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# A Dynamic Model for Road Gasoline and Diesel Consumption: An Application for Spanish Regions

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**ABSTRACT:** This paper analyzes the factors explaining the aggregate fuel consumption for road transport in Spain in a dynamic panel data framework. Three features on this study are the use of a balanced panel using regional data, the distinction between gasoline and diesel and the specification of a dynamic panel data (DPD) model and estimate it by system Generalized Methods of Moments (GMM). Our results show that most explanatory variables are significant in explaining the evolution of gasoline consumption, while diesel consumption is found to be independent of most of these factors. The differences between the markets of the gasoline (most for passenger transport use) and the diesel (passenger and freight transport are important) could explain the results for the diesel model. Moreover, the intensive dieselization process that has taken place in Spain over the last decade, which has resulted in diesel consumption being exposed to factors - i.e., regulatory - which are not of a strictly economic nature. This finding highlights the need to consider different explanatory variables and models for gasoline and diesel consumption, and to go further in the research. Finally, we find that traditional estimation procedures, such as fixed and random effect estimators, produce important differences with respect to system-GMM, which may even change policy recommendations.

**Keywords:** Fuel consumption; Road transport; Dynamic Panel Data model; GMM estimates.
**JEL Classifications:** R41; O13; O56

## 1. Introduction

The Spanish economy experienced one of its largest expansive economic cycle between 1995 and 2006, resulting in, among other things, a large increase in transport demand. As a consequence, road transport energy consumption and emissions delivered by this sector almost double during this period and the Spanish transport sector is currently one of the most important in Europe.

This paper studies the factors explaining aggregate fuel consumption (in per capita terms) for road transport in Spain between 1998 and 2006. In addition to the breakdown by Spanish regions, which allows us to use a panel data approach, another relevant aspect of this research is the distinction made between gasoline and diesel consumption. Polemis (2006), Zervas (2006) and Labandeira and López-Nicolás (2002), among others, have already emphasized the importance of making this distinction, which is especially relevant for the case of Spain, since it is probably, along with France, one of the countries in which the *dieselization* process has been the most significant in the last decade. For instance, the diesel to gasoline consumption ratio in road transport in Spain, which was 1.71 in

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1998, had risen to 3.78 by 2006. This process has led to a very uneven distribution in the consumption of gasoline and diesel, implying that the conclusions derived from an analysis of overall energy consumption could be misleading. Hence, we estimate a *gasoline model* and a *diesel model* and compare their results.[2]

We write the empirical fuel consumption model in a dynamic panel data (DPD) framework, and then properly apply estimation techniques. A DPD approach is shown to have important advantages with respect to a traditional static or time series analysis. First, energy consumption is dynamic by nature (Johansson and Schipper, 1997), mainly because of the persistence of fuel usage habits. Secondly, a DPD approach allows for working with the entire data panel and for specifying unobserved or omitted fixed effects to estimate the relevant parameters in the model [Hsiao (1986)]. With regards to the estimation procedure, we use the one-step system GMM estimator proposed by Arellano and Bover (1995) and Blundell and Bond (1998), which allows for endogeneity, measurement error and omitted variables problems.[3] We compare the system GMM estimates with respect to alternative, more traditional methods –the within groups, pooling-OLS, the first difference GMM of Arellano and Bond (1991). A first important message of the paper, we find that traditional estimation procedures, such as fixed and random effect estimators, produce important differences with respect to system-GMM that may even change policy recommendations at least in our particular case.[4]

The endogenous variable is per capita gasoline and diesel consumption. In addition to the dynamic fuel consumption term (the lagged level of fuel), we consider as explanatory variables the real prices of gasoline and diesel, the per capita GDP, the fleet of gasoline and diesel per capita (the motorization rate by fuel type) and the total fleet divided by the total kilometers of road as a proxy for the saturation of the road network.

This paper is structured as follows. Section 2 presents the DPD fuel consumption model and briefly comments on the system GMM estimation approach. Section 3 estimates the gasoline and diesel model and discusses the main results. Finally, Section 4 presents the main conclusions.

## 2. A Dynamic Panel Data Model for Fuel Consumption

A common starting point in the transport literature is to assume that aggregate fuel can be characterized like any aggregate products demand, that is, as a function of a measure of real income and fuel prices.[5] Specifically, we use a partial adjustment model that states that current fuel consumption growth is proportional to the difference between the current and previous consumption.[6] Thus, the considered specification of the dynamic model for aggregate fuel consumption is:

$$\ln(E_t) = \alpha_0 + \beta \ln(E_{t-1}) + \alpha_1 \ln(PG_t) + \alpha_2 \ln(PD_t) + \alpha_3 \ln(Y_t) + \varepsilon_t , \quad (1)$$

where fuel consumption and income variables would be expressed in per capital terms, $E_t$ and $E_{t-1}$ is actual and previous fuel demand, $PG_t$ is the real gasoline price, $PD_t$ is the real diesel price, $Y_t$, is the real income and $\varepsilon_t$, is an error term, which is assumed to be identically and independently distributed

[2] Although at international level there is an extensive literature that characterizes the consumption of energy in road transport ( Baltagi and Griffin (1997), Johansson and Schipper (1997) for OECD countries, Mazzarino (2000) for Italy, Polemis (2006) for Greece, Tapio et al. (2007) for the EU-15, Zervas (2006) for Ireland and Alves and Bueno (2003) for Brazil, among others); for the case of Spain, the existing literature is scarce and mainly focuses on fuel determinants using micro data (for example, Romero-Jordán et al. (2010)). In this paper, we focus on macroeconomic determinants.

[3] In the growth literature, Forbes (2000), Shioji (2001), Levine et al. (2000) and Bond et al. (2001), among others, use the one-step system GMM estimator that we consider in this paper.

[4] There are few exceptions in the energy literature that seriously consider the weakness of traditional methods in estimating DPD models. For example, Halkos (2003), Gang (2004) and Metcalf (2008) address the endogeneity problem and use the first difference GMM estimator, but this method does not consider the weak instruments problem of this procedure when time series are persistent [Blundell and Bond (1998)], which is the case for aggregate fuel consumption time series. Huang et al. (2008), which revisits the causal relationship between energy consumption and GDP, and Marrero (2010) for emissions and energy in Europe, are some of the few exceptions that properly address both the endogeneity and the weak instruments problems and consider a system GMM approach.

[5] See Dahl and Sterner, 1991; Sterner, (2007); Basso y Oum (2007), among many others.

[6] The partial adjustment model is a ad hoc model and, since the seminal paper of Houthaker et al. (1974), they have been used in many works about fuel demand (Baltagi et al, 2003, Pock, 2009).

with zero mean and constant variance. The specification (1) is commonly called a lagged endogenous model, where lagged endogenous variable can be seen as representing the inertia of the system.[7]

Taking (1) as the point of reference, we can specify a DPD model for gasoline consumption, GASO (*the gasoline model*) and another for diesel consumption, DISL (*the diesel model*), extended with some additional explanatory variables, such as the road network and the stock of vehicles[8]:

$$\begin{aligned}\ln(GASO_{i,t}) &= \alpha_i + \beta \ln(GASO_{i,t-1}) + \lambda_1 \ln(Y_{i,t}) + \\ &+\lambda_2 \ln(PG_{i,t}) + \lambda_3 \ln(PD_{i,t}) + \lambda_4 \ln(FLEETG_{i,t}) + \lambda_5 \ln(FLEETD_{i,t}) + \lambda_6 \ln(SAT_{i,t}) + \varepsilon_{i,t},\end{aligned} \tag{2}$$

$$\begin{aligned}\ln(DISL_{i,t}) &= \alpha_i + \beta \ln(DISL_{i,t-1}) + \lambda_1 \ln(Y_{i,t}) + \\ &\lambda_2 \ln(PG_{i,t}) + \lambda_3 \ln(PD_{i,t}) + \lambda_4 \ln(FLEETG_{i,t}) + \lambda_5 \ln(FLEETD_{i,t}) + \lambda_6 \ln(SAT_{i,t}) + \varepsilon_{i,t},\end{aligned} \tag{3}$$

where *FLEETG* and *FLEETD* are the existing fleet of gasoline and gasoil vehicles per capita (motorization rate), respectively, and *SAT* is the total number of vehicles divided by total kilometers of road, which is a proxy of the saturation of the road network.[9] Fixed factors $\alpha_i$ are time-invariant and inherent to each region, and are not observed or not included in the model, such as geographical, social or local policy regional aspects or initial energy efficiency[10]. Dynamic variables ($GASO_{t-1}$ and $DISL_{t-1}$) control for conditional convergence across regions in terms of fuel consumption, as it is standard in the dynamic literature. Finally, $\varepsilon_{it}$ encompasses effects of a random nature which are not considered in the model, and it is assumed to have a standard error component structure (see Arellano and Bond, 1991 for these technical details).

Traditional procedures for estimating a DPD models like (2) and (3) (i.e., fixed or random effects methods or pooling-OLS) are known to be unsuitable [Anderson and Hsiao (1982); Hsiao (1986)]. Holtz-Eakin et al. (1988) and Arellano and Bond (1991) propose an alternative approach, where first differences in the regression equation are taken to remove unobserved time-invariant country specific effects and then particular moment conditions for lagged variables are exploited to find a set of instruments and construct a GMM-based estimator. Their GMM approach (GMM-DIF) allows us to handle endogeneity problems.

The GMM-DIF approach, however, poses a serious bias problem in small samples when the series used in the model exhibit significant persistence, as is the case with the variables considered in (1). This persistence results in weak instruments in the GMM-DIF approach, meaning that the correlation between the instruments and the variable to be instrumentalized is small. This deficiency also exists for the standard 2SLS estimator. Arellano and Bover (1995) and Blundell and Bond (1998) offer an alternative GMM procedure (GMM-SYS) to overcome this weakness. They propose estimating a system of equations by combining the conditions of the first-difference estimator with those of a level estimator. This procedure estimates a system of equations in both first-differences and levels, where the instruments in the level equations are lagged first differences of the variables. We focus exclusively on GMM-SYS estimates in this paper.

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[7] For an interesting review of the approaches and methods that have been used in automobile fuel demand, see Basso and Oum (2007).

[8] This is one of the alternatives that can be used for analyzing the demand of fuel. It consists of using an equation of fuel demand where some measure of the stock of vehicles is explicitly included (ie, Banfi et. al., 2005; Kayser, 2000; and Puller and Greening, 1999). An alternative procedure is to employ a system of simultaneous equations in which the demand for vehicles and the demand for fuel are analyzed jointly (ie. Belhaj, 2002; Chandrasiri, 2006).

[9] In addition to the dynamic term, the other explanatory variables assumed in (2) and (3) are among those traditionally considered as indicators for characterizing the behavior of the road transportation sector [Eltony (1993), Bentzen (1994), Kirby et al. (2000), Alves and Bueno (2003), Polemis (2006)]. Moreover, we also distinguish between the total diesel and gasoline fleet, as proposed by Pock (2009).

[10] Fixed effects, such as differences in the initial energy efficiency, would be omitted in a standard OLS pool regression, resulting in bias estimates (i.e., the β estimates is upward bias.) See Anderson and Hsiao (1982) and Hsiao (1986) for more details about this point.

## 3. Gasoline and Diesel Model Results

Our goal of this section is twofold. First, we want to emphasize the importance of considering an appropriate quantitative approach when estimating a dynamic fuel consumption model; second, we point out the differences between the gasoline and the diesel model results.

Our data set involves a panel data of 144 observations corresponding to the time period 1998-2006 and 16 Spanish regions.[11] Gasoline and diesel consumption in road transport, measured in kilotons (kt), for every region are obtained from the Statistical Bulletin on Hydrocarbons (CORES, Ministry of Industry, Tourism and Commerce). Real gasoline and diesel prices, measured in euros, obtained from the Ministry of Development;[12] Real Gross Domestic Product (GDP) for all regions and population data are obtained from the National Statistics Institute (INE in Spanish).

In order to see the advantage of considering an appropriate procedure such as GMM-SYS to estimate our DPD model, we compare their results with traditional panel procedures, OLS pooling (OLS-POOL) and Within Group estimates (WG), as well as with the first-difference GMM approach (GMM-DIF) of Arellano and Bond (1991). GMM estimates are shown for the one-step estimator case, with heteroskedasticity-consistent asymptotic standard errors reported. Tables 1 and 2 show the results for the gasoline and diesel model, respectively, for all these alternative methods.

**Table 1. Estimates of the gasoline DPD model**

| | Traditional Methods | | | | GMM Methods | | | |
|---|---|---|---|---|---|---|---|---|
| | *OLS-POOL* | | *WG-Fixed Effect* | | *OLS-POOL* | | *WG-Fixed Effect* | |
| | Estimates | p-value | Estimates | p-value | Estimates | p-value | Estimates | p-value |
| Lag of gasoline consuption pc | 0.853 | 0.000 | 0.387 | 0.000 | 0.343 | 0.010 | 0.588 | 0.000 |
| Gasoline real price | -0.417 | 0.000 | -0.375 | 0.000 | -0.377 | 0.000 | -0.292 | 0.000 |
| Diesel real price | 0.175 | 0.021 | 0.181 | 0.007 | 0.186 | 0.000 | 0.212 | 0.000 |
| Real GDP pc | 0.009 | 0.622 | 0.241 | 0.244 | 0.293 | 0.254 | -0.011 | 0.777 |
| Gasoline fleet pc | 0.163 | 0.013 | 0.640 | 0.000 | 0.707 | 0.009 | 0.639 | 0.000 |
| Diesel fleet pc | -0.065 | 0.002 | -0.264 | 0.006 | -0.284 | 0.009 | -0.083 | 0.014 |
| Total fleet/ Road Network | -0.023 | 0.002 | 0.006 | 0.957 | 0.005 | 0.964 | -0.059 | 0.000 |
| R2 | 0.959 | -- | 0.946 | -- | -- | -- | -- | -- |
| Hausman, random effect test | -- | -- | 53.68 | 0.000 | -- | -- | -- | -- |
| ml-test | -- | -- | -- | -- | -2.564 | 0.010 | -3.368 | 0.001 |
| m2-test | -- | -- | -- | -- | -1.022 | 0.307 | -0.510 | 0.610 |

Note: '*WG*' is Within Groups estimation, *OLS-POOL* is OLS applied to the entire pool of data. For GMM estimates, we take as instruments the lagged levels of $y$ and the endogenous regressors dated t-2 and earlier and the pre-determined regressors dates t-1 and earlier. We use the lagged difference of $y$ and all regressors dated *t-1* as additional instruments in the system GMM estimation. For the DIF-GMM and SYS-GMM, we report their one-step estimations. The null of the Haussman test is the existence of random effects. The null of the m1 and m2 test is the absence of first- and second-order serial correlation between regressors and residuals, respectively. Number of regressors: 8; number of cross sections: 15 (all Spanish regions except Ceuta and Melilla, Balears and Canary islands); number of time periods: 9 (1998-2006); number of time periods adjusted for GMM-DIF and GMM-SYS: 6 (2001-2006).

[11] All Spanish regions with the exception of Ceuta, Melilla and the Canary Islands, which exhibited problems with the data

[12] Petrol prices are retail prices and deflated by each regional CPI .For more details about how petrol prices are determined in Spain, see Perdiguero (2006).

The p-value of the *t*-significance test associated with each parameter is shown. We also show standard specification tests for each model. Notice that the Haussman test rejects the null hypothesis of random effects at any standard level of significance. For any GMM-based estimates, we show the $m_1$ and the $m_2$ tests and conclude that moment conditions underlying GMM estimates seem to be robustly supported.[13]

Based on the results shown in Tables 1 and 2 and following the practical rule proposed by Blundell et al. (2000), OLS-POOL seems to give an upward-biased estimate of the $\beta$ coefficient (0.853 for the gasoline and 0.998 for the diesel model), while WG appears to give a downward-biased estimate of this coefficient (0.387 for the gasoline and 0.495 for the diesel model). Using GMM-DIF, the $\beta$ coefficient is barely lower than the WG estimates, suggesting the possibility of important finite sample bias due to the weak instruments problem [Blundell and Bond (1998)]. This comparison also highlights how the estimated coefficients of the remaining regressors, which are our main interest, differ among the alternative procedures. Hence, using a method resulting in bias estimates (the OLS-POOL, WG or the GMM-DIF) might lead to misleading conclusions.

**Table 2. Estimates of the Diesel DPD model**

| | Traditional Methods | | | | GMM Methods | | | |
|---|---|---|---|---|---|---|---|---|
| | *OLS-POOL* | | *WG-Fixed Effect* | | *GMM_Dif* | | *GMM_SYS* | |
| | *Estimates* | *p-value* | *Estimates* | *p-value* | *Estimates* | *p-value* | *Estimates* | *p-value* |
| Lag of gasoil consumption pc | 0.998 | 0.000 | 0.495 | 0.000 | 0.453 | 0.000 | 0.867 | 0.000 |
| Gasoline real price | -0.113 | 0.285 | -0.101 | 0.265 | -0.116 | 0.044 | -0.047 | 0.551 |
| Diesel real price | -0.049 | 0.502 | -0.083 | 0.205 | -0.075 | 0.100 | -0.027 | 0.666 |
| Real GDP pc | -0.004 | 0.852 | 0.455 | 0.030 | 0.483 | 0.196 | 0.044 | 0.431 |
| Gasoline fleet pc | 0.012 | 0.732 | -0.010 | 0.920 | 0.052 | 0.638 | 0.206 | 0.003 |
| Diesel fleet pc | -0.047 | 0.088 | 0.199 | 0.059 | 0.221 | 0.142 | 0.095 | 0.106 |
| Total fleet/ Road Network | -0.001 | 0.947 | -0.019 | 0.852 | 0.021 | 0.882 | -0.048 | 0.023 |
| R2 | 0.986 | -- | 0.954 | -- | -- | -- | -- | -- |
| Hausman, random effect test | -- | -- | 37.206 | 0.000 | -- | -- | -- | -- |
| ml-test | -- | -- | -- | -- | -2.724 | 0.007 | -3.780 | 0.000 |
| m2-test | -- | -- | -- | -- | -1.288 | 0.198 | -0.827 | 0.409 |

Note: See Note on Table 1.

For example, the coefficients associated with the network saturation variable in the gasoline and diesel model are not significant under the WG and GMM-DIF estimates, while it is significant under the GMM-SYS procedure; for the diesel model, the per capita GDP variable is significant under the WG, while it is not under the GMM-SYS and OLS-POOL; the magnitude of the estimated price-elasticities are smaller under the GMM-SYS than under the WG estimates in the diesel model.

[13] The most frequently used tests to validate the assumptions underlying GMM methods are the $m_1$, $m_2$ and Sargan tests. The $m_1$ and $m_2$ tests are based on the standardized average residuals autocovariance, which are asymptotically N(0,1) distributed under the null hypothesis of no autocorrelation. The Sargan test, in contrast, is distributed chi-squared with degrees of freedom equal to the number of moment restrictions minus the number of parameters, estimated under the null hypothesis that moment conditions are valid. However, the Sargan test is less meaningful since it requires that the error terms be independently and identically distributed, which is not expected in our case. Hence, we will consider primarily the *m1* and *m2* tests.

In summary, this comparison suggests that the WG estimates are severely biased, that there exists a problem with weak instruments and hence that the GMM-DIF is biased similarly to WG, and that the GMM-SYS approach is a convenient way to overcome the weak instruments problem. This conclusion is an important contribution of the paper, and not always properly considered in the related literature.

Next, we compare the results of the gasoline and diesel models, and we find important differences in the magnitude and significance of the variables. We will mainly focus our attention on the one-step GMM-SYS estimates from now on. In general, we find that the coefficients associated with the explanatory variables are less significant in the diesel model than in the gasoline model.[14] This result could be due to different reasons. Following Sterner (2007), the diesel is used heavily in professional transport (buses, heavy trucks, etc.) with different explanatory factors than those used for private use. Moreover, the dieselization process that has taken place in Spain since 1994, approximately, has resulted in diesel consumption being exposed to important regulatory factors, which might have modified expected results (Burguillo et al., 2009). Likewise, since fuel consumption data include both passenger and freight transport, and heavy trucks mainly uses diesel, the diesel model must distinguish between consumption in the passenger and freight transport sector. But, diesel consumption statistics for Spanish regions do not distinguish between consumption in the passenger and the freight transport sectors. Therefore, it would be necessary to further study the characteristics of diesel consumption, which goes beyond the objectives of this work, but they represent a promising extension for future research.

For the diesel and gasoline model, we next comment the estimations for each variable. The parameters estimated for the $DISL_{t-1}$ variable and the $GASO_{t-1}$ are positive and lower than one at the 1% level of significance. The estimate is 0.867 for the diesel model and 0.558 for the gasoline model. Hence, the evidence for conditional convergence is significant in both cases, though it is greater for the gasoline case. The estimates indicate that the rate of conditional convergence for the per capita fuel consumption ratio is about 13% for diesel consumption and about 44% for gasoline.

A common result in the gasoline and diesel model is that per capita GDP is not significant in explaining per capita fuel consumption.[15] Regarding other papers studying the relationship between gasoline demand and income, Dahl and Sterner (1991) showed that short-term income elasticity on gasoline demand varied between 0.30 and 0.52 in the different studies they considered.[16] However, notice that our GDP elasticity under the WG estimate was significant and about 0.44 for diesel, which is indeed consistent with the Dahl-Sterner range; this, however, is the result of a bias estimation procedure, as discussed above. With this example, we are not claiming that Dahl-Sterner estimates are wrong. In fact, differences between their estimates and ours may only be due to differences in the data sample used. We are just stressing the importance of considering an appropriate estimation approach for handling fuel consumption models, because, otherwise, results could lead to misleading conclusions.

Regarding the real price of fuel, the GMM-SYS procedure estimate for its elasticity is negative and significant for the case of gasoline, though its magnitude is well below one (-0.29). This result confirms the evidence that the elasticity of the demand price for gasoline is low in the short term, as verified by, among others, Kayser (2000) and Baltagi and Griffin (1997). Results at the

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[14] For the diesel model, we try with alternative specifications, considering variables such as the percentage of heavy trucks in the total fleet, or the percentage of buses. But these alternative specifications also fail in explaining the recent evolution of diesel consumption in Spain, being in line with the results obtained by Baltagi and Griffin (1983).

[15] A similar result is found in Pock (2009), which estimates a demand function for aggregate gasoline, and finds that, in some models, all coefficients are significant with the exception of the income term. He points out that this result may be due to multicollinearity problems. For the case of diesel demand, Burguillo et al. (2009) find the same result: the coefficient associated to real income was negative, but non-significant. Baltagi and Griffin (1997) obtain that the income elasticities are frequently insignificant in the long run.There exits other articles in the literature which estimates a model for aggregate energy consumption or CO2 emissions whose income-elasticity estimation is very low, and even negative in some cases [Schmalensee et al. (1998), Judson et al. (1999), Holtz-Eakin and Selden (1995) or Marrero (2010)].

[16] More recently, studies such as that by Koshal et al. (2007) gave values of 0.29. For a detailed review, see Graham and Glaister (2002) and Goodwin et al. (2004).

international level place the price-elasticity in the -0.2 and -0.3 range [Dahl and Sterner (1991)], which is consistent with our results. This result indicates that fuel demand is highly inelastic, at least at current price levels. Moreover, it supports a result commonly discussed in the literature: fuel taxes are convenient for increasing fiscal revenues, but they are not effective enough to reduce fuel consumption (Kirby et al., 2000).

In addition, the real price of diesel is significant in explaining short-term changes in per capita gasoline consumption, although its parameter is small (0.21). This last result is also consistent with the transport literature due to the strictness that exists in substituting types of vehicles in the short term (Polemis, 2006). We should emphasize that the recent intensive switch from gasoline to diesel vehicles has been basically due to regulatory reasons (dieselization) rather than to a change in the price of the alternative fuel. For the case of the diesel consumption model, neither its own price nor the price of gasoline is significant. As commented above, differences between the markets of the gasoline (most for passenger transport use) and the diesel (passenger and freight transport are important) could explain this result for the diesel model. Once again, this finding also highlights the need to consider different models for gasoline and diesel consumption, and to go further in the research of the determinants of diesel consumption in Spain.

For the gasoline model, the coefficient of the per capita gasoline fleet variable is highly positive and significant (0.64), while the coefficient of the per capita diesel fleet is negative but much smaller in magnitude (-0.08). Regarding these variables, results for the diesel model are controversial, as with other variables.

The coefficients of the measure of the degree of saturation of the road network (the ratio between total fleet and road network) are negative and significant in both models. Moreover, their estimates are similar: -0.048 for diesel and -0.059 for gasoline. The fact that estimated coefficients are similar in both models is a clear indication that road saturation affects both diesel and gasoline vehicles in a similar way. This result suggests that a reduction in road congestion promotes mobility, which may induce an increment in per capita fuel consumption[17].

## 4. Final Remarks

This paper has analyzed the factors explaining the fuel consumption for road transport in Spain in a dynamic panel data framework in a macroeconomic perspective. Two features on this study are the use of a balanced panel using regional data and the distinction between gasoline and diesel. As explanatory variables, we considered real GDP and fuel prices, which are the most commonly used in the related literature, as well as other relevant and different variables, such as the motorization rate and the saturation of the road network.

We find that most explanatory variables are significant – and with the appropriate signs - in explaining the evolution of gasoline consumption, while diesel consumption is found to be independent of most of these factors. The poorer adjustment of the diesel model could be due to the intensive dieselization process that has taken place in Spain over the last decade, which has resulted in diesel consumption being exposed to factors - i.e., regulatory - which are not of a strictly economic nature. Moreover, differences between the markets of the gasoline (most for passenger transport use) and the diesel (passenger and freight transport are important) could explain this result for the diesel model. This finding also highlights the need to consider different explanatory variables and models for gasoline and diesel consumption, and to go further in the research.

Our estimates confirm that the price elasticity of demand for fuel consumption is low – even negligible for diesel - in the short term, which supports the view that the policy of taxing fuel has little effect on reducing fuel consumption. Our results are also consistent with the evidence of small cross price elasticities for gasoline and diesel consumption. Another important finding of this work is the negative and significant relationship between the degree of saturation of the road network and both types of per capita fuel consumption. This result shows that reducing road network saturation – i.e., by increasing the road network -, could promote mobility and a higher transport demand ("*induced travel demand*"), which can favour higher levels of fuel consumption (*"induced fuel consumption"*). Moreover, we find that the alternative estimation procedures produce important differences that may

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[17] González and Marrero (2012) provided empirical evidence of the existence of a direct relationship between investing in roads and the demand for road transport, in Spanish regions.

even change policy recommendations, thus highlighting the need to carry out further research in this field.

**References**

Alves, D., Bueno, R. (2003). Short-run, long-run and cross elasticities of gasoline demand in Brazil. Energy Economics, 25, 191-199.

Anderson, T.W., Hsiao, C. (1982). Formulation and estimation of dynamic models using panel data. Journal of Econometrics, 18, 47-82.

Arellano, M., Bover, O. (1995). Another look at the instrumental-variable estimation of error-components models. Journal of Econometrics, 68, 29–52.

Arellano, M., Bond, S. (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. Review of Economic Studies, 58, 277-297.

Baltagi, B., Bresson, G., Griffin J., Pirotte, A (2003). Homogeneous, Heterogeneous or Shrinkage Estimators? Some Empirical Evidence from French Regional Gasoline Consumption. Empirical Economics, 28, 795-811.

Baltagi, B., Griffin, J. (1983). Gasoline demand in the OECD: An application of pooling and testing procedures, European Economic Review, 22(2), 117-137.

Baltagi, B., Griffin, J. (1997). Pooled estimators vs. heterogeneous counterparts in the context of dynamic demand for gasoline. Journal of Econometrics, 77, 303-327.

Banfi S., Filippini, M., Chunt, L. (2005). Fuel tourism in border regions: The case of Switzerland. Energy Economics, 25, 5, 689-707.

Basso, L., Oum, T. (2007). Automobile fuel demand: A Critical Assessment of Empirical Methodologies. Transport Reviews, 4, 449-484.

Belhaj, M. (2002). Vehicle and fuel demand in Morocco. Energy Policy, 30, 1163-1171.

Bentzen, J. (1994). An Empirical analysis of gasoline demand in Denmark using cointegration techniques. Energy Economics, 16, 139-143.

Blundell, R.W., Bond, S.R., Windmeijer, F. (2000). Estimation in dynamic panel data models: improving on the performance of the standard GMM estimator. In: Baltagi, B., Editor. Nonstationary Panels, Panel Cointegration, and Dynamic Panels Advances in Econometrics Vol. 15, JAI Press, Elsevier Science, Amsterdam, pp. 53–91.

Blundell, R., Bond, S. (1998). Initial Conditions and Moment Restrictions in Dynamic Panel Data Models. Journal of Econometrics, 87, 115-143.

Bond, S., Hoeffler, A., Temple, J. (2001). GMM Estimation of Empirical Growth Models. Economics Papers 2001-W21, Economics Group, Nuffield College, University of Oxford.

Burguillo-Cuesta, M., Jorge-Garía, I., Romero, D. (2009). Dieselization of passenger cars in the EU-15 in the nineties: environmental implications for transport policy. 8th International Conference of the European society for Ecological Economics, June 2009, Slovenia.

Chandrasiri, S. (2006). Demand for road-fuel in a small developing economy: The case of Sri Lanka Energy Policy, 34, 1833-1840.

Dahl, C., Sterner, T. (1991). Analyzing gasoline demand elasticities: a survey. Energy Economics, 13, 203-310.

Eltony, M. (1993). The demand for gasoline in the GCC: an application of pooling and testing procedures. Energy Economics, 18 (3), 203-209.

Forbes, K. (2000). A reassessment of the relationship between inequality and growth. American Economic Review, 90(4), 869-887.

Gang L. (2004). Estimating Energy Demand Elasticities for OECD Countries. A Dynamic Panel Data Approach. Research Department of Statistics Norway, Dicussion Paper 373.

González, R., Marrero, G. (2012). Induced travel demand in Spanish regions: a dynamic panel data model. Transportation Research Part A: Policy and Practice, 46(3), 435-445.

Goodwin, P., Dargay, J., Hanley, M. (2004). Elasticities of road traffic and fuel consumption with respect to price and income: A review. Transport Review, 24(3), 275-292.

Grahan, D.J., Glaister, S. (2002). The demand for automobile fuel: a survey of elasticities. Journal of Transport Economics and Policy, 36, 1-26.

Halkos, G.E. (2003). Environmental Kuznets Curve for sulphur: evidence using GMM estimation and random coefficient panel data models. Environment and Development Economics, 8, 581-601.

Holtz-Eakin, D., Newey, W., Rosen, H.S. (1998). Estimating vector autoregressions with panel data. Econometrica, 56(6), 1371-1395.

Holtz-Eakin D., Selden, M. (1995). Stoking the Fires? CO2 Emissions and economic growth. Journal of Public Economics, 57, 85-101.

Houtthakker, H., Verleger, P., Sheekan, D. (1974). Dynamic demand for gasoline and residential electricity. American Journal of Agricultural Economics, 56, 412-418.

Hsiao, C. (1986) Analysis of panel data. Econometric Society monographs 11, Cambridge. University Press.

Huang, B.N., Hwang, M.J., Yang, C.W. (2008). Causal relationship between energy consumption and GDP growth revisited: A dynamic panel data approach. Ecological Economics, 67 (1), 41-54.

Johansson, O., Schipper, L. (1997). Measuring long-run automobile fuel demand: separate estimations of vehicle stock, mean fuel intensity, and mean annual driving distance. Journal of Transport Economic and Policy, 31(3), 277-292.

Judson, R., Schmalensee, R., Stoker, M. (1999). Economic Development and the Structure of the Demand for commercial energy. Energy Journal, 20(2), 29-57.

Kayser, H.A. (2000) Gasoline demand and car choice estimating gasoline demand using household information. Energy Economics, 22, 331-348.

Kirby, H.R., Hutton, B., McQuaid, R.W., Raeside, R., Zhang, X. (2000). Modelling the effects of transport policy levers on fuel efficiency and national fuel consumption, Transportation Research Part D, 5, 265-282.

Koshal, R.K., Manjulika, K., Yuko, Y., Sasuke, M., Keizo, Y. (2007). Demand for gasoline in Japan. International Journal of Transport Economics, 34, 351-367.

Labandeira, X., López-Nicolás, A. (2002). La imposición de los carburantes de automoción en España; algunas observaciones teóricas y empíricas. Hacienda Pública Española, 160(1), 177-210.

Levine, R., Loayza, N., Beck, T. (2000). Financial intermediation and growth: causality and causes. Journal of Monetary Economics, 46, 31-77.

Marrero, G.A. (2010). 'Greenhouse gases emissions, growth and the energy mix in Europe,' Energy Economics, 32(6), 1356-1363.

Mazzarino, M. (2000). The economics of the greenhouse effect: evaluating the climate change impact due to the transport sector in Italy. Energy Policy, 28, 957-966.

Metcalf, G. (2008). An empirical analysis of energy intensity and its determinants at the state level. The Energy Journal, 29, 1-26.

Perdiguero, G.J. (2006). Dinámica de precios en el mercado español de gasolina: un equilibrio de colusión tácita, Documento de Trabajo de Funcas , 253.

Pock, M. (2010). Gasoline demand in Europe Energy: New Insight Economics, Energy Economics, 32(1), 54-62.

Polemis, M.L. (2006). Empirical assessment of the determinants of road energy demand in Greece. Energy Economics, 28, 385-403.

Puller, S., Greening, L. (1999). Household adjustment to gasoline price change: an analysis using 9 years of US survey data. Energy Economics, 21, 37-52.

Romero_Jordán, D, del Río, P., Jorge-García, M., Burguillo, M. (2010). Price and income elasticities of demand for passenger transport fuels in Spain. Implications for public policies. Energy Policy, 38 (8), 3898-3909.

Schmalensee, R., Stoker, M., Judson, R. (1998). World Carbon dioxide emissions: 1950-2050. Review of Economics and Statistics, 80(1), 15-27.

Shioji, E. (2001) Public capital and economic growth: a convergence approach. Journal of Economic Growth, 6, 205-227.

Sterner, T. (2007). Fuel taxes: An important instrument for climate policy. Energy Policy, 35, 3194-3202.

Tapio, P., Banister, D., Luukkanen, J., Vehmas, J., Willamo, R. (2007). Energy and transport in comparison: Immaterialisation, dematerialisation and decarbonisation in the EU15 between 1970 and 2000. Energy Policy, 35, 433-451.

Zervas, E. (2006). $CO_2$ benefit from the increasing percentage of diesel passenger cars Case of Ireland. Energy Policy, 34, 2848-2857.