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GEOGRAPHICAL FEATURES VS. INSTITUTIONAL FACTORS: NEW PERSPECTIVES ON THE GROWTH OF AFRICA AND MIDDLE-EAST

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Abstract

This paper examines Africa's and Middle East's growth performance for the period 1990-2005. It employs a Bayesian Model Averaging method that constructs estimates as a weighted average of Spatial Autoregressive estimates for every possible combination of included variables. One of the results of the paper is that the inclusion of spatial dependencies has a direct impact on the determinants of growth in Africa and Middle-East. Indeed, the methodology used in the paper offers an interesting response to the institution/geography debate on the explanation of growth and development. In particular, our methodology allows a selection of the institutional variables that count to explain low development since the geographical variables are partially integrated in the spatial dependence effect.

ملخص

تبحث هذه الورقة أداء النمو في أفريقيا والشرق الأوسط خلال الفترة من 1990 إلى 2005، مستخدمة طريقة نموذج بايز لإيجاد المعدل، التي تشكل التقديرات باعتبارها المتوسط المرجح للتقديرات المتراجعة ذاتيا لكل توافقية ممكنة من عدد من المتغيرات. ومن بين نتائج هذه الورقة أن تضمين توابع مكانية له تأثير مباشر على محددات النمو في أفريقيا والشرق الأوسط. وتعتبر المنهجية المستخدمة في هذه الورقة في حقيقة الأمر ردا شائقا على مناظرة المؤسسة / الجغرافيا عن تفسير النمو والتنمية. وتتيح منهجيتنا على وجه الخصوص، مجموعة منتقاه من المتغيرات المؤسسية المهمة في تفسير انخفاض مستوى التنمية وذلك نظراً لأن المتغيرات الجغرافية تتكامل جزئيا مع تأثير التبعية المكانية.

1. Introduction

Adam Smith is often cited as a precursor in recent papers on development economics (Sachs, 2003; Malik and Temple, 2005). But it seems that macroeconomists might also quote the famous Maghrebi thinker, Ibn Khaldûn, when they deal with the development of Africa and Middle East. Indeed, in his Al-*Muqaddima* written in Algeria in 1377, Ibn Khaldûn clearly distinguishes two principal elements explaining why certain countries are more developed than others - in Ibn Khaldûn's words, why certain parts of the word are more *civilised*. The first reason refers to what we nowadays call geographical factors. Ibn Khaldûn insists on the influence of the climate on the development of civilisation. He concludes that temperate zones offers better conditions than areas with "extreme conditions" for the development of techniques and thus of production (Ibn Khaldûn, 1402, 128-129). The second reason has an institutionalist flavour. According to Ibn Khaldûn, the Bedouin society does not offer (Ibn Khaldûn, 1402, 229-236) an institutional framework that could promote the growth of civilisation. In particular, Bedouin's economic, legal and social structures do not promote productive labour so that profit opportunities disappear and the Bedouin civilisation tends to decline (Ibn Khaldûn, 1402, 231-32).

It is interesting to notice that these factors are still at the heart of current debates on the failure of certain economies to converge towards the rich countries. The recent literature on economic growth suggests two main alternative explanations. *The geography hypothesis* declares that "the role of geography and resource endowments in development shouldn't be underestimated" (Sachs, 2003). Tropical countries are poorer than countries located in temperate climate (Malik and Temple, 2005). The geography hypothesis advances two issues. Firstly, diseases could block long-term economic development. Secondly, particular geographical circumstances - for instance whether a country is landlocked - limit the country's ability to access a large economic market and therefore lower its production efficiency (Sachs and Warner, 1997; Malik and Temple, 2006). The *institution view* considers that institutions are "the fundamental cause of long-run growth" (Acemoglu et al., 2004). The key idea is that macro-economics problems, like the volatility and poor macroeconomic performance suffered by low developing countries, are symptoms of deeper institutional causes (Acemoglu et al., 2003). Likewise, tropics, germs and crops could affect development but through institutions (Easterly and Levine, 2003). The question that many macroeconomists often ask is: How can we select the pertinent explaining factor?

This is where Bayesian Model Averaging enters into consideration. The problem with traditional econometrician methods is that they do not make sense of the empirical evidence on economic growth because of multiple regressors. Classical econometrics thus offers little help since it suggests that all regressors should be included and therefore lead to "spurious correlation". Many studies have paid attention to the problem of the endogeneity of the different variables used as regressors in modelling and testing growth theories. Durlauf (2001) stresses the limit of the instrumental variables used in growth model: ``because so many factors plausibly matter for growth, it is problematic to identify instruments that simultaneously are correlated with those growth determinants that are included in a regression and uncorrelated with the model's residuals. This problem does not possess any econometric solution." Moreover, in empirical studies, a large set of regressions is run with different combinations of variables. Robustness of a given variable is often evaluated relative to the distribution of coefficients and standard errors generated for the variable (Levine and Renelt, 1992). These types of procedures make it possible for one to reject a set of variables as non robust, due to high collinearity, event though the exclusion of all of them substantially degrades the explanatory power of regression.

Consequently, following the seminal works of Kormendi and Meguire (1985) and Barro (1991), recent researchers (Fernández et al., 2001; Sala-i-Martin et al., 2004) suggest to use Bayesian methods to understand the determinants of growth. Assuming that we do not know which model is true, the Bayesian reasoning attach probabilities to different possible models.

Our contribution deals with two aspects. In the first place, our method includes a spatial dimension that has been recently explored in the empirical literature on economic growth. Indeed, the possibility that space could be a determinant of economic growth is suggested in several of empirical contributions that control geographical effects. Quah (1996) formulates criticisms towards the usual measures of convergence. He argues that most studies treat regions as 'isolated islands' without taking into account effects of interaction due to spatial spillovers. Space influences the channels through which countries interact; however these interactions are not modeled explicitly. In this paper, we introduce spatial modeling based on exogenously provided information about the spatial structure. As in LeSage and Parent (2007), we extend the literature on Bayesian model comparison for ordinary least-squares regression models to include spatial autoregressive specification. We construct estimates as a weighted average of Spatial Autoregressive estimates for every possible combination of included variables. In the second place, in order to examine the importance of the spatial element in the determinants of growth, our study focuses on a specific territory, Africa and Middle East. In much of the empirical literature on economic growth, Africa and Middle East exist primarily as a regional dummy. However recent papers (Block, 2001; Masanjala and Papageorgiou, 2005) suggest that the determinants of growth may be different in Africa from the rest of the world. In this paper we extend a Bayesian Model Averaging methodology used, among other, by Masanjala and Papageorgiou (2005) by taking into account spatial proximity to examine the sources of growth in Africa and Middle East.

This last choice can be justified as well by economic as by historical considerations. From an economic point of view, Africa and Middle East constitute an under-developed "block" whose spatial interrelations have not been studied in the literature on economic growth. Now, concerning Africa, Sachs and Warner (1997) conclude that neighbouring effects (using spatial statistical indexes and dummy variables) are unimportant to explain the determinants of growth. Concerning the Middle East, there is no paper that integrates the spatial component of Middle-East growth. From an historical standpoint, Africa and Middle East experience the same colonial heritage, France, the United Kingdom, Belgium and Portugal being the main former colonies.

The paper is organized as follows. Section 2 focuses on the institution/geography debate on the explanation of growth and development. In section 3, we develop the framework that forms the basis of our study. We propose a unified Bayesian approach to model production growth rates in the context of spatial econometric models. We show to what extent this kind of approach can contribute to our understanding of the Solow growth model to explain cross-country growth patterns. Section 4 describes the data used. Section 5 presents the results. An interesting result of the paper is that it allows an assessment of which of two views - geography or institutions- enjoys the most empirical support. Section 6 concludes.

2. Geography, institutions and development: perspectives on the debate

2.1. Theoretical issues

According to Acemoglu and al. (2001), institutions are the key determinants of current economic performance. They implement instruments for measuring current institutions based on the mortality rates expected by the first European settlers in the colonies. Colonies where Europeans faced higher mortality rates are today substantially poorer than colonies that were healthy for Europeans. They conclude that "Africa is poorer than the rest of the world not because of pure geographic or cultural factors, but because of worse institutions." (Acemoglu et al., 2001, p. 1372).

Sachs (2003) observes that this kind of explanation has an ethnocentric bias in that "it attributes high income levels in the United States, Europe, and Japan to allegedly superior social institutions" (Sachs, 2003, p. 38). Indeed, if we admit Acemoglu et al. (2004, p. 9)'s opinion that *good* economic institutions are those that provide security of property rights, one could conclude that the less developing countries have to adopt the "Western" institutions if they want to develop faster. If we return to Acemoglu et al. or North's theory, *good* has to be interpreted as *efficient* property rights as they were developed in Europe in the eighteenth and nineteenth centuries (North, 2005, chapter ten). Efficient property rights encourage productivity and increase market efficiency (North, 2005, p. 2).

It can also be considered that the geography hypothesis has an ethnocentric inclination. This hypothesis has been advanced in colonial geography writings. The French geographer Pierre Gourou offered a framework for thinking and writing geographically about the tropics, which had an impact on the post-war work of many European geographers (Power and Sidaway, 2004, p. 588). Gourou's *Tropical world*, first edited in French in 1947, already examined the impact of geography on development through two effects. The direct effect of the climate is supposed to limit man's physical and mental activity (Gourou, [1947] 1961, p. 4). The indirect effect acts through tropical diseases and the peculiarities of tropical soils (ibid.). In Gourou's works, the connection between tropical geography and empire was close. It served to restate the case for colonial geography in the service of boosting colonial productivity rather than exploring and discovering new territory as in old colonial geography (Power and Sidaway, 2004, p. 588). According to the famous Caribbean anti-colonialist thinker Aimé Césaire, Gourou's work replaced the ethnocentric biological curse by a geographical curse (Césaire, 1955, p. 40).[1] This geographical determinism is even defended by the economic historian Paul Bairoch who considers that the difference in climate has been a limitative factor in the development of tropical countries (Bairoch, 1971, p. 119). It should be noted, however, that current works do not defend any kind of geographical determinism (Mellinger et al., 2000).

Consequently, in our view, the issue is not to choose between two alternatives that could have a potential ethnocentric bias. The first is that geography equals determinism so that African and Middle-East individuals do not manage to work because of their hot and wet environments. The second is that institutions that these countries adopted in the past impeded the development of growth. The question that we ask is the following: Are the geographical and the institutional hypotheses so antithetical?

For instance, if we look seriously to the often quoted (Acemoglu et al., 2004, p. 13) explanation of Montesquieu (1752) that is qualified as "racist" by Easterly and Levine (2003, p. 6), we learn that the geography and institutional hypothesis are intimately connected:

"S'il est vrai que le caractère de l'esprit et les passions du coeur soient extrèmement différents dans les divers climats, les *lois* doivent être relatives et à la différence de ces passions, et à la différence de ces caractères." (Montesquieu, 1752, p. 373, italics in original).

In our opinion, Montesquieu claims that climate directly influences the formation of laws, and thus the formation of institutions. Following our interpretation, Montesquieu's view can be represented in the following framework:

[1]Aimé Césaire was one of the founders of the anti-colonialist movement whose aim was to impulse a renaissance of the black civilization, *la négritude*.

$$\begin{array}{lcl} \text{Climate} & \Rightarrow \text{Passions} \Rightarrow & \text{Laws (in Montesquieu)} \\ \text{Geography} & \Rightarrow \text{Behaviour} \Rightarrow & \text{Institutions (in modern term)} \end{array}$$

In that perspective, it can be considered that both hypotheses are interrelated. The challenge is then to find a methodology that examines the issue of where to draw the line between geographical and institutional determinants.

2.2. Geography, institutions and spatial dependence: an empirical framework

Economic growth and international trade take place within geographical space, and spatial interactions may shape the ways in which economic development is undertaken in the African and Middle East regions. Theoretical and empirical studies often tend to ignore these spatial patterns of the main determinants of economic growth in which we are interested. Several arguments show that including a spatial dimension counts when one deals with economic development. Furthermore, our opinion is that analyzing spatial interactions between regions can help to make a selection between the geographical and the institutional hypotheses.

Firstly, it must be noted that there is a link between space and geography. Several studies have underlined number of geographical features exerting a strong influence on the ways in which countries trade and interact with one another. Using spatial econometrics models and model selection can help to reveal spatial patterns in growth theory. The empirical literature on growth has first introduced geographical factors into standard models using dummy variables, before moving on more complex models of spatial interaction. Temple (1999) emphasizes that disturbances in cross-country regressions may not be independent. They could be correlated over space due to omitted geographical variables such as climate. These variables can also be used as instruments. Adjustment for spatial correlation raises questions regarding interactions between geographical neighbours.

After controlling variables for human capital, economic outcome and general health status, Bloom and Sachs (1998) show that the incidence of malaria has negative effects on economic performance. It has also been argued that natural environment may affect quality of institutions. Acemoglu et al. (2001) implement settler mortality rates as an instrument for current institutions to determine whether or not the colony is a non-constructive institution that affects contemporary economic performance. When the climate conditions of the colonies were not favourable to European settlers, they were inclined to establish an extractive institution in the colony whose weakness persisted to this day.

In these studies, the spatial dimension is included directly in the regression. Allowing the intercept to differ across countries using dummy variables is also another way of accounting for omitted variables climate or culture. However these regional dummies provide no explanation for such divergences in economic growth. Easterly and Levine (1998) specify a model taking into account effects of policies in neighboring areas and show that regional dummies are no longer significant. We will show that this literature would benefit from exploring spatial econometric models, since they provide new tools for modeling spatial effects in the context of growth.

Secondly, a link between space and institutions should be highlighted so one can speak of a *spatial institutional effect*: institutions, and especially political institutions, are sensitive to the influence of their neighbors. It has been argued that civil wars have contributed to Africa's growth tragedy (Collier and Gunning, 1999a, 1999b). Recent works on geopolitics have set forth how externalities from regions in conflict, such as refugee flows, increase the risk of civil war. Cederman and Gleditsch (2004) have shown a particularly strong association between institutions and conflict at the regional level. Democratic countries surrounded by other countries in mixed zones increase the risks of being involved in conflict. In our paper, we do not restrict these externalities only to flows from countries. The spatial dependence we will propose captures the impact of crises in the neighboring countries. Civil wars can spill over in the form of disruption of communication infrastructure, trade links or refugees. Politically unstable regions will therefore serve as a source of burden.

Figure 1 presents a map of data for the number of years of civil war that a country has experienced between 1960 and 1990. The data displayed are available from the Department of Peace and Conflict resolutions at Uppsala University.

The representation of civil war in Africa and Middle-East is clearly not even, nor is distributed randomly across space. There appear to be area of stable peace as well as regions of conflict. We observe high levels of years at peace among countries in East Africa and South Africa. We find many countries with several years of civil war across a band of countries in central Africa and the Middle East. What emerges from this visual display of conflict over time is that the distribution of peace and conflict shows clear spatial patterns. Although most analysis relates these differences to spatial heterogeneity, the distribution of civil war itself across countries seems strongly correlated with regional context. Civil wars in Lebanon, for example, may not stem from problems with its political institutions, but the fact that it is next to antagonistic neighboring countries. Therefore, it could be misleading to assume that countries are independent observations irrespective of their location.

How can we deal with this spatial effect?

Spatial dependence appears when observations at one location depend on neighboring observations. For instance, the economic development of a country surrounded by politically-unstable countries may be affected due to negative spillovers in the form of lower foreign direct investment inflows and disruption to trade routes. A country economic growth is affected by the performance of its neighbors and by its own relative geographical position.

It is usually substantively meaningful to assume that closer countries are more connected than far away states. In this study we identify the relationships between countries by examining dependence determined by geographical as well as ‘political’ proximity. Indeed, positive and negative interactions rely on distance between countries.

Geographical proximity between countries can be identified in many possible ways, including direct contiguity or measures of distance between particular points. Connectivity between countries may also be defined by metrics other than geographical distances, for example, international trade, alliances, technological proximity or cultural similarity. Traditional measures using contiguity ignore any distances between states that do not share a direct border (e.g., Egypt and Saudi Arabia). In order to implement distances between countries, we use some form of mid-points for each country, such as capital cities in our case, which can be quite far from the outer boundaries (e.g., about 1,800 miles between capital cities of Algeria and Mali).

As can be seen, there are many pairs of states that are not connected by a strict criterion of direct contiguity that would be considered connected with a slightly more inclusive threshold. Lebanon, for example, does not have a land border with Jordania, but expanding the threshold to a higher cut-off value (e.g., 1,000 miles) makes these states connected. The relevant Euclidian distance for a given problem is typically not known with certainty in advance. We will choose a cut-off value of 2,000 miles so that all contiguous countries can be accounted for as neighbors. In order to have a local spatial dependency we limit the interactions using the $k-$nearest neighbor approach. Since on average each country in Africa and Middle-East has about 5 neighbors we set $k = 5$. Therefore, each country can not have more that 5 neighbors and may have less if neighboring countries have their capital located more than 2,000 miles away.

Before describing how to implement spatial specification we will focus on model uncertainty and variable selection methods. Since Barro (1991) and Mankiw et al. (1992) many empirical works have focused on cross-country regressions. A generic form of the empirical growth model regression is:

$$y_i = y_{i,0}\beta + X_i\gamma + Z_i\alpha + \varepsilon_i, \tag{1}$$

where y_i is real per capita growth in country i over a given period, $y_{i,0}$ the initial income and ε_i an unobserved component. We can divide the other regressors in two types. The matrix X_i represents variables whose presence is suggested by the Solow growth model: a set of country specific savings and population growth rate controls. The Solow model is often treated as a baseline from which to build up more elaborate growth models, hence these variables tend to be common across studies. In contrast, the variables Z_i are chosen to capture additional causal growth determinants such as geographical or institutional variables.

Numbers of studies (Levine and Renelt, 1992, Sala-i-Martin, 1997) have tried to identify which possible growth determinants X_i and Z_i remain significant in the presence of various other possible variables. These different theories involve a large number of potential explanatory variables. A key empirical finding is that these potential explanatory variables tend to be highly correlated with one another and, hence, a few factors can extract most of the information contained in them. A contribution of the present paper is to implement alternative approaches to modeling with large macroeconomic variables using the Bayesian model averaging (BMA) approach. One of the advantages of using spatial econometrics resides in the possibility of testing for any remaining spatial autocorrelation, since ignoring it could result in biased coefficient. We will now use a variable selection method that is robust to spatial autocorrelation.

3. Model Uncertainty and Bayesian Model Averaging for spatial models

Bayesian model averaging is an approach to model selection and prediction (Madigan and York, 1999). The idea of this approach is to average across several models instead of selecting one model. In computing the average, each model is weighted by its posterior model probability. Empirical and theoretical results over a broad range of model classes indicate that Bayesian model averaging can provide improved predictive performance as compared to single models. For the spatial econometrics models, LeSage and Parent (2007) showed that Bayesian model averaging can offer improved predictive performance as compared to models that are selected when spatial correlation is ignored. This can also influence model selection results. For example, the inclusion or exclusion of particular explanatory variables may not be apparent when spatial correlation is ignored. In this study some of the geographical effects are captured through the spatial econometric specification which removes some geographical factors and gives more weight to the institutional variables.

Different specifications can be adopted to express the spatial dependence. LeSage and Parent (2007) discuss different spatial econometric models. Based on this article, we use an alternative specification that includes an intercept with a non-informative prior placed on the intercept parameter. This approach is based on the methods proposed Fernandez, Ley and Steel (2001), and is better suited to cases where spatial dependence is significantly different from zero.

We initially consider the Spatial Error Model (SEM) model based as shown in (3), where we include the spatial weight matrix W based on geographical distance as well as political instability. We use polar coordinates of the state capitals to calculate the distance between countries.[2] As explained in the previous section, for a set $S = \{1,\ldots,n\}$ of N countries, a connectivity matrix is a $n \times n$ matrix W which coefficients w_{ij} are equal to:

$$w_{ij} = \begin{cases} \exp\{-dist_{ij}/\phi\}\exp\{-years\ of\ war\} & \text{if } j \in V_i \\ 0 & \text{if } j \notin V_i \end{cases},$$

where for each country *i*, its neighborhood V_i is defined as all countries whose capital cities are located less than 2,000 miles and belonging to the five nearest capitals. We also introduce a scalar ϕ which is usual when we introduce Euclidian distances and exponentiate functions.

The spatial error model is therefore written as:

$$y = X\beta + \varepsilon \tag{2}$$

$$\varepsilon = \lambda W \varepsilon + \nu, \tag{3}$$

with $\nu \sim N(0, \sigma^2 I_n)$.

For each of the m alternative models $M = M_1, M_2, \ldots, M_m$ under consideration, the $g-$prior on the regression coefficients that we designate as β_{M_i} takes the form shown in (4). One motivation behind this prior setting is a desire to provide prior information that will not exert undue influence on posterior conclusions regarding choices between alternative models based on different sets of explanatory variables. Another aspect of the $g-$prior that is attractive in situations involving model comparisons based on alternative sets of explanatory variables is the ability of the prior to take the covariance structure of the explanatory variables into account.

$$\pi_b(\beta_{M_i} \mid \sigma^2) \sim N[\beta_0, \sigma^2 (g_i X'_{M_i} X_{M_i})^{-1}] \tag{4}$$

Given the normal prior for the parameter β, an inverted gamma prior for σ^2 shown in (5) with parameters ν and $\bar{s}^2$ allows us to draw on forms from the conjugate nature of these two prior distributions from standard Bayesian regression theory.

$$\pi_s(\sigma^2) = \frac{(\nu\bar{s}^2/2)^{\nu/2}}{\Gamma(\nu/2)} (\sigma^2)^{-(\frac{\nu+2}{2})} \exp(-\frac{\nu\bar{s}^2}{2\sigma^2}) \tag{5}$$

The results we derive can be extended to the case of a non-informative prior on σ^2, since this arises as a special case when $\nu = \bar{s}^2 = 0$.

When considering a prior for the parameter λ, we note that numerical integration will be required with respect to this parameter to produce the marginal posterior distribution for the SEM models. This allows flexibility in specifying a prior $\pi_r(\lambda)$. Values of the parameter λ must lie in the interval $[\phi_{\min}^{-1}, \phi_{\max}^{-1}]$, where $\phi_{\min}$ and $\phi_{\max}$ are the minimum and maximum eigenvalues of the spatial weight matrix W.

We introduce for the parameter λ a Beta (a_0, a_0) prior centered on zero.

[2]We do not use spatial contiguity matrix because of missing countries. Countries like the Islamic Republic of Iran would have interactions with only one neighbor.

$$\pi_r(\lambda)=\frac{1}{Be(a_0,a_0)}\frac{(1+\lambda)^{a_0-1}(1-\lambda)^{a_0-1}}{2^{2a_0-1}} \quad (6)$$

Using the properties of the multivariate normal and the inverted gamma probability distributions to integrate with respect to β and σ, we can arrive at an expression for the log marginal that will be required for model comparison purposes. Details of this derivation are developed in Appendix.

4. Data

We have selected 56 countries to cover the Africa and Middle East area. In the country selection we met the difficulty of defining the Middle East. We refer to two definitions: the World Bank operational definition which considers most members of the Arab league with Iran (Yousef, 2004), and an historical definition that led us include Turkey and Israel (Owen, 1981).

As shown in Table 1, variables are mainly selected from the World Bank dataset. We choose 50 determinants using the following criteria. First, we include geographical and institutional factors to the neoclassical variables. Our selection is guided by our duty to compare our results to the existent literature on economic growth (Sala-i-Martin et al., 2004, Sachs and Warner, 1997, Mankiw et al., 1992). Secondly, we study the 1990-2005 period since on average real per capital GDP did not grow in Africa over the 1965-1990 (Easterly and Levine, 1997). Furthermore, numbers of African country have undertaken a series of economic reforms since the late eighties. For example, at independence in 1975, Mozambique was one of the world's poorest countries. The country was managed in accordance with socialist principles. It also suffered from a brutal civil war during the eighties. But, in 1987, the government engaged a series of macroeconomic reforms designed to stabilize the economy. Since the multi-party elections in 1994, political stability has led to dramatic improvements in the country's growth rate. During the beginning of the nineties, number of countries (Lebanon, Uganda and Chad) made progress toward rebuilding its political institutions after devastating civil war. As we will further discuss, the African and Middle East economy experienced its highest annual growth rate during the 1990-2005 period (shown in Table 1)

Due to missing observation, the GDP growth rate variable for the Kuwait, Saudi Arabia and Djibouti is based on the periods 1992-2005, 1990-1998 and 1998-2005, respectively.

5. Results

What does the introduction of a spatial feature implies for the understanding of the determinants of economic growth?

5.1. On the spatial effect

Our sample of 56 countries (44 from Africa and 12 from Middle East) suggests that rates of economic growth are not constant over time, nor are they equal across the selected countries. Figure 2 shows the growth of GDP per capita at purchasing power parities between 1990 and 2005. The mean of the average annual growth rates for all African regions in our sample is 1.25%, and the variance value is 8.1×10^{-3}. As noted, the average production growth rates over the study period differ between areas. In addition, the fact that African and Middle-East countries are divided by boundaries(see figure 2) which do not always correspond with the real spatial dimension of ethnicity, religiosity or political ideology, can lead to a measurement error problem that need to be take into account.

Most of the countries in Eastern Africa have the highest average annual growth rates: from the south part of Africa (Lesotho, +2.62%; Mozambique, +2.46%; Botswana, 2.39%), to the north (Chad, 2.43%; Uganda, +2.04%; Sudan, +2.32%; Tunisia, +2.19%). We also observe relatively high growth rate of GDP in Middle-East (Lebanon, 3.19%; Iran, 2.05%). On the contrary, countries inside West and Central Africa present the lowest economic growth rates sometimes with negative values (the Democratic Republic of Congo, -1.4%; Burundi, -0.1%).

Given the evidence of clustering provided by the map, the next step is to test whether there is spatial dependence across countries' economic growth. We first carry out a Moran I test which is highly significant and positive. Results in Table 2 clearly suggest the presence of spatial autocorrelation when we measure the interrelationship of economic growth across neighbouring countries. That means that the average annual growth rates of GDP per capita across countries are clustered. Thus, countries with high (low) GDP per capita growth rates are localized near to other countries with high (low) GDP per capita growth rates. (as shown in table 2)

From a theoretical point of view, spatial dependence can lead to least-squares estimates that are biased and inconsistent. This may invalidate the use of conventional least-squares based on Bayesian model averaging (BMA) techniques.

5.2. Geography and institutions: what do we learn using the Bayesian Model Averaging approach?

To illustrate these differences between least-squares and spatial regression, we will run two MC^3 algorithms. The first sampler is introduced by Fernández et al. (2001, a) and used by Masanjala and Papageorgiou (2005) in the context of cross-country growth studies in Africa. The second sampler introduces spatial effects to identify the true model.

Prior specification of these two algorithms are similar to those proposed by Fernández et al. (2001, a) and LeSage and Parent (2007). Given the size of the parameter space, we would expect to need a fairly large amount of drawings of the MC^3 sampler to adequately identify the high posterior probability models. We shall report results from a run with 2,000,000 recorded drawings. The results based on a different run with 1,000,000 drawings are very close for both samplers. In particular, the best 10 models (those with posterior mass above 5%) are exactly the same in both runs. Many more runs, started from randomly drawn points in model space and leading to virtually identical results, confirmed the good behaviour of the samplers.

Table 5 and Table 4 show the variables appearing in the 10 highest posterior probability models, along with the model probabilities. Variables that appear in each model are designated with a '1', and those that do not appear with a '0'.

5.2.1. What do we learn using Least Squares?

In the case of least-squares, a sampling run of 1,000,000 draws produced 53,109 unique models with 3989 of these models having probabilities > 0.0001, accounting for 95% of the probability mass. This suggests that the BMA procedure is finding regions of the large model space with posterior support and ignoring regions with low support. Second part of the Table 3 presents 'model averaged estimates'; based on parameter estimates from non-spatial models using the posterior model probabilities as weights. Each of these models was estimated using MCMC to produce a set of draws that were weighted by the posterior model probabilities. This allows us to present posterior mean estimates that incorporate model uncertainty. In addition to mean estimates, we used the draws to construct 0.01 and 0.99 'credible intervals', which can be used to draw inferences regarding whether the mean estimates differ from zero.

We find that 3 of the 44 variables (*log GDP ppp 90*, *Rule of law* and *Ethnic Fraction*) appear in all of the 10 highest probability models. The variable *gr nat. Sav. 87-90* enters 9 times whereas the variable $Col.Belge$ appears 7 times. Another 33 variables do not appear in any of the top 10 models, leaving 6 variables that appear 1 to 4 times in the set of top 10 models. Those selected variables can be classified in three categories.

The first category consists of the variables explained in neoclassical models of economic growth: *log GDP ppp 90*, *Educ exp* and *gr nat. Sav. 87-90*. The logarithm of the initial GDP per capita ($GDPin1990$) is significant and appears in most of the models having a posteriori probability > 0.0001. As shown in Table 3, the negative coefficient supports to the catching-up process (Sala-i-Martin, 2004). The importance of these variables confirms the hypothesis of β convergence in the growth model: a country with a weak initial GDP has a higher growth rate. The second important implication of this Solow framework is that the savings rate is a fundamental determinant of economic growth. Countries with lower savings rates will have lower per capita incomes in the steady state and may experience higher economic growth. As shown in Table 3, the posterior probability of the growth national rate of savings is negative (-.0014).

The second category of variables corroborates the geography hypothesis. Firstly, the negative effect of the variable *-5 mortality* confirms the idea that diseases, and especially those that affect the young population, worsen the performance of a country. Africa suffers from high mortality rates of children. Moreover, the variable related to life expectancy (*life exp*), which has a high probability of inclusion, appears to have a positive influence on economic growth (+.0021). Those variables summarize as well the quality of public health institutions in the country as the extent of sickness and disease. The variable $tropicar$ which has a negative effect reveals that countries located within the geographical tropics experience lower growth rates. These results are similar to Gallup et al. (1999). Moreover variables $pop100km$ or $pop100cr$ which have a negative effect reveal that countries characterized by a strong interior density can experience high growth rates (for instance, Uganda and Lesotho). This is not so different from Gallup et al. (1999) since they find that higher interior population density is associated with lower growth *if* the malaria variables are not included. Now, we have considered health factors in our sample estimate. Note that being landlocked could isolate the country from large trading networks (see Gallup et al., 1999). However Lesotho, Uganda and Botswana exert the largest average growth rate of GDP leading to positive and significant effects for the dummy variable $landlock$.

The third category of variables (*Ethnic Fraction*, and $Col.Belge$) relates to the institution view. Concerning the variable *Ethnic Fraction*, the result confirms previous results obtained by Easterly and Levine (1997, 2003) or Sachs and Warner (1997). Ethnic diversity leads to social and political divisions that divert attention from sound policy making. Greater ethnic diversity therefore harms growth since it leads to poorer policy choices. In this view, Africa and Middle East's national borders were drawn by the colonial powers that have impeded the development of effective nation-states and effective economic development (Easterly and Levine, 1997). Even if ethnic diversity can be beneficial at higher level of development (Alesina and La Ferrara, 2005), it must be admitted that, concerning Africa and Middle East, there is a negative effect of fractionalization on growth. Alesina and La Ferrara (2005, 772) estimate that "increasing ethnic fractionalization by one standard deviation would reduce growth by 0.6 percentage points per year". Ethno-linguistic diversity may directly hinder economic development and indirectly shape the underlying institutions that influence economic development (Easterly and Levine, 2003, 21). We can assume that the variable ethnic fraction is related to the impact that colonial heritage has on development.

Indeed, we find that the variable Belgian colony is significant and has a negative impact on growth performance. We test the impact of colonization on growth in Africa and Middle East through two variables. First, we use a timing of national independence measure that had no impact. Second, we classified countries according to the nationality of the former colony: U.K., France, Portugal, Belgium, Italy (Germany "lost" its colonies after the First World War). Even if Portugal has been included twice as a significant variable among the 10 best models, it is Belgium who had a significant negative impact on the growth process. Our result confirms the view according to which Belgian powers have been particularly detrimental because of the extreme form of exploitation employed. British domination would have favored the creation of a stronger local ruling class with beneficial consequences for post-independence political stability (Bertocchi and Canova, 2002, p. 1860). (Table 5)

5.2.2. Do the results change when we use a spatial Bayesian model?

For the MC^3 procedure that allows for spatial dependency, 1,000,000 draws produced only 48,465 unique models, a substantially lower number of models than in the previous case.

Focusing on Table 3, the most important point to make is that the measure of the strength of the spatial dependence λ is highly significant with an averaged estimate of 0.43. This is really of importance since we know that OLS estimation method that assumes independence between observations is inefficient in this case. Table 4 shows the variables appearing in the 10 highest posterior probability models, along with the model probabilities. We find that 2 of the 44 variables (*log GDP ppp 90* and *Rule of law*) appear in all of the 10 highest probability models. The variables *Ethnic Fraction*, *Col.Belge* and *gr nat. Sav. 87-90* enter between 6 and 9 times. Another 30 variables do not appear in any of the top 10 models, leaving 9 variables that appear 1 to 4 times in the set of top 10 models.

Introducing spatial dependencies between regions reveals an interesting feature associated with slower economic growth: the negative association between growth and government spending is stronger. Contrary to the non-spatial case, education expenditure (*educ exp*) has a negative impact on economic growth. This negative effect ($-1.05E-04$) corroborates Temple's conclusion (1999, p.139) that human capital accumulation is not a sufficient condition for growth. Furthermore, Bairoch (1971, pp.88-90) has already observed that significant increases of education expenditures are not crucial in the first stages of development. Finally, this negative effect can be interpreted as an indication that education expenditures suffer from low or even negative returns in developing countries because of the brain drain effect.

The comparison of OLS and SEM models leads us to another interesting result. When we add the spatial dependence effect, one of the institutional variables - atheism- appears to have a larger significant and positive effect. At the same time, the effect of colonial heritage is reinforced. A very interesting result is that taking into account spatial dependence between countries reveals that Portuguese colonialism has a larger positive impact on the growth process (Table 3). Now, Bertocchi and Canova (2002) found that colonial heritage, as measured by the identity of the metropolitan ruler and by the degree of economic inter-penetration, matters for the heterogeneity of growth performances in Africa. Our result reveals to what extent this heterogeneity presents a spatial bias. In other words, there is also a spatial effect that should be considered when we analyze the colonial legacy. This significant impact of neighboring countries could be explained by the fact that former Portuguese colonies like Mozambique benefited from the stability of neighboring countries. Even though violent conflicts forced a large number of people to flee Mozambique, the economy has also recovered at a fast pace from these torn conditions. The political stability of Mozambique's neighbors has improved trade links, transportation infrastructure, and finally had a positive impact on economic growth.

Note also that geographical variables like $zdrytemp$, $zsuptrop$ and $rural\_pop90$ are not significant anymore in the spatial case. In our opinion, this result means that our spatial Bayesian model purges the geographical hypothesis from the location element. Thus, on the whole, except to those variables that are indirectly influenced by geography, the use of a spatial Bayesian methodology leads us to conclude that institutional factors prevail over the geography hypothesis. Significant spatial effects might suggest that in peaceful areas, cooperation agreements among countries will be beneficial for the economic performance of Africa and Middle East. Cooperation could be in the form of improving trade relationships and facilitating communications, among others.

6. Conclusion

The paper investigates the sources of low growth in Africa and Middle East. Using a cross-country growth regression based on Solow models, we carry on an empirical analysis that selects the main factors explaining economic growth by taking into account spatial dependency in the convergence process observed across the African and Middle East countries during the 1990-2005 period. In this paper, we use Bayesian model averaging to address the problem of selecting variables when data exhibits spatial dependence. We provide both theoretical and empirical justifications for spatial regression models.

Compared to the existing literature, we set forth two main results. Firstly, we contribute to the empirics of economic growth when we show that there is spatial inertia in the process of slow growth in Africa and Middle East. African and Middle East countries suffer from the fact that their neighbors are stuck at a low level of development. This result features the thesis according to which there are positive spatial externalities to development: the more your neighbors are developed; the highest is your probability to have an elevated growth rate. According to this result, an analysis of the determinants of economic growth and development in Africa and the Middle-East should include this spatial element. Secondly, the methodology used in the paper results in an interesting response to the institution/geography debate in current development economics. When we take the spatial dependence effect into consideration, we observe that the geography hypothesis is not confirmed. In that sense, our result may corroborate the importance in Africa's growth performance of the institutional heritage that mainly appears through the colonial legacy and the ethnicity fractionalization in low developing countries.

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Figure 1: Number of years of civil war between 1960-1990

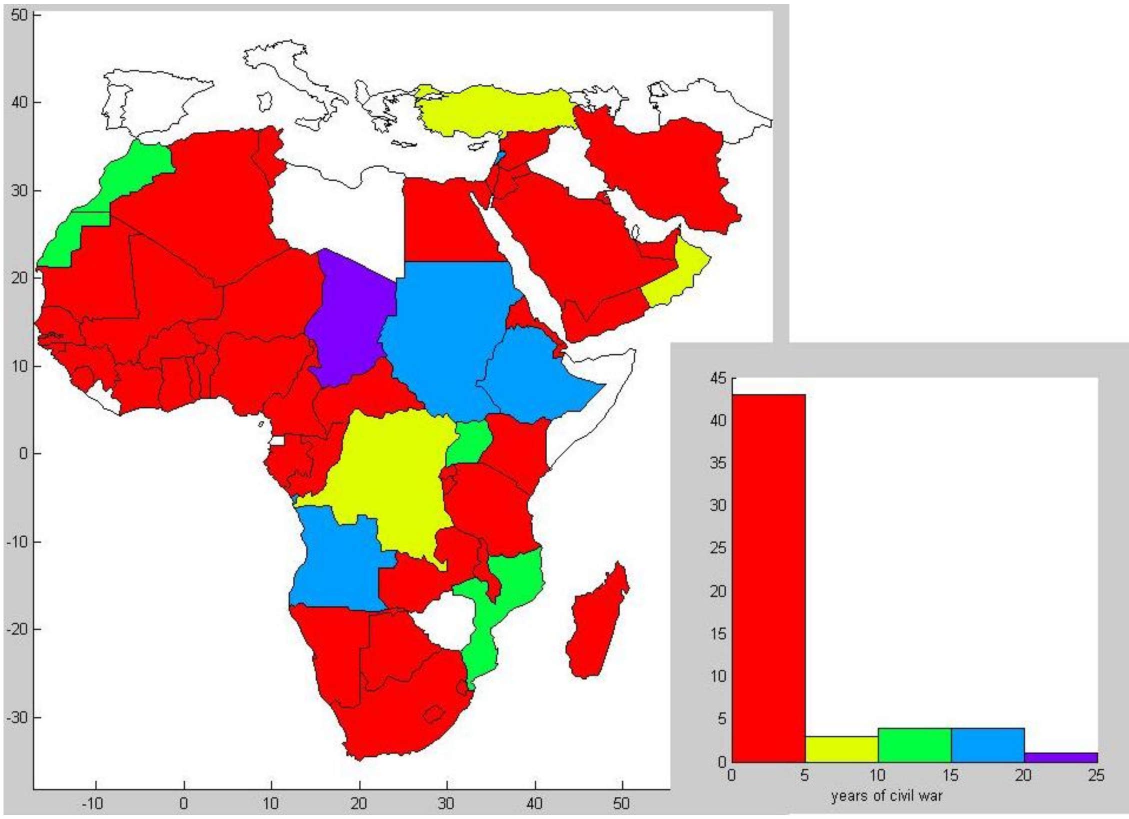

Figure 2: Annualized growth rate of GDP PPP between 1990-2005 (white areas are missing data).

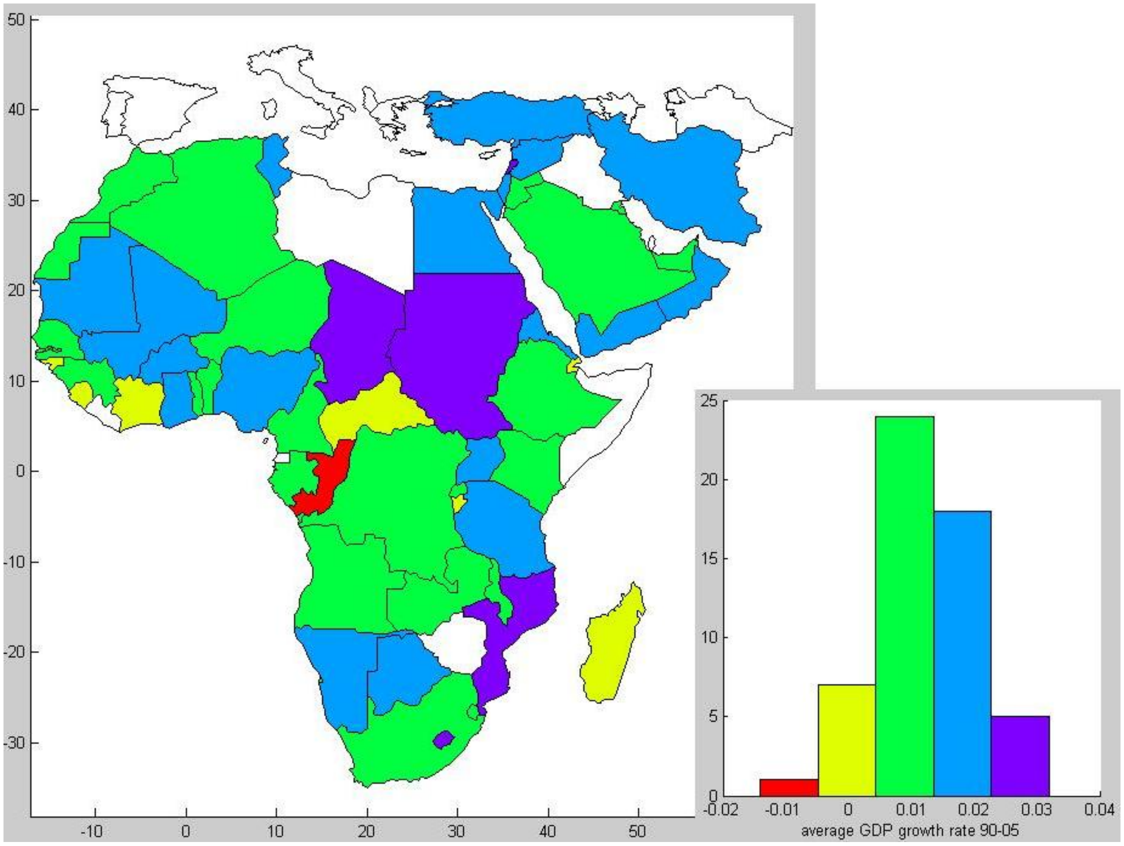

Table 1: Data description and sources

Variable name	Description and sources	Mean	St. D.
Average gr of GDP	Growth of GDP per capita at purchasing power parities between 1990 and 2003. From Development Data Group, The World Bank.	0.029	0.022
GDP in 1990 (log)	Logarithm of GDP per capita at purchasing power parities. From Development Data Group, The World Bank.	3282	4620
Assistance in 1990	Development Assistance: ODA and Aid Received, Current dollars. From Development Data Group, The World Bank.	508.6	758.9
Agri. labour force 90	Labor: Agricultural workers, percentage of total labor force. From Food and Agriculture Organization of the United Nations.	55.5	28.7
Foodprod pc 90	Agricultural Production: Per capita food production index (base year 1999–2001). From Food and Agriculture Organization of the United Nations.	99.8	24.2
Rural pop 90	Rural population (per 1,000 people). From Population Division of the Department of Economic and Social Affairs of the United Nations Secretariat.	8.54	11.05
Life exp 90	Life expectancy, both sexes (1990-1995). From Population Division of the Department of Economic and Social Affairs of the United Nations Secretariat.	54.7	11.4
Liberties	Civil liberties index (1990-1991). From Freedom House.	5.00	1.19
Educ exp 90	Government Expenditure: Public education expenditure as a % of GDP (1990). Development Data Group, The World Bank.	3.91	1.74
GNI PPP 90	GNI: PPP in 1990 (per 10,000 current international dollars). From Development Data Group, The World Bank.	3.17	5.94
Balance 90	Current Account Balance in 1990 (billion dollars). From Development Data Group, The World Bank.	0.011	1.23
Television/1000	Television sets per 1,000 people in 1990.From International Telecommunications Union (ITU).	79.0	129.9
Democracy	Level of democracy/autocracy in 1900 .From Polity IV Project: Political Regime.Characteristics and Transitions.	-5.59	4.83
GN Savings	National Savings: Gross National Savings, percent of GNI in 1990. From Development Data Group, The World Bank.	16.83	10.57
Nb worker in agri	Number of workers in agriculture (thousands) in 1990. From International Labour Organization (Geneva).	3276	4009
Nb worker in manuf	Number of workers in manufacturing sectors (thousands) in 1990. From International Labour Organization (Geneva).	420	688
Nb worker in indu	Number of workers in total industrial sectors (thousands) in 1990. From International Labour Organization (Geneva).	726	1166
Nb worker in services	Number of workers in total in services sectors (thousands) in 1990. From International Labour Organization (Geneva).	1571	2830
Pol rights	Political rights in 1990. From Freedom in the World Country Ratings, Freedom House.	5.50	1.41
Rule of law	Rule of law in 2000. From World Bank Institute, Governance and Anti-Corruption Resource Center.	-0.34	0.74
Ethnic Fraction	Ethnic Fractionalization. From David N. Weil's book, *Economic Growth*	0.61	0.23
Crude oil	Crude Oil Reserves (Billion Barrels) in 2003. From Energy Information Administration, *International Energy Annual* 2002	10.82	40.38
Natural gaz	Natural gaz Reserves (Trillion Cubic Feet) in 2003. From Energy Information Administration, *International Energy Annual* 2002	30.93	116.79
Forest area	Forest area % of total land area in 1990. From Development Data Group, The World Bank.	21.61	21.91
Carbon emission	Carbon dioxide emissions per capita (metric tons) in 1990. From Development Data Group, The World Bank.	2.72	6.08
g/b education	Ratio of girls to boys in primary and secondary education in 1990/91. From Development Data Group, The World Bank.	79.79	16.45
Ratio of literate	Ratio of literate females to males in 1990 (% ages 15-24). From Development Data Group, The World Bank.	77.05	19.41
% women non-agri	Share of women employed in the non-agricultural sector in 1990 (% of total employment in sector). From Development Data Group, The World Bank.	28.48	13.52
Mortality rate -5	Under-five mortality rate in 1990 (per 1,000) .From Development Data Group, The World Bank.	138.21	78.07
Infant mortality	Infant mortality rate in 1990 (per 1,000 live births) . From Development Data Group, The World Bank.	88.07	43.80

Table 1: (Continued)

Variable name	Description and sources	Mean	St. D.
Immunization -12	Immunization rate, measles in 1990 (% of children under 12 months). From Development Data Group, The World Bank.	68.98	18.74
gr pop	From the Population Division of the Department of Economic and Social Affairs of the United Nations Secretariat, World Population Prospects.	2.41	0.63
log G N Saving	Logarithm of the average Gross National Savings between 1990 and 2005 (percent of GNI). From Development Data Group, The World Bank.	15.31	8.40
Independence	Indicator constructed as the inverse of the year of independence.	0.03	0.01
Openness	Ration of exports plus imports to GDP, average over 1990 to 2005 (Barro, 1999). From Development Data Group,The World Bank.	9.16	14.07
Atheist %	Fraction of population Atheist . From the World Christian Database , 2004.	0.001	0.002
Christians %	Fraction of Christian population . From the World Christian Database ,2004.	0.39	0.35
Ethnoreligionist %	Fraction of population Ethnoreligionist . From the World Christian Database , 2004.	0.12	0.15
Jew %	Fraction of Jewish population . From the World Christian Database , 2004.	0.01	0.10
Muslim %	Fraction of population Muslim. From the World Christian Database ,2004.	0.46	0.38
Afr-subtropical	Dummy for sub-tropical African countries.	0.64	0.48
Col France	Dummy for former French Colonies (Barro, 1999).	0.38	0.49
Col UK	Dummy for former British Colonies (Barro, 1999).	0.41	0.50
Col Belge	Dummy for former Belgium Colonies (Barro, 1999).	0.05	0.23
Col Port	Dummy for former Portuguese Colonies (Barro, 1999).	0.07	0.26
Middle East	Dummy for Middle-East countries (Barro, 1999).	0.21	0.41
North-Africa	Dummy for North-African countries.	0.7	0.46
lnd100km	The proportion of the country's land area within 100 kilometers of the coastline, Gallup et al. (1999).	0.24	0.28
pop100km	The proportion of the population within 100 kilometers of the coastline.	0.34	0.32
lnd100cr	The proportion of a country's total land area within 100 km. of the ocean or ocean-navigable river, Gallup et al. (1999).	26.63	31.16
dens95i	*Interior Population/Interior =(Population *(1 − Pop100km))/(Land Area(1 − Lt100km)).* Units: persons per square kilometer, Gallup et al. (1999).	40.98	49.69
landlock	Dummy variable equal to 1 if the country is a landlocked country, and 0 otherwise, Gallup et al. (1999).	0.27	0.45
tropicar	The proportion of the country's land area within the geographical tropics,Gallup et al. (1999).	0.70	0.43
malfal94	Index of malaria prevalence based on a global map of extent of malaria in 1994 (WHO, 1994), and the fraction of falciparum malaria,Gallup et al. (1999).	0.61	0.44
zdrytemp	Holdridge classification for dry-temperate zones ,Gallup et al. (1999).	0.07	0.19
zwettemp	Holdridge classification for wet-temperate zones ,Gallup et al. (1999).	0.02	0.08
zsubtrop	Holdridge classification for sub-tropical zones ,Gallup et al. (1999).	0.36	0.35

Table 2: Tests for spatial autocorrelation

Dependent Variable =	GDP PPP growth rate	
Weight =	row-standardized matrix	
Sample =	56 observations	
Test	Moran I-Statistic	P-value
Global Moran’s I	4.749	0.000
Moran’s I from regression residuals	2.549	0.011

Table 3. Model Averaged estimates

	Spatial	Model			OLS	Model	
Variables	**Posterior mean**	**Lower 0.01**	**Upper 0.99**	**Variables**	**Posterior mean**	**Lower 0.01**	**Upper 0.99**
log GDP PPP 90	-0.0052	-0.0057	-0.0048	log GDP PPP 90	-0.0045	-0.0048	-0.0042
Ethnic Fraction	-0.0027	-0.003	-0.0024	Ethnic Fraction	-0.003	-0.0033	-0.0028
gr nat. sav.87-90	-0.0012	-0.0015	-9.61E-04	gr nat. sav.87-90	-0.0014	-0.0015	-0.0012
col Belge	-9.41E-04	-0.0012	-7.17E-04	col Belge	-0.0011	-0.0013	-9.43E-04
-5 mortality	-4.57E-04	-6.02E-04	-3.05E-04	-5 mortality	-2.45E-04	-3.22E-04	-1.67E-04
pop100cr	-2.10E-04	-2.99E-04	-1.33E-04	tropicar	-1.42E-04	-1.97E-04	-9.06E-05
Forest area	-1.91E-04	-2.61E-04	-1.25E-04	Forest area	-8.94E-05	-1.34E-04	-4.23E-05
lnd100cr	-1.84E-04	-2.62E-04	-1.14E-04	zsubtrop	-4.93E-05	-7.29E-05	-2.55E-05
educ exp	-1.05E-04	-1.62E-04	-5.03E-05	pop100cr	-4.22E-05	-7.16E-05	-1.38E-05
pop100km	-9.86E-05	-1.58E-04	-4.11E-05	pop100km	-3.77E-05	-6.29E-05	-1.22E-05
ztropics	-4.87E-05	-1.00E-04	-1.66E-06	educ exp	-2.05E-05	-3.70E-05	-2.36E-06
tropicar	-4.28E-05	-8.09E-05	-1.25E-05	lnd100km	-2.04E-05	-4.45E-05	-2.90E-06
zsubtrop	-3.44E-05	-8.06E-05	1.25E-05	lnd100cr	-1.72E-05	-3.23E-05	-2.11E-06
Crude oil	-2.50E-05	-6.46E-05	1.72E-05	Ethnoreligionist %	-1.37E-05	-3.35E-05	5.61E-06
Carbon emission	-9.87E-06	-2.60E-05	5.43E-06	ztropics	-1.18E-05	-3.68E-05	-9.40E-06
dens95i	-9.22E-06	-2.25E-05	4.32E-06	Crude oil	-9.21E-06	-2.55E-05	1.05E-05
Ethnoreligionist %	-6.33E-06	-1.95E-05	6.39E-06	Assistance 90	-8.96E-06	-2.56E-05	6.77E-06
Assistance 90	-5.60E-06	-1.67E-05	5.78E-06	Carbon emission	-8.59E-06	-2.80E-05	1.15E-05
dens95c	-3.69E-06	-2.85E-05	1.84E-05	col France	-6.49E-06	-1.74E-05	3.81E-06
Jew %	-2.47E-06	-3.41E-05	2.46E-05	dens95c	-2.15E-06	-1.53E-05	1.04E-05
independance	-2.17E-06	-1.30E-05	9.08E-06	pol right	-2.04E-06	-1.64E-05	1.24E-05
col UK	-2.16E-06	-2.24E-05	1.93E-05	Jew %	-1.92E-06	-1.88E-05	1.80E-05
col France	-2.04E-06	-1.27E-05	9.14E-06	independance	-1.63E-06	-1.55E-05	1.24E-05
g/b education	-1.07E-06	-1.75E-05	1.37E-05	dens95i	-1.38E-06	-1.74E-05	1.39E-05
lnd100km	-5.57E-07	-4.22E-05	4.91E-05	col UK	-9.53E-07	-7.70E-06	5.88E-06
ratio of literate	-1.14E-07	-4.10E-06	3.47E-06	Muslim %	-1.24E-07	-1.70E-05	1.65E-05
pol right	1.03E-06	-2.41E-05	2.81E-05	g/b education	1.53E-06	-9.96E-06	1.35E-05
Christians %	1.22E-06	-1.21E-05	1.25E-05	ratio of literate	1.81E-06	-9.79E-06	1.22E-05
Muslim %	3.18E-06	-1.03E-05	1.69E-05	Christians %	2.58E-06	-4.30E-06	8.56E-06
openness	3.62E-06	-2.74E-06	1.05E-05	gr pop	8.22E-06	-7.07E-06	2.31E-05
gr pop	4.78E-06	-8.05E-06	1.80E-05	democracy	9.88E-06	-6.62E-06	2.67E-05
democracy	8.50E-06	-5.19E-06	2.26E-05	Nb worker in agri	1.18E-05	-8.15E-06	3.13E-05
Nb worker in agri	8.76E-06	-5.80E-06	2.43E-05	Television/1000	1.47E-05	-1.11E-05	4.19E-05
Television/1000	1.25E-05	-5.34E-06	3.03E-05	openness	2.14E-05	-5.33E-06	4.76E-05
zdrytemp	1.93E-05	-1.64E-05	5.14E-05	Atheist %	2.29E-05	-1.34E-06	4.95E-05

Table 3: (Continued)

Variables	Spatial Posterior mean	Model Lower 0.01	Upper 0.99	Variables	OLS Posterior mean	Model Lower 0.01	Upper 0.99
rural pop 90	2.39E-05	-2.73E-05	7.76E-05	GNI PPP	3.35E-05	-7.08E-06	7.58E-05
GNI PPP	2.48E-05	-9.72E-06	5.88E-05	rural pop 90	3.47E-05	1.77E-06	7.16E-05
natural gaz	4.45E-05	-7.17E-06	8.39E-05	zdrytemp	3.52E-05	9.56E-06	6.11E-05
Nb worker in manuf	5.16E-05	7.33E-06	1.24E-04	landlock	3.77E-05	6.51E-06	6.24E-05
landlock	5.94E-05	3.05E-05	8.61E-05	natural gaz	7.53E-05	-7.67E-06	1.29E-04
Atheist %	7.51E-05	3.48E-05	1.17E-04	Nb worker in manuf	7.90E-05	1.88E-05	1.33E-04
col Port	3.95E-04	2.89E-04	5.14E-04	col Port	2.85E-04	2.06E-04	3.70E-04
life exp	0.0026	0.0022	0.0029	life exp	0.0021	0.0019	0.0024
Rule of law	0.0028	0.0024	0.0032	Rule of law	0.0025	0.0022	0.0027
λ	0.4319	0.3609	0.5041				

Table 4: Posterior probabilities for variables entering the spatial model (SEM Model)

Variable /model	10	9	8	7	6	5	4	3	2	1	Prob *
log GDP PPP 90	1	1	1	1	1	1	1	1	1	1	0.995
Assistance 90	0	0	0	0	0	0	0	0	0	0	0.025
rural pop 90	0	0	0	1	0	0	0	0	0	0	0.020
life exp	0	1	1	0	1	0	0	0	1	0	0.612
educ exp	0	1	0	0	0	0	0	0	0	0	0.100
GNI PPP	0	0	0	0	0	0	0	0	0	0	0.055
Television/1000	0	0	0	0	0	0	0	0	0	0	0.025
democracy	0	0	0	0	0	0	0	0	0	0	0.025
Nb worker in agri	0	0	0	0	0	0	0	0	0	0	0.025
Nb worker in manuf	0	0	0	0	0	0	0	1	0	0	0.030
pol right	0	0	0	0	0	0	0	0	0	0	0.030
Rule of law	1	1	1	1	1	1	1	1	1	1	0.970
Ethnic Fraction	1	1	0	1	1	1	1	1	1	1	0.677
Crude oil	0	0	0	0	0	0	0	0	0	0	0.055
natural gaz	1	0	0	0	0	0	0	0	0	0	0.055
Forest area	0	0	1	0	0	0	0	0	0	0	0.110
Carbon emission	0	0	0	0	0	0	0	0	0	0	0.015
g/b education	0	0	0	0	0	0	0	0	0	0	0.025
ratio of literate	0	0	0	0	0	0	0	0	0	0	0.005
-5 mortality	0	0	0	0	0	1	0	0	0	0	0.179
gr pop	0	0	0	0	0	0	0	0	0	0	0.030
independance	0	0	0	0	0	0	0	0	0	0	0.025
openness	0	0	0	0	0	0	0	0	0	0	0.015
Atheist %	0	0	0	0	0	0	0	0	0	0	0.124
Christians %	0	0	0	0	0	0	0	0	0	0	0.010
Ethnoreligionist %	0	0	0	0	0	0	0	0	0	0	0.020
Jew %	0	0	0	0	0	0	0	0	0	0	0.025
Muslim %	0	0	0	0	0	0	0	0	0	0	0.035
col France	0	0	0	0	0	0	0	0	0	0	0.010
col UK	0	0	0	0	0	0	0	0	0	0	0.030
col Belge	1	0	0	1	0	1	1	1	0	1	0.239
col Port	1	0	1	0	0	0	1	0	0	0	0.254
lnd100km	0	0	0	0	0	0	0	0	0	0	0.035
pop100km	0	0	0	0	0	0	0	0	0	0	0.080
lnd100cr	0	0	1	0	0	0	0	0	0	0	0.090
pop100cr	0	0	0	0	1	0	0	0	0	0	0.134
dens95c	0	0	0	0	0	0	0	0	0	0	0.010
dens95i	0	0	0	0	0	0	0	0	0	0	0.010
landlock	0	0	0	0	0	0	0	0	0	0	0.080
tropicar	0	0	0	0	0	0	0	0	0	0	0.060
zdrytemp	0	0	0	0	0	0	0	0	0	0	0.040
zsubtrop	0	0	0	0	0	0	0	0	0	0	0.055
ztropics	0	0	0	0	0	0	0	0	0	0	0.065
gr nat. Sav. 87-90	1	1	0	1	0	1	1	1	1	1	0.388
Variables included	7	6	6	6	5	6	6	6	5	5	
Model Probabilities	0.004	0.005	0.005	0.005	0.006	0.006	0.006	0.007	0.007	0.009	

* : Probability of apparition calculated from the 900 last models (covering 95.0% of the probability mass).

Table 5: Posterior probabilities for variables entering the non-spatial model (OLS Model)

Variable /model	10	9	8	7	6	5	4	3	2	1	Prob *
log GDP PPP 90	1	1	1	1	1	1	1	1	1	1	0.934
Assistance 90	0	0	0	0	0	0	0	0	0	0	0.018
rural pop 90	1	0	0	0	0	0	0	0	0	0	0.050
life exp	0	0	1	0	0	0	1	1	1	0	0.487
educ exp	0	0	0	0	0	0	0	0	0	0	0.044
GNI PPP	0	0	0	0	0	0	0	0	0	0	0.060
TV/1000	0	0	0	0	0	0	0	0	0	0	0.028
democracy	0	0	0	0	0	0	0	0	0	0	0.026
Nb worker in agri	0	0	0	0	0	0	0	0	0	0	0.034
Nb worker in manuf	0	0	0	0	1	0	0	0	0	0	0.052
pol right	0	0	0	0	0	0	0	0	0	0	0.015
Rule of law	1	1	1	1	1	1	1	1	1	1	0.888
Ethnic Fraction	1	1	1	1	1	1	1	1	1	1	0.626
Crude oil	0	0	0	0	0	0	0	0	0	0	0.023
natural gaz	0	0	0	0	0	1	0	0	0	0	0.058
Forest area	0	0	0	0	0	0	0	0	0	0	0.144
Carbon emission	0	0	0	0	0	0	0	0	0	0	0.038
g/b education	0	0	0	0	0	0	0	0	0	0	0.024
ratio of literate	0	0	0	0	0	0	0	0	0	0	0.014
-5 mortality	0	0	0	1	0	0	0	0	0	0	0.096
gr pop	0	0	0	0	0	0	0	0	0	0	0.031
independance	0	0	0	0	0	0	0	0	0	0	0.018
openness	0	0	0	0	0	0	0	0	0	0	0.040
Atheist %	0	0	0	0	0	0	0	0	0	0	0.057
Christians %	0	0	0	0	0	0	0	0	0	0	0.015
Ethnoreligionist %	0	0	0	0	0	0	0	0	0	0	0.026
Jew %	0	0	0	0	0	0	0	0	0	0	0.021
Muslim %	0	0	0	0	0	0	0	0	0	0	0.020
col France	0	0	0	0	0	0	0	0	0	0	0.031
col UK	0	0	0	0	0	0	0	0	0	0	0.017
col Belge	1	1	1	1	1	1	0	0	0	1	0.239
col Port	0	1	0	0	0	0	1	0	0	0	0.162
lnd100km	0	0	0	0	0	0	0	0	0	0	0.026
pop100km	0	0	0	0	0	0	0	0	0	0	0.031
lnd100cr	0	0	0	0	0	0	0	0	0	0	0.028
pop100cr	0	0	0	0	0	0	0	0	0	0	0.046
dens95c	0	0	0	0	0	0	0	0	0	0	0.026
dens95i	0	0	0	0	0	0	0	0	0	0	0.025
landlock	0	0	0	0	0	0	0	0	0	0	0.067
tropicar	0	0	0	0	0	0	0	0	0	0	0.136
zdrytemp	0	0	0	0	0	0	0	0	0	0	0.066
zsubtrop	0	0	0	0	0	0	0	0	0	0	0.059
ztropics	0	0	0	0	0	0	0	0	0	0	0.033
gr nat. Sav. 87-90	1	1	1	1	1	1	1	1	0	1	0.311
Variables included	6	6	6	6	6	6	6	5	4	5	
Model Probabilities	0.004	0.004	0.005	0.005	0.005	0.006	0.006	0.006	0.006	0.011	

* : Probability of apparition calculated from the 3989 last models (covering 95.0% of the probability mass).

Appendix - Markov Chain Monte Carlo Model Composition

A large literature has recently developed computational methods for doing BMA in the regression model when the number of potential explanatory variables is very large. Using Markov Chain Monte Carlo Model Composition (MC^3), LeSage and Parent (2007) have extended the simple linear regression model to different spatial econometric specifications. Here we just summarize their basic ideas in the context of spatial error models. For a regression model with and intercept and k possible explanatory variables, there are 2^k possible ways to select regressors to be included or excluded from the model. For $k = 44$ say, we have over a trillion possible models, ruling out computation of the log-marginal for all possible models as impractical.

To set forth the Bayesian theory of model comparison we specify prior probabilities for each of the m alternative models $M = M_1, M_2, ..., M_m$ under consideration, which we label $\pi(M_i)$, as well as prior distributions for the parameters $\pi(\eta)$, where $\eta = (\lambda, \beta, \sigma)$ (e.g., Fernández et al., 2001). Our focus here is on comparing models with different explanatory variables.

To determine the posterior model probabilities, we assume that the prior probabilities are equal to $1/m$, making each model equally likely apriori. These are combined with the likelihood for y conditional on η as well as the set of models M, which we denote $p(y | \eta, M)$. The joint probability for M, η, and y takes the form:

$$p(M, \eta, y) = \pi(M)\pi(\eta | M) p(y | \eta, M) \tag{7}$$

Application of Bayes rule produces the joint posterior for both models and parameters as:

$$p(M, \eta | y) = \frac{\pi(M)\pi(\eta | M) p(y | \eta, M)}{p(y)} \tag{8}$$

The posterior probabilities regarding the models take the form:

$$p(M | y) = \int p(M, \eta | y) d\eta, \tag{9}$$

This requires integration over the parameter vector η. We focus now on the marginal posterior in (9) for spatial individual effects models since this plays a key role in the MC^3 model comparison methodology.

We consider the SEM model, where the likelihood function for the parameters $\eta = (\beta, \sigma, \lambda)$, based on the data y takes the form shown in (10), where we include the spatial weight matrix W to indicate that the likelihood is conditional on the particular weight matrix employed in the model.

$$L(\eta; y, W) \propto (\sigma^2)^{-n/2} | I_n - \lambda W |^{1/2} \exp\{-\frac{1}{2\sigma^2} e' e\}$$

$$e = (I_n - \lambda W) y - X\beta \tag{10}$$

We can define the prior distributions for the parameters in η using a number of different approaches. An issue that arises in Bayesian model comparison is that posterior model probabilities can be sensitive to alternative specifications for the prior information. We draw on the work of Fernandez, Ley and Steel (2001) for the case of least-squares models and rely on Zellner's $g-$prior for the parameters β in the model. A conventional gamma prior is used for the parameter σ, and a Beta prior is introduced for the spatial dependence parameter λ. We rely on a non-informative prior for the intercept term α that appears in all models.

Using Bayes' theorem and setting $\tilde{y} = (I_N - \lambda W)y$ and $\hat{X} = (I_n - \lambda W)\tilde{X}$, the joint posterior distribution of the SEM model can be written as:

$$
\begin{aligned}
&\int \pi_b(\beta \mid \sigma^2)\pi_a(\alpha)\pi_s(\sigma^2)\pi_r(\lambda)p(y \mid \alpha, \beta, \sigma^2, \lambda)d\beta d\alpha d\sigma^2 d\lambda \\
&= K_1(2\pi)^{-(n+k)/2} \mid C \mid^{1/2} \int \mid I_n - \lambda W \mid \frac{1}{\sigma^{n+\nu+k+2}} \\
&\times \mathbf{exp}\{-\frac{1}{2\sigma^2}[\nu\bar{s}^2 + S(\lambda) + (\beta - \beta_0)'C(\beta - \beta_0) \\
&+ (\beta - \hat{\beta})'(\tilde{X}'\tilde{X})(\beta - \hat{\beta})]\}\pi_r(\lambda)d\beta d\alpha d\sigma^2 d\lambda,
\end{aligned}
\tag{11}
$$

With,

$$
\begin{aligned}
K_1 &= \Gamma\left(\frac{\nu}{2}\right)^{-1}\left(\frac{\nu\bar{s}^2}{2}\right)^{\nu/2} \\
S(\lambda) &= e(\lambda)'e(\lambda) \\
e(\lambda) &= \tilde{y} - \tilde{X}\hat{\beta} - \iota_n\hat{\alpha} \\
C &= g\tilde{X}'\tilde{X} \\
\hat{\beta}(\lambda) &= (\tilde{X}'\tilde{X})^{-1}\tilde{X}'\tilde{y} \\
\hat{\alpha} &= \bar{y} - \lambda(1/n)\sum_i (Wy)_i.
\end{aligned}
$$

Then, we obtain the following expression for the log marginal likelihood:

$$
\begin{aligned}
p(y, X, W) &= K_2(\frac{g}{1+g})^{k/2} \\
&\times \int \mid I_n - \lambda W \mid [\nu\bar{s}^2 + S(\lambda) + Q(\lambda)]^{-\frac{n+\nu}{2}} \pi_r(\lambda)d\lambda \\
K_2 &= \Gamma\left(\frac{\nu}{2}\right)^{-1}\left(\frac{\nu\bar{s}^2}{2}\right)^{\frac{\nu}{2}}(2\pi)^{-\frac{n}{2}}2^{\frac{n+\nu}{2}}\Gamma\left(\frac{n+\nu}{2}\right) \\
&= \frac{\Gamma\left(\frac{n+\nu}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right)}(\nu\bar{s}^2)^{\frac{\nu}{2}}\pi^{-\frac{n}{2}} \\
Q(\lambda) &= \frac{g}{g+1}\hat{\beta}(\lambda)'\tilde{X}'\tilde{X}\hat{\beta}(\lambda)
\end{aligned}
\tag{12}
$$

Details of this derivation can be found in LeSage and Parent (2007).

An important point regarding expression (12) is that we must rely on numerical integration to convert this to a scalar. Whereas for conventional regression models, analytical expression can be used to produce a scalar result, spatial models require numerical integration with respect to the λ parameter to produce the marginal posterior distribution.

In practice, however, computing the posterior distribution through equations (9) and (12) is computationally prohibitive since a very large amount of terms are involved in the sums. In our application, we have $k = 44$ possible regressors, and we would thus need to calculate posterior probabilities for each of the $2^{44} = 2{,}3 \times 10^{15}$ models and average the required distributions over all these models. In order to substantially reduce the computational effort, we use univariate numerical integration methods (LeSage and Pace, 2004), that allows us to construct a Metropolis-Hastings sampling scheme that implements the MC^3 method. A vector of the log-marginal values for the current model M is stored during sampling along with a vector for the proposed model M'. These are then scaled and integrated to produce $O_{M',M}$ used in (13) to determine acceptance or rejection of the proposed model.

$$\min\left[1, \frac{p(M' \mid y)}{p(M \mid y)}\right]. \tag{13}$$

While the simple "birth" or "death" proposals for adding or deleting variables are easy to implement, other choices of M' may lead to algorithms that can move more rapidly through the model space. This "move step" takes the form of replacing a randomly chosen single variable in the current explanatory variables matrix with a randomly chosen variable not currently in the model. Specifically, we might propose a model with one less explanatory variable (death step) and then add an explanatory variable to this new model proposal (birth step). This leaves the resulting model proposal with the same dimension as the original one with a single component altered. This type of sampling process is often labeled 'reversible jump' MCMC. The model proposals that result from birth, death and move steps are all subjected to the Metropolis-Hastings accept/reject decision shown in (13), which is valid so long as the probabilities of birth, death and move steps have equal probability of 1/3.