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Economic Crisis and Elasticities of Car Fuels: Evidence for Spain

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Abstract

This paper provides an updated calculation of the price and income responsiveness of Spanish consumers of car fuels, with an explicit exploration of the effects of the current economic crisis. We examine separate gasoline and diesel demand models using a set of estimators, including generalized method of moments and bias-corrected dynamic fixed-effect models, on a panel of 16 Spanish regions over the 1999-2011 period. The paper confirms the persistence of rather low own-price elasticities both for diesel and gasoline and both in short and long runs. It also shows that the crisis has slightly increased the price elasticity of demand, with a higher effect on gasoline than on diesel. On the contrary, the crisis has hardly affected the income elasticity of car-fuel demand. These updated results are obviously relevant for the current Spanish debate on the design and implementation of energy, environmental, fiscal and distributional policies. Moreover, given the duration and extent of the Spanish economic crisis, our conclusions may be also interesting and useful from an international perspective.

Keywords: diesel, gasoline, income, price, regions, panel data

JEL classification: C23, D12, Q41

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1. Introduction

From the mid 1990s and until the outbreak of the 2008 crisis, the demand of car fuels in Spain saw an impressive and unprecedented evolution: from 1999 to 2007 gasoline and diesel consumption grew at an average annual rate of respectively 5.1% and 6.5%, reflecting both the strong growth of the Spanish economy and a limited responsiveness of demand to price changes (which in this period respectively grew at annual average rates of 1.8% and 3.5%). Yet, three years of deep crisis led to a completely different picture: between 2008 and 2011 gasoline and diesel demand fell at an annual rate of respectively -2.4% and -1.8%, fuelled by strong increases of prices (annual rates of 3.6% and 4.6%). It is clear that such a boom-and-bust evolution, as depicted in Figure 1 later on, brings about remarkable environmental, economic or energy effects.

Given the huge changes seen in this market in the last few years, in this paper we are mainly interested in providing an updated calculation of the price and income responsiveness of car fuel demand in Spain. The availability of reliable demand elasticities is a necessary condition for a proper economic evaluation of policies and strategies in this wide area. Given that Spain is currently considering a wide reform of its tax system that may incorporate new and more intense taxes on car fuels to reduce emissions and energy dependence, or due to the heated debate on car-fuel pricing, the practical relevance of this piece research is clearly vindicated. Even outside Spain, the results of this paper may be useful to anticipate the consequences of a pervasive and long economic crisis on the demand of goods that are so relevant for welfare and economic development.

Yet, there are also strong academic reasons for this paper. Although some authors have pointed out that economic crises are likely to have effects on the price elasticities of goods, due for instance to the larger incentives to react to prices that are associated to less availability of income (Estelami et al., 2001), the academic evidence is so far quite limited. It is also true that the literature generally considers that the price elasticity of demand is countercyclical, that is, sees increases when the economy weakens (van Heerde et al., 2013). This seems to be especially the case in products with a low-price elasticity, as energy goods, and in those that account for a big share of total expenditure (Gordon et al., 2013). However, the actual empirical evidence on the variation of demand elasticities at times of economic crisis is very limited, if it exists at all.

It is well known that the Spanish economy has been much shaken by the global financial crisis and its aftermath, being one of the developed countries that suffered the sharpest falls in growth and unemployment after 2008. As a result, the crisis saw Spanish energy consumption plummeting as households cut consumption spending and Spanish producers scaled down their purchases of energy input. Understanding the effects of the crisis on Spanish energy demand, but particularly on car-fuel demand, is especially important at least for two reasons. First, fuel consumption is an important source of public revenues and thus a likely source of disruptive effects on government budgets. Second, price and income elasticities of demand are important for the choice of domestic energy policies and thus have important implications for energy and environmental policies. Therefore, omitting structural changes in consumer responsiveness to price and income may result in misleading analysis, advice and policies (Hughes et al., 2008).

This paper provides an updated calculation of the price and income responsiveness of Spanish consumers of car fuels, with one of the first explorations of the effects of the current economic crisis. We examine separate gasoline and diesel demand models using a set of estimators, including generalized method of moments and bias-corrected dynamic fixed-effect models, on a panel of Spanish regions covering the 1999-2011 period. We try to reconcile some apparently contradictory evidence available for Spain, dealing carefully with the main econometric problems found for the estimation of this kind of demand models.

The reminder of this paper is structured as follows. Section 2 reviews the related literature. Section 3 describes the methodology used in this analysis. Section 4 presents the empirical analysis discussing the data used and reporting the core results of various estimation techniques. The last section concludes.

2. Literature review

Reduced-form demand models have been extensively used in the specification of automobile fuel demand. Using either static or dynamic forms, in this approach model estimation can have different forms depending on the type of data available, which can be purely time-series data, cross-section data or panel data. In the first category, when data are purely temporal, the partial adjusted model (PAM) stands as one of the preferred alternatives to analyze fuel demand and estimate different elasticities. In contrast to static models that provide average elasticities, the

PAM is a dynamic model that yields short and long run elasticities (Hothakker et al., 1974). The rationale behind this model is that markets are not perfect and some frictions, such as consumer habits, preclude reaching the proper equilibrium. Thus, a model of this type can be defined to capture the limited capability of consumers to adjust immediately to the long-run equilibrium of consumption in response to change in price, income, population and other factors (Li et al.,2010; Banaszak et al.1999; Al-faris, 1997; Sterner and Dahl, 1992). Yet other approaches, e.g. using co-integration techniques, have stressed the need to account for the possible non-stationary nature of the time series. Some initial evidence points into the direction that failure to reach stationarity may lead to overestimation of long-run price elasticities (Eltony and Al-Mutairi, 1995; Samimi, 1995; Ramanathan; 1999; Dahl and Kurtubi, 2001). In line with the cointegration technique, the autoregressive distributed lag (ARDL) bounds-testing approach developed by Pesaran et al. (2001) has been used in various empirical studies to determine long-run elasticities (Boshoff, 2012; Akinboade et al., 2008; De Vita et al., 2006).

During the last decade, developments of panel-data econometric methods allowed for the estimation of energy demand models by combining time-series and cross-section data. The increasing interest in the use of panel-data modeling is largely due to the ability of this technique to sort several econometric problems. For instance, panel data models have offered a solution to the problem of bias caused by unobserved heterogeneity, a common issue in fitting the models with cross sectional data sets. Moreover, panel-data models can account for dynamics that are difficult to detect with cross-sectional data (Hsiao, 2003; Baltagi, 2001; Wooldridge, 2002).

In this context, the fact that fuel consumption decision is made at the household level means that demographic profiles of households play a major role in automobile fuel consumption (Schmalensee and Stoker, 1999; Yatchew and No, 2001; Kayser, 2000). There are also several applications that used aggregate data to implement estimations at local or regional levels. Baltagi et al. (2003) employed a panel dataset from 21 French regions and compared the performance of different sets of homogenous and heterogenous estimators in the calculation of gasoline price and income elasticities. They found that standard homogenous estimators perform better than their counterparts, obtaining short-run price and income elasticities for gasoline of respectively -0.093 and 0.2. Other European studies at a regional level confirmed the prevalence of very small gasoline short-run elasticities: Baltagi and Griffin (1997) found short-run price and income elasticities for gasoline to be -0.09 and 0.5, with a larger long-run price elasticity of -1.39[1]. Liu (2004), who considered a set of different energy types and differentiates residential and industrial sectors, used the one-step GMM estimator to a PAM (Arellano and Bond, 1987), reporting a larger value (in absolute terms) of the short-run gasoline price elasticity and a comparatively lower income elasticities in the residential sector. More recently, Pock (2010) reported very small short-run effects of price and income changes in gasoline consumption (respectively -0.09 and 0.065), which would be probably due to the gradual and generalized switch to diesel cars.

Although studies on the demand for fuels in advanced countries are rather abundant in the economic literature[2], there is a limited number of papers for the Spanish case. Some authors have estimated the price and income elasticities at the household level based on complete demand models: Labeaga and López-Nicolás (1997) used a flexible Almost Ideal Demand System (AIDS), with a special treatment to the problems of zero expenditure and unobserved heterogeneity, and reported price and income elasticities for gasoline of respectively -0.536 and 0.429. Labandeira and López-Nicolás (2002) followed the same methodology for a different time spam and yielded -0.08 and 0.99 for respectively price and income elasticities of car-fuel demand. A study of Labandeira et al. (2006), based on a modified form of the AIDS model (Quadratic-AIDS), estimated price and income elasticities of household energy goods and found that the price elasticity of car fuels ranged between -0.11 and -0.058, while income elasticity was between 1.36 and 1.79. This contrasted with Romero-Jordan et al. (2010), who found larger car-fuel price elasticities, ranging between -0.64 and -0.32, and income elasticities (between 0.92 and 1.45). Such observed differences may be due to the varying time frames and to the different methodological approaches.

Other authors followed a different approach by using aggregate data of peninsular Spanish regions. Danesin and Linares (2013) estimated the aggregate price and income elasticities for both gasoline and diesel. Using a panel data model based on a set of homogeneous estimators, they reported a short-run gasoline price elasticity in the (-0.93, -0.29) interval, and a long-run price elasticity of -0.69, with gasoline income elasticities found to be non-significant. For diesel, short-run price elasticity estimates ranged between -0.22 and -0.21, while short-run income

[1] These values correspond to *the GLS-AR(1)*, which shows the best performance.

[2] Dahl and Sterner (1991), Sterner and Dahl (1992), Dahl (1995), Goodwin et al. (2004), de Jong and Gunn (2001), Graham and Glaister (2002,2004) and Basso and Oum (2007) have provided surveys of the existing literature on fuel demand elasticities.

elasticity were found to be between 0.35 and 0.46. González-Marrero et al. (2012) used the one-step system GMM along with other standard estimators to compute price and income elasticities. They found that one-step system GMM estimator performs better than its counterparts, yielding short and long run gasoline price elasticities of respectively -0.292 and -0.69, with non-significant estimates for diesel and income elasticities.

3. Methodology

3.1. Econometric model

In this paper we employ a PAM with a static representation of a long-run demand function in which *(GAS/CAR)** is the desired fuel (gasoline or diesel) consumption per vehicle, as in Baltagi and Griffin (1983; 1997). Assuming a Cobb Douglas relationship between desired demand and its drivers, Equation (1) defines the long-run demand curve as a function of the real price of the car fuel, $\left(P_{MG} / P_{CPI} \right)$, and a set of covariates, real income per capita $\left(\frac{Y}{N} \right)$ and cars per capita $\left(\frac{CAR}{N} \right)$. To reduce the information bias, total drivers are used instead of total population. The long-run price elasticity of demand is denoted as *β,* with γ and δ as vectors of coefficients that describe the responsiveness of the long-run level of demand to the non-price covariates, and *α* as a constant.

$$\left(\frac{GAS}{CAR} \right)^{*} = \alpha \left(\frac{P_{MG}}{P_{GDP}} \right)^{\beta} \left(\frac{Y}{N} \right)^{\gamma} \left(\frac{CAR}{N} \right)^{\delta} \tag{1}$$

Following Houthakker et al. (1974), a function is introduced to capture the limited capability of consumers to adjust immediately to the long-run equilibrium level of consumption in response to a change in price, income and other variables. Equation (2) indicates this limited capability in the form of a partial-adjustments constraint, designated by a parameter θ that captures the year-to-year inertia of habit persistence of fuel consumers, taking values between zero and one.

$$\left(\frac{\left(\frac{GAS}{CAR}\right)_t}{\left(\frac{GAS}{CAR}\right)_{t-1}} \right) = \left(\frac{\left(\frac{GAS}{CAR}\right)^*_t}{\left(\frac{GAS}{CAR}\right)_{t-1}} \right)^{\theta} \qquad (2)$$

Adding region and time subscripts, and the total fleet per km of roads to control for the saturation level of the road network, the classical dynamic demand equation for fuel per vehicle is expressed as

$$\ln\left(\frac{GAS}{CAR}\right)_{i,t} = \theta \ln\alpha + (1-\theta)\ln\left(\frac{GAS}{CAR}\right)_{i,t-1} + \theta\beta\ln\left(\frac{Y}{N}\right)_{i,t} + \theta\gamma\ln\left(\frac{P_{MG}}{P_{CPI}}\right)_{i,t} + \theta\delta\ln\left(\frac{CAR}{N}\right)_{i,t} \qquad (3)$$
$$+\theta\varphi\ln\left(SAT\right)_{i,t} + u_{i,t}$$

with $u_{i,t} = \mu_i + \varepsilon_{it}$, $i = 1,...,N, t = 1,..,T$, where μ_i denotes a region–specific effect and ε_{it} is white noise. A trend is included in the specification so that technical progress can differently affect demand for fuel through time. Under formulation (3), the short-run elasticities of car-fuel demand per car with respect to *per capita* income, real price, total cars per driver and level of saturation are respectively $\theta\beta, \theta\gamma, \theta\delta$ and $\theta\varphi$. The corresponding long-run responses are given by β, γ, δ and φ, with *(1−θ)* as the speed of adjustment to the long-run equilibrium. Note that the stock of cars thus enters both as dependent and independent variable. Therefore, the short and long run responses of car-fuel demand, relative to changes in the saturation level, are respectively *(1+θδ)* and *(1+ δ)*.

Given that an important goal of this paper is to analyze consumer responses to price changes during the time span 1999-2011, which includes the crisis period, the following empirical model is tested[3]

$$\ln\left(\frac{GAS}{CAR}\right)_{i,t} = \theta\ln\alpha + (1-\theta)\ln\left(\frac{GAS}{CAR}\right)_{i,t-1} + \theta\beta\ln\left(\frac{Y}{N}\right)_{i,t} + (\theta\gamma + \lambda D_{crisis})\ln\left(\frac{P_{MG}}{P_{CPI}}\right)_{i,t} \qquad (4)$$
$$+\theta\delta\ln\left(\frac{CAR}{N}\right)_{i,t} + \theta\varphi\ln\left(SAT\right)_{i,t} + \theta\mu Trend + u_{i,t}$$

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[3] In the empirical application we also allow for different income effects due to the crisis.

where D_{crisis} a dummy variable equal to 1 between 2008 and 2011 and zero otherwise. Thus, the short-run price elasticity in the crisis period will be $\theta\gamma + \lambda$, where λ captures the effects of the crisis period and is expected to be negative. In addition, we included a trend that proxies the technological evolution for gasoline and diesel vehicles.

3.2. Model estimation

To calculate the different elasticities of fuel demand we need to estimate Equations (3) or (4), which is subject to two main methodological challenges: unobserved heterogeneity as a source of effects on the explanatory variables, and the presence of a lagged dependent variable in a panel-data context. Regarding the former, simply regressing fuel consumption on a set of regional explanatory variables may lead to biased estimates unless all relevant variables can be observed. While some of these control variables are periodically published by public entities or statistical agencies, other variables are unlikely to be easily accessed or recorded and thus researchers relying solely on observable variables make the assumption of "unconfoundness" (Imbens and Woodridge, 2009). In doing so, they actually produce incorrect measures of demand responsiveness of consumers and infer spurious policy effects. Nevertheless, under the assumption that the effects of time-invariant factors can be linearly separated, the regional fixed-effects will remove the bias induced by observed and unobserved heterogeneity.

A fixed-effect transformation such as time-demeaning all the variables in Equation (4) has the form $\tilde{y}_t = (1-\theta)\tilde{y}_{t-1} + \beta^* \tilde{x}_t + \varepsilon_t$, where $\tilde{y}_t = y_{it} - \bar{y}_i$ and $\tilde{x}_t = x_{it} - \bar{x}_i$, with x_{it} as the vector of the time-varying right-hand variables. The estimator from this regression would be consistent only if the current values of explanatory variables (real price, real income, fleet per capita, and roads saturation) are completely independent of past realizations of the dependent variable (fuel consumption), i.e., if $E(\varepsilon_{is}|x_{it}) = 0, \forall s,t$. Obviously, the inclusion of lagged-dependent variables violates the strict exogeneity in this equation. Therefore, the fixed-effects estimator is inconsistent and biased in dynamic models. The least squares dummy variables (LSDV) or within-groups estimate is downward biased when considering model (4), and this bias would be especially severe when the autoregressive coefficient $(1-\theta)$ is high or the number of time periods, *T*, is small (Nickell, 1981; Roodman 2006).

To obtain consistent estimates, under the assumption that unobserved heterogeneity exists but it is time-invariant, Equation (4) is estimated using a dynamic generalized method of moments (GMM) estimator[4]. The basic estimation procedure consists of two essential steps: first, the dynamic model in Equation (4) is transformed[5] to eliminate the unobserved effects and subsequently the model is estimated using GMM, including lagged values of explanatory variables as instruments for the current explanatory variables. For these instruments to be valid, they must fulfill two conditions: to provide a source of variation of current explanatory variables, and lagged values have to yield an exogenous source of variation for current fuel consumption. In our empirical analysis we further examine the validity of the exogeneity assumptions using a battery of tests. Under the assumption of exogeneity, the orthogonality conditions satisfy $E(x_{it-s}\,\varepsilon_{it}) = E(y_{it-s}\,\varepsilon_{it}) = 0 \quad \forall s \succ 1$. However the procedure still has several shortcomings: first, differencing the equations in levels may reduce the power of the tests by reducing the variations in the explanatory variables; second, it has been argued that variables in levels may be weak instruments for first differencing equations (Arellano and Bover, 1995); and, finally, first-differencing may aggravate the effects of measurement errors on the dependent variable (Griliches and Hausman, 1986).

Arellano and Bover (1995) and Blundell and Bond (1998) suggested an improved version of the GMM estimator by also including the equations in levels in the estimation procedure. The approach is based on a system of equations that includes equations in both levels and differences, and where the first-differenced variables are used as instruments for the equations in levels. This gives rise to a "system" GMM estimator that hinges on estimating the following system,

$$\begin{bmatrix} y_{it} \\ \Delta y_{it} \end{bmatrix} = \alpha^* + \lambda^* \begin{bmatrix} y_{it-1} \\ \Delta y_{it-1} \end{bmatrix} + \beta^* \begin{bmatrix} x_{it} \\ \Delta x_{it} \end{bmatrix} + \varepsilon_{it} \qquad (5)$$

Unfortunately, equations in levels in this system still contain unobserved heterogeneity. To deal with this issue we assume that any correlation between explanatory variables and unobserved

[4] This approach was introduced by Holtz-Eakin, Newey and Rosen (1988) and Arellano and Bond (1991), and further developed in a series of papers including Arellano and Bover (1995) and Blundell and Bond (1998).

[5] That is, any transformation that permits to rule out the unobserved component. Although we will later refer to first differences, there are other alternatives such as orthogonal deviations (see Arellano and Bover, 1995).

heterogeneity is constant over time (one would suspect that variables such as real income, fleet, and saturation are correlated with unobserved effects that characterize each region). In this setting, the system GMM estimator under the extra set of orthogonality conditions[6] yields efficient estimates while controlling for time-invariant unobserved heterogeneity and the dynamic relationship between current values of the explanatory variables and past values of the dependent variable.

Yet the instrument proliferation in the GMM system does not come without a cost. Roodman (2009) argued that it might bias the coefficient estimates of the endogenous variables due to overfitting, diminish the power of the instrument validity tests, and produce downward-biased standard errors. Windmeijer (2005) addressed the latter by a variance correction for the two-step Blundell and Bond (1988) estimator, which is also considered in this paper. In addition, Roodman (2009) suggested testing results for sensitivity to reductions in the number of instruments.[7]

Another issue is that the instrumental variables are valid for large *N*, and little is known about their performance in small sample sizes. Under the assumption of strict exogeneity of the explanatory variables other than the lagged dependent variable, Kiviet (1995) used an asymptotic expansion technique to correct the biased LSDV estimator for samples where *N* is small. In another study based on Monte Carlo simulations and departing from the results of Kiviet (1995), Judson and Owen (1999) showed that "corrected LSDV" (LSDVC) outperformed the GMM approach in terms of bias and efficiency. Later, Bruno (2005) extended this correction version of LSDV to be applied in unbalanced panels. In a recent study conducted by Flannery and Hankins (2013), the performance of various estimators on simulated datasets of short panels in finance were compared and they concluded that Blundell-Bond and the bias-corrected fixed effects estimators of Kiviet (1995) had the best performance.

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[6] $E\left[\Delta x_{it-s}\left(\mu_i + \varepsilon_t\right)\right] = E\left[\Delta y_{it-s}\left(\mu_i + \varepsilon_t\right)\right] = 0 \qquad \forall s \succ 1$

[7] The STATA *xtabond2* command has the ability to specify, for GMM-style instruments, the limits on how many lags to be included. If *T* is fairly large (more than 7-8 periods), an unrestricted set of lags will introduce a huge number of instruments, with a possible loss of efficiency.

4. Empirical application

4.1. Data

Our dataset consists of a panel of 16 Spanish administrative regions and covers the 1999-2011 period (annual data)[8]. Variables include fuel consumption, disaggregated in regional gasoline and diesel consumption and obtained from the annual reports of National Commission of Energy (CNE its acronym in Spanish); real gasoline and diesel prices, obtained from the Spanish Ministry of Industry; regional Spanish population, from the National Institute for Statistics (INE its acronym in Spanish); number of gasoline and diesel cars (an important determinant of the long-run evolution of car traffic), sourced from the General Direction of Traffic (DGT its acronym in Spanish); total kilometers of regional roads, obtained from the Ministry of Infrastructures (Fomento in Spanish); and household disposable income and price index, both obtained from the INE. As already mentioned, the effect of technical progress on car-fuel consumption is taken into account by including a trend.[9]

Figure 1 depicts the evolution of consumption and real prices of both gasoline and diesel between 1999 and 2011. Since 1999 diesel demand has been steadily increasing, while demand for gasoline has decelerated its growth since 2001. Indeed, due to a favorable tax regime, diesel now makes more than 80% of Spanish demand of car fuels and thus is in a near-saturation stage. However, this growth has been stopped by the recent economic crisis, which strongly affected both gasoline and diesel demand. Spain annual diesel consumption in 2011 was around 31 million litres, or 30% lower than it would have been if the pre-2007 trend in diesel consumption annual growth of 5.6% had continued. Similarly, Gasoline consumption in 2011 was about 6 million litres, or 26% lower than it would have been if the 2004-2006 annual growth of 1.2% had been maintained. In addition, high unemployment during the recent economic contraction has reduced disposable income and has strongly affected car sales and thus the quality of the fleet. For instance, the growth rate of diesel fleet dropped from 10% between 2004 and 2006 to 1.2% in 2011.

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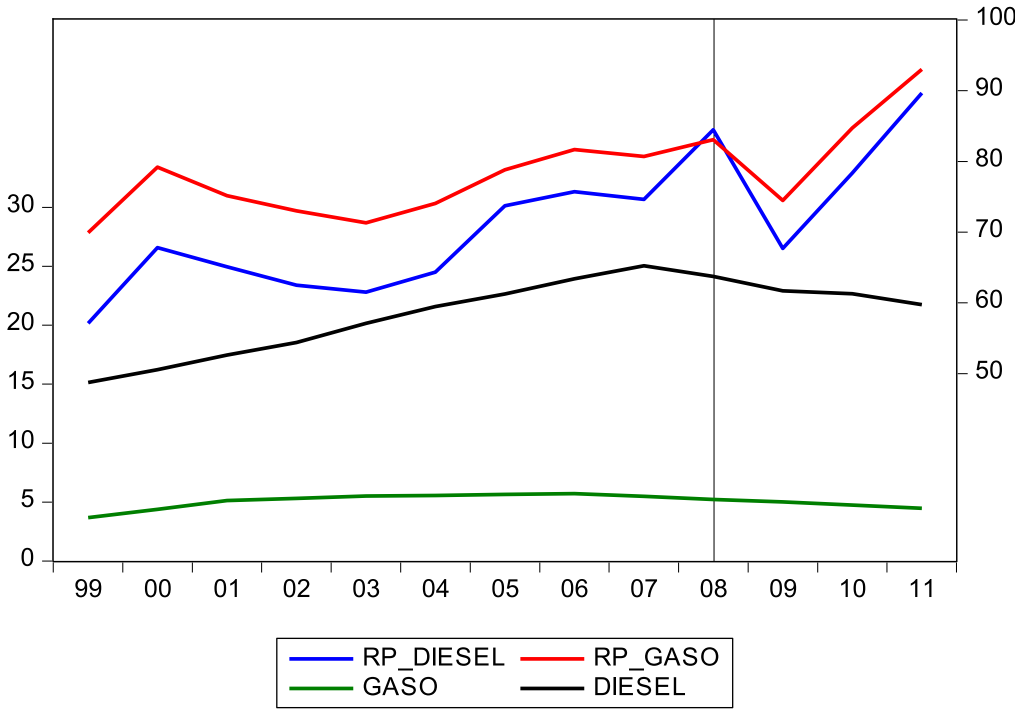
[8] Ceuta, Melilla and Canary Islands were excluded from this analysis as they have a special tax regime that may distort the results.

[9] We are aware that in a model estimated in first differences the first difference of a trend is just a constant.

Figure 1 shows that gasoline and diesel price trends were broadly similar over the period 1999-2011. Real prices increased at a faster rate between 1999 and 2000, bringing about concern and demonstrations across Spain and Europe. After a price-decreasing interval between 2001 and 2003, prices went up again with sharp spikes brought about by the outbreak of the crisis and a strong rebound at the end of the analyzed period.

Figure 1. Gasoline and diesel real prices (Euros/litres) and annual consumption (Million litres) in Spain (1999-2011)



Source: The authors with data from Ministry of Industry and CNE.

As this study is based on panel data analysis, it is important to assess the variations of the variables over time and across regions. Table 1A in the Appendix summarizes the extent of data variation, both inter and intra regionally for the key variables: gasoline and diesel consumption per car, gasoline and diesel prices per capita, income, cars per capita and road saturation. For diesel, price and number of cars per capita, variations were more pronounced within the same region across the years than between regions, whereas the variation of consumption per car was more remarkable between regions than within the same region. For gasoline, price and consumption variations were more intense within each region than between regions, while the variation of gasoline vehicles was more remarkable in per capita terms than within regions.

Finally, road saturation variation was predominantly between regions, whist the variation of real income was less pronounced within the region than between regions.

4.2. Results

Tables 1 and 2 report the main results. We estimate the first-order autoregressive model by OLS and LSDV as reference specifications. The coefficients of the lagged-dependent variable obtained from these two estimators provide the bound limits that are a useful check on the results from a theoretically superior estimator (Bond, 2002). In particular, while the naïve OLS estimator overestimates the coefficient of the lagged dependent variable because regional fixed effects are not accounted for[10], the LSDV estimator produces a downward bias. The preceding tables only report three alternatives to the reference specifications: the Anderson-Hsiao (HS), Arellano-Bond (AB) and Blundell-Bond (BB Full) estimators. The BB Full version involves the use of the full instrument set available in the data[11] and, as explained earlier, the model contains a lag of the endogenous variable and several exogenous explanatory variables. We use as instruments the dependent variable with a lag of two or more periods, also considering the results for a corrected LSDV estimator (Kiviet, 1995; Bruno, 2005).

Tables 1 and 2 also supply the heterosckedasticity-consistent asymptotic standard errors in parenthesis, the t-statistic for the linear restriction test under the null hypothesis of non-significance, and the Hansen test of the overidentifying restrictions. This test is asymptotically distributed as χ^2 under the null of no correlation between the instruments and the error term. Besides, the previous tables report m_i, which is a serial correlation test of order *i* (i = 1, 2) using the residuals in first differences, asymptotically distributed as *N(0, 1)* under the null of no serial correlation (see for details Arellano and Bond, 1991). The tests present no evidence of second-order autocorrelation at 5% significance level in the case of gasoline, although this is rejected in the case of diesel[12]. Based on the robust Hansen test, the overidentification restrictions are valid

[10] The Hausman test rejects the null and concludes that random effects are not appropriate.
[11] We have estimated several alternatives of the BB model in which we restrict the number of instruments following the procedure outlined in Roodman (2009). They produce pretty similar short and long run elasticities to the ones presented and discussed later on. We have also estimated the model using the LSDV estimator proposed by Kiviet (1995) and Bruno (2005). Although we do not present these results in the paper, they are available upon request.
[12] We have tried with instruments with lags of three or more periods, allowing for the presence of measurement error in the consumption of diesel, although the value of the test for second-order autoregressive residuals fails.

at 5% significance level for both diesel and gasoline[13]. The *F*- and χ^2- statistics reject the null hypothesis that estimated parameters are jointly equal to zero in the proposed estimators for diesel and gasoline.

Table 1. Estimates of the diesel dynamic demand model

VARIABLES	OLS	LSDV	AH	AB	BB_Full
Lag of diesel consumption/car	0.981***	0.738***	0.733***	0.581***	0.657***
	(0.0146)	(0.0744)	(0.0753)	(0.0801)	(0.100)
Trend	-0.000597	-0.00910**	-0.00879**	-0.0159***	-0.0158***
	(0.00158)	(0.00423)	(0.00379)	(0.0049)	(0.00333)
Diesel real price	-0.106***	-0.0839**	-0.0645**	-0.0601**	-0.0913***
	(0.0308)	(0.0299)	(0.0322)	(0.0303)	(0.0292)
CrisisXprice	-0.00496***	-0.00517***	-0.00483***	-0.00488***	-0.00595***
	(0.000845)	(0.000959)	(0.000852)	-0.000983	(0.00105)
Real Income	0.0489***	0.298**	0.283***	0.389***	0.325**
	(0.0178)	(0.114)	(0.0891)	(0.141)	(0.150)
Cars per driver	0.0141	0.0198	-0.00471	0.0939	0.0679
	(0.0198)	(0.0649)	(0.0563)	(0.0868)	(0.0742)
Road saturation	-0.00609	-0.144	-0.153*	-0.298***	-0.111**
	(0.00429)	(0.103)	(0.0885)	(0.0968)	(0.0385)
Constant	0.359***	0.599	0.583	1.261**	0.532*
	(0.133)	(0.524)	(0.454)	(0.521)	(0.259)
T	12.73***	8.75***	4.58**	4.47**	10.91***
m1				-3.107***	-2.93
m2				-1.968**	-1.74*
Jointly zero coefficients	2116***	862***	85054***	3378***	442***
Hansen				13.57[a]	14.66
Observations	192	192	176	176	192
R-squared	0.988	0.965			
Number of ccaa	16	16	16	16	16
Number of instruments				70	81

[a] Hansen test is not computable here, so we report Sargan test instead.

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; BB_Full is Blundell and Bond estimator considering all the instruments; Hausman test is 17.98, so the random effects hypothesis is rejected at a 1% level of significance.

Source: the authors.

[13] Since the tests for the validity of the instruments do not reject the null there might be a misspecification problem, even though we expect that it does not affect the elasticity figures.

The results indicate that the time-trend estimates have the right sign and are statistically significant for diesel but not for gasoline. It suggests that technological advances in diesel engines reduced vehicle fuel consumption by 1% per year, which demonstrates the progressive increase in energy efficiency in diesel technologies during the last few years. Regarding the influence of the crisis on the price elasticity of car-fuel demand, our results support the idea that consumers are more price-responsive at times of crisis. To reach this conclusion, we perform the null hypothesis of linear restriction H_0: $\theta\gamma + \lambda = 0$ to check whether the coefficient $\theta\gamma + \lambda$ is statistically different from zero[14]. Recall that during the crisis period, where the dummy variable takes the value of 1, the elasticity coefficient is $\theta\gamma + \lambda$. The null hypothesis is rejected for all the estimators, supporting the above-mentioned finding. The results indicate that the short-run price elasticity of diesel during the crisis period is between -0.097 and -0.065, wich is 0.005 bigger than during the non-crisis period. Similarly, the short-run price elasticity of gasoline demand is shown to be 0.01 larger, in absolute value, during the crisis period.

The price elasticities obtained in this study are broadly in line with those reported by the academic literature. Our diesel results are similar to those found by Labandeira el al. (2006), but lower than the reported by Danesin and Linares (2013). The differences with the latter are probably due to their shorter period of analysis and to their consideration of two types of diesel (95 and 97 octanes) instead of one (diesel 95). However, the size of our gasoline elasticities depend on the method used to estimate the model, which deserves further explanation. In this sense, the estimate of the lagged dependent variable in the AH model, 0.641, is higher than that yielded by LSDV estimator, while the estimated short-run price and income elasticities are higher. In addition, the resulting long-run price and income elasticities from the AH model are higher than the ones corresponding to LSDV. Looking at the BB-version estimators, collapsing and controlling the number of lags used as instruments did not improve the gasoline results. Indeed, the dynamic coefficients fall outside the limits and the AR(2) test yields a value of 2.38, which means that the null hypothesis of no second-order correlation is rejected at 5% significance level. This correlation in turn affects the validity of the instruments that is also corroborated with the Hansen-test. Therefore, in this context it is appropriate to use LSDVC, which has proved to be suitable to

[14] In order to allow for non-linear effects of the crisis we have also tested the interaction with the squared term of the price, but the results are non-significant.

correct the bias in the LSDV estimator and in the case of small samples where the GMM estimator lacks efficiency[15].

Table 2. Estimates of the gasoline dynamic demand model

VARIABLES	OLS	LSDV	AH	AB	BB_Full
Lag of gasoline consumption/car	0.760***	0.620***	0.641***	0.683***	0.631***
	(0.0299)	(0.0412)	(0.0671)	(0.0989)	(0.0459)
Trend	-0.00976***	-0.00377	-0.00731	-0.0131	-0.000507
	(0.00283)	(0.00467)	(0.00524)	(0.0146)	(0.00279)
Gasoline real Price	-0.0364	-0.107*	-0.0622	-0.136**	-0.149***
	(0.0589)	(0.0611)	(0.0671)	(0.0503)	(0.0338)
CrisisXprice	-0.00379	-0.0104***	-0.00805**	-0.0116**	-0.0123***
	(0.00333)	(0.00356)	(0.00400)	(0.00414)	(0.00253)
Real Income	0.0285	0.300***	0.263**	0.161	0.0548*
	(0.0194)	(0.0814)	(0.107)	(0.369)	(0.0270)
Cars per driver	-0.00654	0.00720	-0.0465	-0.542	-0.00620
	(0.0174)	(0.0956)	(0.107)	(0.343)	(0.0172)
Road saturation	-0.0249***	-0.0495	-0.0656	-0.174	-0.0365***
	(0.00528)	(0.0835)	(0.0943)	(0.292)	(0.00633)
Constant	0.0916	-0.283	-0.297		0.398**
	(0.248)	(0.459)	(0.580)		(0.171)
T	0.45	3.56*	1.05	8.31**	8.87***
m1				-3.02***	-3.05***
m2				1.89*	1.75*
Jointly zero coefficients	297***	176***	99042***	95***	390***
Hansen				13.56	15.86
Observations	192	192	176	176	192
R-squared	0.919	0.880			
Number of regions		16	16	16	16
Number of instruments				49	83

Note: The Hausman test is 11.57, therefore the random effects hypothesis is rejected at a 5% level of significance.
Source: The authors.

The results on price effects reported by Table 3 indicate, as expected, that price elasticity is inelastic in the short-run and more elastic in the long run. The results are, to some degree, smaller than those surveyed by Graham and Glaiser (2002) and Basso and Oum (2007), which fall between -0.2 and -0.3 for the short term and between -0.6 and -0.8 for the long term.

[15] Though Alvarez and Arellano (2003) state that the consistency of the GMM estimator should not be a problem when *T/N* tends to *c*, with *0<c<=2*, a condition that holds in our analysis.

However, they are in line with those reported by Pock (2010) for the EU contries (short-run: -0.106; long-run: -0.408), and Baltagi et al. (2003) for French regions: -0.093 and -0.329 for respectively short and long run price elasticities. Our short-run price elasticities is also similar to those reported by Baltagi and Griffin (1997) for 18 OECD countries, including Spain. Yet the studies specifically conducted for Spain have reported slightly higher values of both short and long run price elasticities (González Marrero et al., 2012; Danesin and Linares, 2013).

Table 3. Short and long run elasticities of diesel and gasoline demand

	OLS	LSDV	AH	AB	BB_Full
Diesel					
short-run (crisis period)	-0.111	-0.088	-0.069	-0.065	-0.097
short-run (non-crisis period)	-0.106	-0.083	-0.064	-0.06	-0.091
Long-run (crisis period)	-5.837	-0.336	-0.258	-0.155	-0.283
Long-run (non-crisis period)	-5.579	-0.317	-0.240	-0.143	-0.265
Gasoline					
short-run (crisis period)	-0.039	-0.117	-0.070	-0.147	-0.161
short-run (non-crisis period)	-0.036	-0.107	-0.062	-0.136	-0.149
Long-run (crisis period)	-0.163	-0.308	-0.195	-0.464	-0.436
Long-run (non-crisis period)	-0.150	-0.282	-0.173	-0.429	-0.404

Source: The authors.

To further explore the effect of the crisis on car-fuel demand responsiveness we performed a estimation that, by interacting income with a dummy that controls for the crisis period, evaluated whether the crisis affected the relationship between income and consumption of car fuels. The results show that the short and long-run income elasticities of diesel are not significant when estimated with BB version estimators, while the LSDVC estimator yields a statistically significant value of 0.16 for the income estimate. However, the coefficients of the interaction term show that the income elasticity of diesel demand is lower after 2008, indicating that consumers would have reduced their consumption a 1% in response to a hypothetical increase in their income during this period. Income estimates have the correct sign and are statistically significant for gasoline, although with different significance level and magnitude. The estimated values of the interaction term coefficient are highly significant and consistent, showing that a theoretical increase in income would cause 2% more of gasoline consumption before the crisis than after.

Moreover, the speed of adjustment values estimated from the estimators are close and belong to the bound limits[16], which means that both diesel and gasoline consumption adjust towards their long-run equilibrium levels at a relatively slow rate, with about 35% of the adjustment occurring within the first year. This result is in line with the findings of Danesin and Linares (2013), who suggest four years for long-run equilibrium to be restored.

As expected, the results also demonstrate that road saturation negatively affects car-fuel consumption, showing a negative correlation between road congestion and mobility. However, the respective magnitudes of road saturation coefficients, though not significant for gasoline, reveal a non-negligible effect on diesel consumption per car. Nevertheless, it must be noted that any impact assessment of road improvement on mobility and fuel consumption would require additional variables, such as vehicle-miles travelled, and a rather different approach that is beyond the scope of this paper.

5. Conclusions

In this paper we have presented the results from various specifications of a dynamic demand model for gasoline and diesel (for car use) estimated on Spanish regional data for 1999 to 2011. The paper showed that, after the outbreak of the economic crisis, price and income changes have had an additional effect on car-fuel demand in Spain. Put in other words, consumer response was found to be more elastic during the 2008-2011 recessive period than in the years before the crisis. A consistent finding across the different estimators employed in the analysis is that the diesel (gasoline) price elasticity is 0.005 (0.01) larger with respect to the pre-crisis levels. Besides, estimated income elasticities for diesel and gasoline were respectively 1% and 2% lower during the crisis than in the preceding (pre-crisis) years.

The paper thus suggests that the significant reduction of car-fuel consumption and the concomitant fall in sales and tax revenues, seen in Spain during the crisis, were partly due to changed values of price and income elasticities. It is clear that the behavior of Spanish car-fuel demand after the outbreak of the crisis responded both to soaring fuel prices and to strong economic difficulties for households (wage reductions, unemployment, etc.) and firms (a shrinking

[16] The values yielded by diesel models are outside the bound limits determined by the OLS and LSDV estimators, although they generally remain close.

internal demand). However, our results indicate that these effects were exacerbated by a modification of the demand elasticities. This indicates that the use of pre-crisis elasticities to anticipate the effects of changes (associated or not to public policies) would provide inaccurate results, as can be easily tested for the Spanish case with the pre-crisis existing (*ex-ante*) empirical evidence and real price, income and consumption data.

In addition, the larger (relative to diesel) change of gasoline elasticities observed by this paper suggests that private trips have been adjusted with more intensity during the crisis, as diesel cars are also used with commercial and industrial purposes. Moreover, the quantitative and qualitative changes seen in the stock of vehicles after the outbreak of the crisis provide an indication of the uncertainties and difficulties faced by Spanish households, with important environmental and energy implications. In view of all the preceding, our findings stress the importance of accurate panel data estimation with a special emphasis on the treatment of instrument proliferation problem in the GMM estimator and bias correction in the LSDV estimator. We feel that our empirical approach provides updated, robust and reasonable price and income elasticities of car-fuel demand in Spain, in line with those obtained by, among others, Baltagi and Griffin (1997), Baltagi et al. (2003) and Pock (2010) for different developed countries.

In a moment of pressing distributional constraints and important changes in the Spanish energy and tax domains, largely related to the severe and pervasive economic crisis themselves, it is particularly important crucial to have accurate estimates of the responsiveness of demand to price and income changes. Indeed, our findings suggest that strategies and policies related to car-fuel consumption need to be fully informed so that adaptation to a shifting socio-economic context can proceed in a swift, cost-efficient and equitable manner. This general message, together with the findings that can be derived from the depth and persistence of the Spanish crisis, make the paper interesting and useful for a wide international audience.

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APPENDIX

Table 1A. Tax percentage (including the VAT) in gasoline and diesel prices

	Gasoline	Diesel
2002	62,41%	56,46%
2003	62,30%	56,20%
2004	59,38%	52,72%
2005	55,29%	46,70%
2006	52,65%	44,88%
2007	52,08%	45,30%
2008	49,55%	40,53%
2009	55,89%	49,62%
2010	52,19%	46,23%
2011	48,82%	42,52%
2012	48,03%	42,42%
2013	49,72%	44,22%

Source: IEA (2013)

Table 1B. Variations of the Spanish regional data (n=13, T=1999-2011)

Variable		Mean	Std. Dev.	Min	Max	Observations	
lconsum_gaso	overall	-0.9592527	0.1753074	-1.536482	-0.6403677	N =	208
	between		0.0925207	-1.100147	-0.7951377	n =	16
	within		0.1505617	-1.486363	-0.7670143	T =	13
Lconsum_diesel	overall	0.6324673	0.2822562	-0.1629853	1.187666	N =	208
	between		0.2431682	0.120245	1.058359	n =	16
	within		0.1548084	0.196702	0.9461562	T =	13
lrprice_gaso	overall	4.358753	0.077941	4.229749	4.580325	N =	208
	between		0.0126542	4.336112	4.380669	n =	16
	within		0.0769672	4.229962	4.558409	T =	13
lrprice_diesel	overall	4.254227	0.1272432	4.028561	4.543659	N =	208
	between		0.012601	4.231012	4.27754	n =	16
	within		0.1266541	4.031713	4.520345	T =	13
Lr_income	overall	2.375897	0.1714385	1.942585	2.727612	N =	208
	between		0.1638207	2.116073	2.619407	n =	16
	within		0.0641072	2.161878	2.512158	T =	13
lcar_gaso	overall	-1.14843	0.2051803	-1.394382	-0.3858353	N =	208
	between		0.1929693	-1.33273	-0.5344707	n =	16
	within		0.0837883	-1.355165	-0.8936017	T =	13
lcar_diesel	overall	-1.256323	0.2627841	-1.910612	-0.8201838	N =	208
	between		0.1008541	-1.470117	-1.093262	n =	16
	within		0.2438721	-1.866398	-0.8227273	T =	13
lsaturation	overall	5.047483	0.8537941	3.270527	7.173471	N =	208
	between		0.8693967	3.867079	7.076682	n =	16
	within		0.1301199	4.252027	5.372236	T =	13

Source: Own calculations with data from Ministry of Industry, CNE, DGT and INE.