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The Determinants of CO2 Emissions Differentials with Cross-Country Interaction Effects: A Dynamic Spatial Panel Data Bayesian Model Averaging Approach.

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The Determinants of CO2 Emissions Differentials with Cross-Country Interaction Effects: A Dynamic Spatial Panel Data Bayesian Model Averaging Approach.*

Abstract

This study analyzes the importance of a large number of possible determinants of CO2 emissions per capita during the period 1991-2014 for a sample of 123 countries. They key contributions are methodological given that we consider the effect of a great number of economic, institutional, demographic and socio-cultural factors that could affect CO2 emissions employing Spatial Bayesian Model Averaging techniques while accounting for different concepts of cross-country interactions and different spillover processes. Over the different type of interactions considered: geographical, genetic, linguistic and religious we find that traditional geographical interactions outperform the others. Spatial Bayesian Model Averaging analysis enable us to compute the PIPs for the different indicators to generate a probabilistic ranking of relevance for the various CO2 determinants. Our findings suggest that CO2 emissions are mainly determined by economic factors such

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as the sectoral composition, the prices of gasoline, the intensity of fossil fuels consumption and the level of output. In a intermediate level of importance we find social and demographic factors such as the age composition, the religious attitudes or the social globalization of the population.

Classificazione JEL: C1, O13, C23
Keywords: Dynamic Spatial Panels, CO2 emissions, Determinants, Spatial Bayesian Model Averaging

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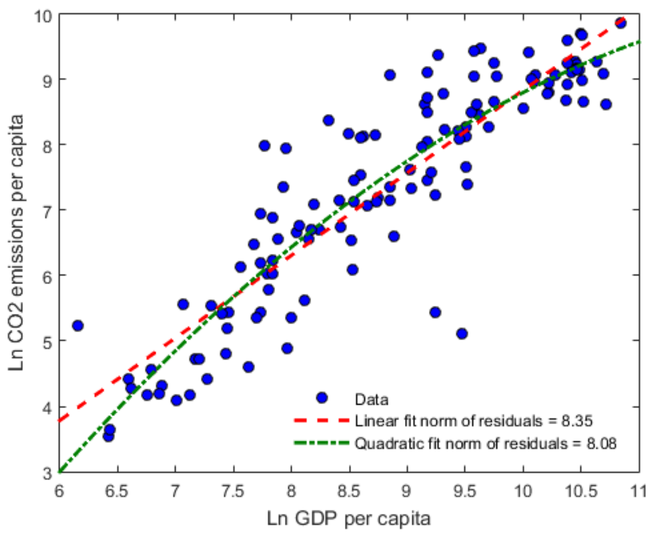
I. Introduction

The causes and consequences of Carbon Dioxide (CO2) emissions to the atmosphere have attracted the attention of many researchers during the last decades also due to the recent Paris agreement on global warming hold in 2015. One of the issues that has received the most attention and promoted heated debate among environmental and economic researchers is the relationship between income and pollution (Grossman and Krueger, 1995), which has crystalized in the Environmental Kuznets Curve (EKC) literature. Nevertheless, the existence of an EKC for the case of Carbon Dioxide (CO2) emissions is far from settled.

Figure (1) provides preliminary evidence on the existence of an non-linear pattern between economic development and CO2 emissions during the period 1991-2014 for a global sample of 123 countries. The fit to the data shows the quadratic fit describes better the data than the linear fit. Hence, the preliminary evidence on the relation between GDP and CO2 emissions per capita suggests that environmental degradation increases with income at lower levels of income and then decreases once a threshold level of per capita income is reached.

Figure 1: Economic Development and CO2 Emissions per capita



Nevertheless, the information provided by Figure (1) can not be understood as a causal link and the relationship should be interpreted with caution because omitted variables may determine the observed connection between CO2 emissions and economic development. In fact, it is likely that the level of CO2 emissions does not depend exclusively on their degree of economic development.

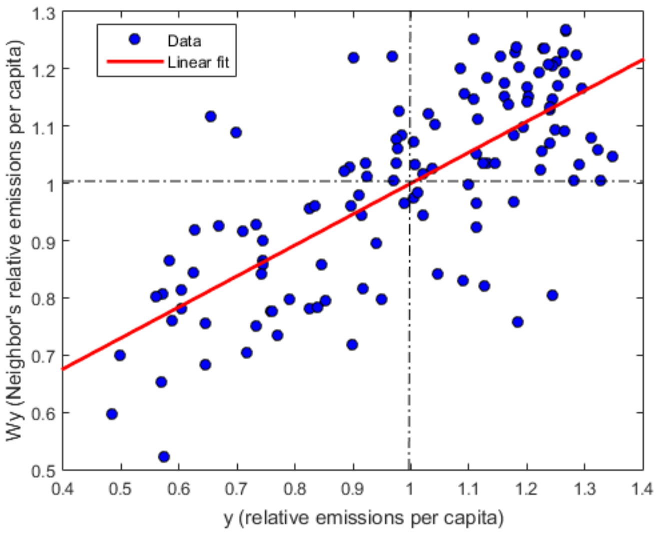
In this regard, the empirical literature has stressed the role played by various factors on CO2 emissions including the initial levels/conditions of CO2 emissions

(Petterson *et al.*, 2014; Ordas-Criado *et al.*, 2011), the share of physical and human capital investment economic growth (Brook and Taylor, 2010), the level of financial development (Tamazian *et al.*, 2009), the degree of trade openness (Frankel and Rose, 2005; Managi *et al.*, 2009), the foreign direct investment flows (Erdogan, 2014; Omri *et al.*, 2014), the employment of fossil fuels (Zhang and Lin , 2012), the degree of economic, social and political globalization (Bu *et al.*, 2016), the different sectoral composition of economic activity (Hocaoglu and Karanfil, 2011), the demographic dynamics involving age structure and urbanization trends (Cole and Neumayer, 2004; Liddle and Lung , 2010; Martinez-Zarzaroso and Maroutti, 2011), the quality of the institutions (Farzin and Bond, 2006; Li and Reuveny, 1995), the ideology of government (Neumayer, 2003; Garmann, 2014), the type of electoral systems and the quality of the political representation (Fredriksson and Wollscheid, 2007; Lipscy, 2014), the corruption of the political system and the media (Lopez and Mitra, 2000; Feldman *et al.*, 2012), the religious and social values of the population (Morrison *et al.*, 2015; Tjernstrom and Tietenberg, 2008) or the degree of gender equality (Agarwal, 2009; Ergas and York, 2012) among other determinants.

Empirical studies are crucial to obtain a deeper understanding of the determinants of the evolution of CO2 emissions by confronting the plausibility of the theories and the explanatory power of the variables involved in them. Nevertheless, the fact that previous studies have employed limited sets of variables to explain the evolution of CO2 emissions is likely to create artificially narrow confidence intervals. Moreover, previous studies have ignored the model uncertainty surrounding the data generating process (DGP) of CO2 emissions, which hampers consensus on the key determinants of CO2 emissions and the validity of previous EKC analysis.

An additional methodological challenge in the analysis of CO2 emissions is that the majority of the studies have focused on time-series issues such as stationarity, co-integration, etc., thus ignoring the fact that CO2 emissions are correlated in space (Maddison, 2006). From the theoretical point of view, spatial dependence in CO2 emissions among economies may arise: (i) as a consequence of countries strategic response to transboundary pollution flows as governments might strategically manipulate environmental standards in an attempt to attract capital, or for trade purposes and/or (ii) because of the geographical interdependence in the technologies used to produced goods and services in the various countries (Ertur and Koch, 2007; Ezcurra and Rios, 2015). The arguments suggesting the relevance of space when modeling the phenomenon of CO2 emissions can be corroborated when looking at Figure (2). Figure (2) displays the Moran's Scatterplot and provides a first insight on the role of space and geography in the emissions per capita of CO2 emissions around the globe during 1991-2014. The positive linear relationship between the logarithm of average C02 per capital emissions during 1991-2014 suggest that space matters. In this regard, the omission of relevant spatial interaction terms in the econometric analysis is of major importance as it could lead to bias/inconsistent and inefficient estimates (LeSage and Pace, 2009, Elhorst, 2014).

Figure 2: Economic Development and CO2 Emissions per capita



To extend our understanding of the determinants of CO2 emissions and the relationship between pollution and economic development this study makes several novel contributions to the literature.

First, we investigate the robustness of the link between income and CO2 emissions per capita at the global level using dynamic spatial panel data econometric techniques. The estimation of the spatial specification is performed employing annual data in a global sample of 123 countries and for the period ranging from 1991 to 2014.

Second, given the uncertainty surrounding the nature of cross-country interactions we perform a Spatial Bayesian Model Selection analysis following LeSage (2014) and Rios (2016). Hence, we extend previous research on CO2 emissions to account for different patterns of cross-country interaction and different connectivity matrices based on geographical, genetic, linguistic and cultural distances to describe the cross-sectional dependence of CO2 emissions among our sample of countries. It represents, as such, a novel application at the worldwide level. In this regard, the model selection analysis performed here is of major importance, as different spatial econometric models ultimately imply different types of spillover processes and different spatial interactions matrices imply different channels through which cross-country interactions occur.

Third, we extend previous work in Bayesian Model Averaging for cross-sectional spatial models by LeSage and Parent (2007) to the context of dynamic spatial panels. The relevance of the determinants of CO2 emissions is analyzed computing Posterior Inclusion Probabilities (PIPs) in a set of more than thirty possible explanatory variables that are expected to affect CO2 emission patterns, which contrasts with the limited set of controls employed in the literature. Therefore, compared with the limited set of regressors considered in the existing empirical literature, this study rigorously assesses model uncertainty over a larger set of environmental quality determinants. These covariates can be grouped into four categories: (*i*) *economic factors*, (*ii*) *institutional and political characteristics*, (*iii*) *demographic factors* and (*iv*) *social cultural factors*. Contrary to previous studies on CO2 emissions where inference is based in single econometric model analysis containing a small set of regressors, the Spatial Bayesian Model Averaging (SBMA) approach employed here considers the full model space. As a consequence, our analysis has the advantage of minimizing the likelihood of producing (*i*) biased estimates and (*ii*) artificially low confidence intervals (Moral-Benito, 2015).

Therefore, the econometric modeling framework employed here has several advantages with respect previous analysis that only consider time or spatial dependence in the observations. First, (*i*) the unrealistic assumption of CO2 emissions to be independent over space and time has no longer to be made, (ii) it enables the investigation of the nature, magnitude and significance of spillovers in a variety of CO2 determinants and (iii) it facilitates assessment of the relative importance of different determinants for explaining CO2 emission patterns.

The paper is organized as follows. After this introduction, Section 2 presents a brief literature review on previous CO2 EKC studies and the determinants of CO2 emissions per capita considered in the present study. Section 3 describes the econometric approach used in the analysis, the Spatial Bayesian Model Selection and the Spatial Bayesian Model Averaging methodologies employed. The empirical findings of the paper are discussed in Section 4. The final section offers the main conclusions from this work and the policy implications of the research.

II. The Determinants of CO2 Emissions

According to the literature, CO2 emissions are driven by a myriad o factors that could explain differences on the pollution patterns across-countries. This is because of certain country-specific characteristics have been identified in the literature as factors that may enhance/diminish CO2 emissions. This section focuses on the determinants of CO2 emissions and summarizes the main findings of previous empirical studies, distinguishing between pollution-enhancing and pollution-hindering factors.

II.A. The Pollution-Income Relationship

Theoretical and empirical contributions of Pollution-Income Relationship (PIR) literature, linking economic growth and pollutant emissions, have considered the later as a byproduct of economic activity (Brook and Taylor, 2010). According to this literature, the PIR may take several forms of which the most widely supported is the EKC, which is an inverted U shape relationship. Table (1) below summarizes some of the findings of this strand of literature over the last 20 years. As it can be observed, the patterns discovered in empirical research are mixed, since the results are sensitive to the sample, the period of analysis, the functional form and the econometric methodology.

In the empirical literature there are three patterns that appear to be consistent with the data.

The first one is the inverted U-type relationship, which implies that environmental degradation increases with income at lower levels of income and then decreases once a threshold level of per capita income is reached. With different sample and methodologies (time series, cross section an panel data), this result is confirmed in Holtz-Eakin and Selden (1995) Tucker (1995), Cole et al. (1997), Schmalensee et al. (1998), Galeotti and Lanza (1999), Taskin and Zaim (2000), Halkos and Tsionas (2001), Galeotti et al. (2006), Narayan and Narayan (2010), Jobert et al. (2014), Apergis (2016),Shahbaz at el. (2017), Shahbaz at el. (2017).

Despite the empirical evidence provided so far, other contributions have argued that such an inverted-U relationship may not hold in the long run. In their contribution Taskin and Zaim (2000), Özokcu and Özdemir (2017), López-Menéndez et al. (2014) obtain the so-called N-shaped relationship, which exhibits the same pattern as the inverted-U curve initially, but beyond a certain income level, the relationship between emissions and income becomes positive again. The existence of an N-shaped curve implies that environmental degradation cannot be solved automatically by economic growth, suggesting that at very high income levels the scale effect of economic activity could become so large that its negative impact on environment might not be counterbalanced by the positive impact induced by better techniques.

Finally, Shafik (1994), De Bruyn et al. (1998), Halkos and Tsionas (2001), Azomahou and Van Phu (2001), Bertinelli and Strobl (2005), Azomahou and Van Phu (2001), Dutt (2009) and Aslanidis and Iranzo (2009) present in their empirical work a different pattern in favor of a monotonically increasing linear relationship, indicating that rising incomes are associated with rising levels of emissions. Their main critique to the inverted U-shape relationship observed in the previous studies comes from the missing distinction between the short-term costs of economic growth, its insecure long-term benefits and the difficulty to capture all the complex factor under the relationship between pollution and income with simple reduced form model.

Table 1: Environmental Kuznets Curve empirical studies for CO2 emission

Author(s) and publication year	**Technique**	**Data sample**	**Time period**	**Shape of EKC**
Shafik (1994)	Fixed country effects/Time trend	149 countries	1960-1990	Linear (positive) relationship
Holtz-Eakin and Selden (1995)	Fixed country/Time effects	130 countries	1951-1986	Inverse U-shape (but turning point is too high)
Tucker (1995)	Cross-section regressions for each year	131 countries	1971-1991	Inverse U-shape (stronger over time)
Cole et al. (1997)	Fixed country effects	7 world regions	1960-1991	Inverse U-shape (but turning point is too high)
De Bruyn et al. (1998)	Time series regressions	4 OECD countries	1961-1990	Linear (positive) relationship
Schmalensee et al. (1998)	Spline model	141 countries	1950-1990	Inverse U-shape
Galeotti and Lanza (1999)	Gamma and Weibull models	110 countries	1971-1996	Inverse U-shape in all the three cases
Taskin and Zaim (2000)	Non-parametric models	52 countries	1975-1990	Inverse U-shape
Halkos and Tsionas (2001)	Cross-section regression	61 countries	1980-1991	Monotonic relationship between environmental degradation and income, so no existence of an EKC
Azomahou and Van Phu (2001)	Parametric and non parametric regression	100 countries	1960-1996	Monotonic relationship in the non-parametric model and inverted-U curve in the parametric model. However, a differentiating test rejects the parametric approach in favor of the non-parametric one.
Martińez-Zarzoso and Bengochea-Morancho (2004)	Pooled mean group estimator	22 OECD countries	1975-1998	N-shape for majority of countries
Müller-Fürstenberger and Wagner (2004)	Panel unit root &cointegration Tests	107 countries	1986-1998	Results are mixed
Bertinelli and Strobl (2005)	Non-parametric models	122 countries	1950-1990	Linear (positive) relationship
Dijkgraaf and Vollebergh (2005)	Polynomial & spline models	24 OECD countries	1960-1997	Inverse U-shapein 11 out of 24 countries
Azomahou and Van Phu (2001)	Non-parametric models	100 countries	1960-1996	Linear (positive) relationship
Galeotti et al. (2006)	Weibull model	125 countries	1960-1997	Inverse U-shape for OECD and concave (but with no reasonable turning point) for Non-OECD
Dutt (2009)	Panel model with fixed effects	124 countries	1960-2002	Linear between 1960-1980 and inverted U-shape between 1984-2002
Aslanidis and Iranzo (2009)	Smooth transition regression models	77 non-OECD countries	1971-1997	Positive but at a slower rate after some income threshold
Narayan and Narayan (2010)	Cointegration test	43 developing countries	1980-2004	Inverse U-shape in 15 countries (time series)in Middle Eastern and South Asia panels
López-Menéndez et al. (2014)	Fixed country/Time effects	27 countries of the European Union	1996-2010	N-shaped curve for models with variables in levels while U patterns for the logarithmic models
Jobert et al. (2014)	Bayesian shrinkage estimator	55 countries	1970-2008	Inverse U-shape is observed some countries but not all of them
Apergis (2016)	Panel/time series contegration analysis	15 countries	1960-2013	Inverse U-shape for 12 out of 15 countries
Grunewald et al. (2017)	Panel fixed effect/group fixed effects	158 countries	1980-2008	Inverse U-shape
Shahbaz at el. (2017)	Non-parametric models	G7 countries	1950-2015	Inverse U-shape for all the countries, except Japan
Özokcu and Özdemir (2017)	Fixed effects panel model	26 OECD plus 52 emerging countries	1980-2010	N-shape and an inverted N-shape relationship for cubic functional form

II.B. Economic Factors

The set of economic determinants is perhaps the most important group of factors driving CO2 emissions.

We first control for traditional economic growth determinants such as (*i*) the *ratio of investment to GDP* and the (*ii*) the *level of human capital*. We expect a positive effect of both human and physical capital since they are the key determinants driving economic growth in standard macro-economic models (Mankiw *et al.*, 1992). Additionally, we control for the (*iii*) *initial levels of CO2 per capita* to check the existence of a process of convergence. While theoretical growth models predict environmental convergence, the empirical literature has shown highly contradictory results finding support to both, the hypothesis of divergence and to the hypothesis of convergence (Petterson *et al.*, 2014).

We also incorporate the share of (*iv*) *trade openness* and (*v*) *financial openness* in the GDP. According to Grossman and Krueger (1991) trade and financial flows can influence the environment through two key channels that may work on opposite directions: the scale and the composition effect. The scale effect refers to the impact of trade on the level of economic activity whereas the composition effect refers to the influence of trade on the productive structure of the economy. While increased openness will lead to greater economic activity contributing to environmental degradation, the composition effect is ambiguous. The empirical evidence for the effect of trade openness is mixed. There are studies finding the effect is that of a reduction of emissions as observed in Frankel and Rose (2005) and Antweiler *et al.* (2001) while others such as Cole and Elliot (2003) find that this effect is dependent on the pollutant and that for the CO2 emissions, increasing trade openness increases emissions. Regarding the effects of foreign direct investment and capital openness, there are two competing hypothesis. The pollution-haven hypothesis (PHH) and the halo hypothesis. The first one suggests that increasing financial openness leads to higher pollutant emissions given that in order to attract foreign investment, the governments of developing countries have a tendency to undermine environment and relax regulations. However, the literature review of Erdogan (2014) suggests empirical studies do not support the PHH. The halo hypothesis suggests that financial openness should decrease emissions through a technique and management effect, given that multi-national corporations tend to introduce clean-state-of-the-art production techniques from high-standard countries of origin to host countries where they are not yet known. The findings regarding the effect of financial openness are also mixed, as there are analysis finding a positive (Omri *et al.*, 2014), insignificant (Lee, 2013, You *et al.*, 2015) and negative (Eskeland and Harrison (2003)) link.

As explained by Dinda (2004), as income grows, the structure of the economy tends to change which may affect the level of emissions. In particular, it is expected that with higher economic development gradually increases cleaner activities that produce less pollution. Specifically, environmental degradation tends to increase as structure of the economy changes from agricultural to industrial, but it starts to fall with another structural change from industry to services and knowledge based technology. For this reason, we control for the sectoral composition of the economy and we consider (*vi*) the *share of agriculture* and (*vii*) the *share of industry* in the value added. We expect a negative effect for the share of agriculture and a positive effect of the industry. We do not include the share of services to avoid multi-collinearity problems.

The different specialization patterns in the production of goods and services may require varying amounts of fossil fuels as inputs for production, which are deemed to be one of the key determinants of pollutant emissions (IEA, 2016). To control for disparities in the production and use of fossil fuels, we add in our econometric analysis (*viii*) the *total production of oil* and (*ix*) the *total production of gas*. Additionally we introduce two demand controls (*x*) the *gasoline prince* and the (*xi*) the *share of fossil fuels in the total energy consumption.* While the effect of producing oil, gas and the intensity in the use of fossil fuels is expected to be positive, the effect of prices is expected to be negative as found in Agras and Chapman (1999).

Finally, we also consider the potential effects of (*xii*) *income inequality* and (*xiii*) *financial development*. Income inequality can affect the evolution of CO2 emissions given that in contexts of high income inequality, agents that bear the cost of pollution will not enjoy a sufficiently strong bargaining position to impose environmental regulations on those who benefit from it (Torras and Boyce, 1998). This, in turn, will result in inefficiently high levels of pollution and a positive correlation between income inequality and pollution. On the contrary, as long as poor agents display higher propensities to consume than rich agents, an increase in the level of income inequality may decrease consumption and CO2 emissions. Contradictory evidence about the effect of income inequality is again observed between the analysis of Torras and Boyce (1998) and Grunewald et al. (2017). On the other hand, a higher financial development is expected to reduce CO2 emissions due to the induced technological innovations in the energy supply sector, the financing of investment in environmental projects at lower costs (Tamazian *et al.*, 2009).

II.C. Institutional and Political Factors

Attempting to explain changes and cross-country differentials in CO2 emissions researchers have also considered the impact of political and institutional factors. Nevertheless, the effect of these factors on the environmental quality, is more indirect than economic ones given that it depends on whether laws enacted and policies ultimately affect the behavior of agents, the production processes and the technological techniques involved in them.

Our first determinant is (*i*) the *level of democracy* for which we do not expect a concrete effect on emissions. On one hand, environmental quality has been linked to political rights, free information and free participation. In this context, a representative democracy, which guarantees wider citizen participation and a greater plurality of political forces, is expected to deliver better public policies than autocratic regimes (Torras and Boyce, 1998; Li and Reuveny, 1995; Farzin and Bond, 2006). This is because of an autocratic system is expected to limit information flows by promoting unilateral decision making and decreasing collective awareness about environmental issues. On the other, as explained by Midlarsky (1998) and Scruggs (1998), a common problem of democratic regimes is the difficulty in identifying, circumscribing, and hence protecting *public goods*. This could lead to the mismanagement of natural resources by some economies which in turn, may decrease environmental standards.

Differences in the (*ii*) *ideology of the party in government* might be a relevant factor influencing the behavior of CO2 emissions as suggested by Neumayer (2003) and Garmann (2014). Left-wing parties are known to be in favor of government intervention and closer to the labor base whereas right-wing governments, are usually closer to capital owners and dislike interventionism. If ecological policies convey substantial tax increases and adjustments costs because of emission reduction requirements, the effect of a right wing-government on emissions should be negative. Similarly, if ecological policies threaten the jobs in heavily-polluting industry sectors, left-wing governments might not promote a reduction of emissions. On the other hand, the traditional left-wing interventionism may translate in the restructuring of the economy towards cleaner technologies and because of the clientele of left-wing parties is more likely to be affected by air pollution, they may have a rationale for ecological policies (Garmann, 2014). Given that the empirical evidence provided by Neumayer (2003) and Garmann (2014) suggests left-wing governments reduce emissions, we expect a negative effect of our ideological variable.

We also take into consideration the (*iii*) *share of seats of the party in government in the legislative chamber* and (*iv*) *the degree of government fragmentation.* Weak governments may face difficulties in changing policy, which may exert a positive effect on emissions as ecological policies aiming at reducing emissions may become more difficult to pass due to policy inertia. Evidence supporting this view is provided by Garmann (2014). Similarly, a high margin of majority or a high share of seats of the government could lead to an increase of the emissions. In this regard, note that electoral rules (i.e, majoritarian/proportional) are a key determinant of the number of parties and the distribution of power across parties in the political system. Electoral rules also provide different incentives to environmental conservation. As explained by Liphart (2012), majoritarian rules usually imply higher concentrations of power whereas proportional rules deliver consensual party systems with a more equally distributed power. These also provide different incentives to environmental conservation. Under proportional rules, political parties consider the welfare of the entire population to maximize its representation, which induces political parties to pay greater attention to issues that are national/global in scope such as the transboundary pollution flows. This contrasts with majoritarian systems, where parties may focus on a subset of population, thus, presenting weaker incentives to enact stringent environmental policies (Fredriksson and Wollscheid, 2007, Lipscy, 2014).

Additionally, we take into account the potential effects of (*v*) *corruption.* Lopez and Mitra (2000) and Welsch (2004) analyze the role that corruption and rent-seeking behavior can play on environmental quality. These studies suggest existence of a positive relationship between corruption and emissions.

Finally, we control for (*vi*) the possible effects of *political globalization* and (*vii*) a *time-dummy* which captures the effect of the adoption of the *Kyoto-protocol.* Theoretically, there are a number of reasons to believe that political globalization and the Kyoto-protocol should decrease emissions. First, countries that are part of intergovernmental organizations (IGOs), can be compelled by member states to obey their rules, they are subject to norms defining good behavior and bad conducts and they are exposed to the other purposes of the organization, such as environmental protection. Taking the Kyoto Protocol as an example, there is evidence that many of the developed countries in Annex I, which faced a reduction target, increased their emissions at a much slower rate than developing countries who had no targets. However, the overall empirical evidence on the effect of these variables is mixed. Bu *et al.* (2016) find a positive link between political globalization and CO2 emissions whereas Aichele and Felbermayr (2012) and Aichele and Felbermayr (2013) find both, negative and positive effects of the Kyoto-protocol. Thus, we do not expect a concrete effect for these regressors.

II.D. Demographic Factors

Other studies identify the connection between demographic factors, urbanization trends and CO2 emissions.

While a decline in the (*i*) *size of the population* or the (*ii*) *population growth rate* is likely to improve environmental quality (Shi, 2003; Cole and Neumayer, 2004), the demographic structure of populations may affect environmental conditions in a variety of ways, especially through the age-dependent levels and patterns of output and consumption (York, 2007; Dalton *et al.*, 2008). Another important channel through which aging may affect environmental quality refers to the demand for environmental regulation and the underlying environmental preferences (Menz and Welsch, 2010). However, the evidence on the effect of population shares across age groups is somewhat mixed (see Liddle (2014) for a recent literature review). We control for the age composition by considering (*iii*) the *share of population below 15 years* old, (*iv*) the *share of population between 30-49 years* old and (*v*) the *share of population above 65 years* old. Thus, the overall expected effect of these factors defining the demographic composition change is ambiguous.

Finally, we control for (*vi*) *urbanization* and (*vii*) *population density.* Urbanization and rural migration into cities are frequently deemed to increase energy consumption and to greater CO2 emissions. However, as Martinez-Zarzaroso and Maroutti (2011) point out, the a priori effect of urbanization is ambiguous. On one hand, urbanization requires transportation systems and usually displaces traditional energy with modern energy, which substantially increases the energy intensity of some activities while decreasing traditional energy use, which ultimately results in increasing emissions. On the other hand, the process of urbanization involves firm concentration and a reduction of the costs needed to enforce environmental legislation encouraging the use of mass transport instead of individual motor vehicles. Additionally, urbanization may decrease emissions through economies of scale in the provision of sanitation facilities. In this regard, empirical studies show mixed results finding both, a positive (Cole and Neumayer (2004); York, 2007; Martinez-Zarzaroso and Maroutti, 2011) and a negative link

(Fan *et al.*, 2006) between urbanization and CO2 emissions per capita. Similarly, the effect expected of population density is ambiguous given that similar arguments to those of urbanization apply. Higher population density may place an excessive burden on the absorptive capacities of the environment. However, countries where most of the population is concentrated in cities with large population densities may have less carbon emissions per capita compared to countries with lower density suburban areas, mainly due to the efficiency gains implied by public transportation services and walking accessibility (Gately *et al.*, 2015).

II.E. Socio-Cultural Factors

The sociological characteristics of a country may also affect the level of CO2 emissions.

We first account for (*i*) the *degree of women empowerment* in the society. Women's traditional roles as caregivers, subsistence food producers, water and fuelwood collectors and reproducers of human life suggests that women more likely to support environmental protection. Ergas and York (2012) and Agarwal (2009) using different methods and samples find evidence supporting hypothesis of societies with greater gender equality have a lower impact in the environment. Thus, we expect that countries with greater gender equality will tend to display lower emissions.

Another potential determinant of CO2 emissions is (*ii*) the *process of social globalization* (Bu *et al.*, 2016). Transportation and lifestyle changes implied by the social globalization process are expected to increase emissions (i.e, transportation systems such as the airplane have contributed greatly to carbon emissions). These lifestyles are often associated with deforestation which makes emissions even worse. However, the dimension of social globalization related to the increase of personal contacts and information flows is expected to increase collective awareness. Therefore, the expected effect of social globalization on emissions is ambiguous beforehand, given that it is likely to produce impacts that go on different directions.

The different values and attitudes towards the environment that different religions carry on may also exert a significant effect on emissions (Tjernstrom and Tietenberg, 2008; Morrison *et al.*, 2015). The intuition is that different religions imply different values and attitudes towards the environment which ultimately gives rise to actions and patterns of behavior that may have a consequence on the overall degree of pollution generated (Tjernstrom and Tietenberg, 2008; Morrison *et al.*, 2015). According to the hypothesis developed in White (1967), Judeo-Christian perspective and desire for dominion over nature which is also present in the Islam, is negatively related to environmental respect and concerns while other religions such as the Buddhism or Hinduism, that reject the dualism between humans and nature, should have a positive effect on environmental conservation. Thus, we expect a positive effect on the level of emissions for the share of (*iii*)

Christian and Islamic population and a negative effect for the share of (*iv*) *Buddhist and Hinduist population.*

Finally, we identify the (*vi*) *corruption of the mass-media* as potential determinant of emissions. Note that quality of the information flows can shape the viewers opinions regarding the challenged implied by global warming and climate change (Feldman *et al.*, 2012; Brulle *et al.*, 2012; McRight and Dunlap, 2011). Hence, we expected that countries with more corrupt media, where the news reported and interviewed scientists are used generate doubts about the human impact in climate change display higher emission levels.

Definitions, abbreviations, descriptive statistics, data sources and expected effects are presented in Table (2).

Table 2: Definitions. sources and descriptive statistics of the explanatory variables

Variable	Definition	Source	Mean	Std	Expected Effect
Outcome variable					
Ln CO2 Emissions per capita	Natural log of the CO2 emissions pc	WB	7.32	1.70	
(i) EKC Profile					
Ln GDP per capita (GDP1)	Natural log of the GDP per capita in PPP	PWT	8.98	1.24	+
Ln GDP per capita^2 (GDP2)	Square of the natural log of the GDP per capita in PPP	PWT	78.89	21.56	?
Ln GDP per capita^3 (GDP3)	Cube of the natural log of the GDP per capita in PPP	PWT	720.52	286.82	?
(ii) Economic Factors					
Investment ratio (INV)	Share of investment in GDP (%)	PWT	20.63	7.91	+
Human Capital[(1)] (HC)	Index of Human Capital	PWT	2.37	0.71	+
Initial Emissions (CO2LAG)	Natural log of the initial CO2 emissions	WB	7.25	1.73	?
Agriculture (AGRI)	Share of GVA in agriculture (%)	WB	15.16	13.85	-
Industry (INDUS)	Share of GVA in industry (%)	WB	30.72	11.68	+
Trade Openness (TRADE)	Share of Exports + Imports in the GDP (%)	WB	75.79	37.07	?
Financial Openness(FDI)	Share of FDI inflows and outflows in the GDP (%)	WB	6.48	12.61	?
Oil production (OIL)	Oil production (in metric tons)	Ross	24433761.32	70076856.23	+
Gas production (GAS)	Gas production (million barrels oil equiv)	Ross	150.37	559.61	+
Gasoline price (PRICEG)	Pump price for gasoline (US$ per liter)	WB	0.89	0.46	-
Fossil fuel consumption (FFUELC)	Share of fossil fuels in total energy consumption (%)	WB	58.82	31.37	+
Financial Development [(2)] (FDEV)	Index of Financial Development	IMF	23.44	9.05	-
Income Inequality (INEQ)	Gini index	SWIID	38.72	8.39	+
(iii)Institutional and Political Factors					
Democracy Index (DEMO)	Index measuring the level of democracy (scale 0 to 10)	Polity IV	6.60	2.99	?
Ideology (IDEO)	Ideological Index measuring the ideology of the government (scale 1 to 3)	DPI	2.08	0.64	?
Political Corruption[(3)] (PCOR)	Index measuring the level of political corruption (scale 0 to 100)	VDEM	50.74	27.98	+
Government Seats Share (GOVS)	Vote share of the parties in government (%)	DPI	64.90	18.87	+
Government Fragmentation [(4)] (GOVF)	Index measuring the fragmentation of the government	DPI	22.68	25.50	+
Political Globalization [(5)] (GLOBP)	Index measuring the degree of political globalization . scale 0 to 100	KOF	68.28	19.65	?
Kyoto [(6)] (KYO)	Dummy variable, 1 if the country signed the Protocol, 0 otherwise	UN	0.60	0.49	?

Definitions. sources and descriptive statistics of the variables (Continued)

Variable	Definition	Source	Mean	Std	Expected Effect
(iv) Demographic Factors					
Ln Population size (POP)	Natural log of the total population (thousands)	WB	16.37	1.44	-
Population growth (POPG)	Growth rate of the population (%)	WB	1.49	1.38	-
Ln Population density (POPD)	Natural log of the population density (thousands/squared km)	WB	4.70	4.95	?
Urban population (URB)	Share of population living in urban areas (%)	WB	54.38	21.96	?
Population $<$ 15 years old (YNG)	Share of total population that is 15 years or younger (%)	WB	31.21	11.09	?
Population 30-49 years old (PMED)	Share of total population with ages between 30 and 49 years old (%)	WB	48.40	9.46	?
Population $>$ 65 years old (OLD)	Share of total population that is 65 years or older (%)	WB	7.69	5.23	?
(v) Sociological Factors					
Media Corruption [(7)] (MCOR)	Index of media corruption (scale 0 to 4)	VDEM	2.61	0.94	+
Women Empowerment [(8)] (WPOWR)	Index of women empowerment (scale 0 to 100)	VDEM	70.376	18.039	-
Social Globalization [(9)] (GLOBS)	Index of social globalization (scale 0 to 100)	KOF	45.75	23.40	?
Dual Religions (RELD)	Share over the total population of catholic christians, muslims and jews (%)	ARDA	78.70	25.86	+
Non Dual Religions(RELND)	Share over the total population of hindus and buddhists (%)	ARDA	6.95	19.98	-

Notes: WB denotes World Bank, PWT: Penn World Tables, IMF: International Monetary Fund, SWIID: Standardized World Income Inequality Database, DPI, Database of Political Institutions, UN: United Nations, VDEM: Varieties of Democracies, ARDA: The Association of Religion Data Archives. (1) The human capital index is based on the average years of schooling and an assumed rate of return to education, based on Mincer equation estimates. (2) The financial development index is a composite indicator that weights 20 sub-indicators to measure the development of (*i*) financial institutions and the (*ii*) development of financial markets in terms of depth, access and efficiency. (3) Political corruption runs from less corrupt to more corrupt. It weights 4 sub-indicators of corruption that cover different areas and levels of the polity realm (*i*) public sector corruption, (*ii*) executive corruption, (*iii*) legislative corruption and (*iv*) judicial corruption. (4) Government fragmentation indicates the probability that two deputies picked at random from among the government parties will be of different parties. (5) Political globalization weights the number of embassies in a country, its membership in IGOs, the participation in U.N. Security Council missions and in International Treaties. (6) The Kyoto dummy is a country specific time-varying variable that takes value of 1 if the country signed the Kyoto protocol and if it belongs to the set of countries included in Annex I.It takes a value of 0 otherwise. (7) The media corruption index is constructed by means of an ordinal scale with the answers to the question: Do journalists, publishers, or broadcasters accept payments in exchange for altering news coverage?. (8) The variable women empowerment measures the extent to which women are increasing their capacity for choice, agency, and participation in societal decision-making. (9) The social globalization index measures the spread of ideas, information, images, and people. It aggregates three sub-indexes with information on personal contact, information flows and cultural proximity. .

III. Econometric Methodology

Most of the empirical cross-country studies analyzing CO2 emissions treat the units of analysis as isolated entities, ignoring the spatial characteristics of the data and the potential role of space modulating the evolution of CO2 emissions.[1] Nevertheless, insofar every country evolves interacting with other countries, as suggested by the preliminary evidence in Figure (2), major problems may arise if the spatial characteristics of the data are ignored. Therefore, our empirical analysis is based on modern spatial econometric modeling techniques.

III.A. Spatio-Temporal Models of CO2 Emissions

In the context of spatial econometrics, model uncertainty stems from various sources. First, there are many candidate functional forms to define the spatial weights matrix. Second, there could be three different types of interaction effects operating through space: (*i*) endogenous interaction effects among the dependent variable, (*ii*) exogenous interaction effects among the independent variables and (*iii*) interaction effects among the disturbance terms (Elhorst (2014)).

To address this issue we begin by considering the *Dynamic Spatial Error Model* (DSEM) and the *Dynamic Spatial Durbin Error Model* (DSDEM) specifications which are given by Equations (1) and (2), respectively:

$$\begin{aligned} Y_t = \alpha\iota_{nt} + \tau Y_{t-1} + \phi W Y_{t-1} + X_t\beta + \epsilon_t \\ \epsilon_t = \lambda W \epsilon_t + \upsilon_t \end{aligned} \tag{1}$$

and

$$\begin{aligned} Y_t = \alpha\iota_{nt} + \tau Y_{t-1} + \phi W Y_{t-1} + X_t\beta + W X_t\theta + \epsilon_t \\ \epsilon_t = \lambda W \epsilon_t + \upsilon_t \end{aligned} \tag{2}$$

Y_t denotes a $N \times 1$ vector consisting of observations for the natural logarithm of the average annual CO2 emissions per capita measured over 5 years windows for every country $i = 1, \ldots, N$ at a particular point in time $t = 1, \ldots, T$, X_t and WX_t are $N \times K$ matrices of exogenous aggregate socioeconomic and economic covariates with associated β response parameters contained in $K \times 1$ vectors, that are assumed to influence CO2 emissions per capita.[2] τ is the response parameter of the lagged dependent variable Y_{t-1}. The variables WY_t and WY_{t-1} denote contemporaneous and lagged endogenous interaction effects among the dependent variable. In turn, λ is the spatial diffusion which captures spatially correlated shocks working through the error term. W is a $N \times N$ matrix describing the spatial arrangement of the countries in the sample. α is the constant term, ι_{nt} is an $NT \times 1$ vector of ones and $\epsilon_t = (\epsilon_{1t}, \ldots, \epsilon_{Nt})'$ is a vector of i.i.d disturbances

[1] The only exceptions are Zheng *et al.* (2014) and Pythagore *et al.* (2014) but these analysis are carried out for samples of countries of the European Union or regions in China.

[2] We use five-year averages to define each time interval t as it is common in the literature economic development.

whose elements have zero mean and finite variance σ^2. In addition, the SDEM includes the spatial lag of the rest of control variables (exogenous effects), WX, whose impact is reflected by the $K \times 1$ vector of coefficients θ. Additionally, we also consider the *Dynamic Spatial Lag Model* (DSLM) and the *Dynamic Spatial Durbin Model* (DSDM) which are given by Equations (3) and (4)

$$Y_t = \alpha\iota_{nt} + \rho WY_t + \tau Y_{t-1} + \phi WY_{t-1} + X_t\beta + \epsilon_t \tag{3}$$

$$Y_t = \alpha\iota_{nt} + \rho WY_t + \tau Y_{t-1} + \phi WY_{t-1} + X_t\beta + WX_t\theta + \epsilon_t \tag{4}$$

Some comments are worth mentioning with respect to the choice of the DSDEM/DSEM and the DSLM/DSDM specifications. First, DSDEM/DSEM do not require a theoretical model for spatial or social interaction process as it is common in the case in spatial models including endogenous interactions. Indeed, as explained by Gibbons and Overman (2012) and Halleck-Vega and Elhorst (2015), spatial models containing endogenous interactions such as the DSDM/DSLM are generally difficult to justify from a theoretical basis. In the context of CO2 emissions, endogenous interactions would lead to a scenario where changes in one country set in motion a sequence of adjustments in (potentially) all units in the sample such that a new long-run steady state equilibrium of CO2 emissions arises. Second, SDEM/SDM specifications also produce local spillovers given by θ, which allows to analyze whether there are important differences in the magnitude of impact associated to a regressor X_k within the country and outside the country WX_k affecting emissions. On the contrary DSLM/DEM do not allow for such type of interactions.

III.B. Spatial Weight Matrices for Cross-Country Interactions

The estimation of the various spatial models described above requires to previously define a spatial weights matrix. Given that this is a relevant issue in spatial econometric and social interactions modeling, a broad range of alternative specifications of W are considered taking into account different concepts of distance. Note that the geographical distance, which is the most common one employed in applied work is only one of the possible concepts of distance defining the interface that connects economic and social processes. Therefore, we also consider genetic, religious and linguistic distances to model the degree of relatedness among countries.

Nevertheless, a complicating factor when modeling interactions is the wide variety of potential forms for modeling spatial and cross-sectional dependence (neighbors, distance, links, etc). Therefore, we also consider different functional forms to model the w_{ij} terms of the W matrix, which denote the spatial weights connecting countries i and j. In particular, we built k-nearest neighbor matrices ($k = 5, 10, 15, 20$), exponential decay matrices ($\omega = 0.01, 0.025, 0.05$) and inverse power-distance based matrices ($\alpha = 1.5, 2, 3$) to reflect that relatedness decreases with distance. Furthermore, as is common practice in applied research, all the matrices are row-standardized, so that it is relative, and not absolute, distance which matters. Moreover, if $i = j$, w_{ij} is set to 0, to avoid self-influence.

Geographical Distance Interactions

Geographical distances are measured as the kilometer-converted great circle distances (d_{ij}) on the sphere:

$$d_{ij} = \arccos\left[(\sin\phi_i \sin\phi_j) + (\cos\phi_i \cos\phi_j \cos|\delta\gamma|)\right] \tag{5}$$

where ϕ_i and ϕ_j are the the latitude of country i and j respectively and $|\delta\gamma|$ reflects the absolute value of the difference in longitude between i and j. The geographical distance d_{ij} used to generate the spatial weights w_{ij} is then normalized by means of a max-min normalization so that it ranges between 0 and 100. The purpose of this normalization is to facilitate the comparison with other concepts of distance.

Genetic Distance Interactions

As explained by Spolaore and Wacziarg (2009, 2016a) populations that share a more recent common ancestry exchange goods, capital, innovations and technologies more intensively. In this regard, genetic distance measures capture how distant human societies are in terms of the frequency of genes among them and constitutes a molecular clock that characterizes the degree of relatedness between human populations. Typically, people over the world tend to share the same set of gene variants (alleles), but with different frequencies across different populations. Thus, we rely on the update of the weighted F_{ST} metric developed by Spolaore and Wacziarg (2016b) that measures the variation in the allele frequencies for each pair of populations. Denote $p = 1, \ldots, P$ the populations of country i, $q = 1, \ldots, Q$ the populations of country j, s_{pi} the share of population p in country i and (similarly for country j) and d_{pq} the genetic distance between populations p and q. Then the weighted genetic F_{ST} distance between a pair of countries i and j is defined as:

$$F^W_{ST,ij} = \sum_{p=1}^{P} \sum_{q=1}^{Q} s_{pi} \times s_{qj} \times d_{ij} \tag{6}$$

The F_{ST} metric takes a value of 1 when genetic distance is maximum and a value of 0 when the distribution of genes is identical. This metric is post-multiplied by 100.

Linguistic Distance Interaction Matrices

Linguistic distance metrics are based on *language trees* which is a methodology borrowed from *cladistics*. Linguists group languages into families based on perceived similarities between them. Specifically, the classification of languages used here relies on the Ethnologue classification and the variation in the number of common nodes (CN) between languages corresponds to variation in linguistic distance. However, rather than using the number of common nodes between the languages of each country i and j in a pair, (CN) we use the expected or weighted common nodes (CN^W). As described in Spolaore and Wacziarg (2009, 2016a) both (CN) and (CN^W) range from 0 to 15. More formally, for each country in a pair CN^W is given by:

$$CN^W = \sum_{p=1}^{P}\sum_{q=1}^{Q} s_{pi} \times s_{qj} \times c_{pq} \tag{7}$$

where s_{pi} is the share of linguistic group p in country i, s_{qj} is the share of linguistic group q in country j, and c_{ij} is the number of common nodes between languages p and q.

To obtain a measure bounded between 0 and 1, a normalization as in Equation (8) is performed. This metric exploits the fact that countries can be linguistically heterogeneous. For each country pair i and j, linguistic distance is calculated as:

$$TLD_{ij} = \sqrt{\frac{15 - CN^W}{15}} \tag{8}$$

This computation implies that after multiplying by 100, the TLD metric also ranges from 0 to 100, where 100 denotes the maximum linguistic distance.

Religious Distance Interaction Matrices

Religion is another feature that characterizes differences and relatedness among human societies. To capture religious distance between countries we use the tree-based distances between world religions developed by Spolaore and Wacziarg (2016a) who built upon the religion trees developed by Mecham, Fearon and Laitin (2006) and the World Christian Database (WCD). As in the context of language, the number of common nodes between religions is a metric of religious proximity. As before, we calculate the expected number of common nodes between the religions of each country in a pair and normalize it using Equations (8) and (7) above.

III.C. Bayesian Model Selection

According to the literature, there are different criteria to determine the spatial weights matrix that best describes the data: the log-likelihood of the model, the variance of the residuals, or the posterior model probability (PMP), among others. In this regard, the employment of PMP's stemming from Bayesian model comparison exercises has been shown to perform with high accuracy (LeSage, 2014). In this study, we draw on work by Rios (2016), where a Bayesian model comparison analysis is used to choose (i) between DSDM, DSLM, DSDEM and DSEM specifications, and thus between different spatial spillovers specifications, and (ii) between different potential specifications of the spatial weight matrix W. The underlying idea of Bayesian model selection is to consider a finite set of alternative models $M_i = M_1, M_2, .., M_N$ based on different spatial weight matrices and/or functional forms, while holding the other model aspects constant. Proceeding in this way, we determine the PMP of the alternative specifications given a particular spatial weight matrix, as well as the PMP of different spatial weight matrices given a particular model specification. These probabilities are based on log marginal likelihood calculations by integrating out all parameters of the model over the entire parameter space on which they are defined. For any model M_i with its corresponding vector of parameters Θ^i log marginal likelihoods can be calculated as:

$$p\left(y|M_i\right) = \int p\left(y|\Theta^i, M_i\right) p\left(\Theta^i|M_i\right) d\Theta^i \tag{9}$$

where $p\left(y|\Theta^i, M_i\right)$ is the probability of the data conditional on the parameters and the model and $p\left(\Theta^i|M_i\right)$ denote the priors of the vector of conditional parameters to the model. [3]

Columns (1) to (4) of Table (3) report PMPs for the different spatial weight matrices given a concrete spatial model specification whereas Columns (5) to (8) report the PMPs for the different spatial model specifications given a particular spatial weight matrix. As it can be observed, the results derived from the calculation of PMPs imply that conditional on the spatial model (DSEM, DSLM vs DSDM, DSDEM) interactions across countries may be driven by either geographical distances or linguistic distances. Additionally, for the various concepts of distance, different functional forms of the W matrix point to different specifications. Nevertheless, averaging the probability over the W's, points to the DSEM as the preferred specification. This is because of it displays a higher cumulative probability (45.2%) than the DSLM (11.7%), the DSDM (19.7%) or the DSDEM (23.4%). Conditional on the use of the DSEM, we find that the geographical distances are preferred over other types of distance and in particular, the functional form with the highest probability is the traditional gravity inverse-squared distance matrix (57.7%). Thus, our model selection favors the DSEM specification with W:

$$W = \begin{cases} w_{ij} = 0 \quad if \quad i = j \\ w_{ij} = \frac{1/d_{ij}^2}{\sum\limits_j 1/d_{ij}^2} \quad if \quad i \neq j \end{cases} \tag{10}$$

[3] In particular, we employ a normal-gamma conjugate prior for $\delta = [\alpha, \beta, \tau, \phi]$ and σ and a beta prior for λ:

$$p(\delta) \sim N\left(c, \Sigma\right)$$
$$p\left(\frac{1}{\sigma^2}\right) \sim \Gamma\left(d, v\right)$$
$$p\left(\lambda\right) \sim \frac{1}{Beta\left(a_0, a_0\right)} \frac{\left(1+\lambda\right)^{a_0-1}\left(1-\lambda\right)^{a_0-1}}{2^{2a_0-1}}$$

To avoid situations where the conclusions depend heavily on subjective prior information we rely on diffuse or non-informative prior distributions. Parameter c is set to zero and Σ to a very large number $(1e+12)$ which results in a diffuse prior for δ. The diffuse priors for σ and λ (in the case of the SLM/SDM ρ), are obtained setting $d = 0$ and $v = 0$ and $a_0 = 1.01$.

Table 3: Model Selection.

	Posterior Probabilities Across Spatial Models				Posterior Probabilities Across Spatial Weight Matrices				
Weight Matrix	DSLM	DSEM	DSDM	DSDEM	DSLM	DSEM	DSDM	DSDEM	
Geographical Distances									
$1/d^{\alpha}$. $\alpha = 1.5$	0.092	0.403	0.000	0.000	0.054	0.946	0.000	0.000	1.00
$1/d^{\alpha}$. $\alpha = 2$	0.788	0.577	0.000	0.000	0.411	0.589	0.000	0.000	1.00
$1/d^{\alpha}$. $\alpha = 3$	0.092	0.006	0.000	0.000	0.838	0.162	0.000	0.000	1.00
K-Nearest neighbors ($K = 5$)	0.000	0.000	0.000	0.000	0.229	0.771	0.000	0.000	1.00
K-Nearest neighbors ($K = 10$)	0.000	0.000	0.000	0.000	0.055	0.945	0.000	0.000	1.00
K-Nearest neighbors ($K = 15$)	0.000	0.000	0.000	0.000	0.006	0.994	0.000	0.000	1.00
K-Nearest neighbors ($K = 20$)	0.000	0.000	0.000	0.000	0.001	0.998	0.000	0.001	1.00
$exp-(\omega d)$. $\omega = 0.01$	0.000	0.000	0.000	0.000	0.000	0.000	0.877	0.123	1.00
$exp-(\omega d)$. $\omega = 0.025$	0.000	0.000	0.000	0.000	0.000	0.000	0.925	0.075	1.00
$exp-(\omega d)$. $\omega = 0.05$	0.000	0.000	0.000	0.000	0.000	0.000	0.919	0.081	1.00
Linguistic Distances									
$1/d^{\alpha}$. $\alpha = 1.5$	0.000	0.000	0.989	0.969	0.000	0.000	0.000	1.000	1.00
$1/d^{\alpha}$. $\alpha = 2$	0.000	0.000	0.011	0.031	0.000	0.000	0.000	1.000	1.00
$1/d^{\alpha}$. $\alpha = 3$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	1.00
K-Nearest neighbors ($K = 5$)	0.000	0.000	0.000	0.000	0.079	0.921	0.000	0.000	1.00
K-Nearest neighbors ($K = 10$)	0.000	0.000	0.000	0.000	0.069	0.848	0.035	0.048	1.00
K-Nearest neighbors ($K = 15$)	0.000	0.000	0.000	0.000	0.037	0.963	0.000	0.000	1.00
K-Nearest neighbors ($K = 20$)	0.000	0.000	0.000	0.000	0.119	0.881	0.000	0.000	1.00
$exp-(\omega d)$. $\omega = 0.01$	0.000	0.000	0.000	0.000	0.000	0.000	0.740	0.259	1.00
$exp-(\omega d)$. $\omega = 0.025$	0.000	0.000	0.000	0.000	0.000	0.001	0.019	0.980	1.00
$exp-(\omega d)$. $\omega = 0.05$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	1.00
Religious Distances									
$1/d^{\alpha}$. $\alpha = 1.5$	0.000	0.000	0.000	0.000	0.000	0.000	0.506	0.494	1.00
$1/d^{\alpha}$. $\alpha = 2$	0.000	0.000	0.000	0.000	0.000	0.000	0.229	0.771	1.00
$1/d^{\alpha}$. $\alpha = 3$	0.000	0.000	0.000	0.000	0.000	0.000	0.051	0.949	1.00
K-Nearest neighbors ($K = 5$)	0.000	0.000	0.000	0.000	0.393	0.607	0.000	0.000	1.00
K-Nearest neighbors ($K = 10$)	0.000	0.000	0.000	0.000	0.380	0.620	0.000	0.000	1.00
K-Nearest neighbors ($K = 15$)	0.000	0.000	0.000	0.000	0.160	0.840	0.000	0.000	1.00
K-Nearest neighbors ($K = 20$)	0.000	0.000	0.000	0.000	0.127	0.873	0.000	0.000	1.00
$exp-(\omega d)$. $\omega = 0.01$	0.000	0.000	0.000	0.000	0.000	0.000	0.862	0.138	1.00
$exp-(\omega d)$. $\omega = 0.025$	0.000	0.000	0.000	0.000	0.000	0.000	0.816	0.184	1.00
$exp-(\omega d)$. $\omega = 0.05$	0.000	0.000	0.000	0.000	0.000	0.000	0.065	0.935	1.00
Genetic Distances									
$1/d^{\alpha}$. $\alpha = 1.5$	0.000	0.000	0.000	0.000	0.096	0.904	0.000	0.000	1.00
$1/d^{\alpha}$. $\alpha = 2$	0.000	0.000	0.000	0.000	0.187	0.813	0.000	0.000	1.00
$1/d^{\alpha}$. $\alpha = 3$	0.000	0.000	0.000	0.000	0.363	0.637	0.000	0.000	1.00
K-Nearest neighbors ($K = 5$)	0.000	0.000	0.000	0.000	0.518	0.482	0.000	0.000	1.00
K-Nearest neighbors ($K = 10$)	0.000	0.000	0.000	0.000	0.093	0.897	0.000	0.010	1.00
K-Nearest neighbors ($K = 15$)	0.000	0.000	0.000	0.000	0.011	0.989	0.000	0.000	1.00
K-Nearest neighbors ($K = 20$)	0.000	0.000	0.000	0.000	0.029	0.971	0.000	0.000	1.00
$exp-(\omega d)$. $\omega = 0.01$	0.020	0.005	0.000	0.000	0.385	0.251	0.292	0.071	1.00
$exp-(\omega d)$. $\omega = 0.025$	0.008	0.008	0.000	0.000	0.043	0.127	0.688	0.142	1.00
$exp-(\omega d)$. $\omega = 0.05$	0.001	0.001	0.000	0.000	0.011	0.041	0.848	0.099	1.00
	1.00	1.00	1.00	1.00	0.117	0.452	0.197	0.234	

Notes: Bayesian Markov Monte Carlo (MCMC) routines for spatial panels required to compute Bayesian posterior model probabilities do not exist yet. As an alternative all cross-sectional arguments of James LeSage routines are replaced by their spatial panel counterparts, for example a block-diagonal $NT \times NT$ matrix, $diag(W, ..., W)$ as argument for W. All W's are row-normalized.

III.D. Bayesian Model Averaging

In this subsection we describe the functioning of the Spatial Bayesian Model Averaging approach used here. A feature of this methodology is that it consider all possible combinations of regressors and takes a weighted average of the coefficients. Sub-structures of the model in Equation (1) are given by subsets of coefficients $\eta^k = (\delta^k, \lambda)$ and regressors X_k. Assuming that the total number of possible explanatory variables is K, the total number of possible models is 2^K and $k \in [0, 2^K]$. Inference on the parameters of the variables X explicitly takes into account model uncertainty and it is based on probabilistic weighted averages of parameter estimates of individual models:

$$p(\eta|y, X) = \sum_{k=1}^{2^K} p(\eta_k|M_k, y, X)\, p(M_k|y, X) \tag{11}$$

The weights, the PMP's are given by:

$$p(M_k|y, X) = \frac{p(y, X|M_k)\, p(M_k)}{\sum_{k=1}^{2^K} p(y, X|M_k)\, p(M_k)} \tag{12}$$

Model weights can be obtained using the marginal likelihood of each individual model after eliciting a prior over the model space. The marginal likelihood of model M_k is given by: [4]

$$p(y, X|M_k) = \int_0^{\infty} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} p(y, X|\delta, \lambda, \sigma, M_k)\, d\delta d\lambda d\sigma \tag{13}$$

The Posterior Mean (PM) of the distribution of η is:

$$E(\eta|y, X) = \sum_{k=1}^{2^K} E(\eta_k|M_k, y, X)\, p(M_k|y, X) \tag{14}$$

while the Posterior Standard Deviation (PSD) reads as:

$$PSD = \sqrt{Var(\eta|y, X)} \tag{15}$$

[4]We use the same prior distribution configurations for the parameters δ, σ and λ employed in the model selection analysis. However, $p(\delta_k)$ is adjusted following the convention in BMA analysis by means of the g-prior hyper-parameter which takes the value of $g_k = 1/max\left\{n, K^2\right\}$ such that:
$p(\delta_k)\left(\delta_k|\sigma^2\right) \sim N\left[0, \sigma^2\left(g_k X_k^{'} X_k\right)^{-1}\right]$
The employment of the g-prior scales the variance of the coefficients in δ_k reflecting the strength of the prior. Lastly, we employ a binomial prior on the model space $p(M_k) = \phi^k (1-\phi)^{K-k}$, where each covariate k is included in the model with a probability of success ϕ. We set $\phi = 1/2$ which assigns equal probability $p(M_k) = 2^{-K}$ to all the models under consideration.

where the $Var\left(\eta|y,X\right)$ is given by:

$$Var\left(\eta|y,X\right) = \begin{array}{c} \sum_{k=1}^{2^K} Var\left(\eta_k|M_k,y,X\right)p\left(M_k|y,X\right) + \\ \sum_{k=1}^{2K}\left(E\left(\eta_k|M_k,y,X\right) - E\left(\eta|y,X\right)\right)^2 p\left(M_k|y,X\right) \end{array} \tag{16}$$

where the first term reflects the variability of estimates across different regression models and the second term captures the weighted variance across different models. We compute the posterior inclusion probability (PIP) for a variable h as the sum of the PMP's including the variable h:

$$PIP = p\left(\eta_h \neq 0|y,X\right) = \sum_{k=1}^{2K} p\left(\eta_k|M_k,y,X\right)p\left(M_k|\eta_h \neq 0,y,X\right) \tag{17}$$

Finally, we compute the conditional posterior positivity of a parameter h as:

$$p\left(\eta_h \geq 0|y,X\right) = \sum_{k=1}^{2^K} p\left(\eta_{k,h}|M_k,y,X\right)p\left(M_k|y,X\right) \tag{18}$$

where values of conditional positivity close to 1 indicate that the parameter is positive in the vast majority of considered models. Conversely, values near 0 indicate a predominantly negative sign.

We use the Monte Carlo Markov Chain Model Composition (MC^3) methodology for spatial models developed by LeSage and Parent (2007) which builds upon Madigan and York (1995) to evaluate a relevant sample of the full model space, which consists in 86,899 million models. The key feature of this econometric procedure is that it eliminates the need to consider all possible models by constructing a sampler that explores relevant parts of the large model space. The algorithm operates in the model space as follows. If we let M denote the current state of the chain, models are proposed using a neighborhood, $nbd(M)$ which consists on the model itself and models containing either one variable more (*birth step*) or one variable less (*death step*) than M. A transition matrix q, is defined by setting $q(M \rightarrow M') = 0$ for all $M' \notin nbd(M)$ and $q(M \rightarrow M')$ constant for all $M' \in nbd(M)$. The proposed model M', is compared with the current model state M using the acceptance probability:

$$P = min\left[1, \frac{p\left(M'|y\right)}{p\left(M|y\right)}\right] \tag{19}$$

The vector of log-marginal values for the current model M and the proposed alternative models M' are scaled and integrated to produce Equation (12). In addition to the birth and death steps, the sampler employed here includes a third strategy to create models which LeSage and Parent (2007) label as *move step* consisting on replacing randomly variables in X with variables not included currently in the model which leaves the model proposal M' with the same dimension as M.

IV. Results

At this point, it is important to discuss the problems that the methodology applied here can handle and the potential problems that may persist which could affect the quality of the estimates. The SBMA methodology employed here accounts for the uncertainty of the parameter estimates across different models when there is spatial dependence in the data while controlling omitted variable bias (LeSage and Parent, 2007, Moral-Benito, 2015). However, it does not correct for the potential negative effect of endogeneity caused by reverse causal relationships or measurement errors. The potential negative effect of reverse causality is partially solved by using data at the beginning of the time-period interval. As an example, if the observation of CO2 emissions per capita at t=1, corresponds to the time interval 1991-1995, the X, is taken at 1991. On the other hand, to minimize the potential problems implied by measurement errors, outliers and heterogeneity we perform a robustness check in a DSEM where heteroscedasticity in the variance of the error terms is allowed.[5]

IV.A. Baseline Results

Table (4) reports the results obtained under the DSEM specification for the 5,000 top models obtained when implementing the MC^3 algorithm, out of the 26,954 generated by the sampler and a W matrix based on the inverse-squared geographical distance.[6] The concentration of the posterior density across models is very high. In particular, the top 1% models concentrate the 26.45% of mass, while the top 5% concentrate the 62.6%. We scale the PIPs of the different variables in quartiles to classify evidence of robustness of CO2 per capita covariates into three categories so that regressors with PIP $\in [0-25\%]$ are considered as weak determinants, variables with PIP $\in [25-75\%]$ as moderate determinants and with PIP $\in [76-100\%]$ as highly important.

Columns (2) to (5) show the mean and the standard deviation of the posterior parameters distributions, along with the lower and upper bounds, conditional on the variable being included in the model.[7] To complement these statistics, Column (6) reports the fraction of models where the t-stat of the corresponding variables is higher than 1.96 (which implies statistical significance at the 5% level),

[5]We do not include here the additional results of the heteroscedastic DSEM given that changes with respect the baseline specification are negligible.

[6]The number of draws in the sampling exercise over the model space was 100,000.

[7]The key difference with respect to unconditional posterior estimates of Equations (14) and (15) is that conditional posterior estimates for a particular variable are obtained as the weighted average over the models where the variable is included. On the contrary, the unconditional posterior estimate is the averaged coefficient over all models, including those in which the variable does not appear, hence having a zero coefficient. Thus, the unconditional posterior mean can be computed by multiplying the conditional mean in Column (3) times the PIP in Column (1)

while Column (7) presents the results of the posterior sign certainty, which measures the posterior probability of a positive coefficient expected value, conditional on inclusion.

As observed, there is a consistent set of top variables that appears with high frequency in the group of very important determinants. Within this group, we find on the top the diffusion error term, the time lag and the space-time lag terms. Some comments about the spatio-temporal parameters (ρ, τ, ϕ) model averaged estimates are worth mentioning. The spatial diffusion parameter λ appears to be positive and significant at the 5% level in the 100% of the models. Similarly, the time lag τ and the space-time lag ϕ are significant at conventional levels in the 100% and the 97.7%. The model averaged estimated time lag is 0.7179, the space-time lag term is -0.0466 whereas the error diffusion term is 0.3962. This implies that a 1% shock to the estimated error term of CO2 emissions per capita in one location propagates to all the other locations of the sample with an average quadratic decay of the 39.62% as distance increases. Importantly, the averaged sum of parameters over models suggest the analysis not suffer from space-time cointegration issues (i.e, $\tau + \phi = 0.67$). Moreover, our findings suggest that lagged values of CO2 emissions per capita in neighboring economies affect emissions per capita of any country. Another salient feature of these results is that of a process of convergence in the evolution of CO2 emissions per capita. The time lag estimated value implies and speed of convergence of the 6.59% per year. This value is higher than previous estimates of convergence in CO2 emissions per capita of Brook and Taylor (2010) who find a speed of convergence of the 1.6%.

To provide further evidence on the relevance of the spatio-temporal terms in the DSEM specification, Figure (3) shows the different PIPs for the full set of regresors when the model is a Dynamic non-spatial panel. As observed, for variables with PIPs above the 75% or below the 25% the differences are small whereas for the set of regressors with PIPs ranging between 25% and 75% accounting for the spatial dependence in the error process implies drastic changes. Variables with marked geographical patterns such as the degree of financial openness, population density, the production of oil, the income inequality, the share of young population and followers of non dual religions experiment fluctuations of probability of an order about the 30%. These suggest that omitting spatio-temporal interactions across-countries and the possibility of spatially correlated shocks when analyzing CO2 emissions may lead to fallacious inferences. All in all, these results stress the relevance of space and confirm that the dynamic spatial panel data modeling framework adopted in this analysis is suitable for studying the evolution of CO2 emissions per capita.

A feature of the group of highly relevant determinants is that it is not only characterized by higher PIPs than the others, but also because of it displays totally certain (or almost totally certain) sign effects (either positive or negative) that are significant at the 5% level in 97 to 100% of the models. The share of agriculture in the GDP (96.4%) is the most clear driver of CO2 emissions

Figure 3: Dynamic SEM vs Dynamic OLS

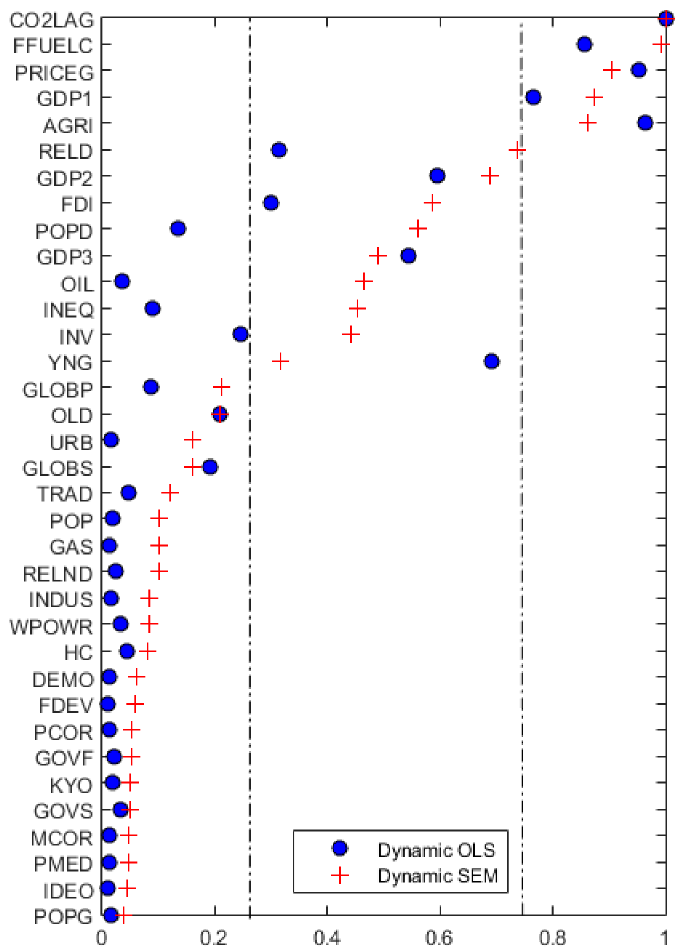


Table 4: Main Results: Dynamic Spatial Error Model Averaged Estimates

Variable	PIP (1)	Lower 5% (2)	Cond Post. Mean (3)	Cond Post. Std (4)	Upper 95% (5)	T-Stat > 1.96 (6)	Sign Pos. (7)
Time lag (τ)	1.000	0.6993	0.7179	0.0138	0.7428	1.000	1.000
Space-Time lag (ϕ)	1.000	-0.0557	-0.0466	0.0062	-0.0355	0.977	0.000
Error Diffusion (λ)	1.000	0.3715	0.3962	0.0161	0.4267	1.000	1.000
Agriculture	0.964	-0.0114	-0.0095	0.0021	-0.0075	1.000	0.000
Gasoline price	0.953	-0.1984	-0.1680	0.0436	-0.1310	1.000	0.000
Fossil fuel consumption	0.856	0.0020	0.0026	0.0008	0.0031	1.000	1.000
Ln GDP per capita	0.766	0.2271	0.7255	0.2979	1.0779	0.972	1.000
Population < 15 years old	0.691	-0.0196	-0.0117	0.0050	-0.0068	0.993	0.000
Ln GDP per capita ^{2}	0.595	-0.0514	-0.0010	0.0427	0.0751	0.964	0.322
Ln GDP per capita ^{3}	0.543	-0.0047	-0.0024	0.0015	-0.0010	0.964	0.034
No Dual Religions	0.314	-0.0018	-0.0013	0.0006	-0.0010	0.972	0.000
Financial Openness	0.301	0.0019	0.0027	0.0012	0.0032	0.928	1.000
Investment Ratio	0.256	0.0041	0.0049	0.0021	0.0057	0.958	1.000
Population > 65 years old	0.209	-0.0286	-0.0201	0.0081	-0.0012	0.908	0.045
Social Globalization	0.191	0.0025	0.0037	0.0015	0.0046	0.759	1.000
Ln Population density	0.135	0.0153	0.0252	0.0094	0.0342	0.712	1.000
Income Inequality	0.090	-0.0051	-0.0040	0.0013	-0.0028	0.529	0.000
Political Globalization	0.086	0.0012	0.0017	0.0005	0.0022	0.458	1.000
Trade Openness	0.048	0.0003	0.0006	0.0002	0.0010	0.226	1.000
Human Capital	0.045	-0.0887	-0.0615	0.0161	0.0008	0.177	0.060
Oil Production	0.036	0.0000	0.0000	0.0000	0.0000	0.177	0.984
Government Strength	0.033	0.0005	0.0016	0.0004	0.0026	0.342	0.997
Women Empowerment	0.032	-0.0014	-0.0010	0.0002	-0.0007	0.010	0.000
Dual Religions	0.024	-0.0015	0.0001	0.0002	0.0009	0.000	0.689
Government Fragmentation	0.021	-0.0007	-0.0005	0.0001	-0.0003	0.000	0.000
Ln Population	0.019	0.0263	0.0446	0.0089	0.0588	0.000	1.000
Kyoto	0.019	-0.0045	0.0079	0.0019	0.0189	0.017	0.922
Population Growth	0.016	-0.0098	-0.0069	0.0014	-0.0023	0.000	0.004
Industry	0.015	0.0000	0.0006	0.0002	0.0014	0.000	0.940
Political Corruption	0.015	0.0001	0.0008	0.0002	0.0014	0.000	0.968
Urban Population	0.014	-0.0010	-0.0004	0.0001	0.0001	0.000	0.104
Population 30-49 years old	0.014	0.0000	0.0000	0.0000	0.0000	0.000	0.876
Gas Production	0.013	-0.0003	0.0005	0.0002	0.0013	0.000	0.823
Media Corruption	0.013	-0.0032	0.0014	0.0008	0.0064	0.000	0.641
Democracy	0.012	-0.0129	0.0005	0.0022	0.0180	0.000	0.393
Financial Development	0.011	-0.0004	0.0000	0.0002	0.0005	0.000	0.439
Ideology	0.011	-0.0065	0.0014	0.0021	0.0067	0.000	0.692

Notes: The dependent variable in all regressions is the CO2 emissions per capita. All the results reported here correspond to the estimation of the top 5,000 models from the 86,899 million possible regressions including any combination of the 33 variables. Prior mean model size is 18. Variables are ranked by Column (1), the posterior inclusion probability. Columns (2) to (5) reflect the lower 5% bound, the posterior mean, standard deviations and upper 95% bound for the linear marginal effect of the variable conditional on inclusion in the model, respectively. Column (6) is the fraction of regressions in which the coefficient has a classical t-test greater than 1.96, with all regressions having equal sampling probability. The last column denotes the sign certainty probability, a measure of our posterior confidence in the sign of the coefficient.

per capita. It is followed by a range of economic factors, including the price of gasoline (95.3%), the share of fossil fuel consumption in the total energy (85.6%) and the GDP (76.6%). As expected, there is a negative relationship between the share in agriculture and CO2 emissions per capita, which is line with the findings of other studies that included this control (Aichele and Felbermayr, 2013). The rationale for this finding is that agrarian economies are characterized by low resource depletion rates and waste generation rates, which results in pristine environmental conditions. Similarly, increasing prices of the gasoline exert a negative effect on CO2 emissions per capita as in Agras and Chapman (1999). The negative link between higher gasoline prices and CO2 emissions, is explainable through economic theory, given that lower gasoline prices result in increased consumption and transportation, and thereby, in increased pollutant emissions. On the other hand, we find that the share of fossil fuel consumption in the total energy is positively related to CO2 emissions per capita, as fossil fuels are the more environmental damaging inputs used in the process of production. Finally, the level of production is observed to have a positive effect on CO2 emissions. If there is no change in the input-output ratio or in the techniques of production, a higher scale of production generates a higher level emissions.

In the group of determinants of medium level of importance, we find the share of population below 15 years old (69.1%), the squared and cubic terms of the GDP with PIPs of 59.5% and 54.3% respectively, the share of population following a non dual-type religion (31.4%), the degree of financial openness (30.1%) and the share of investment in the GDP (25.6%). The negative effect of the share of population with less than 15 is explained by the fact that (*i*) the higher the share of population is in a stage of life characterized by low economic activity and energy consumption (Liddle, 2014) and (*ii*) because of the higher the share of young/old population the stronger the preferences of environmental quality (Menz and Welsch, 2010). Another interesting result is that the higher the share of population following religions where there is no dualism between human and nature, the lower the level of emissions, which goes in line with theoretical insights of White (1967) and the empirical analysis of Tjernstrom and Tietenberg (2008) and Morrison *et al.* (2015). The findings for financial openness and investment suggest they exert a positive impact on CO2 emissions which supports previous findings of Omri *et al.* (2014) and Brook and Taylor (2010) respectively. An explanation for this result is that financial flows may be directed to energy-intensive industries of developing countries with fewer environmental controls and where the level of efficiency in power-generation is low. On the other hand, the positive effect of the overall investment share is explained by the fact that investment promotes GDP growth and the scale effect of GDP rises emissions.

Taking into account the fact that in the group of highly relevant determinants we already observed a positive relationship between pollution and the GDP, an interesting finding that emerges from the model-averaged estimated parameters of the squared and cubic terms of GDP is that the pollution-income relationship in this context appears to be U-shaped, given that both the squared and cubic terms are negative. Hence these findings support previous results of Holtz-Eakin and Selden (1995),Tucker (1995), Galeotti et al. (2006) or Grunewald et al. (2017) who also observed an inverted U-shape relationship. Our parameter values for the linear, quadratic and cubic terms of the logarithm of the GDP per capita suggest the turning point is located in $\ln(10.1) \approx 23,623$ US dollars. However, the uncertainty regarding the sign of the quadratic term is very high. In 32% of the regressions the value is positive while it is negative in 68% of them, which implies that in a substantial number of models, the implied EKC pattern could be N-shaped.

Finally, weak CO2 emissions per capita drivers include other economic factors (e.g. inequality, trade opennesss, human capital, oil and gas production, the share of industry in the GDP and the level of financial development), political factors (the level of democracy, the ideology, fragmentation and the government's strength, the level of political corruption, the degree of political globalization), demographic factors (population density, population growth, the share of urban population, the share of population between 30-49 years old) and social factors (the media corruption, the women empowerment, the social globalization, dual religions). With the exception of the effect of the share of population above 65 years old, social globalization and population density, which are (*i*) either positively or negatively related to CO2 emissions with almost certainty in all regressions in which the variables are included, and (*ii*) appear to be significant at 5 % level in the 70-90% of the models, the results obtained for the other weak determinants do not allow to draw clear conclusions on the effect exerted on CO2 emissions. The reasons are twofold. First, in many cases the posterior sign certainty of these regressors is around 0.3-0.7, suggesting that both positive and negative effects can be observed. Consequently, the causal relationships for this group of variables are not robust. Second, the fraction of regressions where these variables exhibit t-stats above the 5% significance level is always below the 50% and even virtually 0% in many cases.

Overall, our findings suggest that economic factors are the key factors shaping the evolution of CO2 emissions, even though some demographic factors and social factors also play a non-negligible role. On the contrary, political and institutional factors appear to be of minor importance.

V. Conclusions

This study analyzes the importance of a large number of possible determinants of CO2 emissions per capita during the period 1991-2014 for a sample of 123 countries. They key contributions are methodological given that we consider the effect of a great number of determinants employing Spatial Bayesian Model Averaging techniques while accounting for different concepts of cross-country interactions and different spillover processes. Over the different type of interactions considered: geographical, genetic, linguistic and religious we find that traditional geographical interactions outperform the others whereas our findings regarding the spatial interaction model points to the Dynamic Spatial Error model.

Spatial Bayesian Model Averaging analysis enable us to compute the PIPs for the different indicators to generate a probabilistic ranking of relevance for the various CO2 determinants. Our results point out the existence of a set of robust determinants of CO2 emissions. These consist of: (*i*) initial level of CO2 emissions and the initial level of emissions of neighboring countries, (*ii*) the share of agriculture in the value added (*iii*) the gasoline price, (*iv*) the age composition of the population, (*v*) the linear, quadratic and cubic terms of income (*vi*) the share of population following non-dual religions, (*vii*) the level of financial openness and (viii) the ratio of investment to GDP. Therefore, we find strong support to the idea that economic factors are the key sources of CO2 emission differentials while political and institutional factors are of minor importance.

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