agent i has respect to j and DFKj,i as the converse. The equations of these variables are given by:

$$DFK_{i,j}(t) = Tk_i(t) - CK_{i,j}(t) \qquad (4)$$
$$DFK_{j,i}(t) = Tk_j(t) - CK_{i,j}(t) \qquad (5)$$

Note that CK is symmetric between i and j, then $CK_{i,j}(t) = CK_{j,i}(t)$

Now, a key element in the model proposed is that interaction between i and j somewhat must produce new knowledge which would be essential in any framework that attempts to model creativity. Following strictly Berliant-Fujita (2009), knowledge creation (KC) between i and j is ruled by[1]:

$$KC_{i,j}(t) = \beta \cdot \left[CK_{i,j} \cdot DFK_{i,j}(t) \cdot DFK_{j,i}(t)\right]^{1/3} \qquad (6)$$

where beta is a parameter >= 0

In the same way, a transfer of knowledge from i to j (TrK,ij) and from j to i (TrK,ji) are considered by the following expressions:

$$TrK_{i,j}(t) = \gamma \cdot \left[CK_{i,j} \cdot DFK_{i,j}(t)\right]^{1/2} \qquad (7)$$
$$TrK_{j,i}(t) = \gamma \cdot \left[CK_{j,i} \cdot DFK_{i,j}(t)\right]^{1/2} \qquad (8)$$

where gamma is a parameter >= 0

Now, knowledge creation can happen without interaction between i and j, that is, KCi=KCj. We model it, also along the lines of Berliant-Fujita, in its simple dynamic form[2]:

$$KC_i(t) = \alpha \cdot Tk_i(t) \qquad (9)$$

where alpha is a parameter >= 0

With these equations in mind, we will analyze the dynamics of TK by simulations taking a discrete approximation of the last equations. In particular, we consider that Tki at time t + 1 depends on Tki at time t plus knowledge creation between i and j at time t, plus knowledge transfer form j to i also at time t. that is:

$$Tk_i(t+1) = \sum_{k=1}^{m}\left[n_{i,k}(t) - TrK_{i,j}(t)/m\right] + KC_{i,j}(t) + \sum_{k=1}^{m}\left[n_{i,k}(t) + TrK_{j,i}(t)/m\right] \qquad (10)$$

[1] Equation (6) guarantees an important condition in the Berliant-Fujita model that is that the rate of creation of new knowledge is highest when proportions of common knowledge and differential knowledge are in balance. This is an interesting assumption because it implies that knowledge creation would not be highest when common knowledge between *i* and *j*, ideas exclusive of person *i* and ideas exclusive of person *j* are not proportional.

[2] If agent i is a region like in our implementation of the model in the next section, equation (9) could reflect *intra externalities* in the creation of knowledge.

In the same way, we consider that Tkj at time t + 1 depends on Tkj at time t plus knowledge creation between i and j at time t, plus knowledge transfer form i to j at time t. that is:

$$Tk_j(t+1) = \sum_{k=1}^{m}[n_{j,k}(t) - TrK_{j,i}(t)/m] + KC_{i,j}(t) + \sum_{k=1}^{m}[n_{j,k}(t) + TrK_{i,j}(t)/m] \quad (11)$$

As we can see in (10) and (11), the model considers TrK also a lost of knowledge for j and i in a way that it can be considered as depreciation of knowledge due to social interaction. Equation (10) and (11) indicate that depreciation and gain of knowledge from the other agent are both distributed proportionally through all m types of knowledge.

If interaction does not hold, Tki at time t + 1 would depend on Tki at time t plus KCi at time t, that is,

$$Tk_i(t+1) = Tk_i(t) + KC_i(t) \quad (12)$$

Now, we present the central rule of decision of the model. In this rule, the main objective is to model whether agent i is better off if she engages to interaction instead of behaving alone [3].

Therefore,

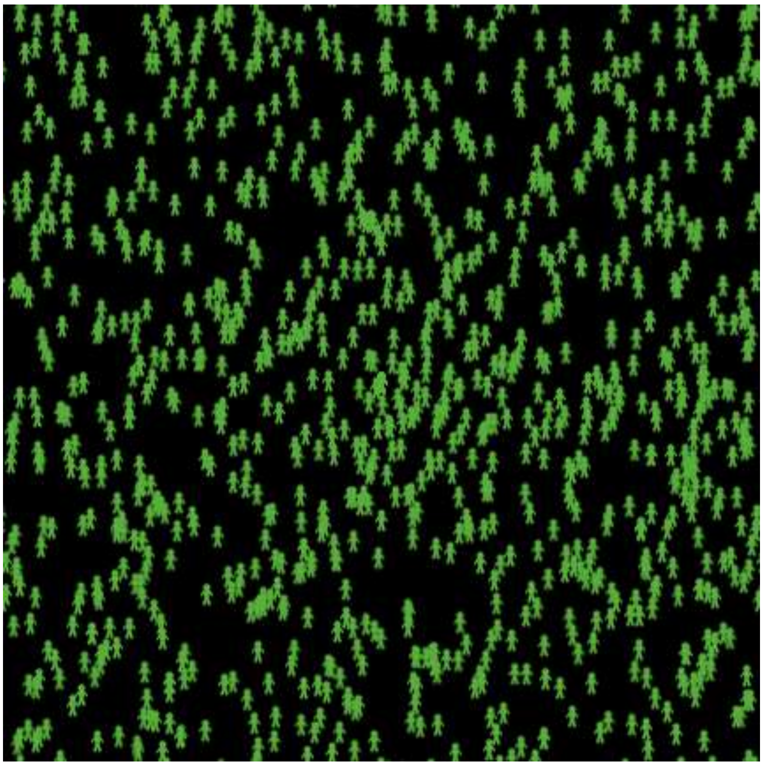
If $KC_{i,j}(t) + TrK_{j,i}(t) > KC_i(t)$, then i interacts with j and equations (10) and (11) apply, otherwise she behaves alone and equation (12) holds

(13)

The next step is to model how i chooses j at time t. It is important to remark that the approach adopted here is in line with the dual case interaction of Berliant-Fujita (2009) because even when we are considering N agents, only pair agent interaction is allowed for all agents at period of time t. Agents are scattered in a two dimensional lattice (D2) under the condition that only one agent can occupy a specific place in the lattice given by the coordinates X,Y –in a realistic implementation of the model in the next section, XY would represent the centroid of a Metropolitan Area. An example of the spatial display commented is illustrated in figure 3 for the case of 1000 agents.

[3] Note that in this formulation *j* is passive in deciding interaction because she is only waiting on what *i* decides.

Figure 3
1000 Random agents displayed in a two dimensional lattice



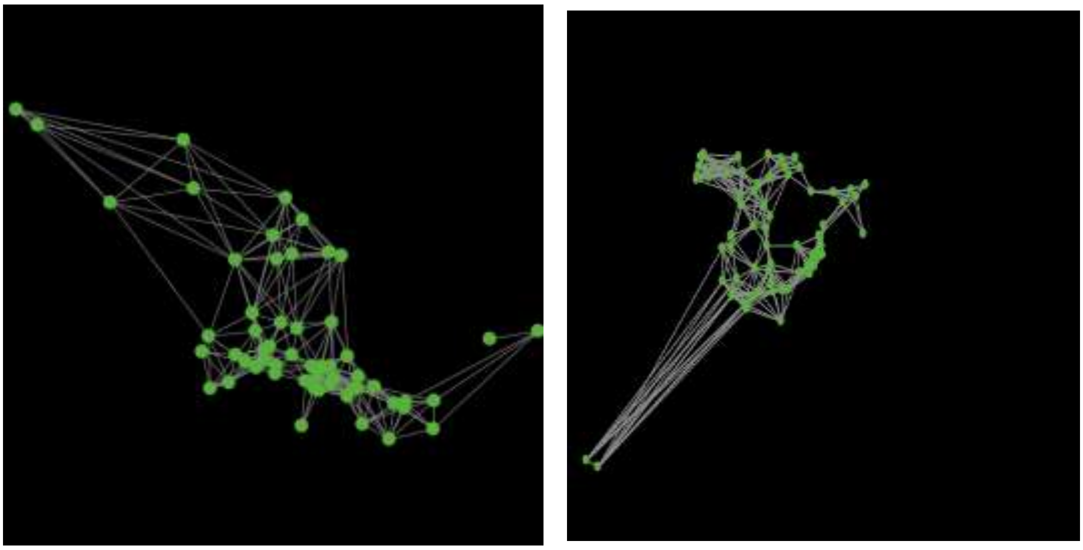
We consider two options of interaction: global and local. Global interaction indicates that agent i chooses j randomly in order to evaluate equation (13). On the other hand, local interaction implies that agent i chooses randomly only one of those j´s that are physically close to i.

To model local interaction, we opt for a network structure of each agent (which other agents they are connected to) based on proximity between agents (given by euclidean distance). The specific rule to create the network structure is through connecting agents by (closest) links, that is, it is a simple graph that does not have loops (self-links) and does not have multiple identical links. The number of agent's links is calculated standardly as follows:

Number of agent links = (average-agent-degree * N) / 2, where average-agent-degree is a parameter that takes a number in the range [0, N] and N accounts for the total nodes which is equal to the number of agents (N).

The average-agent-degree is the same for each agent (because it is a global variable) but the links that connect specific agents tend to be almost different along the range [0, N]. To construct the network, an agent is randomly chosen and connected to the nearest agent that it is not already connected to. This process is repeated until the network has the correct number of links to give the specific average number of neighbors. To illustrate the structure of these networks, figure 4 displays two random networks with an average number of neighbors of 10 for the case of the Metropolitan Areas of Mexico and Spain (each Metro Area is considered an agent). The one on the left corresponds to Mexico while the one on the right to Spain.

Figure 4



With global and local interaction defined, we can define other variables such as total common knowledge (TCK), total differential knowledge of agent i (TDFKij) and total differential knowledge of agent j (DFKji), as follows:

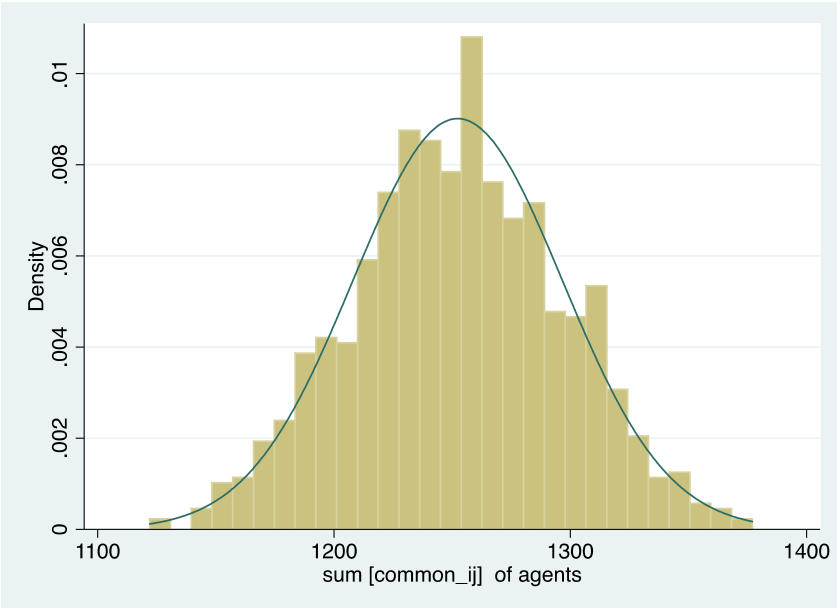
$$TCK_{ij}\,(t) = \sum_{i=1}^{N} CK_{i,j}(t) \qquad (14)$$

$$TDFK_{ij}\,(t) = \sum_{i=1}^{N} DFK_{i,j}(t) \qquad (15)$$

$$TDFK_{ji}\,(t) = \sum_{j=1}^{N} DFK_{j,i}(t) \qquad (16)$$

At each period of time t, all agents execute rule (13) either locally or globally, but note that each agent chooses randomly to whom interact consequently it is important to generate large numbers of t´s to have an idea of how (14), (15) and (16) behave statistically. To illustrate this, Figure 5 displays the histogram of (14) in 1,000 runs of 1,000 agents under the following conditions: t=0 (i.e. initial conditions), m=5 (i.e. no. of creative industries) that are assigned randomly to each agent, and agents chooses globally whom interact to.

Figure 5
Distribution of Common Knowledge of 1000 artificial agents



The standard summary statistics of the last simulations for (14), (15) y (16) is given by table 3.

Table 3
Common and Differential Knowledge

	Obs.	Mean	Std. Dev.	Min	Max
TCK ij	1000	1252.33	44.26	1122	1377
TDFK ij	1000	1248.05	24.90	1166	1329
TDFK ji	1000	1247.87	25.01	1176	1333

* Simulation performed under random conditions

1000 runs, m=5, m´s are assigned randomly

Let us define,

$$M = TCK\,(t) + TDFK_{ij}\,(t) + TDFK_{ji}\,(t) \quad (17)$$

therefore, $\frac{TCK\,(t)}{M} + \frac{TDFK_{ij}\,(t)}{M} + \frac{TDFK_{ji}\,(t)}{M} = 1$. In that way, we could have an estimation of the weight of common knowledge and differential knowledge that prevail in the system. Note that under randomly assigned (0 or 1) values of k to agents, TCK, TDFKij and TDFKji are splitting evenly –and these are the conditions for which Berliant-Fujita establish that the creation of new knowledge is highest. At this point, it is important to mention that in real life is very unlikely that M is divided evenly across TCK, TDFKij and TDFji –see next section for an estimation of Mexico and Spain. Because creative industries are clustered, it would be more likely to find an uneven distribution of common knowledge and differential knowledge.

5. Simulation Results

In this section, we present some simulation results of the model advanced in the last section. As it was mentioned before, the main objective of this paper is to obtain a creativity index from the bottom up and evaluate its performance through different parameter settings.

In order to have an approximation of the three basic variables required in the model, that is, differential knowledge of i, differential knowledge of j, and common knowledge, we use a standard location quotient of the form LQ= ei/e / Ei/E to be applied to each of the sectors (ei) that is part of the creative industries according to UNCTAD classification. Table 4 is a summary of statistics of the LQs for all MAs of Mexico and Spain as dummy variables, that is, if LQi >= 1, LQi =1, otherwise LQi = 0. In that way, each LQi would proxy whether a Metropolitan Area has a type of knowledge (ni) associated with the creative activity of the sector. We are considering 12 creative industrial sectors (following classification of table 1), such that $\sum_1^{12} LQ_i = Tk_i$ would be the total knowledge of Metropolitan Area i. The top panel of table 4 shows estimations of LQi based on total Metro Areas employment in creative industries while the bottom panel displays estimations using total national employment. If we use total MA´s employment as reference (top panel table 4), TK as initial condition (see equation 2) is 92 and 133 for Spain and Mexico respectively from a maximum possible of TK of 804 for Spain and 708 for Mexico (as it is reported in the third row of the table). This implies that 11.4% of MA´s Spain and 18.8% of MA´s Mexico are specialized in at least one of the creative industries. For the case of Spain, Madrid is the Metro Area with the highest Tk (see equation 1) with 12 followed nearly by Barcelona (10); for the Mexican´s case, Mexico City has the highest Tk with 10 followed by Villahermosa (7). A contrasting result between both countries is that 45% of the MA´s Spain is not specialized in any creative industries but only 2% of the MA´s Mexico follows this condition. The mentioned figures change a little bit if we consider total national employment as reference instead of total MA´s employment (see bottom panel of table 4); for example, the percentage of specialized MA´s Spain rises importantly from 11.4% to 17.3% and at least extends in MA´s Mexico from 18.8 to 20.5%. Nevertheless, the number of MA´s Spain without specialization remains relatively high (30%) in contrast to the same figure for Mexico (7%).

Table 4
Total Knowledge (TK) in Creative Sectors

	Spain 2001	Mexico 2003
TK´s based on Metro Areas employment		
No. specialized Metro Areas	92	133
Max of possible specialized MAs.	804	708
% of specialization	11%	19%
1o. Metro Area specialized and No. of specialized sectors	Madrid, 12	Mexico City, 10
2o. Metro Area specialized and No. of specialized sectors	Barcelona, 10	Villahermosa, 7
None specialized MAs (TK = 0)	30	1
% of none specialized	45%	2%
TK´s based on National employment		
No. specialized Metro Areas	139	145
Max of possible specialized MAs.	804	708
% of specialization	17%	20%
1o. Metro Area specialized and No. of specialized sectors	Madrid, 12	Mexico City, 11
2o. Metro Area specialized and No. of specialized sectors	Barcelona, 11	Villahermosa, 8
None specialized MAs (TK = 0)	20	4
% of none specialized	30%	7%

Note: Own estimations calculated with data of INE (2001) and INEGI (2004).TK´s are calculated with location quotients. Only 56 MAs. are considered for the case of Mexico.

Figures 6 and 7 display the histrograms of Tki across metropolitan areas and the normal density associated with data for Mexico (Figure 7) and Spain (Figure 6) using total national employment for the calculations. It can be observed that the distributions are highly skewed to the left (the skewness coefficients are 2.09 and 2.08 for Spain and Mexico respectively) –this is due to truncated data because negative values are not allowed) and that both are significantly peaked (kurtosis coefficients are 7.8 and 9.5 for Spain and Mexico respectively). Also note that the presence of fat right tail in both distributions indicates that some cities (like Madrid, Barcelona or Mexico City) have a relatively large probability to be specialized in almost all creative industries. The means of Tki for both countries are quite similar being 2.46 and 2.07 for Mexico and Spain correspondingly.

Figure 6
Histogram of Tk, Spain (2001)

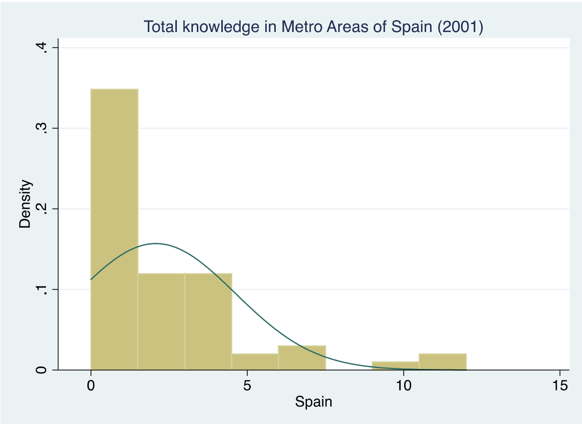
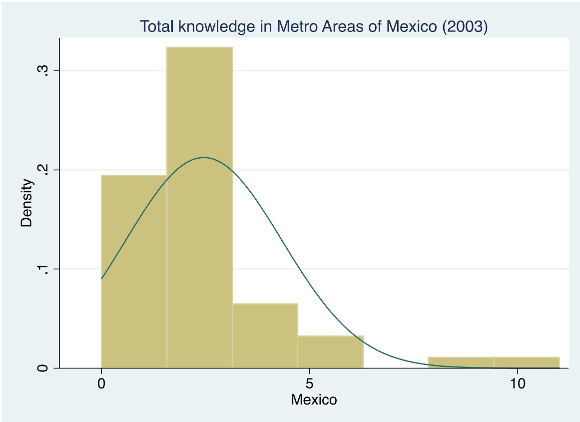


Figure 7
Histogram of Tk, Mexico (2003)



$\sum_1^{56} LQ_{k,i,} = TK_k$ and $\sum_1^{67} LQ_{k,i,} = TK_k$ are both total knowledge by creative sector k across MA´s Spain and MA´s Mexico[4] respectively, and Figure 8 displays the distribution of these TKk of both countries by Spain´s descending order (calculations for LQi are based on national employment). Note that for Spain, R&D in social sciences is the highest TKk concentrating 19% followed by R&D in natural sciences (14%) and Film-Videos (12%) and other artistic activities (12%); while for the case of Mexico, the highest TKk is Radio & TV (16%) followed by visual arts (14%) and other artistic activities (14%)[5]. Likewise, note that computer consulting and publicity are low in both countries.

[4] In the rest of calculations presented, we consider only 56 MAs in Mexico instead of 59 because in 2003 only 56 cities were considered as Metro Areas (see SEDESOL-CONAPO-INEGI (2007).

[5] Mexico reports a low percentage of R&D because census industrial data does not include employment in Universities and other academic places.

Figure 8: TK_k in Metro Areas in Spain and Mexico

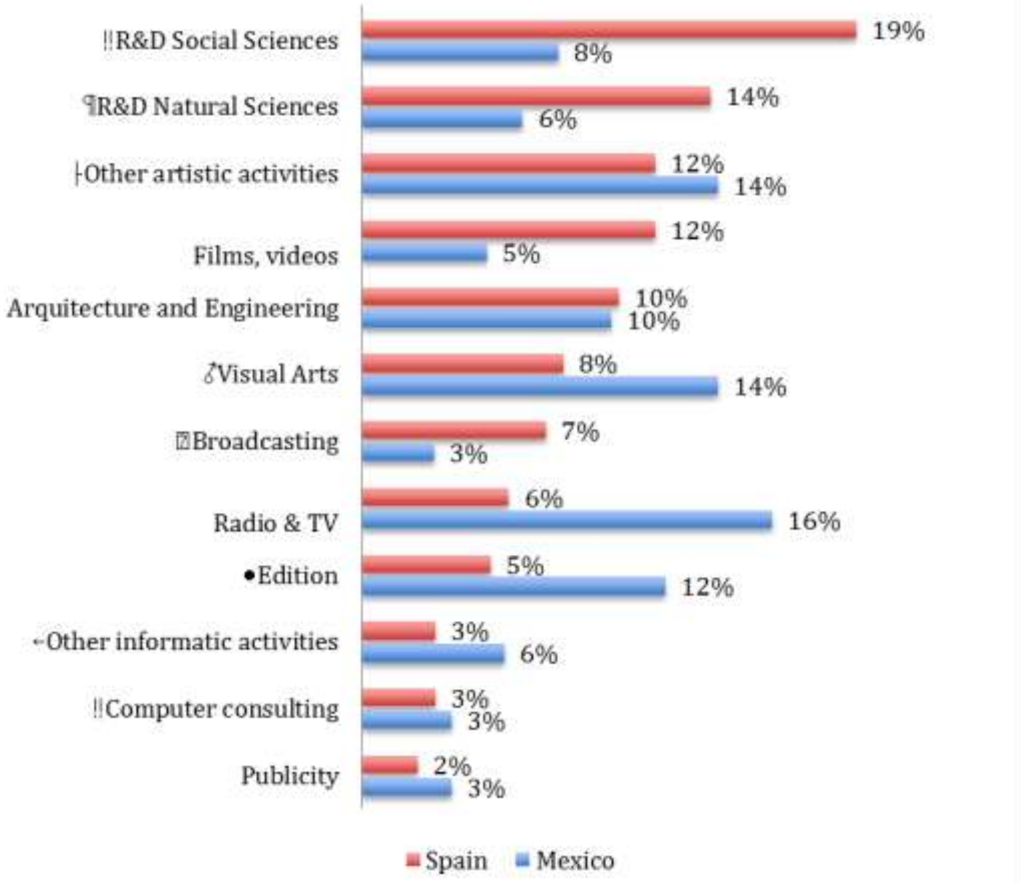


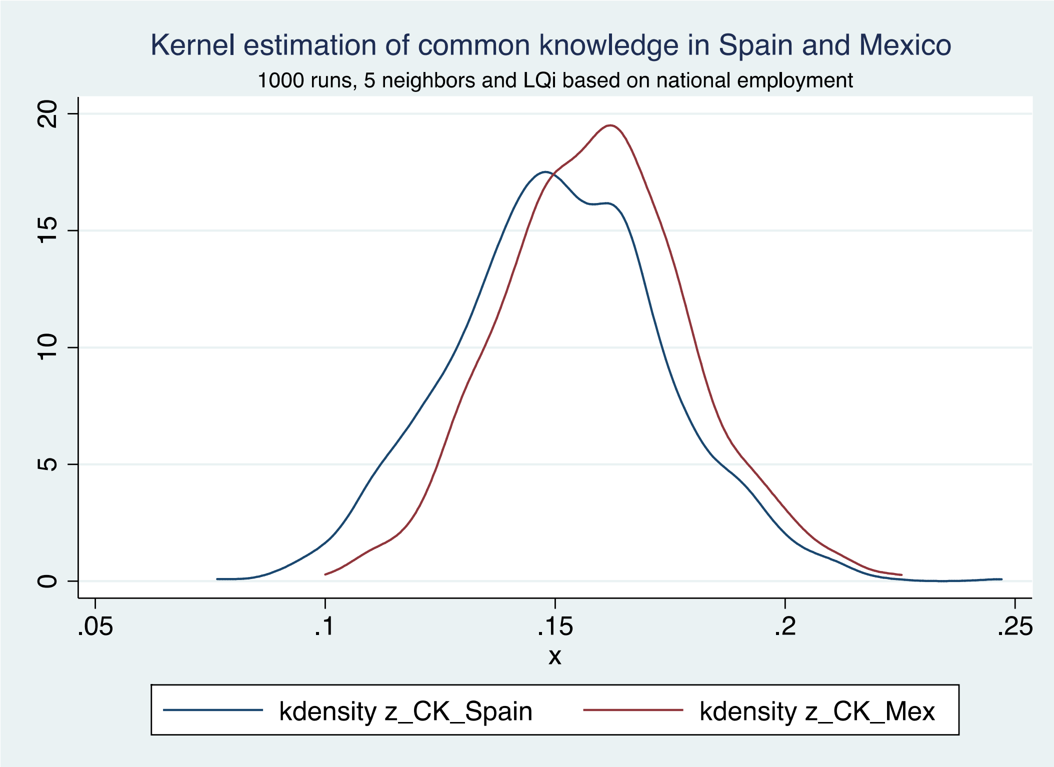
Table 5
Simulation results of Common and Differential Knowledge

	Spain	Mexico
Calculations based on Metro Areas employment		
Common Knowledge, TCK	18	39
Differential knowledge, TDFK ij	74	92
Differential knowledge, TDFK ji	75	93
Total, M	167	224
TCK / M	11%	18%
TDFK ij / M	44%	41%
TDFK ji / M	45%	42%
Calculations based on National employment		
Common Knowledge, TCK	37	40
Differential knowledge, TDFK ij	102	103
Differential knowledge, TDFK ji	105	106
Total, M	244	249
TCK / M	15%	16%
TDFK ij / M	42%	42%
TDFK ji / M	43%	42%

Note: Means of 1000 runs. Simulations performed with 5 neighbors under local interaction conditions.

In table 5 are displayed the means of TCKij (see equation 14), TDFKij (see equation 15) and TDFKji (see equation 16) -and also their proportions according to equation 17- of one thousand runs with an average of 5 MAs local neighbors. If we consider total national employment to calculate LQi´s, Spain and Mexico have 11% and 18% of common knowledge in creative industries respectively and the rest of differential knowledge (44% for Spain and 41% for Mexico). That is, under this experiment, Mexico displays more common knowledge in creative industries than Spain. However, if we consider national employment to calculate LQi´s, the estimation of common knowledge is quite similar in both countries being 15% and 16% in Spain and Mexico respectively. Mexico reduces and Spain increases their common knowledge when national employment is considered in the LQi´s because creative industry employment is more concentrated in the metro areas of Spain (92%) than those of Mexico (84%).

Figure 9

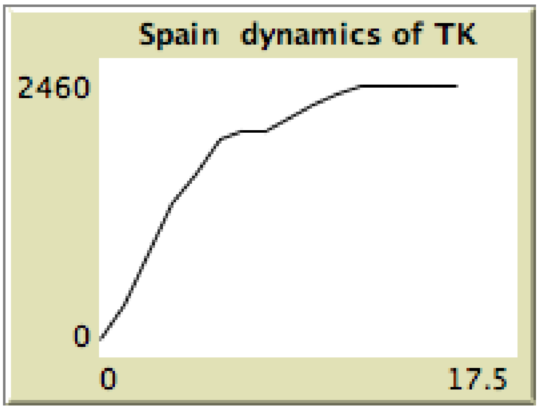


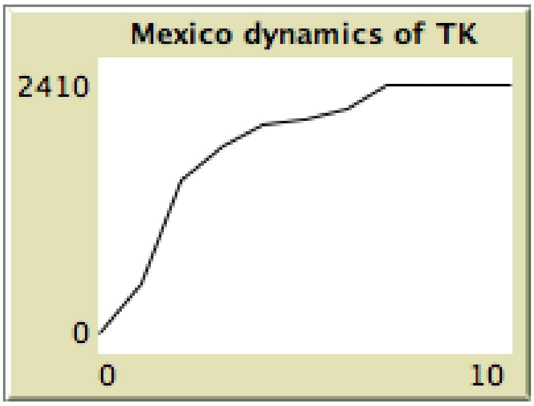
An interesting thing to observe is the distribution of common knowledge. Figure 9 shows the Gaussian kernel distributions for Spain and Mexico of $\frac{TCK(t)}{M}$ (at t=0) based on the simulations performed in table 5 under national employment calculations. Even though the means of common knowledge (TCK/M) are similar between Spain (.151) and Mexico (.159), the estimated distributions are different: Spain´s distribution not only has lower and higher values of common knowledge, but also it seems to display two peaks in the middle of the distribution. Likewise, Spain displays a larger variance than Mexico.

As we mentioned in the last section, we use equation (2) as a measurement of global creativity. Table 4 indicates that if we consider all country employment as reference for the LQ´s calculations, TK at t(0) is 139 and 145 for Spain and Mexico correspondingly. That is, Mexico seems to be more "creative" -under the criteria employed- even when less Metro Areas are considered for the case of Mexico (56) than in Spain (67). Now, given this initial condition, we are interested to evaluate how much TK can rise in both countries under some experiments.

The first experiment presented shows TK dynamics (see equation 13) under some conditions of alpha (associated with individual growth), beta and gamma parameters (associated with collective growth). It is obvious to infer that when alpha > 0, the increase of TK is unbounded; nevertheless, this is not true for positive values of beta and gamma when alpha is zero. This is explained because at some point time new knowledge (see equation 6) and knowledge transfer from j to i and from i to j (equations 7 and 8) are all zero after some periods of interaction. That is, "new knowledge" is a non-renewable resource under the current conditions of the modeling. In general, the increase of TK under the last conditions reaches equilibrium (that is, t+1 = t) in both countries some time before t reaches 15 for the case of Spain and 10 for Mexico. Figures 10 shows two typical runs of the simulation when beta and gamma are equal to 0.1 and alpha is 0. Interestingly, it is that equilibrium is usually different at any run because it depends on initial conditions of interaction.

Figure 10



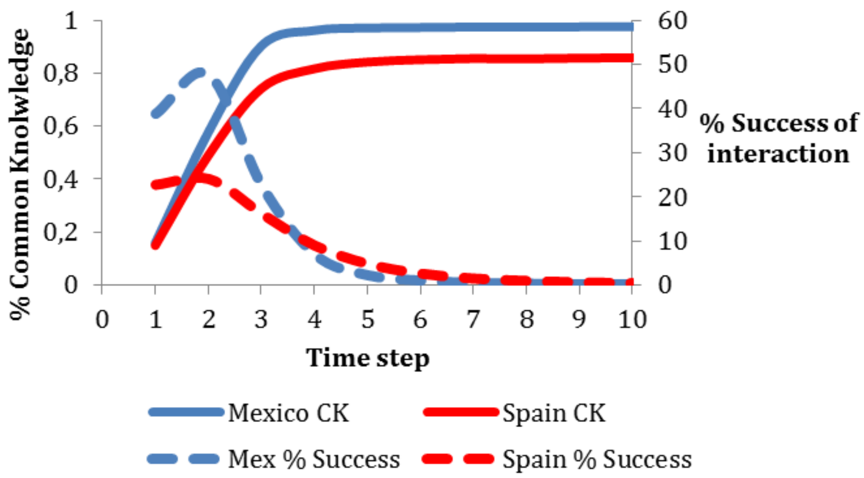


In order to have an idea of how Metro Areas decide to interact to each other, we display in Figure 11 the rate of success of interaction of Metro Areas (see secondary Y´s axes) and common knowledge (primary Y´s axes) produced in the simulations at specific time steps (see X´s axes). We run 1,000 times the simulation and calculate the mean of TK per Metro Area at each time step, values of parameters beta and gamma[6] are set to 0.1 and the simulations are run under local interactions with an average of 5 neighbors. The solid curves of figure 5 show the TCK produced by the simulations and the dashed curves display the % of success of interaction. First, note that success of interaction is higher in Mexico than in Spain in the interval [1, 3]. At t=1 near 40% of Metro Areas in Mexico are better off if they interact to other Metro Area while in Spain that figure is only close to 20%, and when this happens, TCK is around 15% in both countries. At t=2, success of interaction jumps to 50% and 25% for Mexico and Spain respectively, and with TCK of 58% and 49% accordingly. At t > 2, rate of success must fail because at t=2

[6] It is important to remind the reader that in this simulation setting we are considering a rule in where there is a tradeoff of knowledge between *i* and *j*.

TCK reaches the maximum that the theoretical model (à la Fujta-Berliant) establishes (1/3) as benchmark to make a Metro Area better off under interaction. Therefore, a first interesting result derived from the simulations is that even when Spain and Mexico share the same level of TCK in creative industries (see Table 5), Mexico is more suitable to be engaged in Metro Area interaction and able to increase more creativity than Spain.

Figure 11. Dynamic of interaction success



The canonical theoretical model (Fujta-Berliant) predicts that success of interaction would be maximum if TCK is 1/3. In order to see how well this prediction fits under the conditions of the simulations, we display in figures 12 and 13 the scatter plot of TCK (on X´s axes) and rate of success (on Y´s axes) at t=0 for Mexico and Spain. Clearly the central prediction of the model behaves pretty well under the heterogeneity conditions of the model analyzed in this research, in particular, the case of Mexico seems to have a better fit (note that success is maximized close to 1/3).

Figure 12.
Rate of Success of Interaction. Spain (2001)

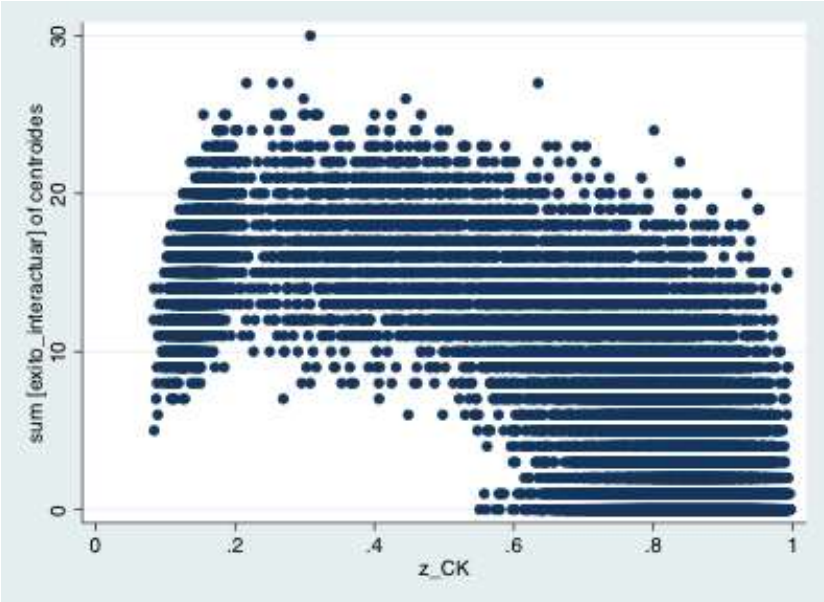
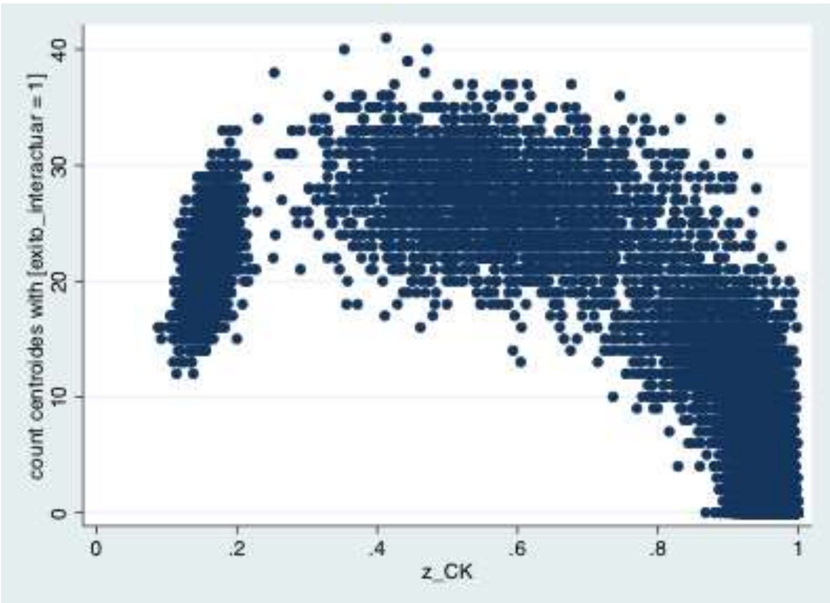


Figure 13.
Rate of Success of Interaction. Mexico (2003)



In order to derive some general patterns of the dynamics, we run 100 times the simulation and calculate the mean of TK per Metro Area at equilibrium under some parameter conditions of beta and gamma (see equations 6-8).[7] Table 6 shows results of several scenarios under the interval parameter [0.1 0.5] of beta, gamma and alpha with increases of 0.1 in each scenario. The particular simulation conditions are the following: 1) local and global interactions imply that in both scenarios alpha is set to 0; 2) local interaction is run with an average of 5 neighbors; 3) non-interaction implies that simulations are run only under equation 12, that is, alpha and gamma are set to 0; 4) policy scenarios imply that at the beginning of the run, we provide arbitrarily specialization in a creative industry -which is chosen randomly- to each of the MAs that does not have previous specialization –this can be understood as a top-down policy that tries to create a "creative cluster" in a Metro Area.

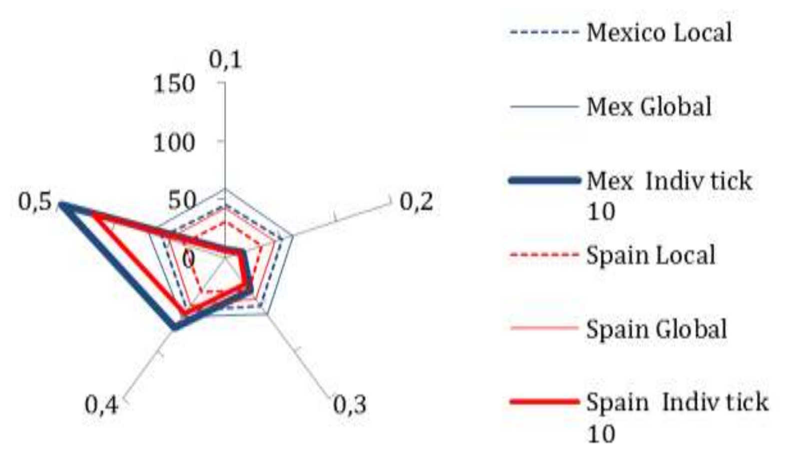
Table 6
TK per Metro Area under different simulation settings

Beta, Gamma, Alpha	0.1	0.2	0.3	0.4	0.5
Mexico					
Local interaction	45	51	52	56	57
Global interaction	59	61	61	63	69
Policy: local interaction	56	56	59	60	67
Policy: global interaction	68	69	65	77	73
Non-interaction	7	16	35	74	147
Policy: non-interaction	7	16	36	75	150
Spain					
Local interaction	31	33	35	36	38
Global interaction	43	45	44	51	50
Policy: local interaction	58	60	66	69	68
Policy: global interaction	86	87	90	89	95
Non-interaction	5	13	29	60	120
Policy: non-interaction	6	15	33	69	137
Ratios Mexico / Spain					
Local interaction	1.5	1.5	1.5	1.6	1.5
Global interaction	1.4	1.3	1.4	1.2	1.4
Policy: local interaction	1.0	0.9	0.9	0.9	1.0
Policy: global interaction	0.8	0.8	0.7	0.9	0.8
Non-interaction	1.2	1.2	1.2	1.2	1.2
Policy: non-interaction	1.1	1.1	1.1	1.1	1.1

Notes: 1) results are the means of 100 runs in each case; 2) in the case of interaction, the average number of neighbors are 5; 3)in local and global interaction alpha parameter is set to 0; 4) in non-interaction beta and alpha are set to 0; TK per Metro Area is measured as TK/N.

[7] It is important to remind the reader that in this simulation setting we are considering a rule in where there is a tradeoff of knowledge between *i* and *j*.

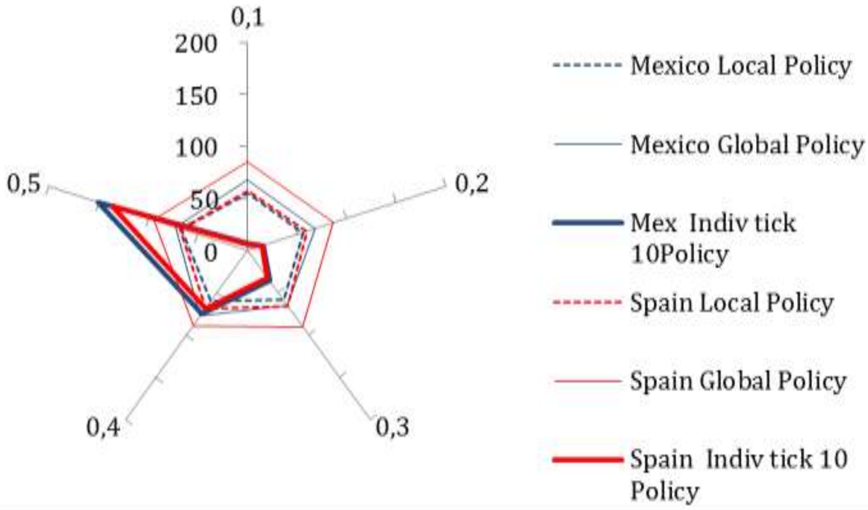
Fifure 14. Simulation scenarios without policy intervention



Firstly, simulation results of Table 6 indicates that TK per Metro Area is most of the times higher in Mexico than Spain across parameter space. For example, in the scenario of local interaction with beta and gamma set to 0.1, Mexico obtains 45 in TK per Metro Area while Spain gets 31; likewise, in the scenario of global interaction with parameter value of 0.5, Mexico has 57 in TK per Metro Area while Spain gets 38 – i.e., 50% more TK. To have a visual idea about the differences between Mexico and Spain across scenarios, we present in Figure 14 a radar chart of the scenarios simulated without policy intervention. The blue lines represent Mexico and the red ones Spain, the solid lines refer to the global case while the dashed lines depict the local interaction scenario, and the wider lines indicate the case without interaction. Figure 14 indicates clearly that Mexico is always above Spain in any of the parameter conditions ("arms" of the chart indicate parameter values). An important result of Figure 14 to highlight is that TK global is in both countries higher than TK local. This is an expected result because transfer and generation of creative knowledge would be greater if every metropolitan area has the chance to interact at least one time with one of the rest of MAs. Nevertheless, local interaction is more likely to happen in real life (because of transportation costs and so forth), which would mean that creative knowledge underperforms under local interactions in both countries. In general the results indicate that Spain gains more from global interaction (an average of 30% premium –calculated over the parameter space) than Mexico (20%). In this sense, it is interesting to see that Spain is pretty close to Mexico when the former is under global interaction and the latter under local interaction; and in particular, Spain reduces its gap when parameter value is 0.4 under global interaction conditions in both countries.

Another important element to point out from Figure 14 is that interaction between Metro Areas either local or global is better than non-interaction (i.e. externalities are only internal to each MAs)8 if the parameter value is less or equal than 0.3. This is an interesting result because it suggests that under these parameter conditions, MAs would be better off –in terms of creativity- if they engage in interaction with the rest of MAs either locally or globally In other words, externalities are better inter than intra when the parameter that boost knowledge (alpha, beta and gamma) is relatively "smaller", otherwise it would be better choosing not to interact with other MAs because intra externalities are more than enough to increase creativity.

Figure 15. Simulation scenarios with policy intervention



The scenarios with policy intervention are displayed in Figure 15. We remind to the reader, that there are 4 and 20 MAs in Mexico and Spain respectively that are not specialized in any of the creative industries –see lower panel of Table 5. Therefore, the policy simulation condition means that at the beginning of the run, it is provided arbitrarily specialization in a random creative industry to any of the MAs that do not have previous specialization. In contrast to the results without policy intervention, now Spain is in general better off than Mexico especially in the case of global interaction in where the gap between Mexico and Spain is wider. The case of local interaction produces nevertheless similar levels of creativity in both countries being slightly higher for Spain. If we contrast the results of policy intervention against those without policy intervention, Spain almost increases –in any condition-

[8] The results of non-interaction are calculated when time step is 10 in both countries, it is important to remark that at this time point almost all global and local runs are quite close to equilibrium in both countries similar to what Figures 10 display for a typical run.

two times its level of creativity per Metro Area while Mexico in average just does it in 10% across parameter space. It is important to remark that the number of Metro Areas that each country has does not bias the results because a standardized measurement (TK per Metro Area) is used in the simulations.

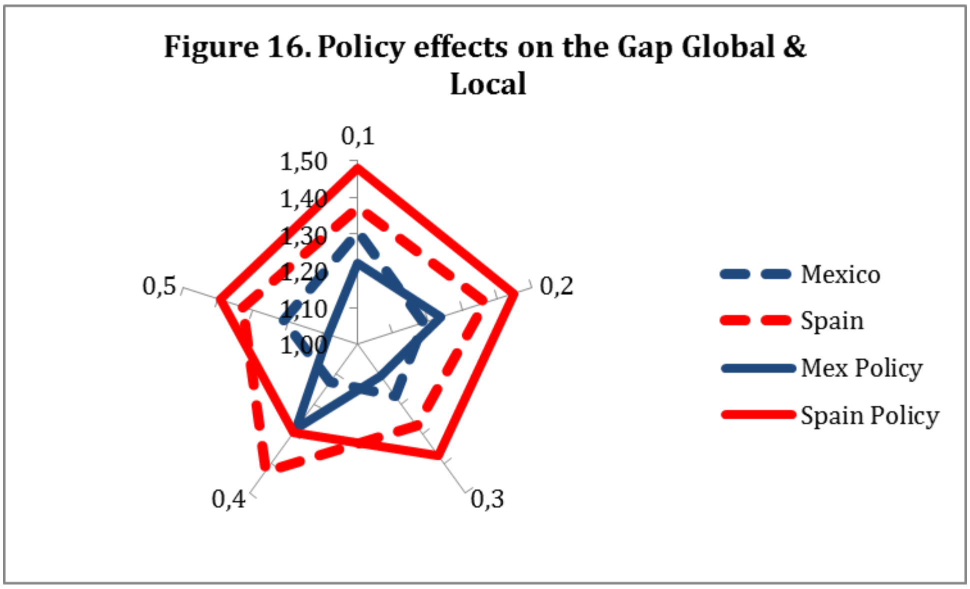


Figure 16 displays how much policy intervention can increase the gap between TK global and TK local interaction (so far, we have showed that in general TK is higher under global conditions of interaction). The results indicate that policy intervention in Spain increases the benefits of global interaction (only the case when the parameter is 0.4, global interaction without policy has a higher ratio), but in Mexico the results are mixed. This last means that even when policy intervention increases TK in Mexico, it could be less effective than in Spain to obtain the benefits of global interaction.

In general, the results under policy intervention increase creative knowledge in both countries but it is more effective for the Spanish case. This is due in part to two spatial components. The first reflects how common and differential knowledge is distributed inter and intra Metro Areas, and the second considers the structure of spatial interaction between MAs that depends on their geographical localization. Therefore, these two elements explain why Spain displays better performance than Mexico even when both countries have the same level of common knowledge in creative industries (around 15%) under the simulation setting adopted. Also, the results can proxy the better infrastructure conditions of transportation (roads, trains, etc.) of Spain that makes global interaction more effective for this country –note that we do not introduce heterogeneity in the distance variable in the modeling which means that transportation costs were homogenous in both countries.

Under the logic of the model advanced in this research, the level of common knowledge must be seen as the benchmark for policy intervention. Table 5 indicates that common knowledge (TCK) –under some parameter conditions– is too low for both countries (around 15%), therefore any attempt to increase TCK would be beneficial because this would increase the interaction and joint knowledge creation between MAs, and regional policy could be a good instrument to do it. In this sense, the key point is to know how much common knowledge and differential knowledge prevail in a specific spatial structure of interaction among MAs; and maybe, this information could be more difficult to obtain for decentralized agents (or MAs) than for a centralized agency.

6. Final Remarks

The model analyzed in this paper establishes that rising creativity depends on the proportions of common knowledge and differential knowledge that a pair of Metropolitan Areas (MAs) face when they interact with each other. Our modeling resembles to that advanced by Berliant-Fuijta (2009) but it differs greatly because is analyzed under less restrictive conditions of agent heterogeneity. We use an agent based approach that allows to incorporate N heterogeneous agents (or MAs), global/local interaction (through networks), and real data with GIS, among other elements that are commonly not suitable for analytical models.

The model analyzed here might provide interesting guidelines for policy design which is oriented to boost creativity in a region or city. First, our approach offers a methodology to measure the aggregate level of common and differential knowledge that prevail in the creative sectors given an initial knowledge (or creativity) endowment. This initial measurement is key to evaluate the potential increase of creativity in a region during a period of time. In the canonical model (à la Fuijta 2007), knowledge creation growth is maximized when there is an even distribution between common and differential knowledge (the same principle can apply for our modeling). This implies that if initial knowledge endowment signals that there is an imbalance between common and differential knowledge then it is likely an under performance of creativity growth, therefore there is room for policy intervention to correct such imbalances.

We have chosen the cases of the Metro Areas of Mexico and Spain to have a first empirical application of the model advanced in this research. We find that under some reliable assumptions, the Metro Areas of Spain and Mexico share the same level of common (15%) and differential knowledge (85%) in the creative industries for the years 2001 (Spain) and 2003 (Mexico). Therefore, there is enough and justified room for policy intervention to try to increase the level of creativity in Metro

Areas by increasing common knowledge throughout –for example– means of public investment in specific creative sectors of Metro Areas. By the same token, this also means that entrepreneurial investment might be substitute of public one to raise creativity in a Metro Area; nevertheless, the actual modeling is quite abstract to analyze this in a coherent way, to do this it is necessary to introduce other economic urban concepts that allow for example to model entrepreneurs (workers) seeking to maximize profits (wages).

An interesting result that our methodology provides is that it indicates clearly when knowledge spillovers spread better under inter metropolitan conditions instead of intra metropolitan ones. There is an important debate in regional economics about the appropriate distance range in which externalities are effective. In the literature of creative industries this debate is also present and, it is not clear under which distance conditions creative spillovers spread better between cities or industries (Boix and Soler, 2014). In the simulation framework that we use in this paper is possible to derive some conditions that make a Metro Area better off in terms of creativity if decides not to interact with other one and, vice versa. In general, it seems that under plausible conditions of simulation –that must be further calibrated in other research– more knowledge externalities are produced if Metro Areas (in Spain and Mexico) interact with another Metro Area instead of engaging in just intra metropolitan dynamics.

Some interesting results of the comparative exercise between Spain and Mexico are the following. First, it is interesting to observe that Mexico (2003) produces higher levels of creativity per Metro Area than Spain (2001) if we consider census data that depicts actual levels of specialization in creative industries in each MA. Nevertheless, this comparative advantage vanishes if we allow policy intervention in the simulation to boost creativity. This happens because simulations suggest that Spain is better suited than Mexico to produce higher knowledge externalities under global interaction between MAs –i.e. interaction that is not conditioned by physical distance. This means that the diffusion and creation of new ideas depends more on short distances for the case of Mexico, in contrast to Spain in where the scope range for diffusion ideas is sensibly larger. Therefore, all this makes policy intervention to diffuse ideas more effective in the Spanish case.

The model analyzed here is at early stage of development. The appropriate extensions must be done in subsequent papers that incorporate a more complex setting of creative industries and occupations with the rest of sectors and, along with the introduction of urban economic concepts. Likewise, it is important to calibrate the model with real data of multiple regions (countries) to have an idea about the distribution of common and differential knowledge worldwide.

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