Flexible-fuel automobiles and CO_2 emissions in Brazil: a semiparametric analysis using panel data

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Abstract

The objective of this paper is to investigate the relationship between the fleet of flex-fuels vehicles and CO_2 emissions in Brazil. We analyzed the robustness of parametric and semiparametric analyses using a panel data set at the state level from 1998 to 2013. In both analyses, we find that there is a strong negative correlation between CO_2 emissions and flex-fuels vehicles. Moreover, our results also suggest that there are: 1) there is evidence of an Environment Kuznets Curve for flex-fuel vehicles; 2) a negative relationship between sugar cane cropped area (due to carbon sequestration) and CO_2 emissions and; 3) a positive relationship between livestock and CO_2 emissions.

***Key words**: flex-fuels vehicles, CO_2 emissions, semiparametric models, Brazil*

***JEL:** C14; O13; Q53*

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1. Introduction

In a context of emerging low-carbon economy and global efforts to reduce dependence on fossil fuels in the energy matrix, Brazil stands out in the technological and productive leading position with regard to the use of biofuels. The country has a long and unique experience in the production of ethanol fuels on large scale as an alternative to gasoline. The production of ethanol started in the 1930s, but its production sharply increased with the creation of Proálcool (Brazilian National Program for Ethanol) in 1975 (Moraes and Zilberman, 2014). Moreover, since 1975, a federal law has mandated that between 20% and 27% of gasoline fuels must be mixed with ethanol from sugar cane (Wills and La Rovere, 2010).

More recently, Brazil has been also a leader in the production of “Flex-Fuel” cars (Moraes and Zilberman, 2014). These vehicles, which started to be manufactured in 2004, are highly cost effective because they engines are capable of running on any arbitrary combination of gasoline and ethanol from sugarcane.[1] In 2014, flexible-fuel light vehicles (including SUVs) composed over 50% of the national vehicle fleet and accounted for more than 90% of actual total car sales (Anfavea, 2015).

Although in Brazil the net CO_2 emissions resulting from the burning of ethanol in car engines are not significantly lower than the emissions due to burning fossil fuels, the use of ethanol as alternative to gasoline is contributing with a reduction around 13% of the GHG (Greenhouse Gas) emissions of whole energy sector (Macedo, 2005). This is because all sources of emissions are reabsorbed by carbon sequestration during the growth of the sugarcane crop in the next season (Macedo, 2005; Goldemberg et al., 2008). Notwithstanding,

[1] Nowadays, the rational choice by the consumer in favor of ethanol is when the price ratio between both fuels is of 70%.

the use of ethanol in place of gasoline appears to be also effective in mitigating hazardous toxic pollutants from lead, carbon monoxide and Sulphur (Macedo, 2005).

Therefore, more economic incentives to encourage not only the production of sustainable biofuels but to keep up the production of flex-fuel automobiles will help Brazil to meet the goals of the intended Nationally Determined Contribution (INDC) for the U. N. Framework Convention on Climate Change (UNFCCC) held in Paris, last year in December. Whether or not the increase of flex-fuel vehicles would indeed contribute to decrease CO_2 emissions is the main research question of this work.

That being said, based on the well-known empirical hypothesis of the Environmental Kuznets Curve (EKC)—that at higher levels of income, higher and more stringent environmental regulations are needed (Grossman and Krueger, 1991, 1995; Dinda, 2004)—we run first a standard parametric analysis using a panel data set at the state level in Brazil, and found that from 2004 there is a strong negative correlation between CO_2 emissions and flex-fuels vehicles, corroborating the EKC hypothesis. However, it is also well-known that economic theory and empirical work do not provide much guidance regarding the choice of functional form for estimation purposes (Schmalensee and Stoker, 1999; Yatchew, 2003). Besides, most empirical research in economics seems to ignore the benefits of nonparametric methods (Henderson and Parmeter, 2015). The major rationale for using the nonparametric or semiparametric methods is to avoid the restrictions or misspecifications that can stem from specific functional forms, which can produce biased estimates (Yatchew, 2003). To address this problem, in this paper a semiparametric method designed specifically for panel data is utilized to analyze the potential relationship between flex-fuel vehicles and CO_2 emissions.

To our best knowledge, the literature of economic studies that investigated the relation between flex-fuel vehicles and GHG emissions is still scarce. This study aims to fill this gap analyzing the relationship of the fleet of flex-fuel cars and CO_2 emissions in Brazil using a well-behaved panel data set at a state level in Brazil for the period 1998-2013.

In addition to this introduction, this paper has more six sections. The second presents a (very) brief literature review on the topic, while the third section details the identification strategy used. The data used in the research are presented in the fourth section. The results are presented and discussed in the fifth section, followed by a robustness check section and the final remarks.

2. The Environmental Kuznets Curve (EKC) and ethanol fuel in Brazil

The issue of CO_2 (carbon dioxide) emissions and its main determinants have been widely discussed in the literature given the growing importance related to environmental policies on a global scale, more specifically related to the possible effects and causes of global warming. The major determinants covers a wide set of economic subjects such as: 1) the Gross Domestic Product (GDP) and trade liberalization; 2) the energy consumption; 3) population growth and urbanization; 4) number of vehicles with new technologies in the industry; 5) alternative energy sources, among others (Bertinelli and Strobl, 2005; Azomahou et al., 2006; Ang, 2007; Martínez-Zarzoso et al., 2007; Jalil and Mahmud, 2009; Chang, 2010; Lee and Mukherjee, 2014; Kang et al., 2016).

In economics prospect, it is well known that the Environmental Kuznets Curve (EKC) proposes the existence of an inverted U-shaped relationship between environmental degradation indicators and per capita income (Dinda, 2004). According to Stern (1998), the EKC suggests that economic growth can mitigate the environmental impacts driven by the initial period of economic development, and consequently to a more stringent regulations and environmental improvements in countries that are traditionally major polluters.

The first empirical analysis of the EKC, according to Stern (1998) and Dinda (2004), refers to the work of Grossmann and Krueger in 1991, published in 1993, which pointed out to an inverted-U relationship between SO_2 (sulfur dioxide) emissions and GDP per capita in different countries. However, the term Environmental Kuznets Curve (EKC) started to be used from Panayotou (1993) (Stern, 1998; Dinda, 2004).

Currently, there are a number of studies that confirm the EKC for various environmental degradation factors, but, when CO_2 emissions considered separately, mixed results are found in the literature (Galeotti and Lanza 1999; Taskin and Zaim, 2000; Harbaugh et al., 2002; Friedl and Getzner,2003; Lantz and Feng, 2006; Apergis and Payne 2009; Jahlil and Mahmud, 2009; Fodha and Zaghdoud, 2010; Iwata et al., 2011; Ahmed and Long, 2012; Farhani and Ozturk, 2015, Kang et al., 2016).

The methodological approaches are also diverse. Usually, much of the research is made using time-series approaches and linear panel data analysis (Stern, 1998; Millimett et al., 2003). However, recently, studies has shown that this type of estimation for some cases might be inadequate due the linearity imposed on the parameters. Therefore, semiparametric and nonparametric approaches for the estimation of EKC is coming up as alternatives (Millimett et al., 2003; Zhu et al., 2012).

That being said, the use of this recent approaches for the study of CO_2 emissions and economic indicators does not seem support the hypothesis of EKC for relationship. Azomahou et al. (2006) estimates a nonparametric panel data for 100 countries from 1960 to 1996 and found a positive relationship between the variables, and was not able to corroborate the EKC hypothesis. Similar results are also found in Bertinelli and Strobl (2005) using semiparametric estimation for panel data in different countries in the period from 1950 to 1990. Zhu et al., (2012) using a dynamic semiparametric model for the relationship between urbanization and CO_2 emissions for 20 emerging countries, and found out that there is little evidence that support the inverted-U curve.

Kang et al. (2016), using a spatial model of panel data for Chinese cities from 1997 to 2012, identified a relationship in the form of N inverted; therefore, not validating the traditional form of inverted U of EKC. In addition, Kang et al. identified that the level of urbanization increases, the CO_2 emissions increases due to the massive burning of coal. On the other hand, trade liberalization tends to reduce the emission of gas, probably because of the pollution heaven effect for some goods and weaker environmental regulations in other countries.

Ang (2007) who ran a time series analysis and error correction models for France with data from 1960 to 2000, was able to corroborate the EKC. Apergis and Payne (2009) also verified the relationship in the form of inverted U using an error correction model applied to panel data to the Central American countries between 1971 and 2004.

Jalil and Mahmud (2009), using time series analysis to China in the 1929-1994 period, identified a weak relationship of foreign trade with CO_2 emissions. Using non-linear estimation techniques, with distributions gamma and weibull for panel data from various countries between 1971 and 1996, Galeotti and Lanza (1999) demonstrated the validity of EKC for the relationship between CO_2 and GDP. The EKC is also verified when they tested other air pollution indicators such as emissions of sulfur dioxide (SO_2) and nitrogen oxide (NOx). Lee and Murkerjee (2014) using nonparametric estimations of panel data models using local linear least squares when fixed effects present for U.S data, also corroborate the EKC for NOx pollutants.

To our best knowledge, the number of studies using parametric and nonparametric estimation in the context of CO_2 emissions is still limited (Gallet (1999), Millimet et al. (2003) and Lee and Mukherjee (2014) are exceptions). In addition, there almost none studies on the determinants of CO_2 emissions as well as about the EKC for Brazil (Pao and Tsai (2011) and Pao and Tsai (2011a) are exceptions). More specifically, using time series analysis for Brazilian data the years 1980-2007, Pao and Tsai (2011) validated the hypothesis of EKC for CO_2 emissions.

Ethanol fuel in Brazil

In Brazil, the fleet of vehicles is quite substantial, and these vehicles are mainly ran by fossil fuels that have high power of emission of pollutant gases (MMA, 2013). However, the country shows a unique situation in the world when analyzed the growth of the flex vehicle fleet that is able to run on any arbitrary combination of gasoline and ethanol, since the introduction of this technology in 2003. According to statistics from the National Association of Automobile Manufacturers (ANFAVEA), by June 2005 flex-fuel vehicles already accounted for over half of all light commercial vehicles of the "Otto cycle"[2] licensed in Brazil. This ratio in 2014 is about 90%, representing more than 50% of the national vehicle fleet.

There are also in other countries a number of agreements for the promotion of biofuels, such as ethanol and biodiesel (REN, 2012). In 2012, for at least 46 countries, public policies was implementing encouraging the use of biofuels. Production subsidies and tax fuel transport are some of examples of these policies (REN, 2012). However, such projects are incipient compared to the Brazilian case.

In 2012, the national fleet of flex vehicles accounted for the consumption of9.5 billion liters of hydrous ethanol (MMA, 2013). Figure 1 shows the evolution of domestic ethanol consumption in road transport by vehicle category since 1980. Clearly, the consumption of sugar cane ethanol by flex-fuel vehicles has sharply increased since 2003.

INSERT FIGURE 1 HERE

[2]The Otto cycle is a set of processes used by sparking ignition internal combustion engines (2-stroke or 4-stroke cycles). Engines based on this cycle are present in most passenger cars. With the Otto cycle engines can be built to four times more efficient and cleaner compared to two-stroke engines.

3. Identification strategy

To examine the impact of flex-fuel vehicles on CO_2 emissions among other determinants, the following full parametric model is estimated under the Environmental Kuznets Curve (EKC) hypothesis framework, and is given by:

$$CO_{2it} = \alpha_i + \beta_1(Vehic_{it}) + \beta_2(Other\_Vehic_{it}) + \beta_3(Vehic\_Flex_{it}) + \beta_4(vehic\_flex_{it}^2) + \beta_5(Cattle_{it}) + \beta_6(Sugar\ Cane_{it}) + \beta_7(GDP_{it}) + \beta_8(GDP_{it}^2) + \varepsilon_{it} \quad (1)$$

where CO_2 are the total amount (GWP-Tons) of all emission pollutants in CO_2 equivalents[3]; *Vehic* is the number of Passenger Cars and SUVs; *Other_Vehic* is the number of other vehicles converted into Passenger Car units[4]; $Vehic\_Flex$ is the number of Passenger Cars times a binary variable ($D = 1\ if\ year \geq 2004\ and\ D = 0, otherwise$); $Vehic\_Flex^2$ is the square of $Vehic\_Flex$; *Cattle* denotes the number of livestock (in heads); *Sugar Cane* is the area of sugar cane (in hectares); *GDP* is *GDP* per capita (in 2000 constant prices); GDP^2 is the square of GDP, and α_i is the state fixed effect. The Livestock is introduced as a predictor is because its current production accounts for between 15% and 24% of current worldwide GHG emissions (Fiala, 2008). Balancing that, sugarcane production accounts for carbon sequestration (Goldemberg et al., 2008).

As an alternative to a full parametric specification, we propose the estimation of a semiparametric regression along with panel data to account for heterogeneity of entities while also relaxing the functional form developed by Henderson et al. (2008). This relationship can be described by the following model:

$$CO_{2it} = \alpha_i + \beta_1(Vehic_{it}) + \beta_2(Other\_Vehic_{it}) + \varphi(Vehic\_Flex_{it}) + \beta_3(Cattle_{it}) + \beta_4(Sugar\ Cane_{it}) + \beta_5(GDP_{it}) + \beta_6(GDP_t^2) + \varepsilon_{it}, \quad (2)$$

[3] CO_2 emissions from land use change (coming mostly from deforestation in Amazon) are not included in the sample.
[4] For more details about this conversion, see DNIT (2006), page 56, table 9.

where the function form $\varphi(\cdot)$ is unspecified. To get consistent estimates, the parameters $\beta' s$ are estimated using OLS procedures, and $\varphi(\cdot)$ is estimated interactively based on a nonparametric kernel approach. Henderson et al. (2008) outline the steps to get consistent and efficient estimates for (2) which are followed here. All variables are firstly standardized and then transformed using the first difference to wipe out the unobserved heterogeneity effect α_i.

4. Data

This study employed annual data for all 27 Brazilian states from 1998 to 2013 period, totalizing 432 observations. The values of greenhouse emissions (GHG) - the dependent variable - are obtained from the Estimate System of Greenhouse Gases in Brazil (SEEG)[5]. The study of the Global approach Warming Potential (GWP) is used as reference for determinate the equivalent carbon emission. It is possible to obtain estimates of the amount of GHGs emitted by the 27 federative units of Brazil.

Figure 2 and Figure 3 show the density estimated of emissions for three selected years of the sample, and the share (%) by state of all pollutants in 1998 and 2003, respectively. Figure 2 shows that when emissions from land use are discounted, as we did, the amount of total emissions in CO_2 has increased from 1998 to 2013. Moreover, Figure 3 show that most of emissions have been concentrated in the most industrialized state units such as *São Paulo*, *Minas Gerais* in the Southeast region, and *Paraná* and *Rio Grande de Sul* in the South. It is important highlight that *Mato Grosso*, which now become one of the most producers of soybeans and cattle of the country and shows an agricultural sector highly capital intensive has overcome state such as *Rio de Janeiro* where has been one of the most oil producers in the country.

INSERT FIGURE 2 HERE

[5] http://seeg.eco.br/en/

INSERT FIGURE 3 HERE

The number (units) of vehicles obtained from the National Traffic Department (DENATRAN), while the annual data regarding to agricultural areas occupied by sugarcane crop and the annual herd cattle are coming from on the Municipality Agricultural Survey (PAM-IBGE) and the Municipality Cattle Survey (PPM-IBGE) [6]. The GDP per capita is from IBGE, the government agency responsible for all official statistics in Brazil.

The variable of interest is the amount of flex-fuel vehicles. However, we were not able to get this particular data, therefore, as presented in the previous section a dummy variable is constructed to capture the importance of the flex-fuel fleet in Brazil introduced in 2004.

Box 1 summarizes the variables considered in this study, the expected regression signals as well as the relevant references.

Box 1- Variables considered in this study, expected regression signals and references.

Variable	Expected sign	References
$\boldsymbol{GDP}$	+/-	Jalil and Mahmud (2009); Ang (2007); Apergis and Payne (2009);
$\boldsymbol{GDP^2}$	-/+	Jalil and Mahmud (2009); Ang (2007); Apergis and Payne (2009);
$\boldsymbol{Vehicles}$	+	Yang, Li and Cao (2015)
$\boldsymbol{Other\_Vehicles}$	+	Yang, Li and Cao (2015)
$\boldsymbol{Vehic\_Flex}$	-	
$\boldsymbol{Vehic\_Flex^2}$	-	
$\boldsymbol{Cattle}$	+	FAO (2006)
$\boldsymbol{Sugar\ Cane}$	-	Macedo (2005)

Source: authors.

[6] http://www.ibge.gov.br/english/

5. Results

Table 1 presents the descriptive statistics of the variables considered in this study. The balanced panel data set consists of repeated cross-sections of observations covering the period 1998 to 2013 for 27 states in Brazil.

The parametric and semiparametric results are reported in Table 2. A comparison of the Hausman specification test of the full parametric OLS fixed effects model versus the full parametric OLS random effects model strongly favored the former at the 1% level. The two semiparametric fixed effects estimates are based on the estimator developed by Henderson et al. (2008) as we mentioned in the previous sections.[7]

The results indicate that the majority of variables in all models are statistically significant at 1%, 5% or 10% levels and show the expected signs. It is important to highlight that no control for endogeneity has been made at this point (an issue to be address in the future).

More specifically, the first point to make is about the main coefficients of interest. The results in all fully parametric models and in the parametric part of the semiparametric model II initially suggest that the fleet of $vehic\_flex$ is negatively contributing to a reduction on CO_2 emissions, as theoretically expected. This result is capturing the effect of flex-fuel vehicles introduced in the Brazilian automobile market in 2004. In addition, the negative sign of the coefficient of $vehic\_flex^2$ in all parametric models and in the semiparametric model I confirms the EKC hypothesis, which drives a preliminary conclusion that the flex-fuel fleet is indeed able to reduce CO_2 emissions.

It is now important to verify if this linear relationship is sustained nonlinearly as we proposed. Thus, we now turn to the nonparametric estimations of $\varphi(Vehic\_flex)$ and

[7]A Hausman test comparing the full parametric versus semiparametric version is still an ongoing research in this study.

$\varphi(Vehic\_flex^2)$ of the semiparametric fixed effects model from expression (2) displayed in the Figures 4 and 5, respectively. The colored lines correspond to 95% confidence intervals (with 500 replicates using the (wild) bootstrap method).[8] The bandwidths are estimated via Least-Square Cross Validation (Li and Racine, 2007).

As we observe, the nonparametric impact of one additional flex-fuel vehicle on CO_2 emissions (Figure 4) is not always linear and always decreasing, as suggested from the fully fixed effects parametric specification. The CO_2 emissions start increasing at lower units levels of flex fuel vehicles, and then decreased at higher units of flex fuel vehicles. The estimate of $\varphi(Auto\_flex^2)$ in Figure 5 is supporting more favorably our hypothesis that flex-fuel vehicles (assuming that more environmental technology for engines is also changing) can indeed contribute to mitigate the effects of CO_2 emissions from 2004. This nonparametric result is clearly corroborating the EKC inverted-U hypothesis. A robustness checking about these estimates will be conducted in the following section.

Back to Table 2, it is also of particular interest here to observe in both parametric and semiparametric results that as long as cropped sugarcane areas expand (assuming that no more forest is been deforested), and holding everything else constant, the result is less CO_2 emissions. This result brings evidence that the carbon sequestration hypothesis is corroborated as suggested by Macedo (2005) and Goldemberg et al. (2008). To add up our conclusions, on the other hand, the impact of livestock herd (cattle) is positive and statistically significant, and should be a concern for the future policy with respect to sustainability and emission reductions for this kind of economic activity. We also find that the GDP increases, CO_2 emissions also increases while the square of GDP is contributing to reduce CO_2 emissions. Such result that is

[8] To get standard errors that are robust to heteroscedasticity a wild bootstrap with 500 replications is used (Cameron and Trivedi, 2005; Henderson and Parmeter, 2015).

also corroborating the EKC hypothesis for the growth (and technological change) of economy as a whole and a subject that has been widely studied in the literature.

As stated before, the application of nonparametric models is still limited; but has been increasing in many fields of research (Henderson and Parmeter, 2015). Henderson and Parmeter also suggest that for policy analysis purposes, a full parametric model is always preferable to a nonparametric one, because it is easier to interpret. However, nonparametric models can help identifying the true underlying structure of the data. In our case, we are interested in investigating how robust of the EKC hypothesis is related to the flex-fuel vehicles and CO_2. Moreover, if our EKC is satisfied, what would be the actual turning point that CO_2 emissions start reducing as long as the fleet of flex-fuel vehicles increases. We will try to check all this issues in the next section by considering all predictors estimated nonparametrically.

6. Robustness checks

In this section, a battery of robustness checking using different nonparametric estimators is executed.[9] We start with the analysis, which all predictors enter in the regression functions nonparametrically. We present two sets of estimations. The first, the nonparametric estimator Local Linear Least Squares (LLLS) is executed in more naïve way, that is, the estimation is obtained by pooling cross-sections to obtain large samples size and ignoring that these cross-sections are measured repeatedly (Henderson and Parmeter, 2015). For this type of dataset, the authors highlight that one of the main theoretical advantages of the LLLS estimator is to provide more an accurate measurement of the conditional mean, while at the same time it provides an estimator of the first derivative of the conditional mean. Thus, consider a full nonparametric model for cross-section as follow:

[9]This section is entirely based on Henderson and Parmeter (2015). The authors also provide in their website R-codes to replicate all examples of the book, and the programing codes can be easily adapted by the users. Their programming codes can be accessed at: http://www.the-smooth-operators.com/.

$$CO_{2_i} = \varphi(x_i) + \varepsilon_i \qquad (3)$$

where for each i, CO_{2i} is the dependent variable, x_i is a vector of exogenous variables, $\varphi(\cdot)$ is an unknown smooth function, and ε_i the error term.

The second set of estimations, which consider that our cross-section data is measured repeatedly over time, a full version of a nonparametric panel data model can be specified as such:

$$CO_{2it} = \varphi(x_{it}) + \varepsilon_{it} \qquad (4)$$

where the error term ε_{it} follows the specification

$$\varepsilon_{it} = \mu_i + \upsilon_{it} \qquad (5)$$

where $\mu_i$and υ_{it} are (un)correlated for all i and j, and for all j=1,2,...,n.

The object of interest is to estimate $\varphi(x_{it})$ at a point x_{it} and the slope of $\varphi(x_{it})$, i.e., $\beta(x_{it}) = \partial\varphi(x_{it})/\partial x_{it}$ (Henderson and Parmeter, 2015). We consider two estimators developed specifically for panel data structure. The first is called by the Local Linear Weighted Least-Squares (LLWLS) estimator and departs from the assumption that individual effect and the regressors are uncorrelated, therefore a Random Effects model (Lin and Carrol, 2000; Henderson and Ullah, 2005; Henderson and Parmeter, 2015). The second estimator (HCL) is based on the work of Henderson et al. (2008), a fixed effects in nature, that assumes that individual effects are correlated with the regressores.[10] This estimator is the same as the one used in the previous section, but now a full nonparametric version of their estimator is presented here.

To make more interesting the analysis, Table 3 and Table 4 present the elasticities for each quartile (25th, 50th, 75th percentiles) from Local Linear Least-Squares (LLLS) estimator

[10] Henderson et al., (2008) developed a Hausman-style test for the presence of fixed versus random effects; and similar to the test of the full parametric versus the semiparametric specifications, is still an ongoing research on this study.

considering the pooled data and two of nonparametric panel data estimators (LLWLS, HCL), respectively. In all of them, under each estimated partial effects is the (wild) bootstrapped standard errors. The bandwidths are estimated via Least-Squares Cross-Validation (LSCV). The elasticity is calculated as follows:

$$elasticity(x_{it}) = \frac{\widehat{\beta}(x_{it})x_{it}}{\hat{Y}_{it}}, \quad (3)$$

for each it, where $\hat{\beta}(\cdot)$is the gradient of the conditional mean with respect to x_{it}, and $\hat{Y}_{it}$ is the fitted value (Henderson and Parmeter, 2015).

Starting with the pooled full nonparametric model (LLLS), Table 3 shows interesting results. First, the R^2 of 0.99 is capable of explaining considerably the variation in the CO_2 emissions. Second, the impact of flex fuel vehicles on CO_2 emissions is the lowest at the elasticity of 25th percentile (-0.0743), but starts increasing up to 0.1342 in the 75th percentile. However, these results are not statistically significant. On the other hand, all nonparametric elasticities of $vehic\_flex^2$ are statistically significant and the magnitude of these results goes from the lower percentile to the higher (-1.1035 to 0.0012), being all statistically significant. Such results bring evidence that pollution emissions would go up under a large flex-fuel fleet, and therefore, would not completely corroborate the EKC hypothesis as we observed in the pooled full parametric specification.

In addition, when the sign of the full parametric model is compared to the nonparametric elasticities of Sugar Cane cropped area, we find evidence that as long as sugar cane is expanding; the impact of this expansion on CO_2 is significantly lower. As we mentioned, carbon sequestration can really play a role during the cultivation of crop. The results show elasticities ranging from -0.23 at 25th percentile to a much higher elasticity of -0.02 at 50th percentile.

In addition, as expected, the nonparametric elasticities of cattle on CO_2 emissions is significantly higher mainly at the 50th (0.48) and the 75th (0.64) percentiles, corroborating the pooled full parametric results.

The impact of GDP and GDP^2 on CO_2 show mixed results and go to a different direction of the fully parametric specification. If the GDP increases, the result is less CO_2 emissions with elasticities ranging from -0.88 to -0.46, if we consider only the estimates that are statically significant. On the other hand, CO_2 emissions seem to increase for higher levels of GDP, that is, the impact of GDP^2 is substantially higher at the last two percentiles (0.68 to 1.29). Therefore, this result does not corroborate the EKC hypothesis for economic growth as is observed in the full parametric models. An issue that is probably related to some endogeneity among the predictors, or because the period of our dataset is too short and do not capture, as it should be, significant technological changes in the Brazilian economy.

We now turn to the full nonparametric panel data results presented in the Table 4. The sign of results are again mixed, and some of them go to different directions as well, and produce estimates unexpected of those that are observed in the previous estimations.

In summary, we see that when unobserved effect is controlled and uncorrelated with the observed factors (LLWLS random effects), one of the nonparametric elasticities of interest, the vehic_flex, is showing results that are aligned with the pooled full nonparametric model, but not with the full parametric random effects model. That is, we find that the contribution of flex-fuels vehicles to reduce emissions is substantially higher at the 25th and 50th percentiles, but not at the 75th percentile. This result is implying in the same conclusion that: when the fleet of flex-fuel vehicles is substantially higher, there is no alleviation on CO_2 emissions, holding everything constant. In addition, when the signs of these results are compared with the signs of the coefficients of full parametric random effects models, clearly, we can see that the latter estimates are not fully able to capture the real impact of flex-fuel vehicles, which highlights as one of the biggest advantages of nonparametric estimations.

The nonparametric elasticities of $vehic\_Flex^2$ are negative and statistically significant but at only the 50th (median) percentile in the LLWLS random effects model. Therefore, we could see that our results is partially corroborated the EKC as it is observed in the random effects parametric estimates.

The signs of the nonparametric elasticities for cattle herd and sugar cane cropped area show reverse results compared to the full parametric random effects. The size of cattle herd turns out be negative and sugar cane is positive. One possible explanation for the latter result is that in many parts of country; sugarcane is harvested by unskilled workers, mostly manually and this traditional harvest method involves burning the planting area to facilitate access to the canes, therefore not contributing to a reduction on CO_2 levels (Chagas et al., 2016). Another possible explanation is that nonparametric techniques are robust to any function form specification; however, they are not robust to omitted variable bias and it would bring some issue here (Delgado et al., 2014).

We also observe that the elasticities for GDP is converging with the results of the full parametric random effect specification, however GDP^2 are not. Notice that the direction of this latter result is different from the ones obtained in the full parametric, leading to some evidence that the EKC hypothesis should be rejected for the relationship between GDP and CO_2.

We now look that the nonparametric fixed effects model (HCL). First, the nonparametric estimations of $Vehic\_Flex^2$ and GDP^2 were omitted due to failing in convergence of the model. Specifically, the nonparametric estimate of vehic_flex is significant at only the 25th and is corroborating the hypothesis that there would not be a reduction in CO2 emissions as long as the fleet of flex fuels increase. The other two percentiles of the nonparametric elasticities are showing a negative signs which are aligned with the other full and semi fixed effects estimates, however they turned out to be not statistically significant.

The nonparametric elasticities for cattle and sugar cane show signs that are similar to the ones of the LLWLS model, however they also present results that are not expected with the theory that guided our work.

Finally, as already mentioned, one of the main advantages of nonparametric modeling is "to let the data speak for itself" (Eubank, 1999), however, nonparametric regressions face substantial challenges during the estimation process. A major one is that if the number of covariates increases, then the rate of convergence of the estimator to its true value decreases, a phenomenon also known as the "curse of dimensionality" (Li and Racine, 2007). Therefore, the use of less predictors--even aware of the omitted bias problem—could cause a substantial difference in the final results.

Not only that, during the use of nonparametric techniques the choice of bandwidth really matters. For any nonparametric estimation, the choice of the bandwidth regulates the trade-off between variance and bias in the estimates (Li and Racine, 2007). For that, and as is recommended, we ran our regressions using optimal bandwidths generated by the Least-Squares Cross Validation method (Henderson and Parmeter, 2015). However, different bandwidths generated from cross-validation based on Akaike information criteria, for instance, would lead to alternative conclusions (Hurvich et al., 1998; Henderson and Parmeter, 2015).

7. Concluding Remarks

This study aimed at verifying the nature of the relationship that exists between the implementation and the increase of fleet of flex-fuel vehicles from 2004 and CO_2 emissions in Brazil. We were also interested in checking if there would be an EKC hypothesis for the use of flex-fuel vehicles. To achieve that goal, we departed with a full panel data parametric model, followed by a fixed-effects semiparametric estimator recently developed by Henderson et al., (2008). We are unware of any application of their estimator in the literature so far.

Among our main results, we found some evidence of a negative relationship between the flex-fleet and CO_2 emissions in the Brazilian States. Based on the parametric e nonparametric estimates we also corroborated the EKC hypothesis. Our results converges with scientific literature studies that highlight the potential for mitigation of greenhouse gas (GHG) emissions with the use of this as a biofuel. However, one particular concern is that even if the number of vehicles adapted for the flex-fuels has substantially increased, so it has also increased the area of sugar cane crops. As we already mentioned in the introduction, the net CO_2 emissions resulting from the burning of ethanol in flex fuel car engines are not significantly lower than the emissions due to burning fossil fuels (Macedo, 2005). However, there is strong evidence that GHG emissions of whole energy sector are reabsorbed by carbon sequestration during the growth of the sugarcane crop in the next season (Macedo, 2005; Goldemberg et al., 2008). Perhaps, the causality between flex-fuel vehicles and sugar cane crop is stronger than we expect. This is an important empirical issue to be address in the future.

We are also aware that our proposal is far from exhausting the subject, and therefore, we expect that our research will offer subsides for the development of new studies under different benchmarks and approaches in helping understanding the substantial impacts of CO_2 emissions and indicators of economic growth.

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Table 1: Sample statistics: variable definitions, means, standard deviations, max and min.

	Description	Mean	SD	Max	Min
CO_2	Amount (GWP-Tons) of all pollutants in CO^2 equivalent‡	26,519,945	27,357,478	129,611,109	11,063.98
Vehic	Passenger Cars and SUVs (units)	1,073,724,930	2,153,746,682	15,643,415,552	2,059,000
Other Vehic	Other vehicles converted into Passenger Car units	451,951,986	755,370,240	6,057,620,992	647,500
Vehic Flex	Passenger Cars (units) x (D=1 if year $\geq$ 2004 and $\leq$ 2013)	788,668,961	2,016,872,311	15,643,415,552	0
Catle	Livestock (in heads)	7,234,403	7,796,707	29,265,718	74,508
Sugar Cane	Sugar cane (in hectares)	257,531	733,790	5,415,013	68,000
GDP	GDP per capita (in 2000 constant prices)	15,000	10,000	60,000	5,000
Year		2006	5	2013	1998

‡ CO2 emissions from land use change (coming mostly from deforestation in Amazon) are not included in the sample.

Table 2: Parametric and semiparametric panel data regressions. Dependent Variable: Total amount (GWP-Tons) of all emissions in CO_2 equivalents.

	Pooled	Fixed Effects	Random Effects	Semiparametric I	Semiparametric II
Vehic	**1.2574**	**0.4455**	**0.9912**	**1.138**	**1.3034**
	(0.0294)	(0.0758)	(0.0395)	(0.032)	(0.0333)
Other Vehic	-0.0169	**0.1272**	**-0.1226**	0.019	0.0123
	(0.0274)	(0.0418)	(0.0242)	(0.0362)	(0.033)
Vehic Flex	**-0.0661**	**-0.0605**	**-0.0376**	-	**-0.212**
	(0.0269)	(0.0152)	(0.0167)	-	(0.017)
Vehic Flex^2	**-0.1804**	**-0.0360**	**-0.1289**	**-0.1716**	-
	(0.0233)	(0.0197)	(0.0173)	(0.022)	-
Cattle	**0.5322**	**0.3991**	**0.5082**	**0.5347**	**0.5472**
	(0.0074)	(0.0233)	(0.0167)	(0.0009)	(0.010)
Sugar Cane	**-0.3585**	**-0.2351**	**-0.1426**	**-0.330**	**-0.4751**
	(0.0234)	(0.0320)	(0.0287)	(0.0009)	(0.0207)
GDP	**-0.0623**	**0.1451**	**0.1517**	-0.0208	-0.0411
	(0.0264)	(0.0381)	(0.0346)	(0.0379)	(0.0369)
GDP^2	-0.0042	**-0.0784**	**-0.1464**	-0.009	-0.0010
	(0.0246)	(0.0322)	(0.0312)	(0.032)	(0.036)
_cons	**0.0788**	**0.0802**	**0.0793**	-0.0001	-0.000002
	(0.0061)	(0.0031)	(0.0209)	(0.008)	(0.008)
N	432	432	432	432	432
Hausman		**122.90**			
r2	0.98	0.83		0.97	0.97
F	**3249**	**242**		**2803**	**2952**

Notes: Standard errors in parentheses.

Notes: Coefficients in bold are equal to p-value $\leq$ 0.10 or lower.

Table 3: Summary of elasticities from the Local Linear Least Squares (LLLS) regression with bandwidths estimated via Least-Squares Cross Validation (LSCV). Dependent Variable: Total amount (GWP-Tons) of all emissions in CO_2 equivalents.

	Q1	Q2	Q3
Vehic	**0.2606**	**0.6909**	**1.2783**
	(0.1581)	(0.0346)	(0.0712)
Other Vehic	**-0.1584**	-0.0092	**0.0480**
	(0.0627	(0.0152)	(0.0126)
Vehic Flex	-0.0743	-0.0172	0.1342
	(0.0605)	(0.0312)	(0.0890)
Vehic Flex^2	**-1.1035**	**-0.4849**	**0.0012**
	(0.1013)	(0.1044)	(0.0001)
Cattle	0.1112	**0.4826**	**0.6444**
	(0.1601)	(0.0204)	(0.0394)
Sugar Cane	**-0.2350**	**-0.0224**	0.0084
	(0.0674)	(0.0025)	(0.0022)
GDP	**-0.8833**	**-0.4681**	-0.0563
	(0.0654)	(0.0572)	(0.4374)
GDP^2	-0.2851	**0.6839**	**1.2958**
	(0.4458)	(0.0821)	(0.2841)
Dummy			
Year		yes	
Observations		432	
r2		0.999	

Notes: Bootstrapped standard errors in parentheses.

Notes: Coefficients in bold are equal to p-value $\leq$ 0.10 or lower.

Table 4: Summary of elasticities for several panel data estimators with bandwidths estimated via Least-Squares Cross Validation (LSCV). Dependent Variable: Total amount (GWP-Tons) of all emissions in CO_2 equivalents.

	Vehic			Other Vehic			Vehic Flex			Vehic Flex^2		
	Q1	Q2	Q3	Q1	Q2	Q3	Q1	Q2	Q3	Q1	Q2	Q3
LLWLS	**0.1461**	**-0.2272**	**-0.2527**	**-0.9630**	**0.1159**	**-0.4299**	**-1.0666**	**-0.2824**	**0.6459**	0.0110	**-0.0931**	-0.1794
	(0.0002)	(0.0572)	(0.0780)	(0.1454)	(0.0432)	(0.0008)	(0.1225)	(0.1188)	(0.0406)	(0.0249)	(0.0330)	(0.2633)
HCL	**0.4027**	-0.2602	-0.2438	**0.3210**	-0.1863	**-0.2462**	**0.9777**	-0.0813	-0.0868			
	(0.0839)	(0.8771)	(9.2122)	(0.0717)	(0.1170)	(0.1334)	(0.3930)	(0.1363)	(0.4940)			

Notes: Table reports elasticities at the mean, 25th, 50th(median), and 75th percentiles along with bootstrapped standard errors in parenthesis.

Notes: Coefficients in bold are equal to p-value ≤ 0.10 or lower.

Table 4 (Cont'd): Summary of elasticities for several panel data estimators with bandwidths estimated via Least-Squares Cross Validation (LSCV). Dependent Variable: Total amount (GWP-Tons) of all emissions in CO_2 equivalents.

	Cattle			Sugar Cane			GDP			GDP^2		
	Q1	Q2	Q3	Q1	Q2	Q3	Q1	Q2	Q3	Q1	Q2	Q3
LLWLS	**0.4930**	**-0.0234**	**-0.3091**	**0.4096**	1.4674	0.0800	**0.0833**	**0.7316**	**0.7291**	**0.0096**	**0.0885**	**1.4133**
	(0.0307)	(0.0172)	(0.1218)	(0.1147)	(1.0892)	(0.1644)	(0.0259)	(0.3415)	(0.0437)	(0.0016)	(0.0422)	(0.1473)
HCL	**0.4524**	**-0.1248**	**-0.0889**	1.5869	0.0819	0.0305	**0.6742**	0.0554	0.0181			
	(0.0632)	(0.0789)	(0.0368)	(1.5937)	(1.9919)	(0.2276)	(0.1379)	(0.0429)	(0.1587)			

Notes: Table reports elasticities at the mean, 25th, 50th(median), and 75th percentiles along with bootstrapped standard errors in parenthesis.

Notes: Coefficients in bold are equal to p-value ≤ 0.10 or lower.

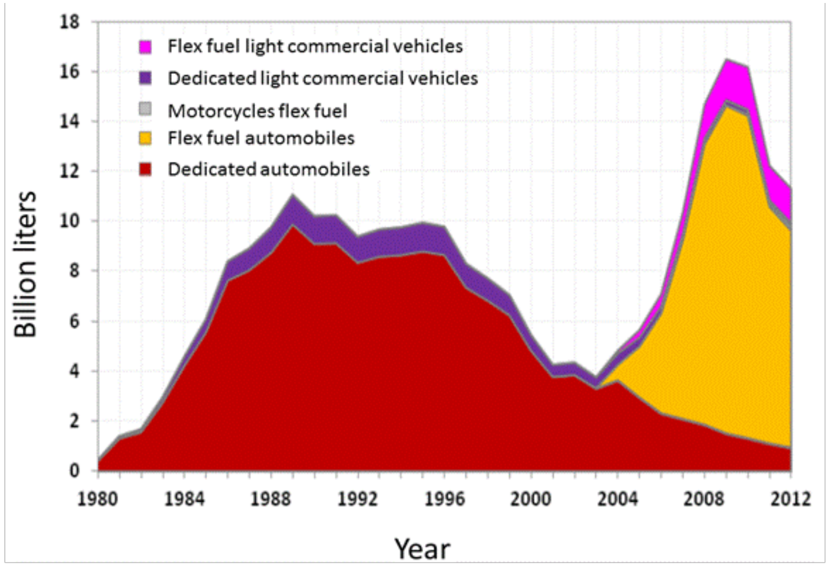


Figure 1: Evolution of the national ethanol consumption in road transport by vehicle category.

Source: Brazilian Ministry of the Environment - MMA (2013).

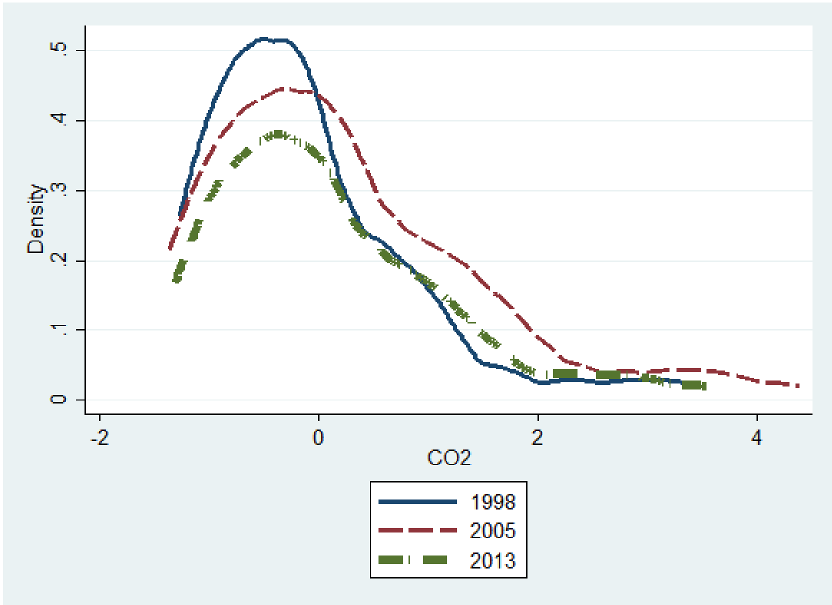
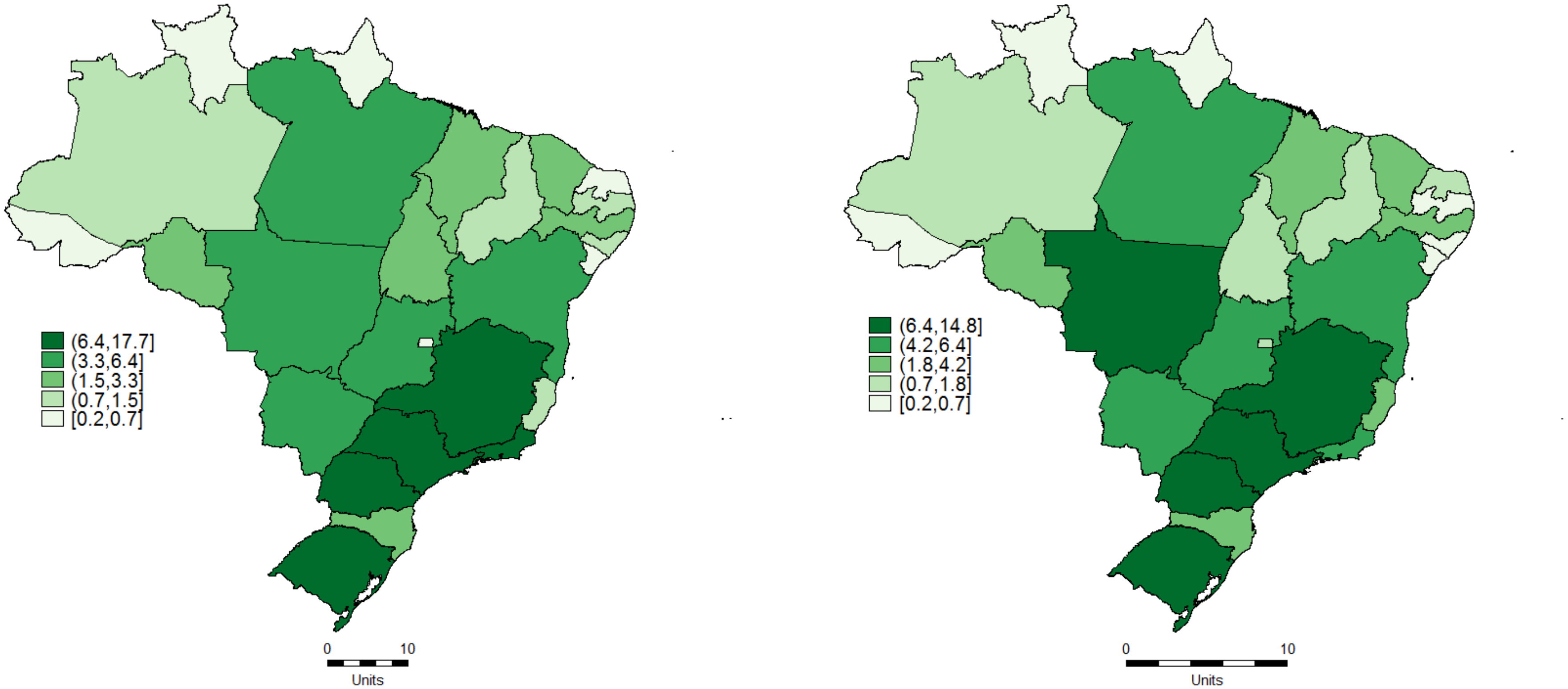


Figure 2: Density estimates of CO_2 in 1998, 2005 and 2013.



(a) 1998

(b) 2013

Figure 3: Share (%) of all pollutants in CO_2 equivalent in 1998 and 2013.

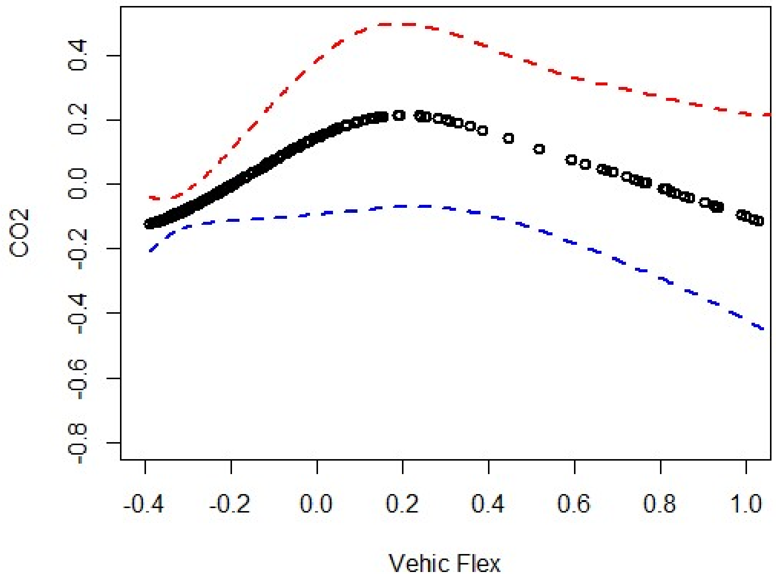


Figure 4: Partial fits of the relationship between flex-fuel vehicles and CO_2 emissions.

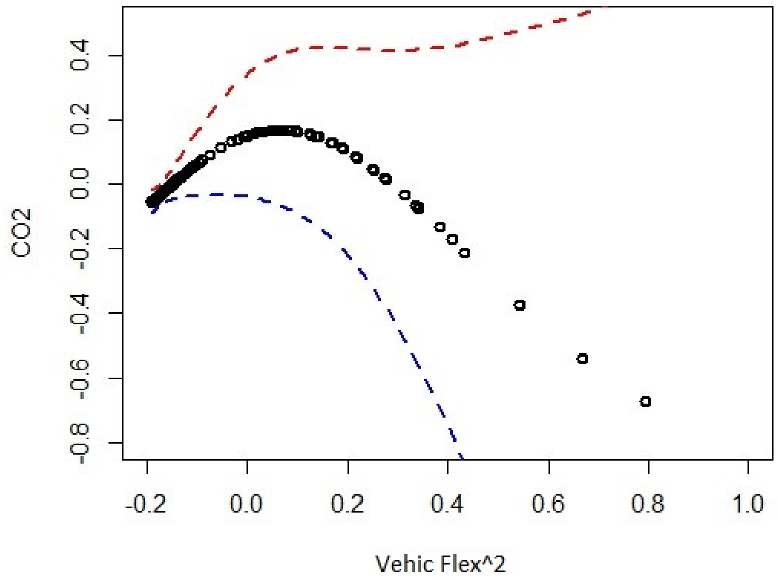


Figure 5: Partial fits of the relationship between flex-fuel^2 vehicles and CO_2 emissions.