Fuel Prices and Pollutant Emissions Spillover: An Analysis for Brazil

Abstract
This study investigates the null hypothesis of no spatial spillover effect of fuel prices on pollutant emissions in Brazil. The analysis draws on data from 379 municipalities between 2002 and 2019, considering ethanol and gasoline prices to represent renewable and non-renewable fuels, respectively. The results indicated that the null hypothesis should be rejected for ethanol prices depending on how agents define the feasibility of traveling to purchase fuel. Specifically, $H0$ can be rejected for ethanol prices in scenarios where fuel from neighboring municipalities is preferred over local fuel, provided that transportation energy efficiency is not particularly low. By contrast, no evidence was found to reject $H0$ for gasoline prices. The results also revealed a positive relationship between local ethanol prices and pollutant emissions. Finally, the main conclusions emphasize that the territorial scope of emission control policies employing fuel prices should be designed with consideration of local consumption patterns of renewable and non-renewable fuels, as well as factors influencing the feasibility of traveling to purchase fuel.
Keywords: Emissions, Environmental Economics, Fuel Prices, Spatial Spillover, Brazil.
JEL codes: O13, P18, P28, Q56.

1 Introduction

Fossil fuels constitute a significant component of the energy matrix in many economies and account for the majority of global energy consumption. Balat (2007) reported that, by the end of the last decade of the 20th century, the consumption of petroleum products, coal, and natural gas represented approximately 86% of global energy demand. Although these resources remain central to the production technologies of contemporary economies, the heavy reliance on fossil fuel consumption raises serious concerns regarding the consequences of pollutant emissions, which may exert adverse effects on public health (Mukhopadhyay and Forssell , 2005) as well as on the environment (Martins et al , 2019; Solarin , 2020; Umair et al , 2024).

An additional challenge emerges when negative externalities arise from the spillover effects of pollutant emissions associated with fossil fuel consumption. In such cases, even economic agents who consume little or no fossil fuel energy are affected by the resulting emissions, particularly when this type of energy use predominates in their vicinity. Bauer et al (2015) and Zeng et al (2021) examined issues related to this phenomenon and demonstrated that economies are interdependent with respect to pollutant emissions stemming from fossil fuel consumption. The findings of these studies suggest that efforts to mitigate the negative externalities of fossil fuel use must account for the potential spillover effects inherent in both the causes and consequences of these externalities.

Given this context, several studies in the literature have investigated how demand-side interventions through price adjustments could mitigate the effects of pollutant emissions resulting from fossil fuel use. Pereira and Pereira (2015) demonstrated that imposing a surcharge on fossil fuel prices can enhance energy efficiency and substantially reduce pollutant emissions. Blazquez et al (2017) further showed that pollutant emissions follow a trajectory parallel to fossil fuel demand, and that this demand responds negatively to positive price shocks.

In addition, empirical evidence frequently indicates that price shocks tend to generate spillover effects (DeFusco et al , 2018; Reboredo and Ugolini , 2020; Wu et al , 2022). Such effects typically arise from the transmission of information among economic agents, leading those operating in markets where prices have not yet changed to anticipate signals from markets where price adjustments have already occurred. Consequently, it is pertinent to raise the following question: If fuel prices influence pollutant emissions, and if changes in product prices can produce spillover effects, can variations in fuel prices within a specific region affect pollutant emissions in neighboring regions? The present study seeks to address this question. Accordingly, the objective is to examine whether a spatial spillover effect of fossil fuel prices on pollutant emissions exists.

To achieve this objective, the present study focuses on municipalities in Brazil. Brazil was selected as the study area for three main reasons. First, the country serves as an international environmental representative and plays a key role in negotiations aimed at establishing sustainable development goals (Loyola , 2014). Second, reliable data are available regarding fuel price monitoring. Third, Brazil has already been the subject of previous research addressing themes similar to the problem examined in this study, including the works of Stevens (2019), Lima Filho et al (2020), Hallack et al (2020), and Amarante et al (2021), allowing for comparison of the results with the consolidated literature.

The central focus of this study is to test a hypothesis in which the null hypothesis (H0) posits that there is no relationship between fuel prices in a specific Brazilian municipality and pollutant emissions in neighboring municipalities. Confirmation of this hypothesis would indicate that changes in fuel prices do not generate spatial spillover effects on pollutant emissions. Conversely, rejection of H0 would imply acceptance of the alternative hypothesis (H1), which asserts that fuel prices exhibit a non-zero intermunicipal association with pollutant emissions. The rationale for focusing on this hypothesis test lies in the potential to determine whether efforts to reduce pollutant emissions are more effective when implemented at the municipal level (if H0 is not rejected) or at the regional level (if H0 is rejected). Such findings could provide a foundation for the more efficient design and application of policies aimed at mitigating the adverse effects of emissions resulting from fuel consumption.

To test the null hypothesis described above, local spatial econometric models were employed. These models are particularly suitable for analyses in which the observed units are spatially delimited territories, especially when the objective is to assess the existence of a potential relationship between the dependent variable and an independent variable in the vicinity of the observed spatial unit. In this context, the principal methodological contribution of this study lies in the use of a spatial weight matrix in which neighborhood conditions are defined based on the feasibility of consumers traveling to purchase the good under investigation (fuels). This definition is grounded in the hypothesis of rational consumption, according to which a rational consumer prefers fuel sold in neighboring locations if the price is lower than the local price and if travel to make the purchase is feasible. Accordingly, the neighborhood matrix adopted in this study is structured not only by the distance between observed units, but also by parameters related to infrastructure, transportation energy efficiency, and consumer preferences regarding the location of fuel purchases.

In order to address the research question, this study is organized into five sections, beginning with this brief introduction. The following section provides a review of the relevant literature. The third section outlines the materials and methods employed. The fourth section presents the results and discussion. Finally, the fifth section offers the concluding remarks.

2 Literature review

The literature contains extensive discussion on the relationship between fuel prices and pollutant emissions, with several schools of thought addressing the connection between these two variables. For example, some studies consider fuel prices as an incentive for travel, which in turn influences pollutant emissions from motor vehicles (Virley , 1993; Scholl et al , 1996; Difiglio and Fulton , 2000). Other studies suggest that fuel prices can serve as an intervention tool to modify pollutant levels (Roy et al , 1995; Bohringer , 1996; Reid and Goldemberg , 1998).

As the literature began to incorporate more studies examining the relationship between pollutant emissions and fuel prices, an increasing number of findings have indicated the existence of a non-zero relationship between these variables. Barker (2005), for example, observed that pollutant emissions tend to decrease more significantly when interventions in the fuel market occur in scenarios where the price elasticity of fuel demand is higher. This suggests that the response of pollutant emissions to fuel price shocks is greater when fuel demand is more sensitive to price.

One explanation for the negative response of emissions to price increases lies in the incentive to adjust fuel supply. Martinsen et al (2007) found that when fuel prices rise significantly, energy production tends to undergo structural changes that expand the supply of renewable energy at the expense of non-renewable sources. According to the authors, this process of structural transformation contributes to a reduction in pollutant emissions. In addition, Newcomer et al (2008) highlighted the possibility that consumer decisions in response to price changes also play a role in reducing pollutant emissions.

Vielle and Viguier (2007) demonstrated that increases in fuel prices tend to compel economic agents to reallocate their resources and reorganize their choices, thereby fostering technological changes that lead to reductions in pollutant emissions. Consistent with these findings, Rout et al (2008) advanced the discussion by proposing that fuel consumption results from rational decisions derived from consumer optimization behavior. Based on this premise, the authors concluded that current pollutant emissions are primarily a consequence of non-renewable energy consumption stemming from the optimal choices of rational individuals. Furthermore, they found that increases in fossil fuel prices exert a negative impact on emissions, as such price rises tend to reduce dependence on fossil fuels.

Another consequence of economic agents' optimizing behavior in response to changes in fuel prices is that, when faced with price shocks, they may substitute fuels in order to minimize costs. Building on this possibility, Ruijven and Vuuren (2009) hypothesized that changes in fossil fuel prices may alter the demand for non-carbon fuels and conversely. Based on this hypothesis, the authors found that the process of fuel substitution resulting from price shocks can also affect the metrics of pollutant emissions and removals. These findings contributed to the literature by suggesting that analyses seeking to relate fuel prices to pollutant emissions become more robust when they account for the fact that economic agents have access to a diversified basket of fuels.

Although many studies highlight an inverse relationship between fuel prices and pollutant emissions, Yang and Timmermans (2012) hypothesized that this relationship may not be homogeneous across individuals with different preferences. Considering fuel consumption for travel, the authors found that variations in fuel prices are negatively associated with the distance traveled by private vehicles, fuel consumption, and CO_2 emissions. However, they also observed that the relationship between changes in fuel prices and the use of public transportation is positive. Thus, their findings contributed to the literature by showing that increases in fuel prices tend to raise the demand for public transportation, thereby reducing pollutant emissions from individual trips.

From this point onward, understanding the regional dimension of the relationship between fuel prices and pollutant emissions gained further contributions when Filippini and Heimsch (2016) hypothesized that the association between emissions and fuel demand in a given location may change as a result of economic shocks occurring elsewhere. Based on this hypothesis, the authors found that taxing pollutant emissions in a specific region can alter fuel demand in surrounding regions. Subsequently, Li et al (2020) expanded on this line of inquiry by investigating how local changes in fuel prices affect pollutant emissions at the regional level. To this end, they hypothesized that changes in fuel prices spill over spatially, influencing pollutant emissions both at the location where the changes occur and in nearby regions.

These contributions represent important advances in the literature linking pollutant emissions to fuel prices. One of the most valuable insights is that, if the hypothesis of spatial spillover effects of fuel price changes on pollutant emissions holds true, the relationship between these variables consists of two components: the local effect and the spillover effect. The local effect refers to the relationship between the two variables that arises solely from the characteristics of a specific observed unit, whereas the spillover effect captures the portion of the relationship in a given unit that results from shocks occurring in other units. Studies such as those by Kalantaripor and Alamdarlo (2021) have examined these concepts in greater detail.

As demonstrated in this section, from earlier studies to more recent investigations, the literature consistently points to an inverse relationship between fuel prices and pollutant emissions. However, the spatial specification of this relationship has enabled studies such as Wu et al (2022) to distinguish between the two effects discussed in the previous paragraph. Building on this approach, the authors found that increases in fuel prices in a specific location reduce pollutant emissions both locally, where the price changes occur, and regionally, in neighboring areas. In other words, the inverse relationship between the two variables can manifest at both local and regional levels. Findings such as these support the hypothesis that local changes in fuel prices can generate broader regional changes in pollutant emissions.

Another possibility that arises when studies employ a spatial specification to examine the relationship investigated in this study is the interregional targeting of policies designed to mitigate pollutant emissions. Research conducted by Cao et al (2023) and Abban et al (2025) demonstrates that, when a spillover effect exists, policies and interventions addressing pollutant emissions should account for the potential regional spillover of their impacts. In other words, policies implemented in a specific location may also produce effects in neighboring areas if the spillover effect is present.

In summary, the studies discussed in this section highlight important conclusions that can make significant contributions to future research examining the relationship between fuel prices and pollutant emissions. The following considerations are particularly noteworthy: (i) the expectation of an inverse relationship between fuel prices and pollutant emissions; (ii) the need to account for the demand for multiple modes of transportation in the empirical analysis of this relationship; (iii) the importance of incorporating the spillover effect into the analysis of the two variables; and (iv) the possibility of a non-zero relationship between local fuel prices and emissions in neighboring regions.

3 Methodology

3.1 Empirical strategy

To test the null hypothesis that there is no intermunicipal relationship between fuel prices and pollutant emissions, it is necessary to embed this hypothesis within a consolidated theoretical framework. For this purpose, the present study adopts the Environmental Kuznets Curve (EKC) theory, initially proposed by Grossman and Krueger (1991) and later reformulated by De Bruyn et al (1998). The original version of the theory posits that the relationship between economic growth and environmental degradation indicators is positive during the early stages of economic development but becomes negative once economies reach an advanced stage of growth. The reformulated version, however, suggests that even at advanced stages of growth, the relationship may again become positive. In other words, Grossman and Krueger (1991) version asserts that the relationship between growth and environmental degradation follows an inverted-U shape, whereas De Bruyn et al (1998) version is based on the hypothesis that this relationship takes the form of an N-curve.

To examine how fuel prices relate to pollutant emissions, this study adopts the strategy of Ebaid et al (2022), who incorporated fuel prices as a covariate in the EKC equation. Formally, let i denote the set of municipalities, where $i = 1, 2, \ldots, N$, and t denote the set of time periods, where $t = 1, 2, \ldots, T$. Define E as pollutant emissions per inhabitant, G as the level of economic growth, and P as the fuel price. Let C represent a matrix of additional covariates included to adjust the regression equation, and let ε denote the estimation error. Based on these specifications, the cubic version of the EKC can be expressed as:

$$E_{i,t} = \alpha + \beta_1 ln(G_{i,t}) + \beta_2 ln(G_{i,t})^2 + \beta_3 ln(G_{i,t})^3 + \gamma ln(P_{i,t}) + \delta C_{i,t} + \varepsilon_{i,t} \tag{1}$$

This equation can be estimated using the within transformation to correct for potential endogeneity related to individual fixed effects. However, this functional form does not allow for testing the null hypothesis, as it only considers the relationship between prices and emissions within a specific municipality. To incorporate the spillover effect of prices into the regression equation, this study follows the principles of Schneiter and Mellon-Bedi (2025), who estimated an EKC with spatial specification. In this framework, let W denote a standarized NxN spatial weight matrix, with non-null values assigned to neighboring municipalities and zero values assigned to non-neighbors. Multiplying W by the fuel price yields a price indicator for neighboring municipalities (i.e., spatial price lags). Incorporating this logic into the previous regression equation, the model can be expressed as:

$$E_{i,t} = \alpha + \beta_1 ln(G_{i,t}) + \beta_2 ln(G_{i,t})^2 + \beta_3 ln(G_{i,t})^3 + \gamma ln(P_{i,t}) + \delta C_{i,t} + \theta W ln(P_{i,t}) + \varepsilon_{i,t} \tag{2}$$

Where θ is a parameter to be estimated. This functional form, however, presents certain statistical challenges that may lead to biased coefficient estimates. The central issue arises from the inclusion of spatial lags of a regressor among the explanatory variables, which can cause specific characteristics of neighboring municipalities—omitted from the regressors and thus captured in the error term—to become correlated with some of the explanatory variables. This correlation may violate the assumption of zero covariance between the error term and the regressors, thereby generating potential endogeneity. To address this issue, the present study relies on the assumptions proposed by Vega and Elhorst (2015). Accordingly, an important assumption must be explicitly specified:

Assumption 1. *Changes in fuel prices within a specific municipality can only influence pollutant emissions in neighboring municipalities. In other words, pollutant emissions in a given municipality are not affected by fuel price changes occurring exclusively in distant municipalities.*

This assumption plays a crucial role in defining the functional form of the regression equation, as it implies that a local model should be estimated rather than a global model. In practical terms, this means that the spatial lag of the dependent variable should not be included on the right-hand side of the regression equation, thereby simplifying the calculation of the linear coefficients. Given this assumption, the regression equation can be more appropriately specified in four functional forms: the common fixed effects model, the SLX model, the SEM model, and the SDEM model. In this study, the selection of the most suitable functional form is guided by the specifications proposed by Vega and Elhorst (2015). Accordingly, the following steps are undertaken:

1. Estimate the conventional fixed effects model following the functional form of Equation 1.

2. Estimate the SLX model with fixed effects according to the following functional form:

$$\begin{aligned}E_{i,t} =&\alpha + \beta_1 ln(G_{i,t}) + \beta_2 ln(G_{i,t})^2 + \beta_3 ln(G_{i,t})^3 + \beta_4 W ln(G_{i,t}) + \beta_5 W ln(G_{i,t})^2 + \\ &\beta_6 W ln(G_{i,t})^3 + \gamma ln(P_{i,t}) + \theta W ln(P_{i,t}) + \delta C_{i,t} + \varphi W C_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{3}$$

3. Use a Wald test to test whether $\beta_4 = \beta_5 = \beta_6 = \theta = \varphi = 0$. If true, then the conventional fixed effects model should be accepted over the SLX model. In this case, the null hypothesis of the study cannot be rejected.

4. Estimate the SEM model with fixed effects according to the following functional form:

$$\begin{aligned}E_{i,t} =&\alpha + \beta_1 ln(G_{i,t}) + \beta_2 ln(G_{i,t})^2 + \beta_3 ln(G_{i,t})^3 + \gamma ln(P_{i,t}) + \delta C_{i,t} + \varepsilon_{i,t} \\ &\text{With } \varepsilon_{i,t} = \lambda W \varepsilon_{i,t} + v_{i,t}\end{aligned} \tag{4}$$

5. Use a Wald test to test whether $\lambda = 0$. If this condition is verified and if the null condition in Step 3 is not true, the SLX model with fixed effects should be preferred over the SEM model. If $\lambda = 0$ and the null condition in Step 3 is also satisfied, then the conventional fixed effects model should be selected over both the SLX and SEM models. In both case, the null hypothesis of the study also cannot be rejected. If $\lambda \neq 0$, two possible cases arise: (i) the SEM model should be selected if the null condition in Step 3 is satisfied; (ii) the next step in the procedure should be tested if the null condition in Step 3 is not satisfied.

6. Estimate the SDEM model with fixed effects according to the following functional form:

$$\begin{aligned}E_{i,t} =&\alpha + \beta_1 ln(G_{i,t}) + \beta_2 ln(G_{i,t})^2 + \beta_3 ln(G_{i,t})^3 + \beta_4 W ln(G_{i,t}) + \beta_5 W ln(G_{i,t})^2 + \\ &\beta_6 W ln(G_{i,t})^3 + \gamma ln(P_{i,t}) + \theta W ln(P_{i,t}) + \delta C_{i,t} + \varphi W C_{i,t} + \varepsilon_{i,t} \\ &\text{With } \varepsilon_{i,t} = \lambda W \varepsilon_{i,t} + v_{i,t}\end{aligned} \tag{5}$$

7. Use a Wald test to test whether $\lambda = \beta_4 = \beta_5 = \beta_6 = \theta = \varphi = 0$. If this condition is verified, the SEM model with fixed effects should be preferred over the SDEM model. If this condition of nullity is not verified, then the SDEM model should be chosen as the best functional form.

3.1.1 A reduced SLX-SEM model

The logic of the SLX model proposed by Vega and Elhorst (2015) is that spatial lags of the regressors eliminate the potential correlation between the error term and a spatial lag included in the regression equation. Since all regressors are spatially lagged and incorporated on the right-hand side of the equation, the error term no longer contains information from neighboring municipalities that could be correlated with a spatially lagged explanatory variable. However, depending on the number of regressors, the inclusion of all spatial lags in the regression equation may render the estimation overidentified and lead to an excessive loss of degrees of freedom. Moreover, when the number of regressors is considerably high, many of the spatial lags may have no effect on the dependent variable and may not exhibit correlation with the regressors in the equation. To address this issue, the present study introduces an additional step in the functional form selection process proposed by Vega and Elhorst (2015), here referred to as the *Reduced SLX-SEM Model* (RSLX-SEM model).

This additional step precedes Step 4 specified above. The basic logic of the RSLX-SEM model is to obtain a spatially lagged error term that captures all unobserved information from neighboring municipalities, except for the information that is the subject of the study and explicitly appears as a spatial lag in the final regression equation (in this study, the price of fuel). This spatially lagged error term is incorporated into the regression to eliminate (or at least reduce) the correlation between the error term and the covariates. In practical terms, the RSLX-SEM model proposed in this study is specified as follows:

1. Estimate the RSLX model with fixed effects according to the following functional form:

$$E_{i,t} = \alpha_1 + \alpha_2 W ln(P_{i,t}) + e_{i,t} \tag{6}$$

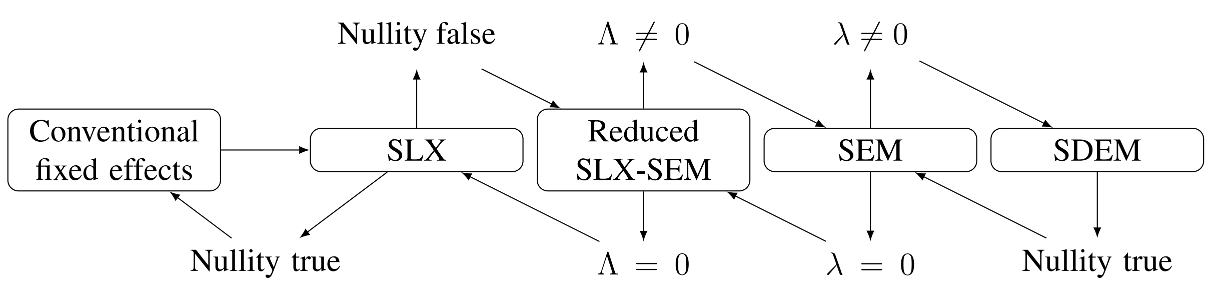
2. Estimate the RSLX-SEM model with fixed effects according to the following functional form:

$$\begin{aligned} E_{i,t} =& \alpha + \beta_1 ln(G_{i,t}) + \beta_2 ln(G_{i,t})^2 + \beta_3 ln(G_{i,t})^3 + \gamma ln(P_{i,t}) + \delta C_{i,t} + \theta W ln(P_{i,t}) + \varepsilon_{i,t} \\ &\text{With } \varepsilon_{i,t} = \mathbf{\Lambda} W e_{i,t} + v_{i,t} \end{aligned} \tag{7}$$

3. Use a Wald test to test whether $\Lambda = 0$. If this condition is verified, the conventional fixed effects model should be preferred over the RSLX-SEM model.

If $\Lambda \neq 0$, the choice of the best specification should follow from Step 4 above following Vega and Elhorst (2015). The difference is that, if the null condition in Step 4 is satisfied and $\Lambda \neq 0$, then the RSLX-SEM model is preferred over the SEM model. Figure 1 presents a detailed summary of the decision-making process employed to select the most appropriate model specification for addressing the research problem.

Figure 1: Visual representation of the process of choosing the functional form of the regression equation.



Source: Own elaboration. Adapted from Vega and Elhorst (2015).

3.1.2 A spatial weight matrix based on rational consumption

An important step in obtaining robust coefficient estimates in spatial models is the construction of a spatial weight matrix that accurately reflects the neighborhood conditions of the observed units. In the literature, it is common to find matrices based on contiguity, proximity, or distance. These approaches are widely adopted because they are straightforward to construct, simple to apply, and easy for readers to interpret. The present study, however, adopts a different strategy in the development of the spatial weight matrix. Since the aim is to examine the intermunicipal association between fuel prices and pollutant emissions, the neighborhood matrix is defined based on the possibility that economic agents may demand fuel in neighboring municipalities rather than exclusively in the municipality in which they operate. To this end, the following assumption is introduced:

Assumption 2. *Economic agents may purchase fuel in any municipality for consumption in the municipality where they operate. In making this decision, they evaluate whether the cost of acquiring fuel in neighboring municipalities is lower than the cost of purchasing fuel in their own municipality.*

Based on this assumption, municipality i is considered a neighbor of municipality j if the cost of purchasing fuel in j is lower than the price of fuel in i . Let $D_{i,j}$ denote the distance between municipalities i and j, Π represent a discount factor, and Δ and π indicate travel cost efficiency. The spatial weight matrix employed in this study is therefore defined as follows:

$$W_{i,j} = \begin{cases} 1 & \text{if} \quad D_{i,j} * P_j/(\pi * (1+\Pi) * \Delta) < P_i \\ 0 & \text{if} \quad D_{i,j} * P_j/(\pi * (1+\Pi) * \Delta) \geq P_i \end{cases} \tag{8}$$

$D_{i,j} * P_j$ represents the financial cost of traveling from municipality i to purchase fuel in municipality j. The parameter $\pi > 0$ is a preference indicator that measures the extent to which an agent prefers fuel from municipality i relative to fuel from municipality j. If $\pi = 1$, the agent is indifferent; if $\pi < 1$, the agent prefers fuel from the municipality in which they reside; and if $\pi > 1$, fuel from the neighboring municipality is preferred over fuel from the home municipality. The parameter $0 \leq \Pi \leq 1$ is an efficiency indicator that captures how transportation conditions affect the cost of purchasing fuel in another municipality. Finally, $\Delta > 0$ captures the energy efficiency of traveling to purchase fuel in another municipality. In theoretical terms, this parameter reflects the amount of fuel consumed per unit of distance traveled between the two municipalities.

The logic of the matrix is straightforward: if an agent considers it more advantageous to purchase fuel in municipality j than in municipality i, then i and j are considered neighbors. Otherwise, they are not considered neighbors in the matrix. In addition to distance, it is assumed that the values of π, Π, and Δ are static, meaning they do not vary over time. Fuel prices, however, fluctuate across periods, which imparts a dynamic characteristic to the spatial weight matrix. In other words, since the neighborhood condition is determined by the cost-benefit of purchasing fuel in neighboring municipalities, and this cost-benefit changes over time, a distinct spatial weight matrix is generated for each period within the planning horizon.

To assign greater weight to municipalities with limited neighborhoods, the structure presented in Equation 6 is modified by standardizing the matrix through the summation of the row components. This is a standard procedure in spatial econometrics and serves to ensure that spatial lags approximate the actual observed values more closely. Let $\dot{W}$ denote the reweighted spatial weight matrix. The standardization procedure is performed according to the following rule:

$$\dot{W}_{i,j} = \frac{W_{i,j}}{\sum_i W_{i,j}} \tag{9}$$

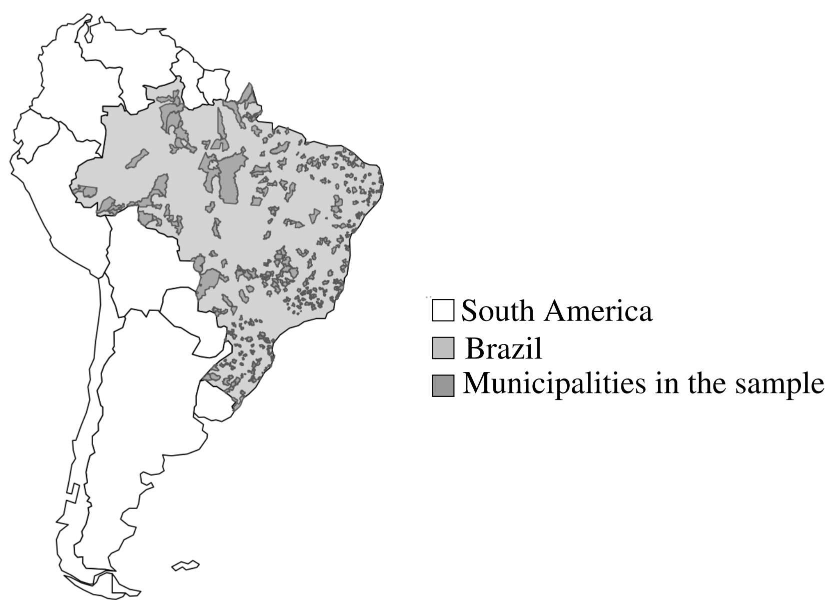
To construct the matrix, $D_{i,j}$ represents the Euclidean distance in kilometers between the centroids of municipalities i and j. Π denotes the average proportion of paved roads in municipalities i and j. The parameter Δ was initially set to 10, indicating that the means of transport used by agents to travel from i to j for fuel purchases can cover an average of 10 kilometers per liter of fuel. Finally, the parameter π was initially set to 2, implying that in each municipality and in each period, agents strictly prefer fuel from municipality j over fuel from municipality i. To ensure robustness, alternative values for both π and Δ were also employed in the analysis.

3.2 Data

The dataset employed in this study encompasses municipalities and annual periods. The sample comprises 397 Brazilian municipalities with information on 15 variables spanning the years 2002 to 2019. The planning horizon begins in 2002 due to the unavailability of data for certain variables in earlier years. The year 2019 was selected as the endpoint in order to avoid potential methodological issues arising from demand shocks associated with the global health crisis that occurred after this period.

It is important to note that Brazil has 5,570 municipalities[1], yet the database used in this study covers only slightly more than 7% of that total. This limited territorial coverage results from the unavailability of certain data for all municipalities in the country, particularly information related to fuel prices. These data were extracted from the price survey conducted by the National Agency of Petroleum, Natural Gas, and Biofuels (*Agência Nacional do Petróleo, Gás Natural e Biocombustíveis* - ANP). According to the agency, fuel prices are collected in only 555 locations[2]. The absence of price data and other relevant variables reduces the sample size, producing an unbalanced panel dataset with a limited number of observed municipalities. Figure 2 illustrates the geographical location of the study area, highlighting the municipalities included in the database.

Figure 2: Geographic location of the study area.



Source: Own elaboration according to research data.

To represent pollutant emissions, this study employs municipal data on "net emissions", calculated according to the methodology of Azevedo et al (2018) and made freely available through the SEEG Brasil platform[3]. This measure corresponds to the difference between greenhouse gas emissions and removals,

[1] See https://www.ibge.gov.br/apps/quadrogeografico/pdf/qg_2024_000_Brasil.pdf.

[2] See notes in https://www.gov.br/anp/pt-br/assuntos/precos-e-defesa-da-concorrencia/precos/precos-revenda-e-de-distribuicao-combustiveis/serie-historica-do-levantamento-de-precos.

[3] See https://seeg.eco.br/.

expressed in carbon-equivalent units. To capture economic growth levels (an essential variable for the methodological framework adopted) the study considers municipal Gross Domestic Product (GDP) per capita, as reported by the Brazilian Institute of Geography and Statistics (*Instituto Brasileiro de Geografia e Estatística* - IBGE (2021)), quantified in Brazilian reais (R$) per thousand inhabitants[4].

As mentioned earlier, fuel prices were extracted from the ANP (2025) price series. Two specific fuels were considered: gasoline and ethanol. Although the ANP (2025) also provides price information for other fuels such as diesel and natural gas, gasoline and ethanol were selected due to their broader territorial coverage and the smaller proportion of missing data compared to other fuels. An additional advantage of this choice is that it enables the research problem to be addressed in two distinct segments: renewable fuels (ethanol) and non-renewable fuels (gasoline). It is also important to note that the ANP publishes both weekly and monthly price series. Given the larger number of municipalities surveyed in the monthly series, this study opted to use monthly data. Since the dataset employed is structured as an annual panel, the reconciliation was achieved by calculating the annual average of the monthly price series for both ethanol and gasoline.

[4] All financial values in the database were monetarily adjusted using the Broad National Consumer Price Index (*Índice Nacional de Preços ao Consumidor Amplo* - IPCA), expressed in December 2023 values.

Chart 1: Description and source of the data.

(i) ***Net emissions per capita:*** This is the dependent variable in the regression equation. It corresponds to the difference between greenhouse gas emissions and removals, expressed in carbon-equivalent units, divided by the number of inhabitants. In the methodology and results sections, this variable is denoted by the pseudonym "E". Source: Azevedo et al (2018).
(ii) ***Per capita GDP:*** Represents municipal economic growth and corresponds to the ratio between GDP and population. It is expressed in R$ 1,000.00 per thousand inhabitants, adjusted to December 2023 values. In the methodology and results sections, this variable is denoted by the pseudonym "G". Source: IBGE (2021).
(iii) ***Gasoline price:*** Represents the price of fuels derived from non-renewable sources, expressed in R$ adjusted to December 2023 values. In the text, this variable is denoted by the pseudonym "$Gasoline\_Price$". Source: ANP (2025).
(iv) ***Ethanol price:*** Represents the price of fuels derived from renewable sources, expressed in R$ adjusted to December 2023 values. In the text, this variable is denoted by the pseudonym "$Ethanol\_Price$". Source: ANP (2025).
(v) ***Number of motor vehicles per capita:*** Represents the total number of motor vehicles per inhabitant. In the text, this variable is denoted by the pseudonym "$Total\_Vehicles$". Source: Brazilian Ministry of Transportation (2025).
(vi) ***Number of cars per capita:*** Represents the number of passenger cars per inhabitant and is intended to capture the relationship between individual fuel demand and pollutant emissions. In the text, this variable is denoted by the pseudonym "$Cars$". Source: Brazilian Ministry of Transportation (2025).
(vii) ***Number of trucks per capita:*** Represents the number of trucks per inhabitant and is intended to capture the effects of demand for fuels derived from non-renewable sources on pollutant emissions. In the methodology and results sections, this variable is denoted by the pseudonym "$trucks$".' Source: Brazilian Ministry of Transportation (2025).
(viii) ***Number of motorcycles per capita:*** Represents the number of motorcycles and scooters per inhabitant and is intended to capture the effects of demand for small vehicles powered by both renewable and non-renewable fuels on pollutant emissions. In the text, this variable is denoted by the pseudonym "$Motorcycles$". Source: Brazilian Ministry of Transportation (2025).
(ix) ***Precipitation:*** Represents the average annual accumulated precipitation, measured in millimeters (mm). These values were calculated following the methodology of Camarillo-Naranjo et al (2019), using data available from the Global Climate System platform. In the methodology and results sections, this variable is denoted by the pseudonym "$prec$". Source: Camarillo-Naranjo et al (2019).
(x) ***Temperature:*** Represents the average annual temperature, measured in degrees Celsius (°C). These values were calculated following the methodology of Camarillo-Naranjo et al (2019), using data available from the Global Climate System platform. In the text, this variable is denoted by the pseudonym "$temp$". Source: Camarillo-Naranjo et al (2019).
(xi) ***Precipitation changes:*** Represents the difference between annual accumulated precipitation and the historical average for the planning horizon in each municipality. In the text, this variable is denoted by the pseudonym "$Deviation\_prec$". Source: Camarillo-Naranjo et al (2019).
(xii) ***Temperature changes:*** Represents the difference between average annual temperature and the historical average for the planning horizon in each municipality. In the text, this variable is denoted by the pseudonym "$Deviation\_temp$". Source: Camarillo-Naranjo et al (2019).
(xiii) ***Vegetation loss***: Represents the proportion of the municipal area with a reduction of at least 75% in vegetation canopy cover. This variable is intended to capture the relationship between deforestation and pollutant emissions. In the text, it is denoted by the pseudonym "$Deforestation$". Source: Global Forest Watch (2025).
(xiv) ***Fire outbreaks:*** Represents the total number of fire outbreaks per square kilometer. This variable is intended to capture the relationship between forest fires and pollutant emissions. In the text, it is denoted by the pseudonym "$Fire$". Source: NASA (2025)

Source: Own elaboration.

For more details on the variables used, Chart 1 presents a list with the description and source of each variable that composes the database. Topic (i) of the list provides details about the dependent variable of the regression equation, while topic (ii) describes the variable used to construct the right-hand side of the EKC equation. Topics (iii) and (iv) present information on the fuel price variables included in the regression equation to address the research question. Beginning with topic (v), the list provides details on the control covariates of the model.

4 Results

4.1 Data analysis

Table 1 presents the descriptive statistics of the variables used in the study. By analyzing the results, the reader can obtain a partial view of the overall profile of the database. Considering all years within the planning horizon, the difference between emissions and removals of pollutants averaged approximately 5.2 carbon-equivalent units per inhabitant. Despite the relatively low average value, this variable exhibits high dispersion among the municipalities observed, as the database includes municipalities with zero net emissions, while others show net emissions exceeding 400 carbon-equivalent units per person. Fuel prices, in turn, display less variability, with the average price of gasoline surpassing the average price of ethanol by approximately 35.5%. This difference is expected and reflects the disparity in energy efficiency between the two types of fuel.

Descriptive statistics also indicate that the municipalities in the sample have an average GDP per capita of approximately R$ 34,000.00, although some municipalities report a GDP per capita exceeding R$ 370,000.00. In addition to the fundamental variables used to develop the model, the descriptive statistics reveal that the sample is composed of municipalities whose average profile is characterized as follows: 17% of the population owns a passenger car; 1.3% owns a truck; 11.2% owns a motorcycle or scooter; 35.4% owns some type of motor vehicle; average accumulated rainfall is 1,454 mm; average annual temperature is 23.7 °C; average climate deviations are practically zero[5]; average vegetation cover loss is approximately 0.2% of the total area; and there are about four fire outbreaks per square kilometer.

Table 1: Descriptive statistics

Pseudonym	Observations	Average	Standard Deviation	Minimum	Maximum
E	6523	5.211	21.973	0.000	461.104
$Ethanol\_Price$		4.446	0.558	3.105	7.271
$Gasoline\_Price$		6.028	0.630	4.761	9.204
$Cars$		0.174	0.116	0.001	0.628
$Trucks$		0.013	0.007	0.000	0.041
$Motorcycles$		0.112	0.073	0.003	0.487
$Total\_Vehicles$		0.354	0.190	0.005	0.948
G		33.919	24.583	5.151	371.699
$prec$		1454.538	528.328	148.250	3631.800
$temp$		23.767	3.048	14.960	30.681
$Deviation\_prec$		-0.184	270.032	-957.382	1299.067
$Deviation\_temp$		-0.001	0.531	-2.259	2.770
$Deforestation$		0.002	0.004	0.000	0.060
$Fire$		0.043	0.114	0.000	2.811

Source: Own elaboration according to research data.

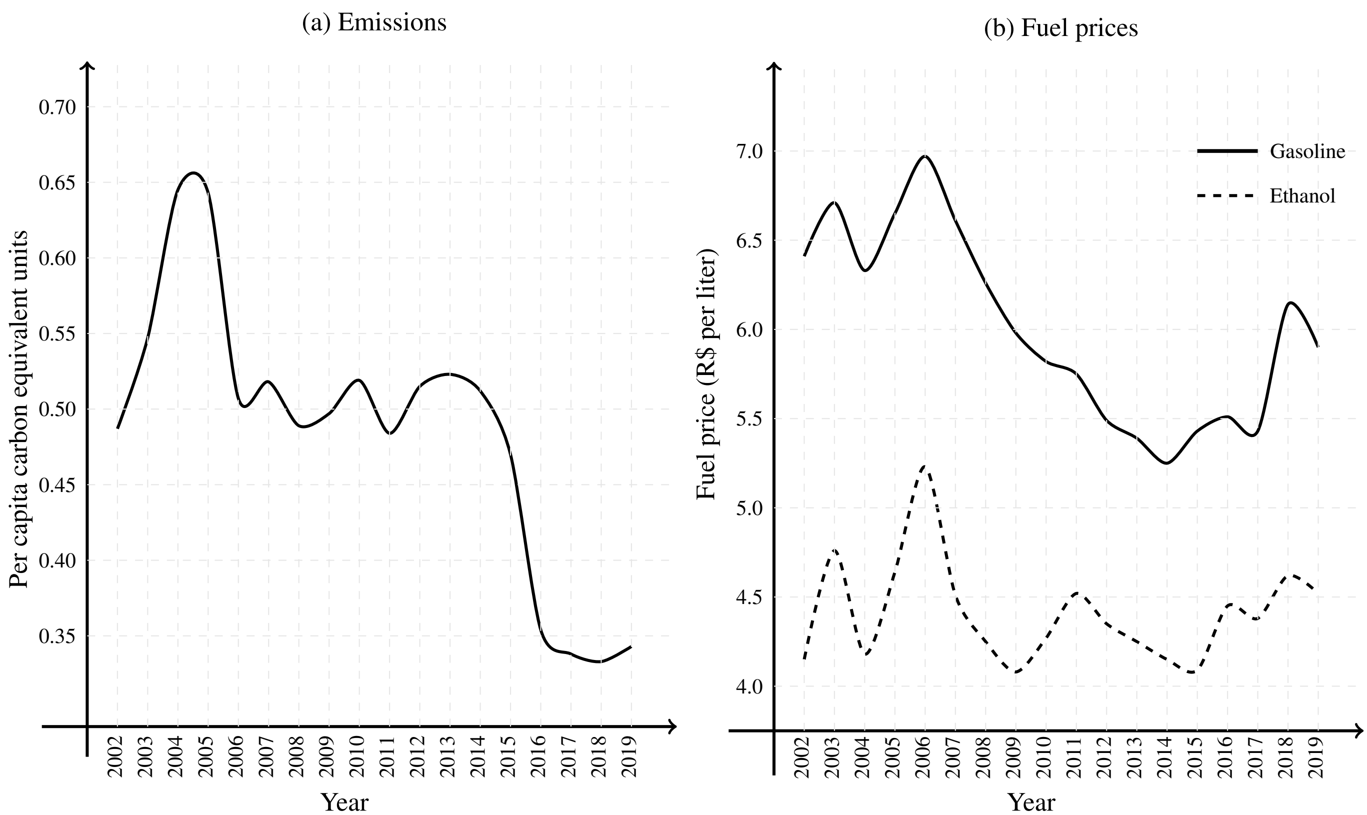
However, since this is a panel dataset, simply presenting descriptive statistics does not allow for an understanding of the dispersion of the main information over time. To address this limitation, Figure 3 was prepared, in which the median emissions (panel (a)) and the median fuel prices (panel (b)) are reported for each year of the planning horizon. From the results shown in the figure, it can be observed

[5] This value, which is very close to zero, is expected, since, as a rule, the average deviation from the mean of a variable should always equal zero.

that the median net pollutant emissions exhibit a downward trend during the study period, reaching their maximum value in 2004 and their minimum value in 2018. In addition, the figure indicates that the median gasoline price also follows a downward trend, which is more pronounced than that observed in panel (a). Regarding the median price of ethanol, although its trajectory correlates with that of the median gasoline price, no clear trend can be observed in the temporal dispersion of values. In this case, the behavior of the median appears to follow a lateral trajectory.

The figure illustrates an apparent correlation between the trajectories of median gasoline prices and net emissions. This apparent similarity may serve as an early indication of a non-zero relationship between these two variables. However, such temporal dispersion is not observed between median emissions and ethanol prices. Moreover, some similarities in the trajectories of the medians occur outside the planning horizon, which could weaken the suggestion of a non-zero relationship between fuel prices and pollutant emissions. For instance, the maximum median value of net emissions occurs in 2004, whereas the maximum median fuel prices are observed in 2006 for both gasoline and ethanol. In addition, in 2018 the median trajectory of net emissions reached its minimum value, while the minimum median fuel prices occurred in 2014 for gasoline and in 2015 for ethanol.

Figure 3: Median emissions and fuel prices over time.



Source: Own elaboration according to research data.

Although the results in Figure 3 provide a basic understanding of the temporal relationship between fuel prices and pollutant emissions, they are not sufficient to yield preliminary evidence regarding the null hypothesis considered in this study. To obtain an initial indication of the relationship between local prices and neighboring emissions using simple data analysis, it is preferable to develop a Bivariate Moran's Global Index (BMGI). This indicator measures the association between a variable in a given location and another variable in neighboring locations, thereby allowing spatial dispersion patterns of the two variables to be detected. Since the spatial weight matrix employed in this study is dynamic (i.e., it varies over time) we calculated the BMGI in two ways: first, year by year, and second, using the complete sample aggregated in a panel. The indicator is based on a hypothesis test in which the null hypothesis states that there is no association between a variable x and another spatially lagged variable y. Thus, if the null hypothesis is rejected, the results provide preliminary evidence that changes in x are correlated with changes in the spatial lags of y.

Since the definition of neighborhood depends on fuel prices, and because two different types of fuel (gasoline and ethanol) were considered, the BMGI was calculated for two specific cases: Case 1, in which gasoline prices were used to construct the spatial weight matrix, and Case 2, in which the spatial weight matrix was constructed using ethanol prices. The results of this procedure are presented in Table 2.

The results indicate that the null hypothesis of the BMGI should be rejected for each year considered in the database and for each of the neighborhood matrices. Furthermore, the indicator was negative, suggesting that pollutant emissions in a specific Brazilian municipality tend to be inversely associated with fuel prices in neighboring municipalities. As noted earlier, the negative sign of the BMGI may also reflect spatial distribution patterns of the two variables. Specifically, a negative BMGI may suggest that municipalities with high levels of pollutant emissions tend to be surrounded by neighbors with lower fuel prices. Although this represents a simplified approach to relating emissions to prices in neighboring municipalities, the result nonetheless points to a potential trend of inverse association between these variables.

The results also indicate that when the BMGI is calculated considering the relationship between pollutant emissions and gasoline prices in neighboring municipalities, the absolute value of the BMGI is higher than when the spatial lag in ethanol prices is considered. This finding suggests that Brazilian municipalities with high levels of pollutant emissions are generally surrounded by municipalities with low gasoline and ethanol prices. However, municipalities with high emission levels tend to have more neighbors where gasoline prices are low than neighbors where ethanol prices are low.

Table 2: Bivariate Global Moran Index: Spatially lagged fuel price x standarized emissions.

	Case 1		**Case 2**	
Year	Gasoline Price	Ethanol Price	Gasoline Price	Ethanol Price
2002	-0.2501***	-0.1873***	-0.253***	-0.1896***
2003	-0.2384***	-0.1919***	-0.2401***	-0.1933***
2004	-0.2627***	-0.1987***	-0.2641***	-0.1999***
2005	-0.2634***	-0.2102***	-0.2665***	-0.2128***
2006	-0.2719***	-0.2287***	-0.273***	-0.2296***
2007	-0.2813***	-0.2199***	-0.2848***	-0.2227***
2008	-0.2867***	-0.2226***	-0.2861***	-0.2221***
2009	-0.2902***	-0.2248***	-0.2895***	-0.2241***
2010	-0.323***	-0.2634***	-0.3221***	-0.2627***
2011	-0.3049***	-0.2649***	-0.3054***	-0.2652***
2012	-0.2819***	-0.2452***	-0.283***	-0.2461***
2013	-0.283***	-0.2426***	-0.2825***	-0.2423***
2014	-0.2612***	-0.2248***	-0.2661***	-0.2289***
2015	-0.2522***	-0.2088***	-0.2551***	-0.2112***
2016	-0.2518***	-0.2208***	-0.254***	-0.223***
2017	-0.2855***	-0.2504***	-0.2869***	-0.2515***
2018	-0.1691**	-0.1437**	-0.1726**	-0.1468**
2019	-0.1394**	-0.1193*	-0.1431**	-0.1225*
All years	-0.2248***	-0.1852***	0.2261***	0.1862***
Average	-0.261	-0.208	-0.263	-0.210

Source: Own elaboration according to research data.

Note: Significance codes: "***" 0.001; "**" 0.05; "*" 0.1

4.2 Findings from estimates

The first step in obtaining the estimation results is to select the model that best addresses the research problem. As specified in the previous section, this choice follows the steps outlined in Figure 1 and the procedures suggested by Vega and Elhorst (2015). To test the null hypotheses at each stage, Wald tests were employed, with the null hypothesis stating that the spatial parameters and/or estimated coefficients of the spatial lags included in the models are equal to zero. Since the spatial weight matrices were constructed based on the prices of two different fuels, separate estimations were conducted for each matrix. Moreover, for each specific matrix, two distinct estimations were considered: one including the prices of both fuels in the regression equation, and another in which the model covariates included only the price of a single fuel. The results of the model selection procedures are presented in Table 3.

The results demonstrate that, for each case considered in the analysis, the SLX model provides the best specification for addressing the research question and testing the null hypothesis of no spatial association between pollutant emissions and fuel prices. Among all the functional forms tested, the SLX model most effectively reduces potential endogeneity arising from the possible correlation between spatial lags in fuel prices and the error term of the estimation. Consequently, selecting the SLX model over alternative functional forms allows for the derivation of more robust coefficients in each of the estimations considered.

After selecting the best model, the next step is to analyze the estimation coefficients. Table 4 presents the results of these procedures, reporting the estimated coefficients of the SLX model for each of the six cases considered. The first part of the table reports the coefficients of the variables at their levels (without weighting by the spatial weight matrix), whereas the second part presents the estimated coefficients of the spatial lags of the variables.

Table 3: Test results for choosing the functional form.

W	**Case 1**		**Case 2**			
	1.1: Gasoline	**1.2: Ethanol**	**Gasoline**		**Ethanol**	
			Case 2.1	**Case 2.2**	**Case 2.3**	**Case 2.4**
SLX	32.1[0.006]	32.1[0.006]	44.4[0.000]	31.3[0.003]	44.1[0.000]	31.5[0.003]
RSLX-SEM	0.53[0.460]	0.45[0.500]	0.73[0.390]	0.54[0.460]	0.64[0.420]	0.47[0.500]
SEM	0.47[0.490]	0.46[0.500]	0.58[0.450]	0.47[0.490]	0.59[0.440]	0.46[0.500]
SDEM (λ)	0.49[0.480]	0.38[0.540]	0.73[0.390]	0.47[0.490]	0.37[0.540]	0.59[0.440]
SDEM (spatial lags)	32.1[0.006]	32.0[0.007]	44.9[0.000]	31.4[0.005]	31.4[0.005]	44.5[0.000]

Source: Own elaboration according to research results.

Note 1: $\Delta = 15$ and $\pi = 2$.

Note 2: P-value in brackets.

Note 3: Case 1: Both fuels in the regression equation. Case 2: Only one of the fuels in the regression equation. Case 1.1: Spatial weight matrix based on gasoline prices and both fuels in the regression equation. Case 1.2: Spatial weight matrix based on ethanol prices and both fuels in the regression equation. Case 2.1: Spatial weight matrix based on gasoline prices and only the price of gasoline in the regression equation. Case 2.2: Spatial weight matrix based on gasoline prices and only the price of ethanol in the regression equation. Case 2.3: Spatial weight matrix based on ethanol prices and only the price of gasoline in the regression equation. Case 2.4: Spatial weight matrix based on ethanol prices and only the price of ethanol in the regression equation.

Examining the coefficients associated with economic growth in first part of the table, the results reveal that the Environmental Kuznets Curve (EKC) exhibits an "N" shape. This pattern indicates that, in the early stages of growth, Brazilian municipalities achieve higher levels of economic development only through an expansion in pollutant emissions. However, once these economies reach more advanced stages of growth, the relationship becomes inverse. Nevertheless, in the long-term scenario, when economic growth levels approach a steady state, growth gains are once again positively associated with pollutant emissions. This "N"-shaped EKC pattern is consistent with expectations and has previously been observed for Brazil in studies such as Freire et al (2023).

Still referring to the first part of the table, the coefficients associated with gasoline prices indicate that there is a direct effect of non-renewable fuel prices on pollutant emissions only when economic agents base their decision-making strategies exclusively on information about either renewable or non-renewable fuel prices. In other words, if economic agents consider prices from both fuel sources (renewable and non-renewable) simultaneously in their decision-making process, no significant association emerges between non-renewable fuel prices and pollutant emissions. However, when decision-making excludes one of the fuel sources, gasoline prices exert a direct positive effect on pollutant emissions, suggesting that increases in gasoline prices in a specific municipality tend to generate upward pressures on pollutant emissions within that same municipality.

The ethanol price coefficients, however, are consistent across all estimations, exhibiting statistical significance and a positive sign. This finding indicates that, regardless of the fuel sources considered by economic agents in their decision-making strategies, ethanol prices always exert a direct positive effect on pollutant emissions. In other words, irrespective of the information available to economic agents about fuel prices, increases in ethanol prices in a specific municipality are positively associated with increases in pollutant emissions in that same municipality. Although this result is consistent with the assumptions of Barker (2005) and Martinsen et al (2007), who examined the existence of a non-zero relationship between fuel prices and pollutant emissions, the positive sign of the ethanol price coefficients diverges from findings reported by Martinsen et al (2007) and Newcomer et al (2008). A plausible explanation for this result lies in the substitution effect: when the price of renewable fuels rises, agents may substitute them with more economically viable alternatives, which often include non-renewable fuels with higher pollution potential.

Analyzing the direct effects of the vehicle fleet profile of municipalities, it is noteworthy that the coefficient associated with the number of passenger cars per inhabitant contradicts intuitive expectations. The negative value of this coefficient suggests that municipalities with lower emission levels are those in which each inhabitant owns more passenger cars. This finding may indicate that Brazilians who do not own a car rely on modes of transportation with greater pollution potential than passenger cars, such as motorcycles, which exhibited a positive coefficient in the estimations.

Finally, the other coefficients obtained in the first part of the table indicate that higher emission levels are positively associated with deforestation, forest fires, and above-average precipitation, while they are negatively associated with precipitation. Of particular note is the magnitude of the coefficients related to deforestation, which are substantially higher than the other estimated coefficients. Although this estimate does not imply a causal relationship, the disparity in values may highlight the importance of forest preservation in achieving lower emission levels and improved air quality, as emphasized by Reddington et al (2015).

However, the results in the first part of the table are not sufficient to draw conclusions regarding the hypothesis tested in this study. To determine whether H0 should be rejected, it is necessary to analyze the coefficients of the spatial lags in the SLX model presented in the second part of the table. The results indicate that, across all specifications tested, the coefficient of the spatial lag of ethanol prices is negative and statistically significant. Based on this evidence, H0 should be rejected in the case of fuels from non-renewable sources, regardless of the price information considered by economic agents in the study area when making their choices. This finding reveals an inverse association between local pollutant emissions and ethanol prices in neighboring municipalities; that is, Brazilian municipalities with higher levels of pollutant emissions tend to be surrounded by municipalities where ethanol prices are lower.

Assuming that local emissions depend on neighboring prices, this result may also suggest that pollutant emissions in a specific municipality increase when ethanol prices decline in neighboring municipalities, and vice versa. This finding provides important insights for the formulation of policies aimed at controlling pollutant emissions, as it demonstrates that interventions in the pricing of renewable fuels in a given municipality affect not only emissions within that municipality but also emissions in neighboring areas. Consequently, if policymakers and decision-makers seek to control pollutant emissions through adjustments in renewable fuel pricing policies, the spatial spillover effects of such measures must be taken into account to ensure greater efficiency in the outcomes achieved.

The negative sign of the spatial lag in ethanol prices is consistent with expectations, as previous studies, such as Wu et al (2022), have demonstrated the existence of a negative spillover effect of fuel prices on emissions. In general terms, this result suggests that increases in ethanol prices in a specific municipality discourage pollutant emissions in neighboring municipalities.

Regarding the spatial lag in gasoline prices, the estimated coefficient was statistically significant only in the case where the spatial weight matrix was constructed using ethanol prices to define neighborhood, and in the specification that excludes ethanol prices from the covariate matrix. This result suggests that, for non-renewable fuel prices, $H0$ should be rejected only when agents consider the price differential of renewable fuels in neighboring municipalities when deciding where to purchase fuel, while assuming that emissions are independent of non-renewable fuel prices. Consequently, for gasoline prices, the rejection of $H0$ is ambiguous in this study (may have a zero value or positive sign) and depends largely on how economic agents form their preferences regarding fuel purchasing decisions. This result provides statistical evidence that if regulators intend to use fuel prices as a mechanism for controlling emissions, it is more effective to intervene in ethanol prices rather than gasoline prices.

It is noteworthy that the estimated coefficients for fuel prices (when statistically significant) are larger in absolute terms in the first part of the table, indicating that the direct effect of changes in fuel prices outweighs the spillover effect. This finding suggests that when an emissions control policy based on fuel price adjustments is implemented in a specific municipality, it is preferable that the policy also be extended to neighboring municipalities to ensure emissions are effectively controlled at the regional level. Nevertheless, the intensity of the price adjustment may vary across municipalities in order to account for the spatial spillover effects of such policies on pollutant emissions.

In addition, the coefficients associated with spatial lags in growth variables indicate that the EKC patterns of Brazilian municipalities do not influence the EKC patterns of neighboring municipalities. By contrast, the estimated coefficient for the spatial lag of fire outbreaks was negative and statistically significant across all cases considered. This finding suggests that pollutant emissions are negatively associated with fire outbreaks at the regional level, with municipalities exhibiting lower emission levels tending to be surrounded by municipalities experiencing higher fire occurrences. The explanation for this negative sign may lie in the efforts to remove emissions undertaken by municipalities located near neighbors with frequent fire outbreaks.

Table 4: Results of the SLX model.

W	**Case 1**		**Case 2**			
	1.1: Gasoline	**1.2: Ethanol**	**Gasoline**		**Ethanol**	
			Case 2.1	**Case 2.2**	**Case 2.3**	**Case 2.4**
$ln(G)$	85.080*	84.220*	81.140*	84.820*	79.980*	84.030*
$ln(G)^2$	-20.710*	-20.420*	-19.580*	-20.640*	-19.190*	-20.360*
$ln(G)^3$	1.703*	1.675*	1.611*	1.697*	1.573*	1.670*
$ln(Gasoline\_Price)$	4.531	4.732	19.750*	-	19.830*	-
$ln(Ethanol\_Price)$	28.940*	28.970*	-	29.410*	-	29.520*
$ln(Total\_Vehicles)$	-4.037	-3.977	-6.004	-3.979	-5.923	-3.882
$ln(Cars)$	-19.360*	-19.370*	-18.450*	-19.490*	-18.460*	-19.530*
$ln(trucks)$	1.415	1.385	1.021	1.525	0.924	1.488
$ln(Motorcycles)$	8.537*	8.601*	8.792*	8.597*	8.848*	8.636*
$ln(prec)$	-8.080*	-8.038*	-7.486*	-8.142*	-7.410*	-8.092*
$ln(temp)$	7.875	7.813	3.632	7.477	3.787	7.582
$Deviation\_prec$	0.008*	0.008*	0.008*	0.008*	0.008*	0.08*
$Deviation\_temp$	-1.102	-1.112	-0.684	-1.111	-0.700	-1.130
$Deforestation$	1215.000*	1216.000*	1227.000*	1215.000*	1229.000*	1215.000*
$Fire$	30.680*	30.670*	32.850*	30.800*	32.860*	30.780*
Spatial lags						
$ln(G)$	-16.790	-11.310	-18.980	-13.560	-12.560	-8.747
$ln(G)^2$	4.199	2.400	5.052	3.252	3.003	1.645
$ln(G)^3$	-0.346	-0.165	-0.439	-0.262	-0.236	-0.098
$ln(Gasoline\_Price)$	2.272	1.750	-4.913	-	-5.405*	-
$ln(Ethanol\_Price)$	-8.049*	-7.858*	-	-7.243*	-	-7.256*
$ln(Total\_Vehicles)$	1.105	0.798	-1.182	0.667	-1.777	0.518
$ln(Cars)$	-0.064	0.789	1.344	-0.052	2.284	0.772
$ln(trucks)$	-0.745	-1.535	-1.265	-0.162	-1.927	-1.104
$ln(Motorcycles)$	1.616	1.625	2.215	1.493	2.288	1.513
$ln(prec)$	2.379	2.201	2.561	2.465	2.306	2.296
$ln(temp)$	5.069	3.311	5.232	5.266	3.403	3.362
$Deviation\_prec$	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
$Deviation\_temp$	0.139	0.246	0.253	-0.002	0.360	0.209
$Deforestation$	-35.760	-30.090	-69.340	-39.410	-61.720	-32.710
$Fire$	-11.070*	-11.480*	-12.040*	-10.330	-12.700*	-10.730*

Source: Own elaboration according to research results.

Note 1: $\Delta = 15$ and $\pi = 2$. P-value in brackets.

Note 2: Case 1: Both fuels in the regression equation. Case 2: Only one of the fuels in the regression equation. Case 1.1: Spatial weight matrix based on gasoline prices and both fuels in the regression equation. Case 1.2: Spatial weight matrix based on ethanol prices and both fuels in the regression equation. Case 2.1: Spatial weight matrix based on gasoline prices and only the price of gasoline in the regression equation. Case 2.2: Spatial weight matrix based on gasoline prices and only the price of ethanol in the regression equation. Case 2.3: Spatial weight matrix based on ethanol prices and only the price of gasoline in the regression equation. Case 2.4: Spatial weight matrix based on ethanol prices and only the price of ethanol in the regression equation.

Note 3: "*" indicates 95% statistical significance

4.3 Changing preference and efficiency parameters

As specified in the methodology, the construction of the spatial weighting matrix was based on the assumption that $\Delta = 15$ and $\pi = 2$. This assumption was necessary to overcome the difficulty of obtaining the actual values of these parameters for each municipality. Consequently, the results reported above rely on the hypothesis that intermunicipal travel for fuel acquisition occurs at an average efficiency of 15 kilometers per liter of fuel, while consumers strictly prefer fuel from neighboring municipalities over fuel sold in their own municipality. Since the results are based on assumed values, it is valid to question whether they would change if these values do not reflect the actual energy efficiency parameters and consumer preferences. To address this issue, the spatial weighting matrix was recalculated and the estimations were repeated under the following neighborhood definition scenarios for high energy efficiency: (i) strict preference for fuel from neighboring municipalities with an energy efficiency of 15 km/L; (ii) indifferent preference between fuel from neighboring municipalities and local fuel with an energy efficiency of 15 km/L; (iii) strict preference for fuel from the municipality of residence with an energy efficiency of 15 km/L. In addition, the following neighborhood definition scenarios were considered for low energy efficiency: (i) strict preference for fuel from neighboring municipalities with an energy efficiency of 7.5 km/L; (ii) indifferent preference between fuel from neighboring municipalities and local fuel with an energy efficiency of 7.5 km/L; (iii) strict preference for fuel from the municipality of residence with an energy efficiency of 7.5 km/L.

Using the SLX model as a basis for comparison[6], the results of these procedures revealed that in scenarios of high energy efficiency, the rejection of the null hypothesis of no spatial spillover effect of fuel prices on pollutant emissions prevails across most of the functional forms tested, regardless of consumers' preference patterns for fuel purchase location. These findings corroborate the results obtained with the previously assumed parameter values. By contrast, when energy efficiency is low, the non-rejection of $H0$ predominates in most of the functional forms considered, particularly in scenarios where consumers strictly prefer fuel sold in their municipality of residence over fuel sold in neighboring municipalities.

This result is consistent with expectations and reflects the fundamental properties of the spatial weight matrix used to construct the spatial lags of the variables. On the one hand, when energy efficiency is low, consumers face higher costs to purchase fuel in neighboring municipalities, making intermunicipal travel for fuel acquisition less viable. Consequently, if surrounding fuel prices are not sufficiently low, demand for local fuel tends to rise, while demand for fuel from neighboring municipalities declines. On the other hand, when consumers prefer local fuel, demand for fuel traded in neighboring municipalities decreases, as consumers prioritize local fuel consumption. Therefore, it is reasonable to expect that both low energy efficiency and a preference for local fuel generate a positive direct effect and a zero spatial spillover effect of fuel prices on pollutant emissions.

Based on this explanation, if energy efficiency increases or if economic agents' preferences for fuels from other municipalities also rise, then local fuel prices must decrease sufficiently, or fuel prices in the vicinity of a given municipality must increase substantially, so that fuel prices in neighboring municipalities do not influence pollutant emissions in that municipality. Following the same logic, if fuel prices rise in neighboring municipalities, the spatial spillover effect of this variation on pollutant emissions can be mitigated either by a reduction in energy efficiency or by consumers developing a strict preference for local fuel over fuel sold in neighboring municipalities.

These findings carry important implications for the design of policies that employ fuel prices as instruments to control pollutant emissions. First, policymakers must understand fuel consumers' preferences and the factors shaping those preferences. Second, they should take into account the average energy efficiency standards of local transportation modes. Finally, since both consumer preferences and

[6] These results are presented in the appendix of the manuscript.

the energy efficiency of transportation modes can influence the existence of spatial spillover effects of fuel prices on pollutant emissions, it is recommended that policies relying on fuel price adjustments be adaptable to shifts in fuel purchase preferences and to changes in transportation energy efficiency.

It is important to note that preferences for local fuel have already been identified in previous studies as a factor to be considered when designing public policies related to fuel consumption. For instance, Gupta and Kohlin (2006) emphasized that socioeconomic profile can be a determining factor in shaping these preferences.

It is also important to emphasize that changes in fuel purchase location preferences and energy efficiency do not alter the direct effect of fuel prices on pollutant emissions. Thus, even under different parameter values, pollutant emissions remain directly associated with the local price of ethanol. However, this association may be null for gasoline prices when both fuels are included in the covariate matrix. This outcome demonstrates that the coefficients estimated in the first part of the table are robust, and it aligns with expectations, given that variations in these parameters only affect the values of the spatial lags of the variables. Consequently, the results obtained under multiple parameter specifications confirm that the spatial weight matrix proposed in this study produces outcomes consistent with theoretical expectations.

5 Concluding remarks

This study aimed to test the null hypothesis of no spatial spillover effect between fuel prices and pollutant emissions in Brazilian municipalities. To this end, a panel dataset covering the period from 2002 to 2019 was employed, containing information on pollutant emissions and the prices of two specific fuels: ethanol and gasoline. Local spatial models were estimated to test the null hypothesis, using a time varying spatial weight matrix constructed on the basis of the potential for intermunicipal fuel consumption. The main scenario was constructed under the assumption that Brazilian consumers strictly prefer fuel sold in neighboring municipalities over local fuel, while transportation energy efficiency is not particularly low. However, alternative scenarios were also examined to assess how the results would change if this assumption does not hold.

In the main scenario, the results indicated that there is no statistical evidence to accept the null hypothesis of no spatial spillover effect of ethanol prices on pollutant emissions in any of the specifications tested. By contrast, the findings for gasoline prices are ambiguous, as $H0$ should only be rejected in cases where economic agents use ethanol prices to define proximity, while emissions remain independent of ethanol prices. These results lead to the conclusion that when fuel prices are employed as instruments to control pollutant emissions, emission reduction policies should account for the spatial spillover effect when interventions target ethanol prices. Consequently, interventions in ethanol prices aimed at controlling pollutant emissions are likely to be more effective when implemented at the regional level rather than locally within a specific municipality. There is insufficient evidence to support the same conclusion for interventions in gasoline prices.

In alternative scenarios where transportation energy efficiency is low and consumers prefer local fuel over fuel from neighboring municipalities, the null hypothesis of no spatial spillover effect of fuel prices on pollutant emissions is accepted for both gasoline and ethanol prices across all statistical specifications tested. This outcome indicates that if preferences for fuel purchase locations and/or transportation energy efficiency fluctuate over time, the territorial scope of policies that employ fuel prices as instruments to control pollutant emissions must account for potential changes in these parameters to ensure that the effects of such measures are more effective.

The results also indicated that ethanol prices exert a direct positive effect on pollutant emissions across all scenarios and statistical specifications tested. In contrast, the direct effect of gasoline prices on pollutant emissions is sometimes ambiguous, as this effect may be either zero or positive depending on how economic agents structure their preferences regarding fuel purchase locations. Based on these findings, it can be concluded that pollutant emissions in a given municipality are directly associated with the price of renewable fuels within that municipality, and may be inversely associated with the price of renewable fuels in neighboring municipalities, depending on consumer preferences for local fuel and the energy efficiency standards of transportation.

However, the results of this study should be interpreted with caution due to important limitations and the assumptions required for the estimation process. The primary limitation concerns the sample size, which is constrained by the limited availability of price information. Another significant limitation is the insufficient availability of data on fuel prices beyond gasoline and ethanol. Furthermore, the construction of the spatial weight matrix relied on assumed values for the π and Δ parameters, as well as an approximation for the Π parameter. Future research could enhance this study by calculating these parameters with greater precision, thereby enabling a more robust and appropriate definition of neighborhood. In addition, advances may be achieved through more comprehensive and accurate surveys of fuel price data.

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Appendices

A Estimates using $\Delta = 15$ and $\pi = 2$

Table 5: Case 1: Both fuels prices in the covariate matrix of the regression equation.

W	1.1: Gasoline					1.2: Ethanol				
	CFE	**RSLX-SEM**	**SLX**	**SEM**	**SDEM**	**CFE**	**RSLX-SEM**	**SLX**	**SEM**	**SDEM**
$ln(G)$	86.889*	87.072*	85.085*	86.943*	85.230*	86.770*	86.930*	84.220*	86.970*	84.380*
$ln(G)^2$	-21.374	-21.422*	-20.710*	-21.387*	-20.760*	-21.340*	-21.380*	-20.420*	-21.400*	-20.470*
$ln(G)^3$	1.776*	1.781*	1.703*	1.778*	1.708*	1.773*	1.777*	1.675*	1.779*	1.679*
$ln(Gasoline\_Price)$	4.544*	4.577	4.531	4.655	4.546	4.652	4.661	4.732	4.629	4.718
$ln(Ethanol\_Price)$	28.651*	28.612*	28.942*	28.499*	28.910*	28.470*	28.430*	28.970*	28.490*	28.940*
$ln(Total\_Vehicles)$	-8.153	-8.284	-4.037	-8.241	-4.060	-8.117*	-8.249*	-3.977	-8.259*	-4.017
$ln(Cars)$	-18.576*	-18.538*	-19.355	-18.531*	-19.370*	-18.570*	-18.530*	-19.370*	-18.530*	-19.380*
$ln(trucks)$	1.975	1.995	1.415	1.984	1.428	1.966	2.001	1.385	2.000	1.410
$ln(Motorcycles)$	11.639*	11.672*	8.537*	11.638*	8.506*	11.610*	11.640*	8.601*	11.650*	8.585*
$ln(prec)$	-7.155*	-7.150*	-8.080*	-7.158*	-8.086*	-7.165*	-7.160*	-8.038*	-7.157*	-8.041*
$ln(temp)$	36.096	36.680	7.875	37.037	9.030	35.860	36.410	7.813	36.960	8.771
$Deviation\_prec$	0.007*	0.007*	0.008*	0.007*	0.008*	0.007*	0.007*	0.008*	0.007*	0.008*
$Deviation\_temp$	-2.338	-2.360	-1.102	-2.374	-1.150	-2.325	-2.346	-1.112	-2.371	-1.151
$Deforestation$	1219.805*	1220.305*	1215.363*	1220.320*	1216.000*	1220.000*	1221.000*	1216.000*	1220.000*	1216.000*
$Fire$	30.293*	30.241	30.681*	30.249*	30.640*	30.300*	30.250*	30.670*	30.250*	30.640*
	Spatial lags									
$ln(G)$			-16.788		-16.890			-11.310		-11.580
$ln(G)^2$			4.199		4.246			2.400		2.486
$ln(G)^3$			-0.346		-0.352			-0.165		-0.174
$ln(Gasoline\_Price)$	0.229	0.223	2.272		2.307	-0.064	-0.069	1.750		1.778
$ln(Ethanol\_Price)$	-0.205	-0.186	-8.041*		-8.005*	0.052	0.067	-7.858*		-7.813*
$ln(Total\_Vehicles)$			1.105		0.753			0.798		0.488
$ln(Cars)$			-0.064		0.083			0.789		0.919
$ln(trucks)$			-0.745		-0.683			-1.535		-1.473
$ln(Motorcycles)$			1.616		1.760			1.623		1.748
$ln(prec)$			2.379		2.406			2.201		2.222
$ln(temp)$			5.069		5.134			3.311		3.463
$Deviation\_prec$			-0.002		-0.002			-0.002		-0.002
$Deviation\_temp$			0.139		0.134			0.246		0.237
$Deforestation$			-35.757		-34.270			-30.090		-28.800
$Fire$			-11.067		-11.180*			-11.480*		-11.560*
	Spatial parameters									
λ				0.019	0.020				0.019	0.017
Λ		0.019					0.017			

Source: Own elaboration according to research results.
Note: "*" indicates 95% statistical significance.

Table 6: Case 2: Only gasoline price in the covariate matrix of the regression equation.

W	**2.1: Gasoline**					**2.3: Ethanol**				
	CFE	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**	**CFE**	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**
$ln(G)$	84.470*	81.140*	84.690*	84.670*	81.330*	84.330*	79.980*	84.530*	84.710*	80.200*
$ln(G)^2$	-20.650*	-19.580*	-20.710*	-20.710*	-19.640*	-20.610*	-19.190*	-20.670*	-20.730*	-19.260*
$ln(G)^3$	1.724*	1.611*	1.729*	1.729*	1.617*	1.719*	1.573*	1.725*	1.731*	1.580*
$ln(Gasoline\_Price)$	17.110*	19.750*	17.120*	17.150*	19.750*	17.020*	19.830*	17.000*	17.120*	19.790*
$ln(Total\_Vehicles)$	-11.940*	-6.004	-12.100*	-12.070*	-6.029	-11.930*	-5.923	-12.080*	-12.100*	-5.970
$ln(Cars)$	-17.480*	-18.450*	-17.430*	-17.440*	-18.470*	-17.430*	-18.460*	-17.390*	-17.430*	-18.470*
$ln(trucks)$	1.725	1.021	1.750	1.740	1.035	1.701	0.924	1.744	1.760	0.955
$ln(Motorcycles)$	12.670*	8.792*	12.710*	12.710*	8.755*	12.640*	8.848*	12.680*	12.720*	8.829*
$ln(prec)$	-6.140*	-7.486*	-6.135*	-6.137*	-7.495*	-6.157*	-7.410*	-6.154*	-6.135*	-7.416*
$ln(temp)$	44.690	3.632	45.420	46.000	5.041	44.660	3.787	45.340	45.940	4.983
$Deviation\_prec$	0.007*	0.008*	0.007*	0.007*	0.008*	0.007*	0.008*	0.007*	0.007*	0.008
$Deviation\_temp$	-2.364	-0.684	-2.392	-2.418	-0.742	-2.359	-0.700	-2.385	-2.416	-0.479
$Deforestation$	1230.000*	1227.000*	1231.000*	1230.000*	1227.000*	1231.000*	1229.000*	1232.000*	1230.000*	1229.000*
$Fire$	32.520*	32.850*	32.460*	32.470*	32.800*	32.500*	32.860*	32.440*	32.470*	32.810*
	Spatial lags									
$ln(G)$		-18.980			-19.130		-12.560			-12.940
$ln(G)^2$		5.052			5.120		3.003			3.122
$ln(G)^3$		-0.439			-0.447		-0.236			-0.248
$ln(Gasoline\_Price)$	-0.035	-4.913	-0.024		-4.827	-0.341	-5.405*	-0.332		-5.331*
$ln(Total\_Vehicles)$		-1.182			-1.608		-1.777			-2.171
$ln(Cars)$		1.344			1.523		2.284			2.453
$ln(trucks)$		-1.265			-1.200		-1.927			-1.854
$ln(Motorcycles)$		2.215			2.394		2.288			2.449
$ln(prec)$		2.561			2.589		2.306			2.326
$ln(temp)$		5.232			5.322		3.403			3.621
$Deviation\_prec$		-0.002			-0.002		-0.002			-0.002
$Deviation\_temp$		0.253			0.284		0.360			0.350
$Deforestation$		-69.340			-67.550		-61.720			-60.210
$Fire$		-12.040*			-12.180*		-12.700*			-12.800*
	Spatial parameters									
λ				0.021	0.024					0.021
Λ			0.022					0.020	0.021	

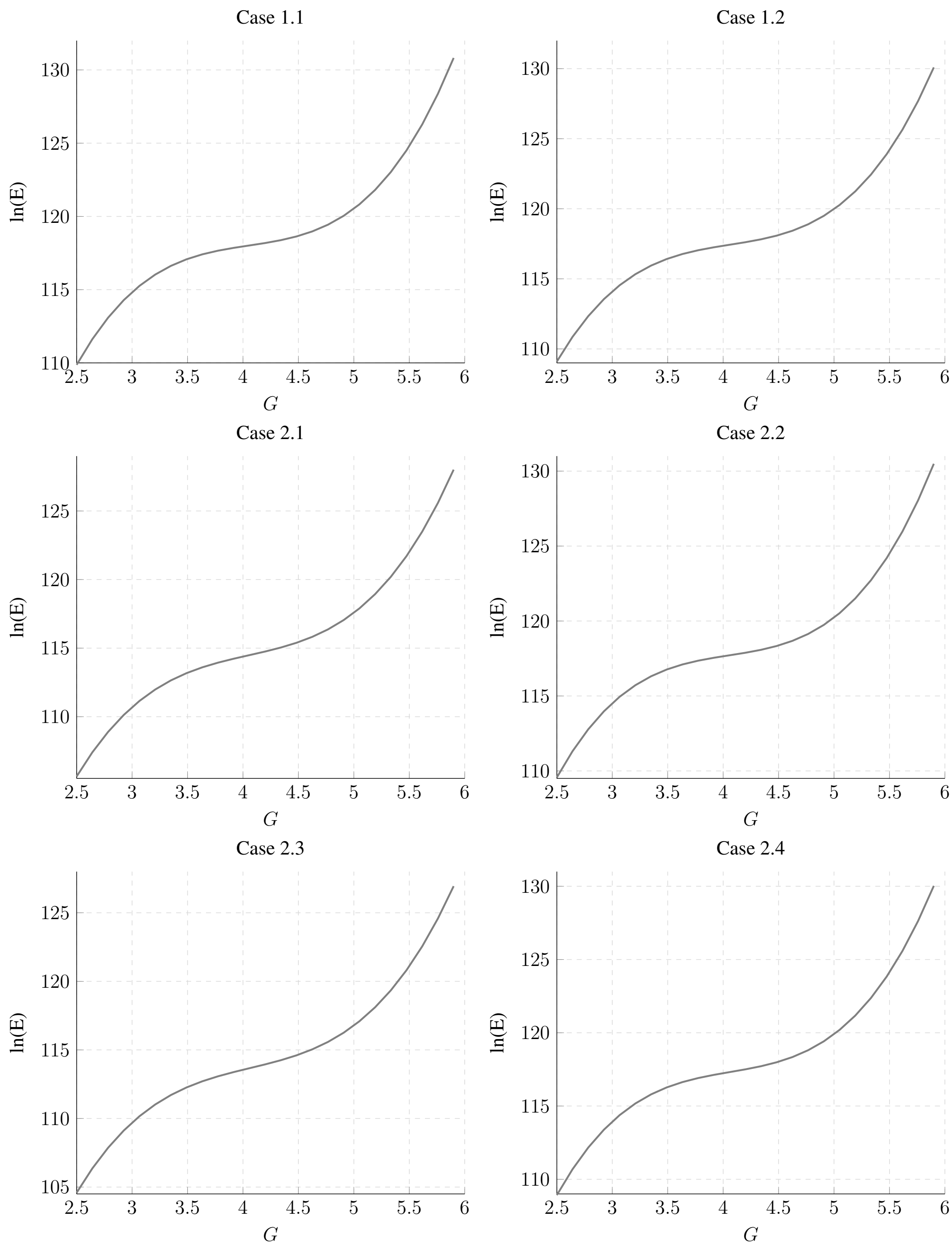
Source: Own elaboration according to research results.
Note: "*" indicates 95% statistical significance.

Table 7: Case 3: Only ethanol price in the covariate matrix of the regression equation.

W	**2.2: Gasoline**					**2.4: Ethanol**				
	CFE	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**	**CFE**	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**
$ln(G)$	86.800*	84.820*	86.970*	86.950*	84.970*	86.790*	84.030*	86.960*	86.980*	84.180*
$ln(G)^2$	-21.340*	-20.640*	-21.380*	-21.380*	-20.680*	-21.340*	-20.360*	-21.380*	-21.390	-20.410*
$ln(G)^3$	1.773*	1.697*	1.777*	1.776*	1.702*	1.772*	1.670*	1.777*	1.778*	1.675*
$ln(Ethanol\_Price)$	29.220*	29.410*	29.190*	29.220*	29.380*	29.230*	29.520*	29.200*	29.210*	29.490*
$ln(Total\_Vehicles)$	-7.977*	-3.979	-8.110*	-8.094*	-4.002	-7.989*	-3.882	-8.124*	-8.113*	-3.923
$ln(Cars)$	-17.770*	-19.490*	-18.730*	-18.730*	-19.500*	-18.750*	-19.530*	-18.720*	-18.730*	-19.540*
$ln(trucks)$	2.067	1.525	2.088	2.082	1.538	2.064	1.488	2.101	2.097	1.513
$ln(Motorcycles)$	11.580*	8.597*	11.610*	11.600*	8.569*	11.580*	8.636*	11.620*	11.610*	8.622*
$ln(prec)$	-7.171*	-8.142*	-7.167*	0.007*	-8.150*	-7.172*	-8.092*	-7.169*	-7.165*	-8.097*
$ln(temp)$	35.320	7.477	35.940	36.440	8.603	35.380	7.582	35.960	36.380	8.592
$Deviation\_prec$	0.007*	0.008*	0.007*	0.007*	0.008*	0.007*	0.008*	0.007*	0.007*	0.008*
$Deviation\_temp$	-2.340	-1.111	-2.364	-2.386	-1.158	-2.341	-1.130	-2.363	-2.383	-1.168
$Deforestation$	1219.000*	1215.000*	1219.000*	1219.000*	1215.000*	1219.000*	1215.000*	1220.000*	1219.000*	1215.000*
$Fire$	30.410*	30.800*	30.360*	30.370*	30.760*	30.410*	30.780*	30.360*	30.360*	30.750*
	Spatial lags									
$ln(G)$		-13.560			-13.620		-8.747			-8.983
$ln(G)^2$		3.252			3.286		1.645			1.721
$ln(G)^3$		-0.262			-0.267		-0.098			-0.106
$ln(Ethanol\_Price)$	0.010	-7.243*	0.021		-7.187*	0.055	-7.256*	-0.046		-7.202*
$ln(Total\_Vehicles)$		0.667			0.320		0.518			0.208
$ln(Cars)$		-0.052			0.090		0.772			0.900
$ln(trucks)$		-0.162			-0.096		-1.104			-1.040
$ln(Motorcycles)$		1.493			1.631		1.513			1.635
$ln(prec)$		2.465			2.494		2.296			2.319
$ln(temp)$		5.266			5.328		3.362			3.507
$Deviation\_prec$		-0.002			-0.002		-0.002			-0.002
$Deviation\_temp$		0.095			0.089		3.362			3.507
$Deforestation$		-39.410			-37.990		-32.710			-31.450
$Fire$		-10.330			-10.430		-10.730*			-10.810*
	Spatial parameters									
λ				0.019	0.019				0.019	0.017
Λ			0.019					0.017		

Source: Own elaboration according to research results.
Note: “*” indicates 95% statistical significance.

Figure 4: Graphical representation of estimated EKC.



Source: Own elaboration according to research results.

B Estimates using $\Delta = 15$ and $\pi = 1$ (local fuel $\sim$ neighbor fuel)

Table 8: Case 1: Both fuels prices in the covariate matrix of the regression equation.

W	**1.1: Gasoline**					**1.2: Ethanol**				
	CFE	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**	**CFE**	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**
$ln(G)$	87.020*	86.370*	87.200*	86.950*	86.580*	86.820*	86.040*	87.000*	86.950*	86.220*
$ln(G)^2$	-21.410*	-21.180*	-21.460*	-21.309*	-21.240*	-21.340*	-21.090*	-21.390*	-21.390*	-21.140*
$ln(G)^3$	1.780*	1.756*	1.784*	1.777*	1.761*	1.773*	1.748*	1.777*	1.777*	1.753*
$ln(Gasoline\_Price)$	4.296	5.445	4.325	4.650	5.468	4.330	5.177	4.354	4.651	5.193
$ln(Ethanol\_Price)$	28.890*	28.700*	28.880*	28.520*	28.690*	28.850*	28.710*	28.850*	28.520*	28.710*
$ln(Total\_Vehicles)$	-8.312*	-4.951	-8.419*	-8.208*	-4.985	-8.273*	-4.985	-8.383*	-8.213*	-5.021
$ln(Cars)$	-18.560*	-19.490*	-18.550*	-18.560*	-19.520*	-18.550*	-19.440*	-18.530*	-18.560*	-19.460*
$ln(trucks)$	2.039	1.421	2.059	1.983	1.433	2.008	1.415	2.027	1.98*	1.428
$ln(Motorcycles)$	11.720*	9.746*	11.780*	11.660*	9.764*	11.700*	9.734*	11.750*	11.660*	9.751*
$ln(prec)$	-7.147*	-8.019*	-7.142*	-7.155*	-8.022*	-7.158*	-8.055*	-7.154*	-7.155*	-8.054*
$ln(temp)$	36.650	24.520	37.050	36.430	25.260	36.750	24.780	37.140	36.470	25.510
$Deviation\_prec$	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.008*	0.007*	0.007*	0.008*
$Deviation\_temp$	-2.358	-1.860	-2.373	-2.348	-1.888	-2.361	-1.873	-2.376	-2.350	-1.902
$Deforestation$	1220.000*	1217.000*	1219.000*	1220.000*	1217.000*	1220.000*	1219.000*	1220.000*	1220.000*	1218.000*
$Fire$	30.250*	30.870*	30.210*	30.260*	30.830*	30.270*	30.840*	30.230*	30.260*	30.800*
	Spatial lags									
$ln(G)$		-39.110			-39.600		33.110			-33.540
$ln(G)^2$		10.960			11.130		79.239			9.369
$ln(G)^3$		-0.953			-0.971		-0.797			-0.810
$ln(Gasoline\_Price)$	0.826	2.346	0.820		2.453	0.542	2.370	0.540		2.479
$ln(Ethanol\_Price)$	-0.990	-8.011*	-0.948		-7.985*	-1.147	-7.776*	-1.111		-7.751*
$ln(Total\_Vehicles)$		-7.837			-8.109		-7.127			-7.323
$ln(Cars)$		6.273			6.380		5.556			5.613
$ln(trucks)$		-0.562			-0.524		-0.350			-0.319
$ln(Motorcycles)$					2.826		2.631			2.751
$ln(prec)$		4.198			4.312		4.588			4.664
$ln(temp)$		9.432			9.368		6.148			6.163
$Deviation\_prec$		-0.003			-0.003		-0.004			-0.004
$Deviation\_temp$		0.008			0.006		0.165			0.159
$Deforestation$		-96.220			-99.820		-108.400			-111.700
$Fire$		-10.970			-11.030		-10.120			-10.170
	Spatial parameters									
λ				0.015	0.021				0.016	0.020
Λ			0.015					0.015		

Source: Own elaboration according to research results.
Note: "*" indicates 95% statistical significance.

Table 9: Case 2: Only gasoline price in the covariate matrix of the regression equation.

W	**2.1: Gasoline**					**2.3: Ethanol**				
	CFE	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**	**CFE**	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**
$ln(G)$	84.330*	82.880*	84.500*	84.640*	83.110*	84.060*	82.580*	84.220*	84.650*	82.780*
$ln(G)^2$	-20.610*	-20.140*	-20.660*	-20.700*	-20.200*	-20.500*	-20.060*	-20.550*	-20.700*	-20.120*
$ln(G)^3$	1.719*	1.673*	1.724*	1.728*	1.679*	1.708*	1.666*	1.713*	1.728*	1.671*
$ln(Gasoline\_Price)$	17.740*	19.700*	17.160*	17.150*	19.720*	17.210*	19.310*	17.230*	17.150*	19.330*
$ln(Total\_Vehicles)$	-11.870*	-7.022	-11.980*	-12.030*	-7.061	-11.770*	-7.109	-11.870*	-12.030*	-7.150
$ln(Cars)$	-17.480*	-18.530*	-17.460*	-17.460*	-18.560*	-17.460*	-18.500*	-17.450*	-17.460*	-18.520*
$ln(trucks)$	1.698	0.738	1.719	1.737	0.748	1.640	0.752	1.659	1.736	0.762
$ln(Motorcycles)$	12.640*	9.876*	12.700*	12.720*	9.898*	12.580*	9.909*	12.640*	12.730*	9.931*
$ln(prec)$	-6.150*	-7.250*	-6.143*	-6.132*	-7.253*	-6.172*	-7.283*	-6.167*	-6.132*	-7.782*
$ln(temp)$	44.390	24.390	44.800	45.230	25.230	44.440	24.520*	44.830	45.280	25.320
$Deviation\_prec$	0.007*	0.008*	0.007*	0.007*	0.008*	0.007*	0.008*	0.007*	0.007*	0.008*
$Deviation\_temp$	-2.351	24.390	44.800	-2.386	25.230	-2.354	-1.591	-2.369	-2.388	-1.623
$Deforestation$	1230.000*	1232.000*	1230.000*	1230.000*	1232.000*	1230.000*	1233.000*	1230.000*	1230.000*	1233.000*
$Fire$	32.530*	33.280*	32.500*	32.490*	33.230*	32.580*	33.203*	32.550*	32.490*	33.200*
	Spatial lags									
$ln(G)$		-39.070			-39.580		-36.440			-36.890
$ln(G)^2$		11.010			11.190		10.350			10.490
$ln(G)^3$		-0.953			-0.972		-0.898			-0.912
$ln(Gasoline\_Price)$	-0.297	-4.410	0.013		-4.284	-0.812	-4.132	-0.790		-4.007
$ln(Total\_Vehicles)$		-10.130			-10.450		-9.353			-9.590
$ln(Cars)$		7.152			7.2298		6.377			6.470
$ln(trucks)$		-0.975			-0.941		-0.680			-0.655
$ln(Motorcycles)$		3.529			3.670		3.369			3.498
$ln(prec)$		4.061			4.168		4.526			4.590
$ln(temp)$		9.327			9.294		6.801			6.855
$Deviation\_prec$		-0.004			-0.004		-0.004			-0.004
$Deviation\_temp$		0.177			0.175		6.801			0.275
$Deforestation$		-157.900			-161.500		-174.700			-177.900
$Fire$		-12.640			-12.710		-10.950			-11.000
	Spatial parameters									
λ				0.014	0.022				0.015	0.020
Λ			0.032					0.013		

Source: Own elaboration according to research results.
Note: "*" indicates 95% statistical significance.

Table 10: Case 3: Only ethanol price in the covariate matrix of the regression equation.

W	**2.2: Gasoline**					**2.4: Ethanol**				
	CFE	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**	**CFE**	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**
$ln(G)$	86.780*	86.080*	86.970*	86.950*	86.260*	86.660*	85.700*	86.860*	86.950*	85.860*
$ln(G)^2$	-21.330*	-21.090*	-21.380*	-21.380*	-21.140*	-21.280*	-21.000*	-21.330*	-21.380*	-21.040*
$ln(G)^3$	1.772*	1.748*	1.776*	1.776*	1.753*	1.767*	1.740*	1.772*	1.776*	1.744*
$ln(Ethanol\_Price)$	29.240*	29.430*	29.250*	29.240*	29.430*	29.310*	29.400*	29.320*	29.240*	29.390*
$ln(Total\_Vehicles)$	-7.981*	-4.870	-8.092*	-8.060*	-4.903	-8.007*	-4.903	-8.121*	-8.064*	-4.937*
$ln(Cars)$	-18.760*	-19.630*	-18.750*	-18.760*	-19.650*	-18.740*	-19.570*	-18.720*	-18.750*	-19.580*
$ln(trucks)$	2.066	1.492	2.087	2.080	1.501	2.055	1.480	2.076	2.080	1.490
$ln(Motorcycles)$	11.580*	9.800*	11.640*	11.620*	9.818*	11.590*	9.783*	11.650*	11.630*	9.800*
$ln(prec)$	-7.172*	-8.045*	-7.167*	-7.167*	-8.050*	-7.178*	-8.085*	-7.173*	0.007*	-8.087*
$ln(temp)$	35.320	23.830	35.760	35.830*	24.490	35.690	24.070	36.110	35.870	24.720
$Deviation\_prec$	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*
$Deviation\_temp$	-2.339	-1.870	-2.356	-2.360	-1.896	-2.353	-1.880	-2.369	-2.362	-1.906
$Deforestation$	1219.000*	1216.000*	1219.000*	1219.000*	1216.000*	1219.000*	1218.000*	1219.000*	1219.000*	1218.000*
$Fire$	30.410*	31.030*	30.370*	30.380*	30.990*	30.420*	31.000*	30.380*	30.380*	30.970*
	Spatial lags									
$ln(G)$		-32.470			-32.700		-26.570			-26.750
$ln(G)^2$		8.999			9.087		7.313			7.369
$ln(G)^3$		-0.773			-0.783		-0.621			-0.627
$ln(Ethanol\_Price)$	-0.093	-7.099*	-0.059		-7.034*	-0.568	-6.852*	-0.534		-6.787*
$ln(Total\_Vehicles)$		-8.662			-8.931		-7.925			-8.123
$ln(Cars)$		6.662			6.762		5.874			5.926
$ln(trucks)$		0.033			0.081		0.235			0.277
$ln(Motorcycles)$		2.572					2.518			2.625
$ln(prec)$		4.173			4.285		4.577			4.653
$ln(temp)$		8.816			8.714		5.479			5.454
$Deviation\_prec$		-0.003			-0.004		-0.004			-0.004
$Deviation\_temp$		-0.012			-0.013		0.147			0.141
$Deforestation$		-97.550			-101.000*		-110.400			-113.500
$Fire$		-10.220			-10.260		-9.687			-9.722
	Spatial parameters									
λ				0.015	0.020				0.016	0.018
Λ			0.015					0.015		

Source: Own elaboration according to research results.
Note: “*” indicates 95% statistical significance.

C Estimates using $\Delta = 15$ and $\pi = 0.9$ (local fuel $\prec$ neighbor fuel)

Table 11: Case 1: Both fuels prices in the covariate matrix of the regression equation.

W	1.1: Gasoline					1.2: Ethanol				
	CFE	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**	**CFE**	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**
$ln(G)$	87.000*	86.720*	87.160*	86.960*	86.880*	87.130*	86.540*	87.290*	86.970	86.710*
$ln(G)^2$	-21.390*	-21.290*	-21.430*	-21.390*	-21.340*	-21.440*	-21.240*	-21.490*	-21.390*	-21.290*
$ln(G)^3$	1.777*	1.767*	1.781*	1.777*	1.771*	1.783*	1.762*	1.786*	1.778*	1.766*
$ln(Gasoline\_Price)$	4.198	5.291	4.212	4.642	5.286	4.226	5.213	4.240	4.642	5.206
$ln(Ethanol\_Price)$	28.960*	28.890*	28.970*	28.520*	28.900*	28.940*	28.910*	28.950*	28.520*	28.920*
$ln(Total\_Vehicles)$	-8.237*	-5.630	-8.320*	-8.204*	-5.658	-8.338*	-5.735	-8.424*	-8.206*	-5.764
$ln(Cars)$	-18.620*	-19.200*	-18.600*	-18.550*	-19.210*	-18.560*	-19.190*	-18.550*	-18.550*	-19.200*
$ln(trucks)$	2.046	1.327	2.062	1.982	1.336	2.053	1.344	2.069	1.983	1.353
$ln(Motorcycles)$	11.660*	10.100*	11.700*	11.650*	10.110*	11.720*	10.240*	11.760*	11.650*	10.250*
$ln(prec)$	-7.171*	-8.018*	-7.167*	-7.157*	-8.016*	-7.149*	-7.912*	-7.146*	-7.157*	-7.911*
$ln(temp)$	36.610	30.870	36.900	36.370	31.370*	36.910	30.860	37.220	36.380	31.400
$Deviation\_prec$	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*
$Deviation\_temp$	-2.352	-2.090	-2.363	-2.346	-2.109	-2.370	-2.089	-2.381	-2.346	-2.110
$Deforestation$	1220.000*	1217.000*	1219.000*	1220.000*	1217.000*	1220.000*	1217.000*	1219.000*	1220.000*	1216.000*
$Fire$	30.230*	30.730*	30.200*	30.270*	30.710*	30.230*	30.760*	30.210*	30.270*	30.730*
	Spatial lags									
$ln(G)$		-40.020			-40.300		-40.160			-40.510
$ln(G)^2$		11.750			11.840		11.780			11.890
$ln(G)^3$		-1.049			-1.059		-1.051			-1.063
$ln(Gasoline\_Price)$	0.532	2.580	0.526		2.637	0.870	2.628	0.863		2.712
$ln(Ethanol\_Price)$	-1.672	-8.157*	-1.650		-8.111*	-1.433	-7.958*	-1.412		-7.922*
$ln(Total\_Vehicles)$		-3.237			-3.417		-3.047			-3.271
$ln(Cars)$		1.234			1.261		1.445			1.517
$ln(trucks)$		-0.385			-0.245		-0.138			-0.016
$ln(Motorcycles)$		2.035			2.121		1.627			1.723
$ln(prec)$		4.994			5.031		4.010			4.054
$ln(temp)$		4.508			4.707		7.230			7.406
$Deviation\_prec$		-0.004			-0.004		-0.003			-0.003
$Deviation\_temp$		0.041			0.029		-0.080			-0.091
$Deforestation$		-55.810			-58.270		-57.500			-60.570
$Fire$		-9.471			-9.499		-10.350			-10.390
	Spatial parameters									
λ				0.013	0.015				0.014	0.016
Λ			0.011					0.012		

Source: Own elaboration according to research results.
Note: “*” indicates 95% statistical significance.

Table 12: Case 2: Only gasoline price in the covariate matrix of the regression equation.

W	**2.1: Gasoline**					**2.3: Ethanol**				
	CFE	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**	**CFE**	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**
$ln(G)$	84.290*	83.240*	84.400*	84.630*	83.390*	84.550*	83.110*	84.670*	84.630*	83.270*
$ln(G)^2$	-20.570*	-20.260*	-20.600*	-20.700*	-20.300*	-20.660*	-20.210*	-20.690*	-20.700*	-20.260*
$ln(G)^3$	1.715*	1.684*	1.717*	1.728*	1.688*	1.723*	1.680*	1.726*	1.728*	1.684*
$ln(Gasoline\_Price)$	17.190*	19.640*	17.200*	17.140*	19.640*	17.200*	19.570*	17.210*	17.140*	19.570*
$ln(Total\_Vehicles)$	-11.640*	-7.961*	-11.700*	-12.010*	-7.987*	-11.800*	-8.044*	-11.860*	-12.010*	-8.070*
$ln(Cars)$	-17.570*	-18.190*	-17.560*	-17.470*	-18.200*	-17.490*	-18.210*	-17.480*	-17.470*	-18.220*
$ln(trucks)$	1.681	0.691	1.693	1.735	0.698	1.699	0.727	1.712	1.735	0.734
$ln(Motorcycles)$	12.490*	10.350*	12.520*	12.710*	10.360*	12.570*	10.460*	12.600*	12.710*	10.470*
$ln(prec)$	-6.191*	-7.216*	-6.189*	-6.134*	-7.214*	-6.161*	-7.103*	-6.157*	-6.134*	-7.101*
$ln(temp)$	43.760*	31.900	43.990	45.090	32.360	44.390	31.950	44.630	45.090	32.450
$Deviation\_prec$	0.007*	0.008*	0.007*	0.007*	0.008*	0.007*	0.008*	0.007*	0.007*	0.008*
$Deviation\_temp$	-2.319	-1.845	-2.328	-2.380	-1.863	-2.351	-1.847	-2.360	-2.380	-1.867
$Deforestation$	1230.000*	1231.000*	1230.000*	1230.000*	1231.000*	1230.000*	1231.000*	1230.000*	1230.000*	1230.000*
$Fire$	32.530*	33.170*	23.520*	32.500*	33.160*	32.530*	33.200*	32.520*	0.011	33.170*
	Spatial lags									
$ln(G)$		-38.370			-38.660		-39.250			-39.560
$ln(G)^2$		11.360			11.450		11.550			11.650
$ln(G)^3$		-1.001			-1.015		-1.015			-1.026
$ln(Gasoline\_Price)$	-1.233	-4.060	-1.226		-3.988	-0.792	-3.967	-0.787		-3.879
$ln(Total\_Vehicles)$		-4.376			-4.530		-3.762			-3.956
$ln(Cars)$		0.697			0.724		0.390			0.456
$ln(trucks)$		-1.021			-0.908		-0.793			-0.695
$ln(Motorcycles)$		2.909			2.985		2.518			2.603
$ln(prec)$		4.891			4.915		3.865			3.895
$ln(temp)$		2.825			3.026		5.779			5.951
$Deviation\_prec$		-0.004			-0.004		-0.003			-0.003
$Deviation\_temp$		0.221			0.210		0.092			0.083
$Deforestation$		-104.100			-106.000		-103.300			-105.600
$Fire$		-11.170			-11.190		-12.010			-12.050
	Spatial parameters									
λ				0.011	0.013				0.011	0.014
Λ			0.008					0.008		

Source: Own elaboration according to research results.
Note: “*” indicates 95% statistical significance.

Table 13: Case 3: Only ethanol price in the covariate matrix of the regression equation.

W	**2.2: Gasoline**					**2.4: Ethanol**				
	CFE	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**	**CFE**	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**
$ln(G)$	86.880*	86.370*	87.040*	86.960*	86.520*	86.940*	86.210*	87.100*	86.970*	86.360*
$ln(G)^2$	-21.340*	-21.200*	-21.380*	-21.380*	-21.240*	-21.370*	-21.140*	-21.420*	-21.380*	-21.190*
$ln(G)^3$	1.772*	1.758*	1.776*	1.776*	1.762*	1.775*	1.754*	1.779*	1.777*	1.758*
$ln(Ethanol\_Price)$	29.440*	29.600*	29.450*	29.240*	29.610*	29.300*	29.610*	29.320*	29.240*	29.610*
$ln(Total\_Vehicles)$	-7.982*	-5.498	-8.068*	-8.057*	-5.524	-8.011*	-5.618	-8.100*	-8.058*	-5.645
$ln(Cars)$	-18.810*	-19.390*	-18.800*	-18.750*	-19.400*	-18.760*	-19.360*	+18.740*	-18.750*	-19.370*
$ln(trucks)$	2.101	1.426	2.118	2.079	1.434	2.084	1.438	2.102	2.080	1.446
$ln(Motorcycles)$	11.560*	10.130*	11.600*	11.620*	10.140*	11.580*	10.270*	11.620*	11.620*	10.280*
$ln(prec)$	-7.190*	-8.063*	-7.187*	-7.166*	-8.062*	-7.173*	-7.956*	-7.169*	-7.166*	-7.956*
$ln(temp)$	35.580	29.730	35.900	35.770	30.180	35.600	29.640	35.940	35.780	30.120
$Deviation\_prec$	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*
$Deviation\_temp$	-2.343	-2.077	-2.355	-2.357	-2.094	-2.350	-2.073	-2.362	-2.358	-2.091
$Deforestation$	1219.000*	1216.000*	1218.000*	1219.000*	1216.000*	1219.000*	1216.000*	1219.000*	1219.000*	1216.000*
$Fire$	30.370*	30.880*	30.340*	30.390*	30.860*	30.400*	30.900*	30.370*	30.390*	30.880*
	Spatial lags									
$ln(G)$		-32.730			-32.870		-33.210			-33.350
$ln(G)^2$		9.642			9.692		9.747			9.789
$ln(G)^3$		-0.860			-0.866		-0.867			-0.873
$ln(Ethanol\_Price)$	-1.163	-7.197*	-1.148		-7.132*	-0.524	-6.990*	-0.513		-6.925*
$ln(Total\_Vehicles)$		-5.105			-5.295		-4.775			-5.007
$ln(Cars)$		2.461			2.496		2.574			2.650
$ln(trucks)$		0.387			0.525		0.584			0.707
$ln(Motorcycles)$		2.027			2.107		1.608			1.697
$ln(prec)$		5.134			5.175		4.150			4.199
$ln(temp)$		3.756			3.916		6.605			6.727
$Deviation\_prec$		-0.004			-0.004		-0.003			-0.003
$Deviation\_temp$		0.031			0.020		-0.096			-0.105
$Deforestation$		-58.930			-61.310		-61.830			-64.780
$Fire$		-8.628			-8.648		-9.485			-9.515
	Spatial parameters									
λ				0.013	0.014				0.014	0.015
Λ			0.011					0.012		

Source: Own elaboration according to research results.
Note: "*" indicates 95% statistical significance.

D Estimates using $\Delta = 7.5$ and $\pi = 2$ (local fuel $\succ$ neighbor fuel)

Table 14: Case 1: Both fuels prices in the covariate matrix of the regression equation.

W	1.1: Gasoline					1.2: Ethanol				
	CFE	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**	**CFE**	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**
$ln(G)$	87.020*	86.370*	87.200*	86.950*	86.580*	86.820*	86.040*	87.000*	86.950*	86.220*
$ln(G)^2$	-21.410*	-21.180*	-21.460*	-21.390*	-21.240*	-21.340*	-21.090*	-21.390*	-21.390*	-21.140*
$ln(G)^3$	1.780*	1.756*	1.784*	1.777*	1.761*	1.773*	1.748*	1.777*	1.777*	1.753*
$ln(Gasoline\_Price)$	4.296	5.445	4.325	4.650	5.468	4.330	5.177	4.354	4.651	5.193
$ln(Ethanol\_Price)$	28.890*	28.700*	28.880*	28.520*	28.690*	28.850*	28.710*	28.850*	28.520*	28.710*
$ln(Total\_Vehicles)$	-8.312*	-4.951	-8.419*	-8.208*	-4.985	-8.273*	-4.985	-8.383*	-8.213*	-5.021
$ln(Cars)$	-18.560*	-19.490*	-18.550*	-18.560*	-19.520*	-18.550*	-19.440*	-18.530*	-18.560*	-19.460*
$ln(trucks)$	2.039	1.421	2.059	1.983	1.433	2.008	1.415	2.027	1.983	1.428
$ln(Motorcycles)$	11.720*	9.746*	11.780*	11.660*	9.764*	11.700*	9.734*	11.750*	11.660*	9.751*
$ln(prec)$	-7.147*	9.746*	-7.142*	-7.155*	-8.022*	-7.158*	-8.055*	-7.154*	-7.155*	-8.054*
$ln(temp)$	36.650	24.520	37.050	36.430	25.260	36.750	24.780	37.140	36.470	25.510
$Deviation\_prec$	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.008*	0.007*	0.007*	0.008*
$Deviation\_temp$	-2.358	-1.860	-2.373	-2.348	-1.888	-2.361	-1.873	-2.376	-2.350	-1.902
$Deforestation$	1220.000*	1217.000*	1219.000*	1220.000*	1217.000*	1220.000*	1219.000*	1220.000*	1220.000*	1218.000*
$Fire$	30.250*	30.870*	30.210*	30.260*	30.830*	30.270*	30.840*	30.230*	30.260*	30.800*
	Spatial lags									
$ln(G)$		-39.110			-39.600		-33.110			-33.540
$ln(G)^2$		10.960			11.130		9.239			9.369
$ln(G)^3$		-0.9563			-0.971		-0.797			-0.810
$ln(Gasoline\_Price)$	0.826	2.346	0.820		2.453	0.542	2.370	0.540		2.479
$ln(Ethanol\_Price)$	-0.990	-8.011*	-0.948		-7.985*	-1.147	-7.776*	-1.111		-7.751*
$ln(Total\_Vehicles)$		-7.837			-8.109		-7.124			-7.323
$ln(Cars)$		6.273			6.380		5.556			5.613
$ln(trucks)$		-0.562			-0.524		-0.350			-0.319
$ln(Motorcycles)$		2.697			2.826		2.631			2.751
$ln(prec)$		4.198			4.312		4.588			4.664
$ln(temp)$		9.432			9.368		6.148			6.163
$Deviation\_prec$		-0.003			-0.003		-0.004			-0.004
$Deviation\_temp$		0.008			0.006		0.165			0.159
$Deforestation$		-96.220			-99.820		-108.400			-111.700
$Fire$		-10.970			-11.030		-10.120			-10.170
	Spatial parameters									
λ				0.015	0.021				0.016	0.020
Λ			0.015					0.015		

Source: Own elaboration according to research results.
Note: "*" indicates 95% statistical significance.

Table 15: Case 2: Only gasoline price in the covariate matrix of the regression equation.

W	2.1: Gasoline					2.3: Ethanol				
	CFE	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**	**CFE**	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**
$ln(G)$	84.330*	82.880*	84.500*	84.640*	83.110*	84.060*	82.580*	84.220*	84.650*	82.780*
$ln(G)^2$	-20.610*	-20.140*	-20.660*	-20.700*	-20.200*	-20.500*	-20.060*	-20.550*	-20.700*	-20.120*
$ln(G)^3$	1.719*	1.673*	1.724*	1.728*	1.679*	1.708*	1.666*	1.713*	1.728*	1.671*
$ln(Gasoline\_Price)$	17.140*	19.700*	17.160*	17.150*	19.720*	17.210*	19.310*	17.230*	17.150*	19.330*
$ln(Total\_Vehicles)$	-11.870*	-7.022	-11.980*	-12.030*	-7.061	-11.770*	-7.109	-11.870*	-12.030*	-7.150
$ln(Cars)$	-17.480*	-18.530*	-17.460*	-17.470*	-18.560*	-17.460*	-18.500*	-17.450*	-17.460*	-18.520*
$ln(trucks)$	1.698	0.738	1.719	1.737	0.748	1.640	0.752	1.650	1.736	0.762
$ln(Motorcycles)$	12.640*	9.876*	12.700*	12.720*	9.898*	12.580*	9.909*	12.640*	12.730*	9.931*
$ln(prec)$	-6.150*	-7.250*	-6.143*	-6.132*	-7.253*	-6.172*	-7.283*	-6.167*	-6.132*	-7.282*
$ln(temp)$	44.390	24.390	44.800	45.230	25.230	44.440	24.520	44.830	45.280	25.320
$Deviation\_prec$	0.007*	0.008*	0.007*	0.007*	0.008*	0.007*	0.008*	0.007*	0.007*	0.008*
$Deviation\_temp$	-2.351	-1.594	-2.367	-2.386	-1.627	-2.354	-1.591	-2.369	-2.388	-1.623
$Deforestation$	1230.000*	1232.000*	1230.000*	1230.000*	1232.000*	1230.000*	1233.000*	1230.000*	1230.000*	1233.000*
$Fire$	32.530*	33.280*	32.500*	32.490*	33.230*	32.580*	33.230*	32.550*	32.490*	33.200*
					Spatial lags					
$ln(G)$		-39.070			-39.580		-36.440			-36.890
$ln(G)^2$		11.010			11.190		10.350			10.490
$ln(G)^3$		-0.953			-0.972		-0.898			-0.912
$ln(Gasoline\_Price)$	-0.297	-4.410	-0.274		-4.284	-0.812	-4.132	-0.790		-4.007
$ln(Total\_Vehicles)$		-10.130			-10.450		-9.353			-9.590
$ln(Cars)$		7.152			7.298		6.377			6.470
$ln(trucks)$		-0.975			-0.941		-0.680			-0.655
$ln(Motorcycles)$		3.529			3.670		3.369			3.498
$ln(prec)$		4.061			4.168		4.526			4.590
$ln(temp)$		9.327			9.294		6.801			6.855
$Deviation\_prec$		-0.004			-0.004		-0.004			-0.004
$Deviation\_temp$		0.177			0.175		0.281			0.275
$Deforestation$		-157.900			-161.500		-174.700			-177.900
$Fire$		-12.640			-12.710		-10.950			-11.000
					Spatial parameters					
λ				0.014	0.022				0.015	0.020
Λ			0.013					0.013		

Source: Own elaboration according to research results.
Note: “*” indicates 95% statistical significance.

Table 16: Case 3: Only ethanol price in the covariate matrix of the regression equation.

W	**2.2: Gasoline**					**2.4: Ethanol**				
	CFE	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**	**CFE**	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**
$ln(G)$	86.780*	86.080*	86.970*	86.950*	86.260*	86.660*	85.700*	86.860*	86.950*	85.860*
$ln(G)^2$	-21.330*	-21.090*	-21.380*	-21.380*	-21.140*	-21.280*	-21.000*	-21.330*	-21.380*	-21.040*
$ln(G)^3$	1.772*	1.748*	1.776*	1.776*	1.753*	1.767*	1.740*	1.772*	1.776*	1.744*
$ln(Ethanol\_Price)$	29.240*	29.430*	29.250*	29.240*	29.430*	29.310*	29.400*	29.320*	29.240*	29.390*
$ln(Total\_Vehicles)$	-7.981*	-4.870	-8.092*	-8.060*	-4.903	-8.007*	-4.903*	-8.121*	-8.064*	-4.937
$ln(Cars)$	-18.760*	-19.630*	-18.750*	-18.760*	-19.650*	-18.740*	-19.570*	-18.720*	-18.750*	-19.580*
$ln(trucks)$	2.006	1.492	2.087	2.080	1.501	2.055	1.480	2.076	2.080	1.490
$ln(Motorcycles)$	11.580*	9.800*	11.640*	11.620*	9.818*	11.590*	9.783*	11.650*	11.630*	9.800*
$ln(prec)$	-7.172*	-8.045*	-7.167*	-7.164*	-8.050*	-7.178*	-8.085*	-7.173*	-7.164*	-8.087*
$ln(temp)$	35.320	23.830	35.760	35.830*	24.490	35.690	24.070	36.110	35.870	24.720
$Deviation\_prec$	0.007*	0.007*	0.007*	0.007*	0.07*	0.007*	0.007*	0.007*	0.007*	0.007*
$Deviation\_temp$	-2.339	-1.870	-2.356	-2.360	-1.896	-2.353	-1.880	-2.369	-2.362	-1.906
$Deforestation$	1219.000*	1216.000*	1219.000*	1219.000*	1216.000*	1219.000*	1218.000*	1219.000*	1219.000*	1218.000*
$Fire$	30.410*	31.030*	30.370*	30.380*	30.990*	30.420*	31.000*	30.380*	30.380*	30.970*
	Spatial lags									
$ln(G)$		-32.470			-32.700		-26.570			-26.750
$ln(G)^2$		8.999			9.087		7.313			7.369
$ln(G)^3$		-0.773			-0.783		-0.621			-0.627
$ln(Ethanol\_Price)$	-0.093	-7.099			-7.034*	-0.568	-6.852*	-0.534		-6.787*
$ln(Total\_Vehicles)$		-8.662	-0.059		-8.931		-7.925			-8.123
$ln(Cars)$		6.662			6.762		5.874			5.926
$ln(trucks)$		0.033			0.081		0.235			0.277
$ln(Motorcycles)$		2.572			2.688		2.518			2.625
$ln(prec)$		4.173			4.285		4.577			4.653
$ln(temp)$		8.816			8.714		5.479			5.454
$Deviation\_prec$		-0.003			-0.004		-0.004			-0.004
$Deviation\_temp$		-0.012			-0.013		5.479			0.141
$Deforestation$		-97.550			-101.000		-110.400			-113.500
$Fire$		-10.220			-10.260		-9.687			-9.722
	Spatial parameters									
λ				0.015	0.020				0.016	0.018
Λ			0.015					0.015		

Source: Own elaboration according to research results.

Note: "*" indicates 95% statistical significance.

E Estimates using $\Delta = 7.5$ and $\pi = 1$ (local fuel $\sim$ neighbor fuel)

Table 17: Case 1: Both fuels prices in the covariate matrix of the regression equation.

W	1.1: Gasoline					1.2: Ethanol				
	CFE	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**	**CFE**	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**
$ln(G)$	86.940*	87.250*	87.040*	86.920*	87.330*	87.020*	87.110*	87.130*	86.920*	87.200*
$ln(G)^2$	-21.390*	-21.400*	-21.410*	-21.370*	-21.420*	-21.410*	-21.380*	-21.440*	-21.370*	-21.410*
$ln(G)^3$	1.777*	1.775*	1.779*	1.776*	1.777*	1.779*	1.774*	1.781*	1.776*	1.776*
$ln(Gasoline\_Price)$	4.430*	4.163	4.406	4.628	4.171	4.412	4.211	4.386	4.624	4.217
$ln(Ethanol\_Price)$	28.770*	28.960*	28.810*	28.560*	28.990*	28.780*	29.000*	28.820*	28.570*	29.040*
$ln(Total\_Vehicles)$	-8.324*	-6.888	-8.351*	-8.155*	-6.883	-8.324*	-6.824	-8.357*	-8.160*	-6.825
$ln(Cars)$	-18.530*	-19.360*	-18.540*	-18.580*	-19.360*	-18.540*	-19.380*	-18.550*	-18.580*	-19.380*
$ln(trucks)$	2.028	1.856	2.045	1.992	1.861	2.030	1.909	2.051	1.996	1.917
$ln(Motorcycles)$	11.720*	11.040*	11.730*	11.630*	11.040*	11.720*	-6.824	11.730*	11.630*	10.970*
$ln(prec)$	-7.149*	-7.529*	-7.145*	-7.156*	-7.525*	-7.145*	-7.480*	-7.141*	-7.158*	-7.476*
$ln(temp)$	36.560	34.090	36.640	36.050	34.130	36.670	33.900	36.760	36.060	33.940
$Deviation\_prec$	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*
$Deviation\_temp$	-2.359	-2.227	-2.361	-2.332	-2.228	-2.363	-2.222	-2.365	-2.333	-2.223
$Deforestation$	1220.000*	1216.000*	1220.000*	1220.000*	1216.000*	1220.000*	1216.000*	1219.000*	1220.000*	1216.000*
$Fire$	30.260*	30.270*	30.240*	30.270*	30.260*	30.260*	30.270*	30.240*	30.270*	30.250*
	Spatial lags									
$ln(G)$		-38.820			-38.140		-35.100			-34.240
$ln(G)^2$		10.510			10.400		9.319			9.164
$ln(G)^3$		-0.856			-0.856		-0.764			-0.759
$ln(Gasoline\_Price)$	1.678	3.798	1.640		3.733	1.686	2.765	1.649		2.718
$ln(Ethanol\_Price)$	-2.027	-8.443	-1.991		-8.384	-2.209	-7.905	-2.167		-7.854
$ln(Total\_Vehicles)$		-14.750			-15.000		-17.130			-17.220
$ln(Cars)$		14.460			14.460		14.920			14.840
$ln(trucks)$		0.323			0.514		1.706			1.811
$ln(Motorcycles)$		2.154			2.251		3.142			3.205
$ln(prec)$		6.780			6.800		3.172			6.175
$ln(temp)$		5.235			5.117		8.111			7.823
$Deviation\_prec$		-0.005			-0.005		-0.004			-0.004
$Deviation\_temp$		-0.097			-0.085		-0.209			-0.189
$Deforestation$		-23.290			-25.980		-19.500			-22.580
$Fire$		1.229			1.182		-0.450			-0.471
	Spatial parameters									
λ				0.022	0.017				0.022	0.019
Λ			0.014					0.016		

Source: Own elaboration according to research results.
Note: “*” indicates 95% statistical significance.

Table 18: Case 2: Only gasoline price in the covariate matrix of the regression equation.

W	1.1: Gasoline					1.2: Ethanol				
	CFE	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**	**CFE**	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**
$ln(G)$	84.460*	84.410*	84.470*	84.540*	84.440*	84.720*	84.300*	84.740*	84.540*	84.330*
$ln(G)^2$	-20.650*	-20.580*	-20.650*	-20.670*	-20.590*	-20.720*	-20.560*	-20.720*	-20.670*	-20.570*
$ln(G)^3$	1.724*	1.715*	1.724*	1.725*	1.716*	1.729*	1.714*	1.730*	1.725*	1.715*
$ln(Gasoline\_Price)$	17.130*	17.250*	17.130*	17.130*	17.260*	17.160*	17.360*	17.750*	17.130*	17.370*
$ln(Total\_Vehicles)$	-11.870*	-10.230*	-11.870*	-11.960*	-10.20*	-11.830*	-10.120*	-11.840*	-11.960*	-10.120*
$ln(Cars)$	-17.510*	-18.330*	-17.510*	-17.480*	-18.330*	-17.510*	-18.350*	-17.510*	-17.480*	-18.350*
$ln(trucks)$	1.726	1.492	1.728	1.736	1.494	1.699	1.511	1.702	1.737	1.515
$ln(Motorcycles)$	12.640*	11.900*	12.640*	12.690*	11.890*	12.610*	11.800*	12.610*	12.690*	11.790*
$ln(prec)$	-6.148*	-6.596*	-6.147*	-6.135*	-6.594*	-6.140*	-6.545*	-6.139*	-6.135*	-6.543*
$ln(temp)$	44.760	41.360	44.770	44.770	41.380	44.810	41.180	44.830	44.770	41.200
$Deviation\_prec$	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*
$Deviation\_temp$	-2.336	-2.201	-2.366	-2.367	-2.201	-2.368	-2.197	-2.368	-2.367	-2.197
$Deforestation$	1230.000*	1227.000*	1230.000*	1230.000*	1227.000*	1230.000*	1227.000*	1230.000*	1230.000*	1227.000*
$Fire$	32.530*	32.590*	32.530*	32.520*	32.590*	32.540*	32.600*	32.540*	32.520*	32.590*
	Spatial lags									
$ln(G)$		-41.060			-40.830		-36.190			-35.860
$ln(G)^2$		11.860			11.830		10.250			10.190
$ln(G)^3$		-1.016			-1.016		-0.874			-0.872
$ln(Gasoline\_Price)$	-0.316	-2.783	-0.317		-2.793	-0.614	-3.600	-0.615		-3.606
$ln(Total\_Vehicles)$		-17.270			-17.360		-20.070			-20.100
$ln(Cars)$		15.980			15.890		16.400			16.370
$ln(trucks)$		-0.690			-0.613		0.910			0.959
$ln(Motorcycles)$		2.521			2.557		3.689			3.714
$ln(prec)$		7.190			7.200		6.461			6.463
$ln(temp)$		2.077			2.044		5.269			5.174
$Deviation\_prec$		-0.005			-0.005		-0.005			-0.005
$Deviation\_temp$		0.078			0.084		-0.039			-0.030
$Deforestation$		-54.500			-55.420		-47.010			-48.130
$Fire$		0.205			0.187		-1.351			-1.363
	Spatial parameters									
λ				0.009	0.006				0.009	0.007
Λ			0.002					0.002		

Source: Own elaboration according to research results.
Note: "*" indicates 95% statistical significance.

Table 19: Case 3: Only ethanol price in the covariate matrix of the regression equation.

W	1.1: Gasoline					1.2: Ethanol				
	CFE	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**	**CFE**	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**
$ln(G)$	86.800*	87.170*	86.900*	86.930*	87.260*	86.900*	87.080*	87.010*	86.930*	87.170*
$ln(G)^2$	-21.340*	-21.380*	-21.360*	-21.370*	-21.400*	-21.360*	-21.370*	-21.390*	-21.370*	-21.390*
$ln(G)^3$	1.773*	1.773*	1.775*	1.775*	1.775*	1.775*	1.773*	1.777*	1.775*	1.775*
$ln(Ethanol\_Price)$	29.240*	29.520*	29.280*	29.280*	29.560*	29.230*	29.590*	29.270*	29.290	29.630*
$ln(Total\_Vehicles)$	-7.965*	-6.786	-7.999*	-8.009*	-6.781	-7.971*	-6.723	-8.012*	-8.015*	-6.724
$ln(Cars)$	-18.770*	-19.500*	-18.780*	-18.780*	-19.510*	-18.770*	-19.530*	-18.780*	-18.780*	-19.540*
$ln(trucks)$	2.072	1.929	2.091	2.089	1.935	2.065	1.983	2.088	2.093	1.991
$ln(Motorcycles)$	11.570*	11.060*	11.590*	11.600*	11.050*	11.570*	10.990*	11.590*	11.600*	10.980*
$ln(prec)$	-7.174*	-7.559*	-7.169*	-7.165*	-7.555*	-7.169*	-7.501*	-7.164*	-7.166*	-7.496*
$ln(temp)$	35.410	33.240	35.510	35.470	33.290	35.460	33.140	35.580	35.480	33.190
$Deviation\_prec$	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*
$Deviation\_temp$	-2.343	-2.222	-2.346	-2.344	-2.223	-2.345	33.140	-2.384	-2.345	-2.223
$Deforestation$	1219.000*	1215.000*	1219.000*	1219.000*	1215.000*	1219.000*	1215.000*	1218.000*	1219.000*	1215.000*
$Fire$	30.410*	30.400*	30.390*	30.390*	30.390*	30.410*	30.380*	30.390*	30.390*	30.370*
	Spatial lags									
$ln(G)$		-36.770			-36.110		-33.890			-33.040
$ln(G)^2$		9.942			9.847		9.022			8.869
$ln(G)^3$		-0.820			-0.820		-0.751			-0.746
$ln(Ethanol\_Price)$	-0.171	-7.032	-0.176		-6.997	-0.258	-6.916	-0.259		-6.882
$ln(Total\_Vehicles)$		-16.980			-17.210		-18.930			-19.000
$ln(Cars)$		15.960			15.940		16.320			16.230
$ln(trucks)$		0.734			0.924		1.947			2.052
$ln(Motorcycles)$		2.285			2.381		3.179			3.242
$ln(prec)$		7.155			7.167		6.416			6.414
$ln(temp)$		5.857			5.733		8.720			8.426
$Deviation\_prec$		-0.005			-0.005		-0.004			-0.004
$Deviation\_temp$		-0.186			-0.173		-0.284			-0.264
$Deforestation$		-19.270			-21.950		-17.300			-20.300
$Fire$		1.584			1.527		-0.102			-0.131
	Spatial parameters									
λ				0.022	0.017				0.023	0.019
Λ			0.015					0.017		

Source: Own elaboration according to research results.
Note: “*” indicates 95% statistical significance.

F Estimates using $\Delta = 7.5$ and $\pi = 0.9$ (neighbor fuel $\succ$ local fuel)

Table 20: Case 1: Both fuels prices in the covariate matrix of the regression equation.

W	1.1: Gasoline					1.2: Ethanol				
	CFE	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**	**CFE**	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**
$ln(G)$	87.010*	87.800*	87.060*	86.880*	87.870*	87.140*	87.250*	87.190*	86.870*	87.330*
$ln(G)^2$	-21.410*	-21.550*	-21.420*	-21.360*	-21.560*	-21.440*	-21.430*	-21.450*	-21.360*	-21.440*
$ln(G)^3$	1.779*	1.786*	1.780*	1.775*	1.788*	1.782*	1.778*	1.783*	1.775*	1.779*
$ln(Gasoline\_Price)$	4.391	4.026	4.359	4.595	4.018	4.372	4.367	4.346	4.603	4.356
$ln(Ethanol\_Price)$	28.790*	29.030*	28.810*	28.540*	29.040*	28.860*	29.020*	28.870*	28.540*	29.030*
$ln(Total\_Vehicles)$	-8.309*	-7.415*	-8.342*	-8.187*	-7.417*	-8.453*	-7.608*	-8.498*	-8.193*	-7.600*
$ln(Cars)$	-18.560*	-19.140*	-18.570*	-18.580*	-19.140*	-18.500*	-18.920*	-18.500*	-18.570*	-18.930*
$ln(trucks)$	2.043	1.998	2.058	1.995	1.990	2.054	1.982	2.072	2.000	1.991
$ln(Motorcycles)$	11.700*	11.310*	11.720*	11.660*	11.300*	11.780*	11.350*	11.810*	11.660*	11.340*
$ln(prec)$	-7.146*	-7.321*	-7.145*	-7.163*	-7.321*	-7.129*	-7.306*	-7.129*	-7.163*	-7.306*
$ln(temp)$	37.200	33.620	37.250	35.990	33.660	37.670	33.730	37.730	36.010	33.730
$Deviation\_prec$	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*
$Deviation\_temp$	-2.383	-2.202	-2.384	-2.330	-2.204	-2.404	-2.216	-2.406	-2.331	-2.216
$Deforestation$	1220.000*	1217.000*	1220.000*	1220.000*	1217.000*	1220.000*	1218.000*	1220.000*	1220.000*	1219.000*
$Fire$	30.260*	30.320*	30.250*	30.280*	30.320*	30.250*	30.320*	30.250*	30.280*	30.310*
	Spatial lags									
$ln(G)$		6.337			8.301		-13.590			-12.300
$ln(G)^2$		-4.056			-4.550		2.792			2.594
$ln(G)^3$		0.635			0.669		-0.151			-0.152
$ln(Gasoline\_Price)$	2.307	6.683	2.229		6.563	2.897	3.888	2.806		3.776
$ln(Ethanol\_Price)$	-3.265	-9.928	-3.175		-9.811	-3.155	-8.457	-3.067		-8.337
$ln(Total\_Vehicles)$		-12.250			-12.950		-10.250			-11.190
$ln(Cars)$		13.140			13.170		10.070			10.310
$ln(trucks)$		0.064			0.625		2.347			2.857
$ln(Motorcycles)$		2.016			2.330		1.387			1.740
$ln(prec)$		8.528			8.430		5.499			5.671
$ln(temp)$		-13.420			-13.050		2.074			1.881
$Deviation\_prec$		-0.006			-0.006		-0.004			-0.004
$Deviation\_temp$		0.583			0.583		-0.125			-0.102
$Deforestation$		-99.740			-116.800		-145.100			-162.600
$Fire$		-8.376			-8.539		-9.126			-9.136
	Spatial parameters									
λ				0.022	0.017				0.020	0.019
Λ			0.012					0.012		

Source: Own elaboration according to research results.
Note: "*" indicates 95% statistical significance.

Table 21: Case 2: Only gasoline price in the covariate matrix of the regression equation.

W	**1.1: Gasoline**					**1.2: Ethanol**				
	CFE	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**	**CFE**	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**
$ln(G)$	84.310*	84.620*	84.330*	84.540*	84.670*	84.470*	84.200*	84.490*	84.530*	84.260*
$ln(G)^2$	-20.610*	-20.630*	-20.610*	-20.670*	-20.640*	-20.660*	-20.540*	-20.660*	-20.670*	-20.550*
$ln(G)^3$	1.720*	1.718*	1.720*	1.725*	1.720*	1.724*	1.712*	1.724*	1.725*	1.713*
$ln(Gasoline\_Price)$	17.110*	17.070*	17.100*	17.110*	17.060*	17.120*	17.330*	17.110*	17.110*	17.320*
$ln(Total\_Vehicles)$	-11.750*	-10.610*	-11.760*	-11.980*	-10.620*	-11.910*	-10.800*	-11.930*	-11.980*	-10.790*
$ln(Cars)$	-17.560*	-18.080*	-17.560*	-17.480*	-18.090*	-17.490*	-17.900*	-17.490*	-17.480*	-17.920*
$ln(trucks)$	1.703	1.569	1.710	1.741	1.572	1.723	1.580	1.730	1.743	1.589
$ln(Motorcycles)$	12.580	12.050*	12.590*	12.700*	12.040*	12.660*	12.090*	12.680*	12.700*	12.070*
$ln(prec)$	-6.157*	-6.380*	-6.156*	-6.137*	-6.379*	-6.140*	-6.364*	-6.140*	-6.138**	-6.364*
$ln(temp)$	43.890	38.840*	43.920	44.750	38.880	44.630	39.250	44.670	44.750	39.260
$Deviation\_prec$	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*
$Deviation\_temp$	-2.331	-2.104	-2.332	-2.366	-2.105	-2.362	-2.128	-2.364	-2.366	-2.128
$Deforestation$	1230.000*	1228.000*	1230.000*	1230.000*	1228.000*	1230.000*	1229.000*	1230.000*	1230.000*	1229.000*
$Fire$	32.530*	32.650*	32.520*	32.520*	32.650*	32.520*	32.640*	32.520*	32.520*	32.640*
	Spatial lags									
$ln(G)$		5.794			7.073		-5.526			-4.762
$ln(G)^2$		-2.928			-3.239		0.797			0.737
$ln(G)^3$		0.441			0.460		0.016			0.004
$ln(Gasoline\_Price)$	-0.754	-0.941	-0.758		-0.970	-0.104	-2.196	-0.113		-2.224
$ln(Total\_Vehicles)$		-14.190			-17.790		-11.120			-12.000
$ln(Cars)$		12.960			12.990		9.436			9.672
$ln(trucks)$		0.344			0.828		2.127			2.593
$ln(Motorcycles)$		2.734			3.002		2.050			2.375
$ln(prec)$		8.889			8.87		5.540			5.726
$ln(temp)$		-15.710			-15.310		-2.568			-2.661
$Deviation\_prec$		-0.006			-0.006		-0.004			-0.004
$Deviation\_temp$		0.842			0.843		0.284			0.308
$Deforestation$		-139.500			-153.300		-181.100			-196.300
$Fire$		-8.479			-8.536		-8.887			-8.795
	Spatial parameters									
λ				0.012	0.014				0.011	0.016
Λ			0.004					0.005		

Source: Own elaboration according to research results.
Note: “*” indicates 95% statistical significance.

Table 22: Case 3: Only ethanol price in the covariate matrix of the regression equation.

W	1.1: Gasoline					1.2: Ethanol				
	CFE	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**	**CFE**	**SLX**	**RSLX-SEM**	**SEM**	**SDEM**
$ln(G)$	86.730*	87.690*	86.800*	86.890*	87.770*	86.820*	87.250*	86.900*	86.880*	87.330*
$ln(G)^2$	-21.320*	-21.520*	-21.330*	-21.360*	-21.540*	-21.340*	-21.420*	-21.360*	-21.360*	-21.440*
$ln(G)^3$	1.771*	1.784*	1.772*	1.774	1.786*	1.773*	1.777*	1.775*	1.774*	1.778*
$ln(Ethanol\_Price)$	29.240*	29.580*	29.260*	29.250*	29.590*	29.230*	29.660*	29.250*	29.250*	29.660*
$ln(Total\_Vehicles)$	-7.879*	-7.339*	-7.950*	-8.044*	-7.341*	-8.009*	-7.523*	-8.079*	-8.050*	-7.514*
$ln(Cars)$	-18.810*	-19.220*	-18.820*	-18.770*	-19.230*	-18.750*	-19.050*	-18.750*	-18.770*	-19.070*
$ln(trucks)$	2.067	2.032	2.088	2.092	2.035	2.066	2.047	2.091	2.097	2.057
$ln(Motorcycles)$	11.530*	11.330*	11.570*	11.620*	11.330*	11.600*	11.370*	11.640*	11.620*	11.360*
$ln(prec)$	-7.178*	-7.348*	-7.175*	-7.171*	-7.347*	-7.171*	-7.323*	-7.169*	-7.172*	-7.323*
$ln(temp)$	35.090	32.570	35.220	35.410	32.630	35.320	32.910	35.480	35.430	32.920
$Deviation\_prec$	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*	0.007*
$Deviation\_temp$	-2.329	-2.190*	-2.333	-2.342	-2.192	-2.340	-2.215	-2.345	-2.343	-2.215
$Deforestation$	1219.000*	1216.000*	1219.000*	1219.000*	1216.000*	1219.000*	1218.000*	1219.000*	1219.000*	1218.000*
$Fire$	30.410*	30.450*	30.400*	30.390*	30.450*	30.410*	30.450*	30.400*	30.390*	30.440*
	Spatial lags									
$ln(G)$		11.040			13.090		-7.963			-6.754
$ln(G)^2$		-5.107			-5.626		1.287			1.118
$ln(G)^3$		0.689			0.726		-0.029			-0.033
$ln(Ethanol\_Price)$	-0.693	-7.399	-0.691		-7.320	0.224	-7.059	0.201		-6.974
$ln(Total\_Vehicles)$		-16.120			-16.800		-13.040			-13.950
$ln(Cars)$		15.280			15.270		11.760			11.970
$ln(trucks)$		1.133			1.716		3.129			3.641
$ln(Motorcycles)$		2.096			2.431		1.453			1.819
$ln(prec)$		9.487			9.359		5.869			6.030
$ln(temp)$		-13.770			-13.370		1.685			1.504
$Deviation\_prec$		-0.007			-0.007		-0.004			-0.004
$Deviation\_temp$		0.458			0.461		-0.193			-0.168
$Deforestation$		-111.000			-128.900		-150.500			-168.300
$Fire$		-7.320			-7.524		-8.632			-8.667
	Spatial parameters									
λ				0.022	0.018				0.021	0.020
Λ			0.015					0.015		

Source: Own elaboration according to research results.
Note: "*" indicates 95% statistical significance.