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Robust Determinants of CO_2 Emissions

Carlos Aller* Lorenzo Ductor† Daryna Grechyna‡

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Abstract

We synthesize the findings of a large number of recent papers on the determinants of CO_2 emissions and identify the most robust determinants accounting for model uncertainty using two different approaches: Bayesian Model Averaging and Cluster-LASSO. Our results show that GDP per capita, the share of fossil fuels in energy consumption, urbanization, industrialization, democratization, the indirect effects of trade (networks effects) and political polarization are the robust determinants of CO_2 emissions per capita. All of these determinants negatively affect the environment, with the exception of greater political polarization, which reduces the level of CO_2 emissions. We also find that the determinants of CO_2 emissions depend on the level of income per capita of a country. In low-income economies, foreign direct investment increases environmental degradation, while tourist arrivals have a negative impact on the environment in high-income economies.

Keywords: carbon dioxide emissions; model uncertainty; Bayesian Model Averaging; LASSO estimator.

JEL classification: D14, K42, O17.

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1 Introduction

Environmental quality and global warming are significant concerns in the modern world economy. Recently, these concerns have intensified as climate change experts released updated numbers pointing to an acceleration in global environmental degradation (World Meteorological Organization, 2020). Every country has experienced, at least to some extent, the impact of climate change. Carbon Dioxide (CO_2) emissions from fuel combustion processes are responsible for a major share of greenhouse gases (Pazienza, 2019). According to Garmann (2014), CO_2 emissions are the main cause of global warming. Despite researchers. intense focus on the deterioration of environmental quality and recent international cooperation efforts to tackle it, global CO_2 emissions are still rising rapidly: from around 23 Gt in 2000 to around 33 Gt in 2019 (International Energy Agency, 2019).

This paper contributes to the literature by conducting a systematic review of the potential determinants of CO_2 emissions and carrying out an empirically-robust and scientifically sound analysis of their relative importance. We extract eight different categories of factors considered independently in most empirical studies of countries' CO_2 emissions: *economic development*(Selden and Song, 1994; Grossman and Krueger, 1995; among many others); *sectoral composition* (Panayotou, 1997); *international trade* (Taylor, 2005; Aller et al. 2015); *financial development* (You et al. 2015); *foreign direct investment* (Cardoso Marques and Caetano, 2020; Acharyya, 2009); *urbanization* (Sardosky, 2014); *sources of energy* (Shafiei and Salim, 2014); and the *quality of political institutions* (Purcel, 2019).

The variety of studies on the factors influencing country-level CO_2 emissions can be explained by model uncertainty: there is no unified theoretical and empirical framework for examining the drivers of CO_2 emissions from an economic perspective. Instead, analyses tend to rely on small, predefined sets of potential determinants, depending on the data, methodology, and variables considered.

This approach can lead to pre-testing bias and increases the risk of "researcher degrees of freedom" and "p-hacking" where the estimation is conducted using multiple combinations of regressors with the aim of obtaining statistically significant estimates (Simmons et al., 2011). Besides, it can also give rise to the problem of omitted variables, which may lead to biased estimates. As suggested in Sala-i-Martin et al. (2004), a natural way to think about model uncertainty is to admit that we do not know which model is "true" and instead attach probabilities to different models. This is the main idea behind Bayesian Model Averaging (BMA), which consists in estimating all possible combinations of the regressors and taking a weighted average over all the candidate models, where the weights are the probabilities that the candidate model is the true model. Another regression analysis method that performs both variable selection and regularization in order to enhance the prediction accuracy and interpretability of a model is the Cluster Least Absolute Shrinkage and Selection Operator (Cluster-LASSO). The Cluster-LASSO method minimizes the sum of squared errors, with an upper bound imposed on the sum of the absolute values of the model parameters. The method entails applying a shrinking (regularization) process whereby the coefficients of the regression variables are penalized, shrinking some of them to zero.

We account for uncertainty in CO_2 emissions models and identify robust determinants of CO_2 emissions by using a BMA panel data approach, the Cluster-LASSO method, and the Weighted Least Squares estimation method. To the best of our knowledge, this is the first study that addresses model uncertainty when identifying the main drivers of CO_2 emissions over time. Moreover, we control for country fixed effects that include geographical, cultural and sociological factors which are relatively stable over time, and use lagged values of the potential determinants to avoid reverse causality issues.

We conduct the analysis using longitudinal data on 92 countries over the period 1995-2014. The findings indicate that the most important determinants of emissions per capita are the following: *GDP per capita* which is positively associated with CO_2 emissions, supporting the existing evidence of the *scale effect*[1]; the *share of fossil fuels in energy consumption*, which plays an important role in explaining environmental degradation, suggesting that increasing use in renewable energies is crucial to improving environmental quality; *urbanization* and *industrialization*, which increase environmental degradation; *political polarization* which reduces the level of CO_2 emissions; and the *indirect effects of trade* captured by the measures of centrality in the world trade network. Our results suggest that more central positions in the world trade network are associated with a higher level of CO_2 emissions.

Moreover, the determinants of CO_2 emissions depend on the level of income per capita. In particular, we find that CO_2 emissions in high- and medium-income economies are affected by the share of industry in GDP, political polarization and tourism, while the CO_2 emissions in low-income economies are positively affected by foreign direct investment (FDI), the level of democracy and corruption.

The rest of the paper is organized as follows. Section 2 describes the potential determinants of

[1]However, our results do not support the Environmental Kuznets Curve (EKC) hypothesis, i.e. we do not find a non-linear relationship between GDP per capita and CO_2 emissions per capita.

CO_2 emissions, drawn from related studies. Section 3 explains the methodology used in this study, based on the BMA and Cluster-LASSO estimation approaches. Section 4 reports and discusses the results and robustness checks. Section 5 concludes.

2 Data and related literature

We use a representative panel sample of 92 countries, covering last two decades, 1995-2014. Our main variable of interest is CO_2 emissions per capita as a proxy for environmental quality. The data on CO_2 emissions and most of the potential determinants are sourced from the World Bank, unless specified otherwise.

Given that the effects of the determinants on environmental degradation can depend on the level of income in a country (see, for example, Aller et al., 2015), we follow the methodology adopted by a number of authors (Shafik, 1994; Poumanyvong and Kaneko, 2010; Aller et al., 2015; Shahbaz et al., 2015; Le et al., 2016; Kolcava et al., 2019) and group observations according to the country's income level. We use the World Bank gross national income per capita classification 2019 to split the sample between high/medium ($4,046 per capita or more) and low income economies ($4,045 per capita or less).[2] We draw on the literature to identify the potential determinants of CO_2 emissions and consider several categories of variables, as described below.

2.1 Potential Determinants of CO_2 Emissions

2.1.1 Economic Development

The state of the environment non-trivially depends on the level of economic development. The related studies use GDP per capita to account for the so-called "scale" effect: the economic growth produced by an increase in economic activity is likely to increase pollution. However, as countries grow wealthier, they may specialize in producing more environmentally-friendly goods. For this

[2] High/medium-income countries: Albania, Algeria, Angola, Argentina, Australia, Austria, Azerbaijan, Bahrain, Belarus, Belgium, Brazil, Bulgaria, Canada, Chile, Colombia, Costa Rica, Croatia, Denmark, Ecuador, Finland, Gabon, Greece, Hungary, Iceland, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kuwait, Latvia, Lebanon, Libya, Malta, Mauritius, Mexico, Netherlands, New Zealand, Norway, Oman, Panama, Peru, Poland, Portugal, Qatar, Romania, Saudi Arabia, Singapore, Slovenia, Spain, Sweden, Thailand, Tunisia, Turkey and Uruguay. Low-income countries: Armenia, Bangladesh, Bolivia, Cambodia, Cameroon, Core d'Ivoire, El Salvador, Georgia, Ghana, Guatemala, Haiti, Honduras, India, Indonesia, Kenya, Moldova, Mongolia, Morocco, Mozambique, Myanmar, Nepal, Nicaragua, Niger, Nigeria, Paraguay, Philippines, Senegal, Sri Lanka, Tajikistan, Tanzania, Togo, Ukraine, Vietnam, Zambia and Zimbabwe.

reason, the literature has extensively explored the Environmental Kuznets Curve (EKC) hypothesis, generally claiming an inverted U-shaped relationship between income and environmental pollution (see, for example, Selden and Song, 1994; Grossman and Krueger, 1995; Harbaugh et al., 2002; Apergis, 2016.; Balogh and Jámbor, 2017). Thus, we include both the level and the square of real GDP per capita as potential determinants of CO_2 emissions.

2.1.2 Sectorial Composition

In line with the previous subsection, the composition effect refers to changes in the economic structure of a country. The typical transition from an agricultural to a (pollution-intensive) industrial economy contributes to climate change by adding CO_2 (Panayotou, 1997) and other heat-trapping gases to the atmosphere, whereas just the opposite occurs when an economy evolves from heavy industry to clean manufacturing and services (Kolcava et al., 2019). However, agricultural activities involving harvesting, deforestation and the export of agricultural products can contribute significantly to carbon emissions (see, for example, Foley et al., 2011; Baccini et al., 2012; Henders et al., 2015; Balogh and Jámbor, 2017).[3] Thus, we include the agriculture value added per hectare and per worker in constant US dollars and the industry value added as a share of GDP in our estimations.[4]

2.1.3 International Trade

The inverted U-shaped relationship between GDP per capita and CO_2 emissions (EKC hypothesis) could be explained by cleaner domestic production, as a country grows, and by changes in trade patterns. Developed economies tend to import non-environmentally-friendly goods (i.e., energy, resource-intensive goods or raw materials) from less developed countries (*pollution haven hypothesis*). Thus, the impact of international trade on CO_2 emissions depends on the level of development of the country (see, for example, Antweiler et al., 2001; Frankel and Rose, 2005; Le at al., 2016; Balogh and Jámbor, 2017; Kolcava et al., 2019). In addition, trade can be a channel through which

[3] In particular, Foley et al. (2011) and Baccini et al. (2012) estimated that tropical deforestation contributes 6-17% of global anthropogenic CO_2 emissions to the atmosphere.

[4] Agriculture value added is the net output from forestry, hunting, and fishing, as well as cultivation of crops and livestock production. Industry value added is the net output, as a share of GDP, of construction, electricity, water, and gas.

the so-called technique effect operates: a transfer of knowledge resulting in the use of less-polluting technologies, mitigating environmental degradation (Herrerias et al., 2013). In our estimations, we include a country's trade openness measured as the sum of its exports and imports as a share of GDP (direct effects), and its net energy imports as a percentage of total energy use.[5]

There are also indirect effects of trade that have consequences for the environment (Aller et al, 2015; Zhang et al. 2020). Aller et al. (2015) introduced two indirect effects: *congestion externalities* and *market power*. First, *congestion externalities* reflect the fact that resources are limited and when a country i increases its exports to another country j, the other trade partners of country i may receive fewer imports from i. Thus, these other trade partners of country i make more use of domestic resources and increase their level of emissions. The second indirect trade effect is *market power*. The role of a country in connecting the trade between two other countries defines its *market power* and, consequently, pricing and efficiencies. A higher level of trade between two countries that passes through an intermediary country increases the latter's market and bargaining power in trade negotiations (Choi et al., 2017) giving it more opportunities to reduce its pollutant emissions at the expense of less critical countries (Aller et al., 2015). The net indirect effects of trade, captured by measures of centrality in the world trade network, is the sum of the *congestion externalities* and *market power* effects. The measures of each country's centrality in the world trade network are *degree* (number of trade partners), *betweenness*, *closeness*, *in-closeness*, *out-closeness* and *eigenvector* centralities. These measures were obtained based on social network analysis and the world trade network, using data on bilateral imports retrieved from the UN Comtrade database, as in Aller et al. (2015). In the world trade network, countries are nodes and trade relationships are links, where the links are weighted by the volume of imports between the countries. For a formal definition of each network variable, see Aller et al. (2015).

2.1.4 Tourism

According to the World Tourism Organization (2019), transport-related CO_2 emissions from tourism represented 5% of all anthropogenic emissions in 2016. Tourism involves travelling from one place to another and most of these trips are made by plane, generating substantial CO_2 emissions.[6]

[5]Net energy imports data are from the IEA statistics and are estimated as energy use less production, both measured in oil equivalents.

[6]For example, a Boeing 737-400 jet is typically used for short-haul international flights. For a distance of 926 km, the amount of fuel used is estimated at 3.61 tonnes, including taxiing, take-off, cruising and landing. Based on a

Moreover, tourists increase the consumption of resources in the visited regions (e.g., when they choose to drive their own vehicles at their destination). Recent studies have found that tourism intensity can contribute to CO_2 emissions (see, for example, Lee and Brahmasrene, 2013, for an EU context; and Zaman et al., 2016 and Paramati et al. 2017 for differences between developed and developing economies). Following these studies, we include the number of tourist arrivals to a given country as a potential determinant of CO_2 emissions.

2.1.5 Financial Development

The characteristics of a country's financial sector and the level of financial openness are key elements of a country's economic performance (Ductor and Grechyna, 2015). Several studies have pointed out that financial development can influence the state of the environment. In particular, a more developed financial sector could enable the faster adoption of new energy-saving technologies by providing more financing at lower cost. Similarly, greater financial openness could facilitate positive spillovers from technological innovations abroad. Focusing on BRIC economies, Tamazian et al. (2009) find that financial development is associated with lower CO_2 emissions in a model including a set of variables capturing characteristics of the banking and financial system. Tamazian and Rao (2010) report that financial liberalization contributes to a reduction in CO_2 emissions in European transitional economies, while You et al. (2015) find no relation between financial openness of a country and its level of pollution. In this paper, we include the domestic credit to the private sector (% GDP) –a proxy for financial development–, as a potential determinant of CO_2 emissions.

2.1.6 Foreign Direct Investment

The effect of FDI on the environment is a matter of controversy in the literature. Following Cardoso Marques and Caetano (2020), the adoption of new technologies promoted by FDI can be beneficial for the environment if it involves the transfer and uptake of greener technology (Melane-Lavado et al., 2018; Pazienza, 2019; Xing-gang et al., 2019). However, FDI could also increase emissions by boosting the presence of multinationals and big polluting companies (Acharyya, 2009). In this vein, the *Pollution Haven Hypothesis* states that developed industrialized countries tend to invest in

capacity of 164 people and a load factor of 65%, resulting fuel use is 36.6 g per passenger km.

the countries with the lowest environmental standards or weakest enforcement, usually developing economies, and import polluting goods produced in these economies (see, for example, Omri et al., 2014; Baek, 2016; Millimet and Roy 2016; Bae et al., 2017). Based on these studies, we include the share of FDI in GDP as a potential determinant of CO_2 emissions.

2.1.7 Urbanization

There is no consensus on the effect of urbanization on the environment. Following Sadorsky (2014), a higher level of urbanization is associated with higher economic activity, which in turn generates higher wealth. Whereas wealthier people often demand more energy intensive products, the also tend to care more about the environment. Several papers conclude that higher urbanization rate can contribute to environmental degradation. Focusing on developed economies, Poumanyvong and Kaneko (2010) and Salahuddin et al. (2016) find a positive relation between urbanization and CO_2 emissions. In developing countries, Martínez-Zarzoso and Maruotti (2011) find an inverted U-shaped relationship between urbanization and CO_2 emissions while Sadorsky (2014) concludes that the two opposing effects cancel each other out. We include the standard measure of urbanization, the share of the population living in urban areas, as a potential determinant of CO_2 emissions.

2.1.8 Sources of energy

Sources of energy vary from very environmentally friendly (renewable energy sources such as wind-power, hydro-power, geothermic energy) to very harmful for the environment (energy from oil, coal, natural gas). Several studies analyse the effect of sources of energy on the level of CO_2 emissions per capita (see, for example, Shafiei and Salim, 2014; Dogan and Seker, 2016; Jebli et al., 2016), accounting for both renewable and non-renewable energy consumption; they generally conclude that the use of non-renewable energy have a positive impact on pollutant emissions.

To account for the potential impact of the sources of energy, we include a variable capturing the percentage of fossil fuels in the total energy consumption by country and year.

2.1.9 Political Institutions Quality

Countries with better political institutions are more likely to have stricter environmental policies and respect international environmental agreements aimed at reducing emissions. We capture the quality of political institutions through the level of corruption, political instability, democracy and political polarization in a country.

Corruption could directly reduce the stringency of environmental regulations and thereby increase pollution (Fredriksson and Svensson, 2003). It could also reduce pollution indirectly through the reduction in income per capita. Welsch (2004) and Cole (2007) find evidence of these tow opposite mechanisms, resulting in a non-significant total effect (except for high-income economies, where the total effect of corruption on emissions is found to be negative and significant).

The effect of corruption on the environment may also depend on the political instability of a country, where political stability is understood as the government'S ability to perform its declared tasks and stay in office (Muhammad and Long, 2020). Fredriksson and Svensson (2003) find that political instability is negatively (positively) associated with the stringency of environmental regulations in countries with low (high) levels of corruption. A number of other studies have also examined the link between political instability and the environment: Fredriksson and Wollscheid (2014) study the role played by party strength in the effect of political stability on environmental policies; Abid (2017) reports a negative relation between political stability and pollution; Purcel (2019) finds that political stability helps to reduce CO_2 emissions only after a certain threshold of political stability is reached; and Muhammad and Long (2020) find that political stability reduces emissions only in high-income countries and is not significant in the rest of the country income groups.

The degree of political and economic freedom in a country can influence the country's environmental policies. In particular, Farzin and Bond (2006) state and test the hypothesis that "democracy and its associated freedoms provide the conduit through which agents can exercise their preferences for environmental quality more effectively than under an autocratic regime". The authors emphasize that the impact of democracy on environmental quality is conditional on other political and economic characteristics of the country, such as income inequality or the urbanization rate. A number of empirical papers studying the determinants of environmental pollution have included measures of democracy as an explanatory variable (see, for example, Harbaugh et al., 2002; Bernauer and Koubi, 2009; Adams and Klobodu, 2017).

Another variable that could capture the quality of political institutions is *political polarization*, defined as the ideological distance between parties. Political polarization has increased in recent years, especially among high/middle-income countries (see, for example, Wagner and Meyer, 2017). This growing polarization is associated with an increase in political uncertainty, which could discourage investment (Azzimonti, 2011) and therefore reduce CO_2 emissions. Besides, political polarization could lead parties to adopt more extreme policies to fight against pollution and environmental degradation in general. The related study by Garmann (2014) focuses on the influence of government ideology and fragmentation on reducing CO_2 emissions.

We include proxies for public corruption, political instability, democracy, and political polarization as potential determinants of CO_2 emissions. For *public corruption*, we use the political corruption index from the *Quality of Government Data* (2019). For *democracy*, we use the democratization index developed by Vanhanen (2019), which is calculated by multiplying the political competition and political participation variables and then dividing the outcome by 100. The *political competition* variable is the percentage of votes gained by the smaller parties in parliamentary and/or presidential elections. *Political participation* is calculated as the percentage of the total population who actually voted in the election. *Political instability* is the percentage of veto players who drop out of the government in any given year and comes from the *Database of Political Institutions* (2017). *Polarization* is obtained from the *Database of Political Institutions* (2017) and is the maximum difference between values of the chief executive's party–coded as Right (1); Left (3); Center (2); No Information (0)–and the values of the three largest government parties and the largest opposition party.

2.2 Descriptive statistics

Descriptive statistics for the level of CO_2 emissions and its potential determinants are reported in Table 1. We observe that, on average, high- to medium-income countries are significantly more polluting (around 10 times more) than low-income countries. These economies present higher shares of industry and services, higher domestic credit to the private sector, and they have better institutions (as reflected by lower corruption and higher democracy scores). Moreover, high/medium-income economies trade more and are more central in the world trade network (as captured by closeness, betweenness, degree and eigenvector centralities). The political polarization index in high/medium-income economies doubles that in low-income economies.

3 Methodology

Our aim is to identify the robust determinants of environmental quality, proxied by CO_2 emissions per capita. The general model is defined as follows:

$$log(CO_{2i,t}) = \alpha_i + \mu_t \gamma' + x'_{i,t-1}\rho + \epsilon_{i,t}, \tag{1}$$

where $CO_{2i,t}$ is the level of CO_2 emissions measured in metric tonnes per capita in country i and year t; $x'_{i,t-1}$ includes a set of potential determinants of CO_2 for country i, as described in section 2.1. The determinants are included with a lag, at $t-1$, to avoid simultaneity bias between CO_2 emissions and the potential determinants.[7] α_i captures the time-invariant unobservable factors in country i, such as cultural factors and its geographical situation, among others, and μ_t refers to year fixed effects and captures world oil prices, technological progress, growing globalization, and international environmental regulation, among others; ϵ_{it} is the disturbance term.

We consider two different approaches to identify the underlying factors explaining CO_2 emissions per capita: BMA and LASSO. BMA addresses model uncertainty by estimating model (1) for all possible combinations of the regressors and taking a weighted average over all the candidate models, where the weights are determined by applying Bayes' rule. The probability that model j, M_j, is the "true" model given the data, y, i.e., the posterior model distribution given a prior model probability, is defined as

$$P(M_j|y) = \frac{P(y|M_j)P(M_j)}{\Sigma_{i=1}^{2k} P(y|M_i)P(M_i)}, \tag{2}$$

where $P(y|M_j)$ is the marginal likelihood of Model j, $P(M_i)$ is the prior model probability, and $\Sigma_{i=1}^{2k} P(y|M_i)P(M_i)$ is the integrated likelihood of model j. We use the priors specified in Magnus et al. (2010). In particular, they consider uniform priors on the model space, so each model has the same probability of being the true one. Moreover, they use a Zellner's g-prior structure for the regression coefficients and set the hyperparameter $g = \frac{1}{max(N,K^2)}$, as in Fernandez et al. (2001), where K is the number of regressors and N the number of observations. This hyperparameter measures the degree of prior uncertainty over the coefficients. For the sake of robustness, we also consider 'random theta' and 'fixed' priors for the model space. In the next section, we present the estimates of the *posterior inclusion probability (PIP)* of an explanatory factor, which can be

[7] As a robustness check, we also consider a specification with determinants at t: the results are qualitatively the same.

interpreted as the probability that a particular regressor belongs to the true model of CO_2 emissions. We also present results for the posterior mean, the coefficients averaged over all models, and the posterior standard deviation, which describes the uncertainty in the parameters and the model.

The second approach we use to identify the main determinants of CO_2 emissions per capita is LASSO. The LASSO method puts a constraint on the sum of the absolute values of the model parameters; it applies a 'shrinking process' penalizing the coefficients of the regression variables, shrinking some of them to zero. The variables that still have a non-zero coefficient after the shrinking process are selected to be part of the model. The goal of this process is to minimize the prediction error. We consider the LASSO estimator proposed by Belloni et al. (2016), who use a clustered covariance structure (Cluster-LASSO) to account for the correlation between observations within the same country. Accounting for this intra-cluster correlation in high dimensional models is crucial ensure sampling variability is not understated, which could lead to the selection of too many variables, many of which may have no true association with the dependent variable (Belloni et al., 2016). The first step in the estimation process is to remove the country fixed effects by demeaning the data within countries:

$$log(CO_{2i,t})^{\star} = log(CO_{2i,t}) - \frac{1}{T}\sum_{t=1}^{T} log(CO_{2i,t}). \tag{3}$$

The same transformation is applied to all the determinants included in the vector ${x'}_{i,t-1}$. Let denote $x'^{\star}_{i,t-1}$ the demeaned vector of determinants. Following Belloni et al. (2016), the Cluster-LASSO coefficient estimate $\widehat{\rho}_L$ is defined by the solution to the following penalized minimization problem on the model after demeaning all the variables:

$$\widehat{\rho}_L \in \underset{\rho}{\operatorname{argmin}} \frac{1}{nT}\sum_{i=1}^{n}\sum_{t=1}^{T}(log(CO_{2i,t})^{\star} - \mu_t\gamma' - x'^{\star}_{i,t-1}\rho)^2 + \frac{\lambda}{nT}\sum_{j=1}^{p}\widehat{\phi}_j|\rho_j| \tag{4}$$

where p denotes the number of different determinants. This problem has two tuning parameters: the main penalty level, λ, which dictates the amount of regularization in the LASSO procedure and reduces overfitting and bias concerns; and the covariate specific penalty loading, $\widehat{\phi}_j$ which is important for dealing with data that may be correlated within clusters, heteroscedastic, and non-Gaussian (see Belloni et al., 2016, for further details on the penalty parameters). In the next section, we present the determinants selected by means of BMA and LASSO.

4 Results

Table 2 shows the main determinants of CO_2 emissions obtained using the BMA panel approach over the period 1995-2014 for 92 developed and developing countries. Column 1 presents the PIP of each potential time-varying determinant of CO_2 emissions. As a rule of thumb, a factor is considered very robust if the PIP is greater than or equal to 0.80. We find that the most robust determinants for the full sample are the variables capturing GDP per capita and its square, the share of fossil fuels in energy consumption, urban population, share of industry in GDP, democracy index, political polarization, share of agriculture in GDP and indirect measures of trade captured by the world trade networks (weighted closeness and weighted eigenvector). All these determinants, with the exception of share of agriculture and the square of GDP per capita, are also selected by the LASSO estimator (Table 3).

We also find that most of these determinants affect CO_2 with the expected sign (see the posterior mean in column 2 of Table 2). We find strong evidence of the *scale effect* as *GDP per capita* is positively associated with CO_2 emissions per capita. The turning point of the effect of *GDP per capita* on emissions is 12.42 (-1.465/(2*(-0.059))), which is higher than the maximum of the log of GDP per capita in the sample (11.66). Moreover, the quadratic term of GDP per capita is not selected by the LASSO estimator. These two findings imply that the relationship between GDP and CO_2 is linear, contrary to the EKC hypothesis. In particular, column 2 of Table 2 shows that the posterior mean of GDP per capita is 1.47, indicating that a 1% increases in GDP per capita is associated with a 1.47% increases in CO_2 emissions per capita. We also find a linear relationship between GDP per capita and CO_2 emissions for high, medium- and low-income economies. For high/medium-income economies, the turning point (11.72) exceeds the maximum value of log GDP per capita in the sample (Table 4) while for low-income economies, the square of log GDP per capita is not a robust determinant. These findings are consistent with those reported by Shafik (1994), Holtz-Eakin, Selden (1995), and Sheldon (2019) and point to the importance of investing in more environmentally–friendly technologies and clean modes of transport to break the positive relationship between GDP and emissions, and achieve sustainable growth. In fact, we find that investing in renewable energies and reducing the share of fossil fuels in energy consumption improves environmental quality in both high/medium- and low-income economies (see Tables 4–7). According to the posterior mean presented in Table 2 the effect is quantitatively large: a 1 percentage point increase in the share of fossil fuels in energy consumption increases the level of emissions by 1.4%.

This is consistent with the results obtained by Hanif et al. (2019) for developing economies and by Hamilton and Turton (2002) for developed economies. The results presented in column 2 of Table 2 also provide evidence of the *composition effect*, since greater industrialization, as captured by industrial output (% of GDP), leads to a higher level of emissions. Specifically, a 1 percentage point increase in industrial output variable is associated with an increase in CO_2 emissions of 0.6%. This result is consistent with those of Aller et al. (2015), who document a positive relationship between industry value added and CO_2 emissions for their sample of 177 countries. The composition effect is not observed in low-income economies, since the shares of industry and agriculture have a PIP lower than 0.8 and are not selected by the LASSO estimator. These results show that a shift in favour of less energy intensive–sector, e.g. services, can help high- and medium-income economies to reduce the environmental impact of their economic activity.

The transition from an agrarian to an industrial society involves migration from rural areas to the cities, increasing the population density there creating an excessive burden on the absorptive capacities of the local environment (Martínez-Zarzoso and Maruotti, 2011). The results presented in columns 2 of Tables 4 and 6 show a large effect of urbanization on the environmental quality: a 1 percentage point increase in the share of the urban population is associated with an increase in emissions of 1% and 1.9% in high/medium- and low-income economies, respectively. This is consistent with Poumanyvong and Kaneko (2010), who find a stronger positive association between urbanization and emissions in developing economies.

Political institutions are also important in explaining emissions. We find that a higher level of democracy, especially in low-income economies, is associated with a higher level of emissions (see column 2 of Tables 2 and 6). This results contrasts with the findings of Panayotou (1997) and Farzin and Bond (2006), but is consistent with Hosseini and Kaneko (2013), who find that democracy can increase environmental degradation.

Democracy is associated with private property and, as stated by Hardin (1968) in *The Tragedy of the Commons*, "our particular concept of private property, which deters us from exhausting the positive resources of the Earth, favors pollution". Moreover, in democratic societies, candidates standing for government office need financial support, which is often provided by companies that expecto to be compensated if the candidate is elected. These companies seek to maximize profit but not necessarily to improve environmental quality (Dryzek, 1987). According to our results, this mechanism is likely to operate in low-income economies.

Indeed, in low-income economies, corruption leads to environmental degradation (see column 2 of Table 6): a 1 percentage point increase in the corruption index leads to an increase in the level of emissions of 0.4%. As documented by Stern (2012), a lower of corruption is associated with higher energy efficiency, reducing CO_2 emissions. However, corruption is not selected by the LASSO estimator and we must interpret this result with caution.

Our study is the first to document the importance of political polarization as a robust determinant of CO_2 emissions, registering a PIP of 0.99 (see column 1 of Table 2). Political polarization is also selected by the LASSO estimator. The results presented in column 2 of Table 2 show that greater political polarization is beneficial for the environment as a 1 unit increase in the polarization index (the maximum is 2) reduces the level of emissions by 2.8%. This negative association between political polarization and CO_2 emissions may be explained by the impact of political inefficiencies on economic policies and their subsequent impact on investment and the environment. Political polarization increases policy uncertainty and thus reduces investment in the economy (Azzimonti, 2011). In turn, lower levels of investment lead to lower productivity and lower CO_2 emissions.

As has been explained in section 2, bilateral trade between two countries affects other trade partners or trade partners' partners (Aller et al., 2015) through two main channels: *congestion externalities* and *market power*. The first has a negative effect on the environment as it increases the exploitation of domestic resources, while market power is associated with higher energy efficiency and, subsequently, lower emissions.

These indirect effects of trade are captured in our CO_2 model by different centrality measures from the world trade network: *closeness weighted*, *eigenvector weighted*, *in-closeness weighted*, *out-closeness weighted* and *degree* (all of them measured in logs). We find that indirect effects of trade have important consequences for environmental degradation (unlike the direct effects, measured by the total trade, which are found to be a non-robust determinant using both BMA and LASSO). The results presented in column 2 of Table 2 show that a 1% increase in *closeness* and *eigenvector centrality* leads to an increase of 0.67% and 0.91% in emissions, respectively. The positive relationship between the centrality measures and environmental degradation suggests that congestion externalities play a more important role than market power in the world trade network.

Finally, in line with Acharyya (2009), we find that in low-income economies FDI – e.g. the presence of multinationals– increases the level of CO_2 emissions: a 1 percentage point increase in FDI leads to a 1.2% increase in CO_2 emissions (see Table 6). These results support the aforementioned *Pollution Haven Hypothesis*: multinationals tend to locate their production plants in places with laxer environmental regulations and less environmental awareness.

4.1 Sensitivity Analysis

In this section, we check the robustness of the results to the use of different priors in the BMA model and a different method used to identify the most robust drivers of CO_2 emissions. First, we present results for an analysis using two alternative priors for the model probability: the 'random theta' prior proposed by Ley and Steel (2009), who suggest a *binomial-beta hyperprior* on the *a priori inclusion probability*; and *fixed common prior inclusion probabilities* for each regressor as in Sala-i-Martin et al. (2004). The results, presented in Figure 1, show that the main findings are robust to the specification of the model priors. Overall, we find that the most important drivers of CO_2 emissions are the same regardless of the model priors. Second, we also check if our results hold when using an additional alternative method to deal with model uncertainty. To that end, we use the weighted-average least squares (WALS) method introduced by Magnus et al.(2010); the rule of thumb with this method is that an explanatory factor is considered robust if the absolute value of the t-statistic is above 2. The results for the full sample, presented in Table 8, show that the most robust drivers are consistent with the findings presented in Tables 2–7, but this approach is less conservative and the number of significant factors is larger than in the BMA approach and in the LASSO estimator.

Our study shows that higher production, fossil fuel consumption, urbanization, democratization, industrialization and the indirect effects of trade are detrimental for the environment. In contrast, greater political polarization is associated with less environmental degradation.

5 Conclusions

Environmental degradation is one of the main challenges facing that the world today. Using the standard proxy for environmental degradation considered in the literature, the level of CO_2 emissions per capita, we adopt an agnostic perspective and rely on Bayesian Model Averaging (BMA) panel data regressions to account for model uncertainty. The reasoning behind this approach is that there are many potential factors that could affect CO_2 emissions, but the theoretical literature provides only weak guidance on the specification of the CO_2 model. BMA addresses model uncertainty by weighting the various models based on fit and then averaging the parameter estimates they produce across models. We also consider, for the sake of robustness, the *Cluster Least Absolute Shrinkage and Selection Operator* (Cluster-LASSO) to select the most important drivers of CO_2 emissions.

We find that, out of 22 potential determinants, the most robust drivers of environmental degradation are, in order of importance: GDP per capita, fossil fuel consumption, urbanization, industrialization, indirect effects of trade (networks effects), level of democracy and political polarization. All of these determinants have a negative effect on the environmental quality negatively, with the exception of political polarization, which improves environmental quality.

Our results show that policies aimed at increasing the share of renewable energy consumption in the economy, at reducing the impact of urbanization on the environment (e.g. private and public policies promoting 'working from home') as well as at increasing the efficiency of the industrial sector (e.g. cleaner technology) could reduce emissions and mitigate the environmental degradation caused by economic activity. We also find that the determinants of CO_2 emissions depends on the level of income per capita in an economy. In high-income economies, the number of tourist arrivals has a negative impact on the environment. It is thus important to promote policies that seek to ensure sustainable tourism (e.g. limiting the number of tourists or cruises per day, as it was done in Venice). In low-income economies, we find that higher FDI, and presence of foreign multinationals increase environmental degradation, consistent with the *pollution haven hypothesis.* Along the same lines, the level of corruption plays a role in environmental degradation for low-income economies.

In contrast, other variables discussed in the literature are not found to be robust. This is the case with financial development, political instability and direct trade effects (as measured by trade openness and the share of energy imports in total energy use).

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6 Tables and Figures

	High-Medium		Low	
Variable	Mean	Std. dev.	Mean	Std. dev.
Per capita CO_2 (log)	8.53	0.74	6.32	0.96
Per capita GDP ppp adjusted (log)	9.55	0.98	7.11	0.63
Industry output (% of GDP)	29.29	10.75	25.9	6.78
Agriculture output (% of GDP)	4.91	3.72	20.59	9.53
Private Credit (% of GDP)	3.92	0.88	3.09	0.75
FDI (% of GDP)	7.25	26.46	3.57	4.63
Trade (log)	4.32	0.55	4.11	0.92
Democracy index	24.22	12.36	12.73	7.77
Closeness Weighted (log)	0.85	0.09	0.78	0.16
In-Closeness Weighted (log)	0.85	0.14	0.73	0.28
Out-Closeness Weighted (log)	0.8	0.2	0.78	0.22
Betweenness Weighted (log)	0.02	0.04	0.01	0.02
Eigenvector Weighted (log)	0.07	0.12	0.01	0.02
Degree	163.4	26.1	139.12	35.87
Urban Population (% of total)	73.99	14.82	40.01	15.07
Fossil energy consumption (% of total)	77.93	19.19	42.05	25.42
Energy Imports (log)	1.66	4.69	1.68	3.88
Corruption Index	0.35	0.3	0.73	0.15
Political Instability	0.14	0.28	0.11	0.26
Political Polarization	0.85	0.92	0.37	0.73
Tourist arrivals (log)	15.05	1.29	13.55	1.27
N. observations	758		454	

Notes: Income group is based on World Bank gross national income per capita 2019 fiscal year classification. High-Medium (Low) observations are those associated with countries' GNI per capita $4,046 per capita or more ($4,045 per capita or less) as of July 1, 2019.

Table 1: Descriptive statistics by level of income

	PI prob.	Pt. Mean	Pt. Std.
Per capita GDP ppp adjusted (log)	1	1.465	0.185
Per capita GDP ppp adjusted squared (log)	1	-0.059	0.011
Democracy index	1	0.005	0.001
Fossil energy consumption (% of total)	1	0.014	0.001
Urban Population(% of total)	1	0.016	0.003
Industry output (% of GDP)	1	0.006	0.001
Closeness Weighted (log)	1	0.671	0.121
Political Polarization	0.99	-0.028	0.008
Agriculture output (% of GDP)	0.98	0.008	0.002
Eigenvector Weighted (log)	0.93	0.908	0.36
Degree	0.56	0.001	0.001
Private Credit (% of GDP)	0.37	0.01	0.015
In-Closeness Weighted (log)	0.3	-0.03	0.051
FDI (% of GDP)	0.21	0.0001	0.0002
Energy Imports (log)	0.16	-0.001	0.004
Tourist arrivals (log)	0.15	0.004	0.012
Trade (log)	0.04	0.001	0.004
Out-Closeness Weighted (log)	0.04	0.003	0.023
Betweenness Weighted (log)	0.03	0.004	0.06
Corruption Index	0.04	0.00004	0.025
Political Instability	0.04	-0.0005	0.004
Year FE	✓	✓	✓
Country FE	✓	✓	✓

Notes: Robust determinants are those with a PIP higher than 0.8, in bold. All the regressors are computed at $t-1$. Column 1 presents the posterior inclusion probability. Column 2 shows the posterior mean. Column 3 reports the posterior standard deviation. The sample includes 92 countries and 1,212 observations. The dependent variable is log CO_2 emissions per capita. The results are obtained by using a uniform prior for the prior model probability and a BRIC prior for the hyperparameter that measures the degree of prior uncertainty on coefficients, $g = 1/max(N, K^2)$.

Table 2: Determinants of CO_2 emissions: A BMA approach. Period: 1995-2014

Selected variable	Lasso coefficient
Per capita GDP ppp adjusted (log)	0.41
Industry output (% of GDP)	0.002
Fossil energy consumption (% of total)	0.013
Tourist arrivals (log)	0.019
Democracy index	0.001
Closeness Weighted (log)	0.32
Eigenvector Weighted (log)	0.46
Urban Population(% of total)	0.011
Political Polarization	-0.010
Year FE	✓
Country FE	✓

Notes: The sample includes 92 countries and 1,212 observations. This table shows the variables selected by *lassopack* (Ahrens et al., 2020), which implements the Cluster-Lasso method of Belloni et al. (2016). Country and year fixed effects are included.

Table 3: Selected Determinants of CO_2 emissions: A Cluster-LASSO approach. Period: 1995-2014

	PI prob.	Pt. Mean	Pt. Std.
Per capita GDP ppp adjusted (log)	1	1.572	0.512
Per capita GDP ppp adjusted squared (log)	0.92	-0.067	0.029
Fossil energy consumption (% of total)	1	0.015	0.001
In-Closeness Weighted (log)	1	-0.357	0.072
Eigenvector Weighted (log)	1	1.254	0.258
Degree	1	0.003	0.001
Tourist arrivals (log)	1	0.075	0.018
Urban Population (% of total)	0.98	0.01	0.003
Political Polarization	0.93	-0.022	0.009
Industry output (% of GDP)	0.8	0.004	0.002
Democracy index	0.37	0.001	0.001
Agriculture output (% of GDP)	0.36	0.003	0.004
Closeness Weighted (log)	0.23	-0.12	0.247
Corruption Index	0.22	-0.0004	0.092
Private Credit (% of GDP)	0.08	-0.001	0.005
FDI (% of GDP)	0.06	0.00001	0.00007
Betweenness Weighted (log)	0.05	0.01	0.077
Political Instability	0.05	-0.001	0.004
Trade (log)	0.04	0.00004	0.00778
Out-Closeness Weighted (log)	0.04	-0.002	0.027
Energy Imports (log)	0.04	0.00005	0.00099
Year FE	✓	✓	✓
Country FE	✓	✓	✓

Notes: Robust determinants are those with a PIP higher than 0.8, in bold. All the regressors are computed at $t-1$. Column 1 presents the posterior inclusion probability. Column 2 shows the posterior mean. Column 3 reports the posterior standard deviation. The sample includes 57 countries and 758 observations. The dependent variable is log CO_2 emissions per capita. The results are obtained by using a uniform prior for the prior model probability and a BRIC prior for the hyperparameter that measures the degree of prior uncertainty on coefficients, $g = 1/max(N, K^2)$.

Table 4: Determinants of CO_2 emissions: A BMA approach. High-Income economies. Period: 1995-2014

Selected variable	Lasso coefficient
Per capita GDP ppp adjusted (log)	0.31
Industry output (% of GDP)	0.002
Fossil energy consumption (% of total)	0.012
Tourist arrivals (log)	0.06
Degree	0.0002
Eigenvector Weighted (log)	0.66
Urban Population(% of total)	0.004
Political Polarization	-0.011
Year FE	✓
Country FE	✓

Notes: The sample includes 57 countries and 758 observations. This table shows the variables selected by *lassopack* (Ahrens et al., 2020), which implements the Cluster-Lasso method of Belloni et al. (2016). Country and year fixed effects are included.

Table 5: Selected Determinants of CO_2 emissions: A Cluster-LASSO approach. High-Income economies. Period: 1995-2014

	PI prob.	Pt. Mean	Pt. Std.
FDI (% of GDP)	1	0.012	0.002
Democracy index	1	0.009	0.002
Closeness Weighted (log)	1	1.021	0.156
Fossil energy consumption (% of total)	1	0.011	0.002
Per capita GDP ppp adjusted (log)	0.97	1.17	0.724
Urban Population (% of total)	0.96	0.019	0.006
Corruption Index	0.85	0.004	0.222
Per capita GDP ppp adjusted squared (log)	0.63	-0.054	0.053
Political Polarization	0.48	-0.017	0.02
Trade (log)	0.31	0.012	0.021
Private Credit (% of GDP)	0.19	0.008	0.019
Industry output (% of GDP)	0.14	0.001	0.002
Agriculture output (% of GDP)	0.13	0.001	0.002
Tourist arrivals (log)	0.09	-0.003	0.012
Betweenness Weighted (log)	0.07	-0.033	0.194
In-Closeness Weighted (log)	0.06	0.002	0.013
Eigenvector Weighted (log)	0.06	0.036	0.252
Degree	0.06	0.00003	0.00022
Energy Imports (log)	0.06	-0.0004	0.0028
Out-Closeness Weighted (log)	0.05	0.002	0.03
Political Instability	0.05	0.00006	0.00571
Year FE	✓	✓	✓
Country FE	✓	✓	✓

Notes: Robust determinants are those with a PIP higher than 0.8, in bold. All the regressors are computed at $t-1$. Column 1 presents the posterior inclusion probability. Column 2 shows the posterior mean. Column 3 reports the posterior standard deviation. The sample includes 35 countries and 454 observations. The dependent variable is log CO_2 emissions per capita. The results are obtained by using a uniform prior for the prior model probability and a BRIC prior for the hyperparameter that measures the degree of prior uncertainty on coefficients, $g = 1/max(N, K^2)$.

Table 6: Determinants of CO_2 emissions: A BMA approach. Low-Income economies. Period: 1995-2014

Selected variable	Lasso coefficient
Per capita GDP ppp adjusted (log)	0.24
Fossil energy consumption (% of total)	0.007
Degree	0.0002
Eigenvector Weighted (log)	0.50
Urban Population(% of total)	0.002
Closeness Weighted (log)	0.67
FDI (% of GDP)	0.004
Democracy index	0.003
Private Credit (% of GDP)	0.0008
Year FE	✓
Country FE	✓

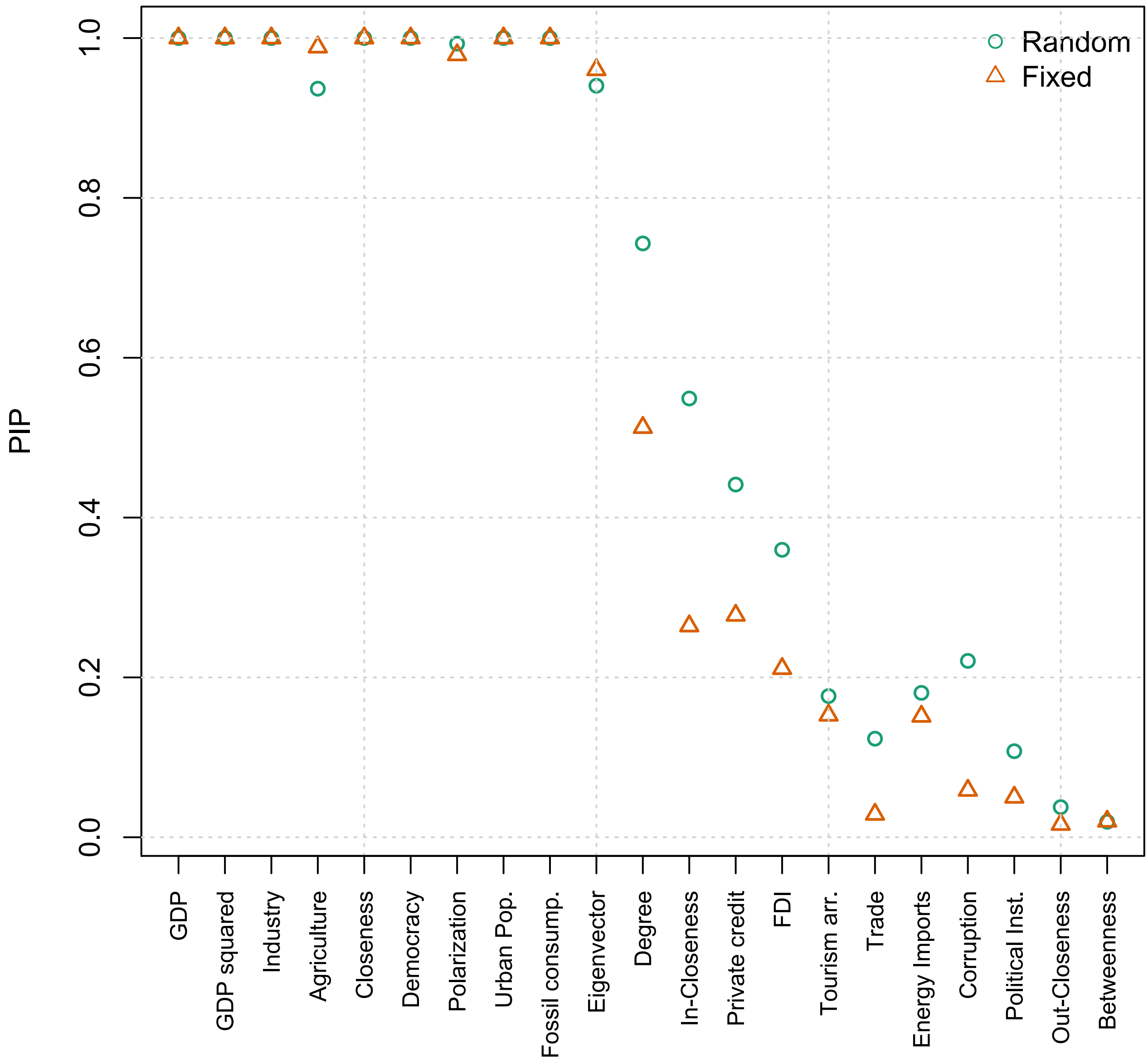
Notes: The sample includes 35 countries and 454 observations. This table shows the variables selected by *lassopack* (Ahrens et al., 2020), which implements the Cluster-Lasso method of Belloni et al. (2016). Country and year fixed effects are included.

Table 7: Selected Determinants of CO_2 emissions: A Cluster-LASSO approach. Low-Income economies. Period: 1995-2014

	Coef.	Std.	t-stat.
Per capita GDP ppp adjusted (log)	0.0124	0.001	12.01
Per capita GDP ppp adjusted squared (log)	1.2094	0.1843	6.56
Industry output (% of GDP)	0.0143	0.0023	6.26
Agriculture output (% of GDP)	0.6374	0.11	5.79
Private Credit (% of GDP)	0.006	0.0013	4.55
FDI (% of GDP)	0.0043	0.001	4.46
Tourist arrivals (log)	-0.0463	0.0111	-4.17
Political Polarization	-0.0252	0.0067	-3.73
Trade (log)	0.9831	0.266	3.7
Democracy index	0.0017	0.0005	3.22
Closeness Weighted (log)	0.0056	0.002	2.84
In-Closeness Weighted (log)	0.0232	0.0107	2.16
Out-Closeness Weighted log)	0.0005	0.0002	2.08
Political Instability	-0.0799	0.0396	-2.02
Corruption Index	-0.0086	0.0043	-1.99
Betweenness Weighted (log)	0.0197	0.013	1.51
Eigenvector Weighted (log)	0.0135	0.0142	0.95
Degree	0.0664	0.0818	0.81
Urban Population (% of total)	0.0415	0.0828	0.5
Fossil energy consumption (% of total)	0.0643	0.2503	0.26
Energy Imports (log)	-0.0187	0.013	-1.44
Year FE	✓	✓	✓
Country FE	✓	✓	✓

Notes: The results are obtained by using the Weighted Average Least Squares approach introduced by Magnus et al. (2010). Determinants with a t-statistics larger than 2 are considered robust. All the regressors are computed at $t-1$. The sample includes 92 countries and 1,212 observations.

Table 8: Determinants of CO_2 emissions: A Weighted Average Least Squares approach. Full sample. Period: 1995-2014



Note: The random prior corresponds to the 'random theta' prior by Ley and Steel (2009), who suggest a binomial-beta hyperprior on the a priori inclusion probability. The fixed is the fixed common prior inclusion probabilities for each regressor as in Sala-i-Martin, Doppelhofer, and Miller(2004). The sample includes 92 countries and 1,212 observations.

Figure 1: Determinants of CO_2 emissions: PIP using different model priors

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