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Cultural Action and Regional Economic Development: An Audit in the Cameroonian Context

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Abstract

This article highlights the cultural action's usefulness on Cameroonian regions' economic development. The implementation of a spatial econometric model based on cultural corporate data from the GCC (2009) yields the following findings: -A 1% increase in innovation spending on cultural activities in a given region leads to an increase of 1.213% of the region's added value. -A 1% increase in innovation spending by its neighbors increases its added value by 0.782%. -A 1% increase in a region's economic activity level increases its added value by 1.952%. -The increase in subsidies of a unit decreases its added value by 0.330%. Theoretical implications are also presented as well as future research avenues.

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1. Introduction

The regional economic development issue has been tackled by many schools of thought. They are primarily theories on space economics, international trade and geographic economics (Krugman 1991). Then comes the theory of evolutionary economics (Patel and Pavitt 1997) followed by approaches on innovative environments and innovation systems (Edquist 1997). Alongside these theories, a new trend of thought demonstrates the cultural action's role on a locality's economic development. This cultural action[1] aims at developing and sustaining cultural activities in a locality to make them more attractive not only through the creation of cultural structures and products, but also, by innovating[2] on this property.

Some authors (Crouzet et al. 2004, Camors and Soulard 2010, Soldo 2010) view cultural action being undoubtedly an instrument of territorial development. Indeed, the integration of cultural dimension in territorial development's strategies appears as an essential element as far as the cultural influence is a phenomenon testifying the impact of society on others (Soldo 2010). It is a perceived indicator of a city or country towards the outside regardless of its geographical boundaries (Greffe 2006). In other words, cultural action has positive effects on firms' attractiveness (Crouzet et al. 2004). For instance, a museum can provoke new investments in hotels' or catering field, aim at attracting tourists and capturing their purchasing power. In the same vein, artists' presence is also likely to attract companies working in graphic arts and having occasional creative staff. Cultural action also has an important impact on residential choice (DeKeersmaecker 2006). In this case, the residential attractiveness is due to the cultural offer's quality within the territory, the residential offer's level as well as service in transportation means; in short, the quality of services and equipment. Finally, culture and tourism have a mutually beneficial relationship likely to enhance the attractiveness and competitiveness of places, regions and countries (Greffe 2006, OECD 2009). According to these studies, cultural or sporting activities are key drivers for choosing touristic destinations. Touristic and residential choices often yield beneficial effects on neighbouring regions which manage to capture the economic benefits of cultural investments of a locality (Greffe 2006). Thus, one of the main cultural attractiveness' levers lies in the improvement linked to the image portrayed by territories and the living environment they provide.

Yet, this sector long unknown in terms of economic analysis (Benhamou 2008), is still neglected by many African countries (Camors and Soulard 2010, Boucher 2011). It is not prioritized by many developing countries' leaders. Some investigations (IBF-CE 2008, Balamine and Mballa 2010, Four 2010, Boucher 2011, BBEA-UNESCO 2012) on the topic show that there are several hindrances to the emergence of a genuine cultural industry in these countries. According to Balamine and Mballa (2010), funding received by cultural entrepreneurs are generally very scarce and insignificant. In addition, the cultural sector is scarcely considered in national budgets or international aid programs. Boucher (2011) shows that in these countries, few studies (IBF-CE 2008, BBEA-UNESCO 2012)[3] and reliable data can adequately measure the cultural sector's impact. This does not allow rulers to be

[1] It operates on all cultural assets classified in six sectors according to UNESCO and IFO: Music and live performance industry (music publishing, musical concert, theater, ...); Publishing and digital (print or online press, book industry), Cinema and audiovisual production (cinema industry, movie theater, photography, ...), Media and communication (radio station, television, communication agency, internet access provider, ...), Crafts and antiques (plastic art products: sculpture, sewing, basketry, pottery, ...), Visual and graphic arts (painting, choreography, decoration, architecture, ...).

[2] This is cultural innovation.

[3] Studies carried out in Mali and Burkina Faso respectively.

informed about its situation, potentials and needs so that provisions for its development are considered (Four 2010).

Drawing inspiration from the IBF-CE's (2008) and BBEA-UNESCO's (2012) works, the Economic Community of West African States (ECOWAS) set up a methodological guide aimed at preparing studies on African culture's socio-economic impact in its Member States. This methodology was adopted by Mballa et al. (2012) who in a study carried out by the International Francophone Organization (IFO), demonstrate the dynamism of this sector in the Cameroonian landscape. However, these studies are limited in determining the direct contribution of culture economy, thus overshadowing the influence of cultural innovation on regional economic development. This observation leads us to explore the actions of cultural effects on Cameroon[4] regional' economic development, given the overflow effects incorporating cultural investment (Soldo 2010). Our investigation thus aims at determining the impact of cultural action carried out in a region on its economic development and that of its neighbours.

The interest of this investigation lies in helping African governments and particularly that of Cameroon to finance the development of cultural activities in their regions for two main reasons: Firstly, many laws were implemented in the early 2000s for the Cameroonian cultural development (Mballa et al. 2012). However, there is still a keen need for works carried out to support the full inclusion of such a policy in the public budget. Secondly, despite the fruitfulness of empirical research on the cultural economic significance (Benhamou 2008), few works (D'Almeida 2004, Balamine and Mballa 2010) seem to be interested in African countries. Filling this gap could be useful. The rest of this article is organized as follows: Section 2 describes the methodology. Section 3 provides the comments and interpretation of findings. Section 4 concludes and provide some future research avenues.

2. Research methodology

Cultural activities, also called creative activities, affect both creation, production and commercialization of cultural and intangible contents (Thuriot 2010). These activities, being of paramount importance in States' economic and social development (Tiendrebeogo 2010), lead to implementing the production functions widely used in innovation economics to provide measurements to externalities' phenomena. Applying the spatial econometrics techniques to these functions allows to measure in a fine way the extent of interdependence effects in space (Anselin 2003), that is externalities. Therefore, hypothesis tests are implemented to capture the spatial autocorrelation type in data used[5]. In fact, there are three types of spatial specifications as we will see below. Before seeking the appropriate specification, it is recommended to ensure the presence of autocorrelation in the data. Moran's I test is the most applied for this purpose. It is therefore important to present these analytical tools as well as data sources used, before to describe the operationalizing procedure of cultural investments' effects on regions' economic development.

2.1. Analytical tools and data sources

This section presents the basic model used, the Moran's test statistic, the different specifications of spatial models, the test for specification used and the data sources.

2.1.1. The basic model

[4] Cameroon is divided into 10 regions: Adamawa, Center, East, Far North, Littoral, North, Northwest, West, South and Southwest.

[5] If there is no autocorrelation, the OLS are applied.

The functions generally used to capture the overflow effects of an economic activity are the Cobb-Douglas equations in which authors (Anselin et al. 1997, Autant-Bernard 2000, Bottazzi and Peri 2003) integrate slight modifications to consider the distance role between the different production districts. This investigation adopted the Autant-Bernard's (2000) specification because it allows to clearly capture the overflow effects beyond neighbouring regions. The resulting wording is as follows:

$$Log\left(av_{ij}\right)=\alpha+\beta_1 Log\left(inv_{ij}\right)+\beta_2 Log\left(invv_{ij}\right)+\beta_3 Log\left(invvv_{ij}\right)+\beta_4 Log\left(inov_{ij}\right)+\beta_5 Log\left(inovv_{ij}\right)$$
$$+\beta_6 Log\left(inovvv_{ij}\right)+\beta_8 Log\left(sub_{ij}\right)+\beta_9 Log\left(pay_{ij}\right)+\beta_{10} Log\left(wo_{ij}\right)+\beta_7 Log\left(loan_{ij}\right)+\varepsilon_{ij} \quad (1)$$

where :-*Log(av$_{ij}$)* : Logarithm of the annual added value level influenced by the innovation degree in sector i of region j ; -*Log(inv$_{ij}$)* : Logarithm of the investment spending level in sector i of region j; -*Log(invv$_{ij}$)* : Logarithm of the investment spending level in sector i of all regions neighbours to region j ; -*Log(invvv$_{ij}$)*: Logarithm of the investment spending level in sector i of all neighbours to neighbouring regions to j ; -*Log(inov$_{ij}$)* : Logarithm of the innovation spending level in sector i of region j ; -*Log(inovv$_{ij}$)* : Logarithm of the innovation spending level in sector i of all neighbours of region j; -*Log(inovvv$_{ij}$)* : Logarithm of the innovation spending level in sector i of all neighbours to neighbouring regions to j. -*Log(pay$_{ij}$)* : Logarithm of the payroll level in sector i of region j; -*Log(sub$_{ij}$)* : Logarithm of the subsidy level in sector i of region j; -*Log(wo$_{ij}$)* : Logarithm of the workforce level in sector i of region j; -*Log(loanij)* : Logarithm of the level of loans granted in region j to sector i by local banks which allows to take into account the regions' economic size effects[6].

2.1.2. Moran's *I* test statistic

The formula of the Moran's *I* is given by: $I=\frac{n}{s}\left(\frac{\varepsilon' W\varepsilon}{\varepsilon'\varepsilon}\right)$ (2)

Where ε is the vector of error terms ε_{ij} in equation (1), n the number of observations in the regions, n a standardization factor corresponding to the sum of the elements of the spatial weight matrix $W=\left(w_{ij}\right)$ with: $w_{ij}=\begin{cases}1 & if \quad j\in J\\ 0 & if \quad j\notin J\end{cases}$, $w_{ii}=0 \quad \forall i$ (3)

In the context of a contiguity matrix where the regions share the same boundary. J being the set of neighboring regions to i.

In the case of distance, we have: $w_{ij}=\begin{cases}\left(d_{ij}\right)^{-a}\left(\beta_{ij}\right)^{b} & \forall i\neq j\\ 0 & \forall i=j\end{cases}$ (4)

Where d_{ij} represents the distance between the spatial units i and j; β_{ij} the relative part of the distance between i and j in the perimeter of the region i. a and b are parameters fixed a priori. Cliff and Ord (1981) show that this test can be conducted under the null hypothesis of spatial randomization under which the statistic asymptotically follows a standard normal distribution: $Z\left(I\right)=\frac{I-E\left(I\right)}{\sqrt{Var(I)}}\sim N\left(0,1\right)$ (5)

Where: $E\left(I\right)=\frac{n}{s}tr\frac{\left(MW\right)}{n-k}$ and $Var\left(I\right)=\left(\frac{n}{s}\right)^2\frac{\left\{tr\left(MWMW'\right)+tr\left(MW\right)^2+\left[tr\left(MW\right)\right]^2\right\}}{\left(n-k\right)\left(n-k-2\right)}$

[6] The level of loan is used as a proxy in terms of economic activities which reflects the region's size.

$M = I - (X'X)^{-1} X'$ is the usual symmetrical and idempotent matrix; X is the matrix of the explanatory variables of the basic model. The hypothesis of no autocorrelation is rejected when the residues of the OLS lead to a value of Z greater than the threshold value of the standard normal distribution.

2.1.3. Spatial specifications

Anselin et al. (1996) present the three main kinds of spatial autocorrelation specifications. They are:

1) The Spatial Autoregressive Model (SAR), which results from the introduction of a spatially shifted endogenous variable among the explanatory variables of the standard linear model:

$$y = \rho W y + X\beta + \varepsilon \tag{6}$$

With y being the column vector of the dependent variable, ρ the spatial autoregressive coefficient, W the matrix of spatial weights, X the matrix of explanatory variables, β the vector of the regression coefficients and ε the vector of error term.

In a reduced form:

$$y = (I - \rho W)^{-1} X\beta + (I - \rho W)^{-1} \varepsilon \tag{7}$$

This form exhibits the correlation existing between the spatial shift Wy and the error term ε. This correlation is independent of ε distribution. Thus, when ε is such that its elements are $\varepsilon_i \sim iid(0, \sigma^2)$, the mathematical expectation of y can be written:

$$E(y) = (I - \rho W)^{-1} X\beta \tag{8}$$

2) The Spatial Error Model (SEM) is based on the rejection of the hypothesis of spherical errors in the standard linear model, and on the adoption of a spatial process for the error term ε. We thus have:

$$\begin{cases} y = X\beta + \varepsilon \\ \varepsilon = \lambda W \varepsilon + u \end{cases} \tag{9}$$

where λ represents the spatial autoregressive coefficient related to the error term ε, and u a vector of homoscedastic errors. The reduced form of this specification is:

$$y = X\beta + (I - \lambda W)^{-1} u \tag{10}$$

This model is usually implemented to consider the effects of external shocks and/or spatially correlated omitted variables.

3) The third combine the two later into a general spatial model or Spatial Autocorrelation Model (SAC) as follows:

$$\begin{cases} y = \rho W_1 y + X\beta + \varepsilon \\ \varepsilon = \lambda W_2 \varepsilon + u \end{cases} \tag{11}$$

As in the previous cases, this model can be rewritten in a reduced form as follows:

$$y = (I - \rho W_1)^{-1} X\beta + (I - \rho W_1)^{-1} (I - \lambda W_2)^{-1} u \tag{12}$$

2.1.4. The tests for specification

The choice of one of the previous specifications is based on the principles of Wald, Likelihood Ratio or Lagrange Multiplier (LM) test, such that the alternative hypothesis offers an explicit spatial specification (Florax and Nijkamp 2005). Only the LM test is presented because of its robustness. Burridge (1980) and Bivand (1984) show that, after having carried out these specification tests which allow to detect an omission of the spatial autocorrelation and its shape in the model, other specification tests must be carried out to test the presence of offset exogenous variables and to determine the structure of the spatial dependence reflected by the choice of the weight matrix.

2.1.4.1. LM tests for spatial correlation

Developed in a maximum likelihood framework, the LM test refers to a unidirectional alternative hypothesis with one specific misspecification (LM_{ρ}, LM_{λ}) and a multidirectional alternative ($LM_{\lambda\rho}$) comprising various misspecifications tests ($LM_{\lambda}^{*}, LM_{\lambda}^{A}$ $LM_{\rho}^{*}, LM_{\rho}^{A}$).

1) The formula for LM_{λ} is:
$$LM_{\lambda} = \frac{1}{T}\left(\frac{\tilde{\varepsilon}'W\tilde{\varepsilon}}{s^2}\right)^2 \tag{13}$$

Where, $\tilde{\varepsilon} = y - X\tilde{\beta}$ are the OLS residuals, with $s^2 = \frac{\tilde{\varepsilon}'\tilde{\varepsilon}}{n}$ the variance, $T = tr\left(W'W + W^2\right)$ the trace of a quadratic expression in the weight matrix. LM_{λ} follows a χ^2 with one degree of freedom, that is: $LM_{\lambda} \sim \chi^2_{(1)}$. The null hypothesis is $H_0 : \lambda = 0$.

2) The formula of LM_{ρ} looks similar:
$$LM_{\rho} = \frac{1}{nJ_{\rho\beta}}\left(\frac{\tilde{\varepsilon}'Wy}{s^2}\right)^2 \tag{14}$$

where $J_{\rho\tilde{\beta}} = \frac{\left[\left(WX\tilde{\beta}\right)' M\left(WX\tilde{\beta}\right) + Ts^2\right]}{ns^2}$ is the part of the estimated information matrix, $\tilde{\beta}$ the OLS estimated parameter vector, and M the projection matrix $I - X\left(X'X\right)^{-1}X'$. For this case the null hypothesis is $H_0 : \rho = 0$.

In these two unidirectional tests, it is assumed that $\rho = 0$ in the case of LM_{λ} test, and $\lambda = 0$ in the case of LM_{ρ} . For that, Anselin and Bera (1998) remark that these tests will have wrong size due to the existence of the nuisance parameter. In fact, for example, if $\rho \neq 0$ the LM_{λ} test is not more valid, even asymptotically. And, the statistic of the test is no longer distributed according to a χ^2 with one degree of freedom. For a valid statistical inference, it is necessary to take into account the possible endogenous lag variable when testing the autocorrelation of errors and vice versa. In other words, it involves performing a multidirectional test to determine the appropriate specification (Anselin et al. 1996).

3) The multidirectional approach to test spatial correlation in the presence of a nuisance parameter. Anselin (1988) propose a test for both ρ and λ based on the OLS estimation. The statistic of this test is:
$$LM_{\rho\lambda} = \frac{\left(\tilde{\varepsilon}'Wy/s^2 - \tilde{\varepsilon}'W\tilde{\varepsilon}/s^2\right)^2}{nJ_{\rho\beta} - T} + \frac{\left(\tilde{\varepsilon}'W\tilde{\varepsilon}/s^2\right)^2}{T} \tag{15}$$

It is assumed that $W_1 = W_2 = W$, where W_1 is a weight matrix associated to the spatially shifted endogenous variable and W_2 that for the spatial process linked to the error term ε. This statistic follows a χ^2_2 distribution. Anselin et al. (1996) show that this statistic will result in a loss of power compared with the proper one directional test when only one of the two forms of misspecification is present. Then, they proposed two approaches that allow determining the appropriate spatial specification for the data used. In the first approach, they derived a modified LM test statistic for the null hypothesis $H_0 : \lambda = 0$, which is

$$LM_{\lambda}^{*} = \frac{\left[\tilde{\varepsilon}'M_2\tilde{\varepsilon}/s^2 - T_{21}\left(nJ\rho\right)^{-1}\tilde{\varepsilon}'W_1y/s^2\right]^2}{T_{22} - \left(T_{21}\right)^2\left(nJ_{\rho}\right)^{-1}} \tag{16}$$

Where $\left(n\tilde{J}_{\rho\beta}\right)^{-1} = \tilde{s}^2\left[\left(W_1 X\tilde{\beta}\right)' M\left(W_1 X\tilde{\beta}\right) + T_{11}\tilde{s}^2\right]^{-1}$, $T_{ij} = tr\left[W_i W_j + W_i' W_j\right]$, $i, j = 1, 2$ and tr denoting the trace of a matrix. They show that, when $W_1 = W_2 = W$ the trace matrix expressions can be written $T_{11} = T_{21} = T_{22} = T = tr\left[\left(W' + W\right)W\right]$ and the statistic LM_λ^* becomes

$$LM_\lambda^* = \frac{\left[\tilde{\varepsilon}' M_2 \tilde{\varepsilon} / s^2 - T\left(nJ\rho\right)^{-1} \tilde{\varepsilon} W_1 y / s^2\right]^2}{T\left[1 - T\left(n\tilde{J}_{\rho\beta}\right)\right]^{-1}} \tag{17}$$

Setting $\rho = 0$, yields to the conventional one directional test statistic, LM_λ given by Burridge (1980), ie equation (13). Alternatively, considering the LM test $H_0 : \lambda = 0$ in the presence of ρ parameter, they derived the statistic of this test, denoted LM_λ^A, by:

$$LM_\lambda^A = \frac{\left[\hat{\varepsilon}' W_2 \hat{\varepsilon} / \hat{s}^2\right]}{T_{22} - \left(T_{21A}\right)^2 \, \hat{\operatorname{var}}\left(\hat{\rho}\right)} \tag{18}$$

Where $\hat{\rho}$ is a vector of ML residuals under the null model, $y = \rho W_1 y + X\beta + \varepsilon$ obtained by means of no-linear optimization, $T_{21A} = tr\left[W_2 W_1 A^{-1} + W_2' W_1 A^{-1}\right]$, with $A = I - \hat{\rho} W_1$. According to these authors, LM_λ^A cannot be computed using OLS residuals (this is not a problem for LM_λ^*) since in the spatial case the model requires nonlinear optimization even under $H_0 : \lambda = 0$.

In the second approach, they derived a modified LM test for $H_0 : \rho = 0$ denoted:

$$LM_\rho^* = \frac{\left[\tilde{\varepsilon}' W_1 y / \tilde{s}^2 - T_{12} T_{22}^{-1} \tilde{\varepsilon}' W_2 \tilde{\varepsilon} / \tilde{s}^2\right]^2}{n\tilde{J}_{\rho\beta} - \left(T_{21}\right)^2 T_{22}^{-1}} \tag{19}$$

Assuming $W_1 = W_2 = W$ in the context of local misspecification in the form of a spatial MA error process or properly identified AR error process, Anselin et al. (1996) simplified the above expression to:

$$LM_\rho^* = \frac{\left[\tilde{\varepsilon}' W y / \tilde{s}^2 - \tilde{\varepsilon}' W_2 \tilde{\varepsilon} / s^2\right]^2}{n\tilde{J}_{\rho\beta} - T} \tag{20}$$

If $\lambda = 0$, the standard one-directional LM test statistic, LM_β derived by Anselin (1988) is obtained from (20):

$$LM_\rho = \frac{\left[\tilde{\varepsilon}' W_1 y / \tilde{s}^2\right]^2}{n\tilde{J}_{\rho\beta}} \tag{21}$$

Similarly to the LM_λ^A case, the LM test for $H_0 : \rho = 0$ in the presence of λ parameter yields to test statistic denoted by LM_ρ^A:

$$LM_\rho^A = \frac{\left[\hat{\varepsilon}' B' B W_1 y\right]^2}{H_\rho - H_{\theta\rho} \, v\hat{a}r(\hat{\theta}) H_{\theta\rho}'} \tag{22}$$

Where $\hat{\varepsilon}$ is a vector of residuals, in the ML estimation of the null model with spatial AR errors, $y = X\beta + \left(I - \lambda W_2\right)^{-1} \varepsilon$ with $\theta' = \left[\beta' \lambda s^2\right]$, $B = I - \lambda W_2$. $v\hat{a}r(\hat{\theta})$ is the estimated variance matrix for the parameter vector θ in the null model. H_ρ and $H_{\theta\rho}$ are respectively defined as follows: $H_\rho = trW_1^2 + tr\left(BW_1 B^{-1}\right)'\left(BW_1 B^{-1}\right) + \frac{1}{S^2}\left(BW_1 X\beta\right)'\left(BW_1 X\beta\right)$ and

$$H_{\theta\rho} = \begin{bmatrix} \frac{1}{s^2}(BX)' BW_1 X\beta \\ tr\left(W_2 B^{-1}\right) BW_1 B^{-1} + trW_2 W_1 B^{-1} \end{bmatrix}$$

When the P-value of the attached χ^2-statistic of these tests is less than the selected critical value, the null hypothesis is rejected.

2.1.4.2. Tests for the spatial dependence due to the weight matrix choice and offset exogenous variables

Among these tests, there is the common factor test initiated by Burridge (1980) and extended to spatial lags and time delays by Blommestein (1983). There is also the specification test developed by Davidson and Mackinnon (1981) and adapted to space models by Anselin (1984). In the same way, DeBenedictis and Giles (1998, 1999) show that, as many Regression Specification Error Tests (RESET) developed by authors[7], the Ramsey (1969)'s test and the Davidson and Mackinnon (1981)'s test can be extended to non-linear functions by using Fourier's approximation. Their demonstration based on the usual specification test can be summarized as. Consider the following model of interest:

$$y = X\beta + \varepsilon \qquad (23)$$

where X is $(T \times k)$, of rang k, and ε is a Normal, zero-mean disturbance. DeBenedictis and Giles (1999) assume that, if the equation (23) which the appropriate form in this study is equation (1), is misspecified so that $E[\varepsilon/X] = \xi \neq 0$, the RESET test approximates ξ by $Z\theta$ and tests $H_0 : \theta = 0$ in the model $y = X\beta + Z\theta + u$ (24)

They show that, in equation (23), if ε_t s are independent, X is non-stochastic, and Z is random only by being a function of the OLS estimator, b of β, the RESET statistic is exactly F-distributed under H_0. They also found that, generally, Z has t'th row vector given by:

$$Z_t = \left[(Xb)_t^2, (Xb)_t^3, ..., (Xb)_t^{p+1}\right] \qquad (25)$$

so that the F-statistic has p and $(T - k - p)$ degrees of freedom. As in Ramsey and Gilbert (1972) and Thursby (1989), where p is commonly assume to be equal to 1, 2, 3, they set $p = 3$ and support that, as Z is random, the distribution of the RESET test is nonstandard under alternative. And, when X is random (for example, if the model of interest (23) is dynamic) and /or the error terms are autocorrelated, the RESET statistic will not be Fisher (F) under the null, but will asymptotically follow the chi-square when scaling it by its degrees of freedom. In view of this result, they finally approximate ξ with a Fourier expansion to build a test that they call FRESET. The F refers to Fourier. For this purpose, they firstly set: $Z_t = \left[\sin(w_t), \cos(w_t), \sin(2w_t)\cos(2w_t), ..., \sin(p'w_t), \cos(p'w_t\right]$, for some p', where $(Xb)_t$ is transformed to w_t in $[-\pi, +\pi]$. Secondly, they extract from the existing literature two types of Fourier transformation to build their test: A sinusoidal transformation of w_t gives $w_t = 2\pi \sin^2\left[(Xb_t)\right] - \pi$, which defines a specification test called by the authors the FRESETS test. And, a linear transformation defined by $w_t = \pi\left\{2(Xb)_t - \left[(Xb)_{\max} - (Xb)_{\min}\right]\right\} / \left\{(Xb)_{\max} - (Xb)_{\min}\right\}$ which defines FRESETL test. They conclude that the FRESET statistics are Fisher with $2p'$ and $(T - k - 2p')$ degrees of freedom under the null.

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[7] See for example : Ramsey (1969), Hausman (1978), Breusch and Pagan (1979).

Using a Monte Carlos experiment to determine the power properties of FRESET (FRESETL and FRESETS), compared to the RESET proposed by Ramsey (1969), they concluded that their test has a *global validity* contrary to more traditional (local) Taylor's series approximations. DeBenedictis and Giles (1999) have applied this suggested test in the context of auto correlated disturbances and found that it is quite robust to common forms of non-independent errors. The FRESETS and FRESETL tests, without a Newey-west (1987)'s correction, are recommended by the authors if MA (1) or positive AR (1) are respectively suspected. This power of FRESET and the ease of its application lead authors (Drukker et al. 2011, Shehata 2012) to provide researchers with some user-written softwares add-ons that handle and analyze spatial data, and particularly to deal with Regression Specification Error in this context. Recently, the RESET approach has been used by Linderhof et al. (2011) and Katchova and Sant'Anna (2019) to test misspecification and omitted variable bias in their spatial models. Like Ramsey (1969)'s RESET, the FRESET also allows the addition of linear auto correlated variables (L1, L2, and L3) when misspecification is occurred in the model. This variables addition aims to improve the functional form of the model.

In view of the above, the robust specification test developed by DeBenedictis and Giles (1998, 1999) can be conducted to test misspecification and omitted variables bias in our spatial models. The null of this test is H0: Model is specified. As in the previous case, when the P-value of the attached F-statistic is less than the selected critical value, the null hypothesis is rejected.

2.2. Data used and the type of weight matrix chosen

Corporate cultural data were drawn from the database of the General Corporate Census (GCC) conducted in 2009 by the National Institute for Statistics. Cultural firms grouped by sector and region helped to build a base of 72 individuals[8]. These are quantified data for all cultural sectors in each region as the study aims to identify the investment and innovation expenditures' effects in cultural activities on the regions' economic development.

The choice of a type of spatial weight matrix has an impact on the value of spatial correlation coefficients and the estimated regression parameters. However, as it is shown in LeSage and Pace (2011), the sensitivity of these coefficients to the weight matrix is less strong than commonly believed. In this study, a binary weight matrix has been created using the STATA command called "spatweight". This type of weight matrix is chosen because it is the most appropriate (Linderhof et al. 2011). In fact, with this type of matrix, the spatial autocorrelation occurs between nearest neighboring spatial units of the region under study; whatever is their size and shape (Katchova and Sant'Anna 2019). And, the spatial weight matrices are commonly constructed using mathematically computed distances. Then, geographical proximity being the unique criterion to explain neighborhood effects, the size of neighborhoods might be inappropriate. In that vein, Stakovych and Bijmolt (2008) and Farber et al. (2009) showed that less connected weight matrices, ie the contiguity or binary weights matrices, perform better in tests than the matrices with high connectivity, namely distance weights matrices.

2.3. Operationalization of cultural effects on Cameroon's economy

We aim at this level to focus on a descriptive analysis of the variables used and to search the spatial specification, specific to cultural corporate data in Cameroon through the STATA software.

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[8] The number of individuals is 72 because data relate to the six cultural sectors surveyed in each Cameroonian region (10), plus Yaoundé and Douala metropolises set apart because of the magnitude of economic activities in these two regions.

2.3.1. Descriptive statistics of the variables used

Table 1 presents the characteristics of the central tendency and dispersion of the variables used. They have variation coefficients ranging from 7.8% to 62.2%. Those with a variation coefficient less than 30% seem the most stable. These are *Log(invij), Log(invvij), Log(invvvij), Log(inovvvij)* and *Log(loanij)* which variation coefficients are 28.17%, 19.1%, 7.8%, 25.2% and 10.7% respectively. This assumes that the investment's spending evolution in cultural activities is stable, as well as that of the levels of loans granted, thus leading to a quite stable growth in the cultural corporate added value *Log(avij)*, which has a variation coefficient of 34.3%. On the other hand, the *Log(inovij)* variables have variation coefficients of 31.1%. This underlies the differences in innovation spending by cultural industries compared to other investment expenditures. Yet, by summing innovation spending from neighbouring regions to any other region, these factors are found to be quite stable. They are the *Log(inovvij)* and *Log(inovvvij)* variables with variation coefficients of 30.5% and 25.2% respectively. However, this stability degree is not very far from that of the *Log(inovij)* variable, that is, 31.1%. This situation would come from the neighbourhood effect, since the addition of expenditures made by neighbouring regions seems to reduce the differences observed between regions taken individually.

Table 1: Some descriptive statistics of variables used

Variables	Number of observations	Mean	Standard deviation	Variation Coefficient
$Log(av_{ij})$	N=72	8.087	2.775	0.343
$Log(inv_{ij})$		4.892	1.378	0.281
$Log(invv_{ij})$		4.769	0.912	0.191
$Log(invvv_{ij})$		5.605	0.442	0.078
$Log(inov_{ij})$		2.310	0.719	0.311
$Log(inovv_{ij})$		2.480	0.758	0.305
$Log(inovvv_{ij})$		3.044	0.770	0.252
$Log(sub_{ij})$		2.434	1.136	0.466
$Log(pay_{ij})$		2.868	1.806	0.629
$Log(wo_{ij})$		2.322	0.745	0.321
$Log(loan_{ij})$		4.078	0.438	0.107

Source: Author, Data from GCS-Cameroon (2009)

The $Log(subs_{ij})$, $Log(pay_{ij})$, $Log(wo_{ij})$ variables are all very unstable, with variation coefficients of 46.67%, 62.9% and 32.1% respectively. This observation reflects the reality compared to the findings in some investigations (Balamine and Mballa 2010, Dama 2015). Thus, with regard to subsidies ($Log(subs_{ij})$), Dama (2015) shows that there are huge gaps in payrolls' and subsidies' distribution[9]. These differences in grant agreement are not only related to the intensity of cultural activities in regions, but also, to the formal exercise of these activities. This seems to explain the high variation coefficients of the $Log(pay_{ij})$ and $Log(wo_{ij})$ variables. Indeed, companies operating formally receive subsidies, pay better wages and use skilled labor. They are found in Douala and Yaounde metropolises according to this author. The variability degree of the explanatory variables retained, and the output level of cultural sectors have just been apprehended. The spatial dimension should be integrated in this analysis to find the appropriate form of cultural activities' income distribution model.

[9] For instance, using data from the Statistical and Tax Statements, the author shows that the amounts of subsidies granted range from 43,250,000 CFA Francs for the Northern Region, 77,750,000 CFA Francs for the Far North Region, 192,274,000 CFA Francs for the West and 1,375,753,000 CFA Francs for the Douala and Yaounde metropolises.

2.3.2. Seeking for the appropriate specification

This search for the appropriate form of our spatial model required three steps. In the first, we conducted the Moran's I tests. In the second, LM tests were conducted. Lastly, the Robust LM and DeBenedictis-Giles tests were applied. Table 2 presents the Moran's *I* test results. In this table, we note that the global Moran's *I* test applied to the three types of specification confirms the existence of an autocorrelation in the data at 1% or 5% threshold.

Table 2: Moran's *I* and LM tests on types of space effect models

Tests	**Types of specification**		
	SAR	**SEM**	**SAC**
Moran's *I* **Global Moran's *I* test:** (H_0: Data have no autocorrelation)	0.123***	-0.146**	-0.213***
Moran's *I* Error test: (H_0: Error has no spatial autocorrelation)	0.526	2.353**	2.386***

Source: Author, data from GCC-Cameroon (2009)
*** Significant at 1% threshold; ** Significant at 5% threshold.

But, when the test is applied only to the error terms, while using the estimation residuals of the SAR model, no spatial autocorrelation occurs. This is not the case for the SEM and SAC specifications which exhibit an autocorrelation of error terms at 5% threshold. Since the SEM and the SAR are nested in SAC model, more investigations through LM tests are needed to find the exact spatial specification. Table 3 presents the simple and Robust LM tests following Burridge (1980), Anselin (1988) and Anselin et al (1996).

Table 3: Simple and Robust LM tests

Null hypothesis	Parameter		Test statistic	Simple test	Robust test
	Spatial error, λ	Spatial lag, ρ			
$H_0 : \lambda = 0$ (Error has no spatial autocorrelation)	-	-set to zero	LM_{λ}	205,67 (0,0000)	243,70 (0,0000)
		-unrestricted estimated	LM_{λ}^{A}	-	23,31 (0,0000)
		-unrestricted, not estimated	LM_{λ}^{*}	3,97 (0,0461)	3,26 (0,0710)
$H_0 : \rho = 0$ (Spatial lag dependent variable has no autocorrelation)	-set to zero	-	LM_{ρ}	20,05 (0,0000)	19,33 (0,0000)
	-unrestricted estimated		LM_{ρ}^{A}	-	596,28 (0,0000)
	-unrestricted, not estimated		LM_{ρ}^{*}	352,57 (0,0000)	390,61 (0,0000)
$H_0 : \lambda = \rho = 0$ (No General spatial autocorrelation)	-	-	$LM_{\rho\lambda}$	380,47 (0,0000)	380,47 (0,0000)

Source: Author, data from GCC-Cameroon (2009). The p-value are given into brackets.

The simple LM test confirms the existence of spatial autocorrelation in the three types of specification after the use of the OLS residuals got from their estimation. In fact, the p-values are less than 5% leading to the rejection of the hypothesis of no autocorrelation, ie $H_0 : \lambda = 0$, $H_0 : \rho = 0$ and $H_0 : \lambda = \rho = 0$. This results are confirmed by the robust tests which use ML residuals. These robust tests in the context of unrestricted and estimated ρ (for $H_0 : \lambda = 0$) and unrestricted and estimated λ (for $H_0 : \rho = 0$) also lead to presence of spatial error and spatial lag in data used. But, in the case of the $H_0 : \lambda = 0$ test with the unrestricted and not estimated ρ , the p-value is equal to 7.1% up to 5% and less than 10%. This result and the appearance of a spatially autocorrelated error term after the use of SAR model residuals leads to apply the DeBenedictis-Giles' Regression Specification Error Test (FRESET) to verify if there is misspecification due to the choice of the weight matrix and offset exogenous variables or not. Table 4 presents this test results.

Table 4: DeBenedictis-Giles test on types of space effect models

DeBenedictis-Giles misspecification test: (H0 : Model is specified)	**Types of specification**		
	SAR	**SEM**	**SAC**
FRESET-L1	5.114 (0,0090)	0.959 (0,3893)	3.054 (0,057)
FRESET-L2	2.952 (0,0275)	0.651 (0,6284)	1.569 (0,1948)
FRESET-L3	2.594 (0,0276)	0.914 (0,4917)	1.679 (0,1435)

Source: Author, data from GCC-Cameroon (2009). The p-value are given into brackets.

DeBenedictis-Giles test confirms that the data used are not suitable for the use of spatial autoregressive (SAR) model. Indeed, the p-values of the statistics of this test, after using the residues for the SAR model, are less than 5% threshold; leading in the rejection of the H0 hypothesis of good specification. The p-values of SEM model are very high underlying that, it is the best specification. However, the results obtained from the robust LM tests (especially for LM_λ^A , LM_ρ^A and $LM_{\rho\lambda}$ cases) and the p-values of the SAC models obtained from the DeBenedictis-Giles test (5.7% for FRESET-L1, 19.48% for FRESET-L2 and 14.35% for FRESET-L3 up to 5% threshold), show that the specification suitable for this study is the SAC model. The next step is to economically interpret the results provided by this model.

3. Comments and interpretation of results: SAC model

From the previous section, we conclude that the specification specific to data used in this work is the general spatial autocorrelation model (SAC). Table 4 presents the ML results of this specification. Before to comment these results, we provide a rough idea of the quality of this model by giving at the fifth row of this table the log-likelihoods for the three types of spaces model (SAR, SEM and SAC). We note that there is an edge in favor of the SAC model in term of overall fit comparing to SAR and SEM model. In fact, the SAC model log-likelihood is -151.3703 higher than the SEM log-likelihood (-152.08251) which is also higher than the SAR log-likelihood (-155.0007). Also, at the sixth raw, the R^2 obtained in the OLS regression of the equation (1) as well as the R^2 obtained in the OLS regression after transforming the data using the weight matrix are given for this aim. The OLS-R^2 after transforming the data (0.9838) is too higher than that for the case where data are not transformed (0.2659) ie equation (1); showing the overall quality of fit of the SAC model. With these observations, we definitely conclude that the SAC model fit better contrary to the impression that the SEM model do it, as indicated by the DeBenedictis-Giles test: the SEM model p-values for this test are higher than that for SAC model.

Table 4: Results of the appropriate specification

Variables	**SAC model**
Log(av)	**Coefficients**
Log(inv_{ij})	0.758***
Log($invv_{ij}$)	0.288
Log($invvv_{ij}$)	-3.342***
Log($inov_{ij}$)	1.213***
Log($inovv_{ij}$)	0.782**
Log($inovvv_{ij}$)	-2.204***
Log(sub_{ij})	-0.330
Log(pay_{ij})	-0.014
Log(wo_{ij})	0.685**
Log($loan_{ij}$)	1.952***
Constance	8.958
Rho (ρ)	-0.060
Lambda (λ)	0.063***
Sigma (δ)	1.903***
Log-likelihood (SAC model)	-151.3703
Log-likelihood (SEM model)	-152.08251
Log-likelihood (SAR model)	-155.0007
OLS-R^2 (no transformed data)	0.2659
OLS-R^2 (transformed data using weigt matrix)	0.9838

Source: Author, data from GCC-Cameroon (2009)
* Significant at 10% threshold; ** 5% threshold; *** 1% threshold

Now, being convinced that the spatial specification specific to this work is the SAC model, it remains to interpret ML results given in the table. These results are interpreted following the spatial correlation coefficients and the explanatory variables.

3.1. The meaning of spatial coefficients

After controlling for error dependence using our three spatial models (SAR, SEM and SAC), we observed that the SEM and SAC models furnish parameter estimates with the same sign and, with the closer numerical value (see Table A3 in Appendices). Observing the spatial coefficients in the SAC model, $\lambda = 0.063$ is positive and $\rho = -0.060$ is negative. This may indicate that the SEM model is the favorite model for the data used (Golgher and Voss 2015). In fact, as mentioned by the latter, it is not current to observe negative values for spatial coefficient estimates. When they appear in empirical studies, one have to examine them carefully from a theoretical perspective. Thus, following these authors' recommendations, the negative sign for ρ in our SAC model represents residual spatial dependence after accounting for the high ascendency of spatial tessellation in these data reflected in the estimated λ parameter; which exhibit a positive spatial dependence. Nevertheless, this negative sign for ρ is generally treated as the result of competition between firms in different areas or between regions (Elhorst and Zigova 2014, Lu and Cao 2019). The analyzes of competition between firms or regions are generally carried out using their size in terms of turnover, added value, investment, etc. Therefore, we conclude that in our dataset, there are several small regions with low cultural spending , subsidies, payroll and added value; while the metropolitan areas of Douala and Yaoundé, taken apart, have high levels of cultural spending and revenue. On the other hand, their closest neighbors, which are the littoral and southwest regions (for Douala) and the southern, central and eastern regions (for Yaoundé), have low levels of cultural spending and revenue. This interpretation is consistent with the comments we made above on the data description, which accounts for the presence of heteroscedasticity in the dataset. This heteroscedasticity stands for the spatial heterogeneity between the regions. The λ parameter characterizes a dominant positive spatial dependence with regard to the statistical inference conducted previously. Then, the ρ parameter only reflects a residual negative spatial dependence observed essentially around the metropolitan areas of Douala and Yaoundé. This result is similar to those of Golgher and Voss (2015) on the spatial study of poverty in 20 counties in Washington.

The presence of spatial heterogeneity measured by sigma ($\delta = 1.903$) is attributed to structural differences between regions. From the foregoing, one can note that the economic meaning of spatial coefficients indirectly challenges structural factors either by establishing a spatial correlation between regions through the database structure used, or by illustrating the existence of a spatial heterogeneity between these different areas of study. It's therefore essential to identify the interest variables' effects on the Cameroonian economic development.

3.2. The scope of the regression coefficients

Concerning the regression coefficients, the results of the spatial SAC equation estimation give an elasticity of 1.213 for innovation spending in cultural activities in a region j of the sample; 0.782 for innovation spending made by neighbouring regions to j and -2.204 for spending made by neighbouring regions to those close to j. Economically speaking, these findings imply that a 1% increase in innovation investment in the region's cultural activities results in a 1.213% increase in this region's added value. Likewise, a 1% increase in innovation spending on neighbouring regions' cultural activities increases the added value by 0.782%, and a 1% increase in neighbouring regions to those close to j reduces its added value by 2.204%. These findings implies that innovation actions in cultural activities are not permanent in Cameroon regions. Indeed, cultural goods are easily perishable. Tourists generally look for territories that offer new cultural products. Thus, the ability of a territory to produce these goods helps to attract tourists and economic agents from other regions. Then, in Cameroon, any cultural novelty set up in a remote region from a considered region contributes to attracting, for a long period of time, tourists and economic agents from the latter; what could explain the negative impact of remote region innovation spending. However, the closest regions to the innovative one benefit from the externalities due to the passage of tourists through their territories. These results corroborate those of Bottazzi and Peri (2003) who in their investigation on European regions found that a 1% increase in the region's research and development spending is followed by a significant increase of 0.83% of its innovation capacity. Also, a 1% increase in research and development spending in neighbouring regions significantly increases this capacity by 0.25%. In their study, expenditures made by very remote regions are not significant, and do not improve the capacity of the said region.

In the same vein, investments' level made in cultural sectors by a region j significantly increases this region's added value by 0.758%, while a 1% increase in investment expenditures made by neighbouring regions increases, but not statistically significant, this added value only by 0.288%. Also, an increase in investment expenditures by remote regions from the region considered significantly reduces its added value by 3.342%. This finding implies that investment spending carried out by remote regions relative to any region contributes to reducing consumption spending of cultural products in this region. This could explain the tourists' influx in these remote areas and consequently the externalities affecting the nearest regions.

With regard to variables as subsidies and wage expenditures, it should be noted that a 1% increase in the first factor in a region negatively affects the locality's added value by 0.330%, and 1% increase in the second slightly decreases the added value by 0.0142%. This means that a further wages' increase in Cameroonian cultural firms could hinder the creativity spirit and reduce workers' productivity. This observation assumes that the little subsidies granted to cultural firms (D'Almeida and Alleman, 2004) lead cultural entrepreneurs to inefficiently use them. Indeed, instead of reinvesting this money in cultural activities by improving salaries and procuring new production technologies, they prefer to directly use it to create unprofitable activities or purchase physiological maintenance products. In fact, African cultural actors in general and Cameroonians usually underestimate their economic gains (Balamine and Mballa, 2010). In contrast, a 1% increase in cultural jobs in a region improves its added value only by 0.685%. This means that despite the difficulties faced by cultural entrepreneurs, many are those carrying out this activity just out of love for the job, and the sector is still attracting many workers.

Each region's size in terms of economic activities also plays a paramount role in the region's economic development. Indeed, a 1% increase in the economic activity level ($Log(loan_{ij})$) in a given region reflects a rise of 1.952% of this region's added value. These findings illustrate the positive relationship between expenditures in cultural activities and each region's size in terms of activities, synonymous with local economic development.

4. Conclusion and future research avenues

This article aimed at determining the role of cultural action on regions' or countries' economic development. To achieve this goal, theories on cultural resources' attractive role were reviewed before empirically evaluating their influence on Cameroon's regional economies. Marshallian theories on economic agents' location helped to understand cultural resources' attractive role. These theories, supported by the knowledge and innovation economy, address the issue of a locality's cultural notoriety on its attractiveness. The empirical verification of these theories from the Autant-Bernard's (2000) model yields the following results: (a)-A 1% increase in innovation spending in a region's cultural activities leads to a 1.213% increase of this region's added value and therefore in its innovation capacity; (b)-A 1% increase in innovation spending in cultural activities in neighbouring regions increases this capacity by 0.782%, (c)- A 1% increase in neighbouring regions to those close to j reduces its added value by 2.204% ; (d)-A 1% increase of a given region's economic activity level reflects an increase of 1.952% of this region's added value. These findings call for regions and nations to develop cultural activities being effective engines for driving agglomeration economies.

The outcomes of this survey lead us to take a closer look on more conceptual works on cultural action and regional economic development. Extending findings to specific cultural action's techniques is an interesting research avenue. The cultural action's impact on a business sector, its size as well as the regional economic development's effect on residential populations' well-being are equally interesting research topics.

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Appendices

<u>Table A1</u>: OLS regression before applying weight matrix

```
. reg logavij loginvij loginvvij loginvvvij loginovij loginovvij loginovvvij logloa
> nij logsubij logpayij logwoij
```

Source	SS	df	MS			
Model	145.405137	10	14.5405137	Number of obs	=	72
Residual	401.477888	61	6.58160473	F(10, 61)	=	2.21
Total	546.883025	71	7.70257782	Prob > F	=	0.0289
				R-squared	=	0.2659
				Adj R-squared	=	0.1455
				Root MSE	=	2.5655

logavij	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
loginvij	.4122476	.2560159	1.61	0.113	-.0996879	.9241831
loginvvij	-.0901147	.3460242	-0.26	0.795	-.7820328	.6018034
loginvvvij	-.9530396	1.402266	-0.68	0.499	-3.757043	1.850964
loginovij	.670594	.5635054	1.19	0.239	-.4562046	1.797393
loginovvij	1.052194	.581226	1.81	0.075	-.1100389	2.214428
loginovvvij	-.6653451	.8857954	-0.75	0.455	-2.436602	1.105912
logloanij	1.554557	.9635991	1.61	0.112	-.3722784	3.481393
logsubij	-.4337543	.2853414	-1.52	0.134	-1.00433	.1368212
logpayij	.0481214	.1792087	0.27	0.789	-.3102285	.4064713
logwoij	.3462592	.4234763	0.82	0.417	-.500534	1.193052
_cons	3.481628	8.798059	0.40	0.694	-14.11118	21.07443

Table A2: **OLS regression after transforming data by the weight matrix**

```
. reg w1y_logavij w2y_logavij w1x_loginvij w1x_loginvvij w1x_loginvvvij w1x_loginov
> ij w1x_loginovvij w1x_loginovvvij w1x_logsubij w1x_logpayij w1x_logwoij w1x_loglo
> anij
```

Source	SS	df	MS			
				Number of obs	=	72
				F(11, 60)	=	331.10
Model	22359.8774	11	2032.71613	Prob > F	=	0.0000
Residual	368.351695	60	6.13919491	R-squared	=	0.9838
				Adj R-squared	=	0.9808
Total	22728.2291	71	320.115903	Root MSE	=	2.4777

w1y_logavij	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
w2y_logavij	.0466344	.0203389	2.29	0.025	.0059506	.0873183
w1x_loginvij	1.465415	.2089004	7.01	0.000	1.047552	1.883278
w1x_loginvvij	.0877539	.2458855	0.36	0.722	-.4040903	.5795981
w1x_loginvvvij	-1.638121	.7681805	-2.13	0.037	-3.17471	-.1015308
w1x_loginovij	.4624864	.4759147	0.97	0.335	-.4894847	1.414457
w1x_loginovvij	.2207236	.3472765	0.64	0.527	-.4739328	.9153799
w1x_loginovvvij	-.9601795	.6642398	-1.45	0.154	-2.288857	.3684979
w1x_logsubij	.5741323	.1848078	3.11	0.003	.2044616	.9438029
w1x_logpayij	-.6132704	.1233011	-4.97	0.000	-.8599092	-.3666315
w1x_logwoij	.5070891	.3300817	1.54	0.130	-.1531726	1.167351
w1x_logloanij	1.289771	.8712018	1.48	0.144	-.4528924	3.032434
_cons	16.43139	5.155994	3.19	0.002	6.117864	26.74491

Table A3: **LM parameter estimates for the SAR, SEM and SAC models**

Variables	Coefficients		
Log(av$_{ij}$)	**SAR model**	**SEM model**	**SAC model**
Log(inv$_{ij}$)	0.821***	0.821***	0.758***
Log(invv$_{ij}$)	0.231	0.297	0.288
Log(invvv$_{ij}$)	-1.342	-3.347***	-3.342***
Log(inov$_{ij}$)	1.033**	1.216***	1.213***
Log(inovv$_{ij}$)	1.050**	0.804*	0.782**
Log(inovvv$_{ij}$)	-1.370*	-2.257***	-2.204***
Log(sub$_{ij}$)	-0.341	-0.338	-0.330
Log(pay$_{ij}$)	0.038	-0.007	-0.014
Log(wo$_{ij}$)	0.690**	0.737**	0.685**
Log(loan$_{ij}$)	1.896***	2.053***	1.952***
Constance	-3.634	8.426**	8.958**
Rho (ρ)	0.065***		-0.060
Lambda (λ)		0.049***	0.063***
Sigma (δ)	2.024***	1.972***	1.903***

Source: Author, data from GCC-Cameroon (2009)

* Significant at 10% threshold; ** 5% threshold; *** 1% threshold